THE IMPACT OF COVID-19 ON SEABORNE TRADE CONNECTIVITY: EVIDENCE FROM THE GREECE-CENTERED NETWORK OF CONTAINERSHIP MOVEMENTS

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Abstract
Maritime transportation is regarded as the backbone of global trade, and container shipping as a major driver of globalization. The shock of COVID-19 pandemic had unprecedented adverse effects on the operation of container shipping industry. This paper investigates a multitude of these effects focusing on their network dimension. It exploits the ConTraffic database covering about 2,494,606 containership movements between Greek and non-EU ports during the period 2017-2022 to construct a Greece-centered global matrix of container shipping flows. The use of an advanced spatial network analytics framework, combining pattern recognition, community detection and decomposition methods, allows discerning several unique features of the container shipping markets, such as the relatively stable hub position of countries and trade flow imbalances between East and West. It further signifies the multiple scaling impacts of the pandemic shock on the container shipping connectivity at the country origin-destination level. The findings facilitate the identification of a few maritime trade communities among countries, with structurally resilient composition for the buyers' network between the two (pre- and during-pandemic) periods, albeit the reduction in the number of communities, increased regionalization, expanded spatial scope and weakened centrality and hierarchy. Conversely, the sellers' network shows reduced hub dependence, increased concentration and contracted spatial scope. The results help to evaluate the redistributed roles among countries as suppliers or buyers and new, emerging country hubs in the container shipping network, thus offering wider implications for the strategic and resilient (re)organization of the network connectivity in the post-pandemic era.
Keywords: maritime connectivity; container shipping; network structure; transportation hubs; COVID-19.

1. INTRODUCTION

Container shipping is crucial for the global economy, as it allows for the safe, cost-effective and efficient movement of goods across long distances and the easy transfer of cargo units between different transportation modes, streamlining the logistics process. Hence, it enables companies to access distant markets and expand their operations and opportunities to reach new customers and buy or sell goods from different areas of the world. In turn, container shipping services create jobs and stimulate investment in infrastructure, playing a vital role in connecting and integrating economies across countries and regions.

Among others, container shipping connects European ports with ports along the Maritime Silk Road, which is part of China's Belt and Road Initiative (BRI), allowing for the efficient transportation of goods and promoting trade and economic ties between East and West. The Chinese investments in European ports and related logistics infrastructure, particularly the investment of COSCO in Piraeus port, started with the leasing of one pier in 2009 and ended up (as of 2020) with the 67% of the port company's share capital, contributed to the presence of Chinese companies and the attraction of container liners to facilitate the transportation of goods between Far East and distribution centres across the European hinterland (Wang et al., 2019; Haralambides and Merk, 2020). Besides, the Thessaloniki's port was privatized in 2018; Belterra Investments Ltd owns about 72% of the company's share capital, while other significant parts are owned by Terminal Link (French CMA CGM and China Merchants Port Holding) and the Greek state. In this regard, Greece upgraded its overall port capacity and maritime hub position, becoming the major transshipment hub for Asian exporters in south Europe and the surrounding East Mediterranean region, allowing the accommodation of larger container ships and managing increased trade volumes.

A major challenge for container shipping is the ability to mitigate risks and support the resilience of maritime supply chains, through diversifying shipping routes/services and providing redundancy in case of negative circumstances, such as adverse weather, port congestion phenomena, canal closures and trade disruptions due to geopolitical turmoil, economic crisis, natural disasters, piracies/terrorist attacks, production line shutdown or other unforeseen events (Montes et al., 2012; Mesa-Arango et al., 2019; Kosowska-Stamirowska, 2020). In turn, these events can considerably affect the trade relationships and scale economies between production and consumption areas and their logistical hubs (Xu and Itoh, 2018). In the given context, the performance of container port terminals and their interconnectivity among countries are crucial to ensure the smooth operation of global and regional trade, through efficiently accommodating container shipping liner services.

The COVID-19 pandemic can be regarded as the most characteristic example of such a challenge, because of its extraordinary impacts on the global container shipping and container port operations. These impacts encompass disruptions in supply chains due to lockdowns, transportation and other restrictions, port labour, shipping crew and equipment shortages, and reduced vessel schedules or cancelled calls in response to lower demand. These impacts brought about trade flow imbalances, increased costs, loss of perishable goods, decline in customer satisfaction, delays in berthing, cargo handling and clearance processes, and congestion at ports, also given the imposition of health and safety protocols and the need of compliance with varying regulations (UNCTAD, 2021; Chua et al., 2022; Dirzka and Acciaro, 2022; Komaromi et al., 2022; Wang et al., 2022, Rogerson et al., 2024). The observed trade flow imbalances essentially reflected changes in consumer and production patterns across different regions, and growing freight rates and costs for shipping lines and import and export companies (Deuss et al., 2022), which are associated with longer turnaround times and limited capacity to serve demand. Hence, the COVID-19 pandemic highlighted the underlying vulnerability of the global container shipping industry and prompted efforts to examine how it can become more resilient and adaptable to changing supply chain conditions.

In this respect, the importance of using network analysis has been increased in order to comprehensively address complex interrelationships among countries (and ports) in the container shipping network and identify their critical position and varying impacts of exogenous shocks that more severely affect the global container shipping (Wang and Cullinane, 2014; Xu et al., 2015), compared to other types of freight shipping networks (Peng et al., 2018). The main hypothesis to be tested here is the existence of geographical shifts in the seaborne container trade, through changes in the maritime trade connectivity, hierarchy and clustering of countries, after the outbreak of the COVID-19 pandemic. For this purpose, a unique dataset containing information about the Greece-centered seaborne global trade connectivity is processed. In comparison to the individual port-level performance analysis, the present country-level perspective is crucial for strategic decision-making in areas such as trade policy, economic market integration and infrastructure planning. The study of the hierarchical structure of maritime container shipping can offer insights into which and how countries control or dominate container flows. The focus on geographical patterns of this structure also facilitates the explanation of where and why these flows occur.

The present analysis offers a comprehensive understanding of how a country-centered global container trade is dispersed, while hierarchy reveals power asymmetries, market concentration, and the strategic role of major trade partners. Besides, the quantitative analysis of spatial imbalances among core and peripheral economies in the container shipping network help us to explain interregional dependencies, trade polarisation and inequalities in global trade. It can also support realistic investment decisions, service design, alliance formation, regional trade agreements, and the identification of national and supranational logistics needs, e.g., along the maritime Silk Road between East Asia and Europe. In particular, the weakening of centrality and hierarchy in the container shipping network can be regarded as reducing vulnerability, since the global propagation of trade disruptions is attenuated, while higher clustering amplifies systemic risk. Last, geographical shifts in maritime container trade patterns are related to changing scale economies, and adjustments in vessel deployment and accessibility to hinterland destinations.

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

As far as the organization of the paper is concerned, Section 2 provides a review of the scholarly literature on the network analysis of container shipping services and, especially, the impact of COVID-19 pandemic shock. Section 3 describes the data and methodological issues about the graph modeling, the representation of network topology used for the analysis of the container shipping network and the related network metrics and community detection techniques, formulating the specific research (sub)questions to be addressed in the study. Section 4 reports and discusses the results, distinguishing ingoing/buyer (import) and outgoing/seller (export) flows of the container shipping network for two consecutive study periods, before and during the outbreak of the COVID-19 pandemic, i.e., during 2017-2019 and 2020-2022. Section 5 summarises and concludes with implications of the findings for understanding the structural properties of container shipping network and promoting its resilience and the interconnectivity among trading countries.

2. LITERATURE REVIEW

In the past two decades, there is a growing body of literature for the network analysis of container shipping networks, spanning different time periods and covering various types of regional and global networks and levels of spatial detail (e.g., Ducruet et al., 2010a; Ducruet et al., 2010b; Ducruet and Notteboom, 2012; Ducruet and Zaidi, 2012; Viljoen and Joubert, 2016; Cheung et al., 2020; Tsiotas and Ducruet, 2021; Ducruet, 2022; Ducruet and Notteboom, 2022). The main focus of this strand of research, which was considerably enlarged after the outbreak of the COVID-19 pandemic, concerns the investigation of the main structural components of the container shipping network, including the key role of container port terminals/regions, the distances between them, the criticalities/vulnerabilities and the robustness and resilience, in the presence of a variety of shocks, failures and attack strategies.

Particularly in the context of the COVID-19 pandemic shock, a handful of studies have attempted to determine its heterogeneous impact on various container shipping network metrics using the direct port-to-port connections (space-L) across different spatial scales and time periods. These data typically refer to the Automatic Identification System (AIS) which detects vessel movements. More specifically, Notteboom et al. (2021) examined the short-term demand and supply impacts of COVID-19 during the first two pandemic waves in 2020. They found that the impact on liner shipping connectivity, in terms of maximum size (TEU) of container ships visiting a port and the deployed capacity per port, had considerable variations among global regions and ports. The vulnerability of ports was found to be affected by several factors, such as the cargo mix, the port call choices of carriers, and the position of the port in the global shipping network and in its hinterland. However, they argued that shipping lines, terminal operators, and ports generally demonstrated an increased resilience, arguably as result of knowledge accumulated from the 2008/2009 financial crisis, and organizational changes in these industries, such as the vertical integration of container shipping and terminal operators.

Dirzka and Acciaro (2022) applied network theoretical indicators and simulations to measure the effect of shipping network disruptions during the pandemic's initial phases from January to May 2020. They identified shifting network dynamics through local propagations in geographically constrained clusters (mostly in East Asia) and stressed the importance of agile liner shipping operations to mitigate the adverse impacts of such catastrophic events. Among others, they highlighted the role of diversification and polycentric network structure, planned service suspensions, introduction of parallel or shared liner services and diversion to longer routes to handle operational capacity and maintain higher ship utilization rates during such events. The network analysis of Wu et al. (2024) also demonstrated the significance of shorter and more trans-regional routes, even with the reduction in the number of ports called on the routes, on the resilient response of global container shipping companies to the COVID-19 pandemic.

Li et al. (2024) employed network analysis using data for 2019 and 2020 to underline the critical role of the port size in the short-term COVID-19 pandemic impact. They found that major container ports, especially those with long-distance links across regions, experienced a greater decline in throughput on average than smaller ports. At the same time, they identified an increase of the global container shipping network robustness during the pandemic, due to the increased connections from/to the hub ports as well as the increase in cross-regional links and denser connections among the small- and medium-sized ports.

Pais-Montes et al. (2024) found that during the first period (2020-2021) of COVID-19 pandemic, the incidence of call cancellations affected more the ports attracting a large share of mega vessels along the Europe-Far East route, and European ports were significantly less affected than their counterparts in the other regions. They also found that the share of cancellations was generally larger at ports with higher betweenness centrality and clustering degree, implying a higher vulnerability (and substitutability) of hubs during disruption events. In opposite, Guerrero et al. (2022), using data for the period Spring-Summer-Autumn of 2019 and 2020, concluded that very large ports and small but densely inter-connected ones showed higher resistance to the pandemic shock than the others, while small ports playing hub or bridge functions appeared to have been more negatively impacted. They further mentioned that the pandemic effects were different according to the region, the containment measures and the underlying changes in the macroeconomic environment. Moreover, Bai et al. (2022) found considerable dynamic changes in the connectivity/centrality positions among container ports even within neighbouring regions, while Nguyen et al. (2024) identified a significant spatial and time heterogeneity in the recovery of port connectivity (in Southeast Asia) during the COVID-19 pandemic. The increased

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

heterogeneity was attributed to the stringency, timing and effectiveness of mitigation and reopening policies, including the financial support measures and digital solutions, the amount and efficiency of port infrastructure, as well as external factors, such as those related to the local economic growth and occurrence of natural disasters.

This paper investigates the long-run impacts on intercountry container shipping connectivity of the COVID-19 pandemic spanning the period 2020-2022, compared to the 2017-2019 period. In contrast with previous efforts to assess container shipping network metrics largely using the direct port-to-port connections in the space-L, this study employs a suitable space-P network reconfiguration (Section 3), disentangling buyers and sellers, using the rich dataset of ConTraffic and a spatial network analytics framework. This framework combines spatial network pattern recognition, community detection and decomposition methods to demonstrate changes in the cross-country maritime shipping connectivity, the hierarchical structure and the geographical deconcentration (regionalization) following the pandemic outbreak.

The hierarchical structure has been identified in the specific industry (Hu and Zhu, 2009) where many regions' secondary ports have been found to grow strongly and have lowered the centrality of larger ones (Seoane et al., 2013; Tran and Haasis, 2014; Kosowska-Stamirowska et al., 2016). In the present context, the detailed analysis centred around a country's port system can offer insightful explanations of the impact of COVID-19 pandemic, especially in the light of the significant investment and functioning of Greece as a major transshipment hub of the East Asia to south Europe and the surrounding East Mediterranean region. Besides, the country-level approach provides a macro-level view of the global maritime container shipping, allowing for the analysis of the trade integration, clustering and vulnerability of countries in response to the COVID-19, which the port-level analysis might obscure. In turn, the study of these changes from a national perspective can facilitate the comprehensive understanding of the role and vulnerability of countries in the entire maritime container shipping network, so that support more effective government policies and strategic infrastructure decisions to counter risks of such extensive and persistent disruptions.

Furthermore, the analysis and interpretation of the COVID-19 pandemic impacts are examined here from the perspective of the transportation and economic geography of the interconnected port countries/regions. Specifically, these interconnections enable varying access to world markets and shape heterogeneous regional clusters (Kaluza et al., 2010; Bouveyron et al., 2015). Also, containership flow imbalances can be seen from the spectrum of the spatial and strategic coupling among port regions/countries (as container trade market origins and destinations) having uneven ability to match local assets with global demands and combine logistical needs with wider economic functions in their own or neighbouring (cluster) areas (Jacobs and Lagendijk, 2014; Ducruet and Itoh, 2016).

3. DATA AND METHODS

3.1. Study Area and Data Description

The current study employs a unique dataset originating from the ConTraffic, that is a research project of the European Commission developed by the Joint Research Centre in collaboration with the European Antifraud Office and DG Taxation and Customs to provide information on container routes (between the EU and non-EU ports), as well as risk assessment services to users from customs and security authorities. The dataset, which includes information about the container liner shipping connections between the Greek ports and all ports beyond the EU, reveals the directional trade flow asymmetries between East-West, which were intensified during COVID-19 pandemic. Specifically, on the one side, the total number of containership movements from Greek to non-EU ports during the period 2017-2022 amounted to 1,123,033, showing a reduction of 26.5% between 2017-19 and 2020-22 (from 647,225 to 475,808 movements, respectively). On the other side, the total number of containership movements from non-EU to Greek ports during the period 2017-2022 amounted to 1,371,573, showing a reduction of 15.8% between 2017-19 and 2020-22 (from 744,665 to 626,908 movements, respectively) (Fig.1). In order to show the existence of statistically significant imbalance among the containership flows departing from and arriving to the Greek ports, we use the unpaired Welch's two-sample t-test analysis (Welch (1947). This analysis provides a comparison of the average container vessel loading values corresponding to the two groups, while allowing for the possibility their variances to be different. The test results show the statistically significant difference (directional imbalance), $\mu_{FROM} < \mu_{TO}$, between the population means of the containership flows departing from (μ_{FROM}) and arriving to (μ_{TO}) the Greek ports to/from the non-EU ports, both before and during the pandemic, with values t = -81.261 and t = -69.551, both having Pr(T < t) = 0.000.

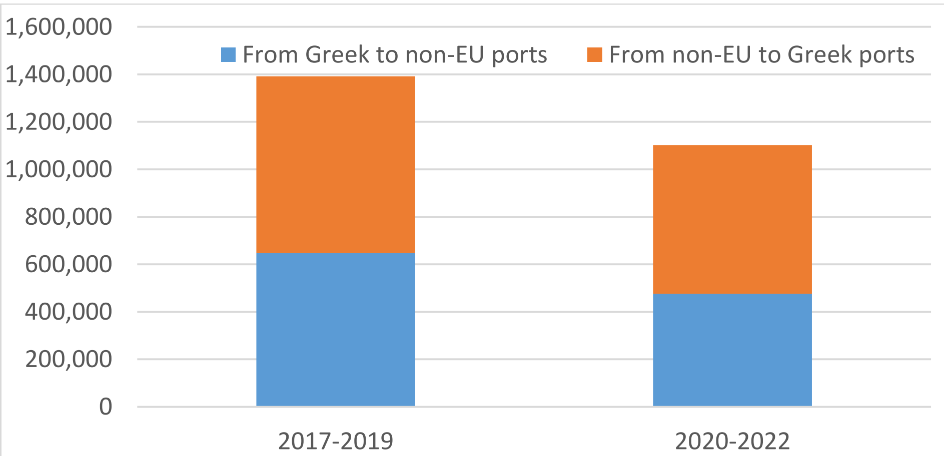


FIGURE 1 - TOTAL NUMBER OF CONTAINERSHIP MOVEMENTS BETWEEN THE GREEK AND NON-EU PORTS DURING THE PERIODS BEFORE (2017-2019) AND AFTER (2020-2022) THE OUTBREAK OF THE PANDEMIC

Theoretical and Empirical Researches in Urban Management

Volume 21 Issue 2 / May 2026

Theoretical and Empirical Researches in Urban Management

Volume 21 Issue 2 / May 2026

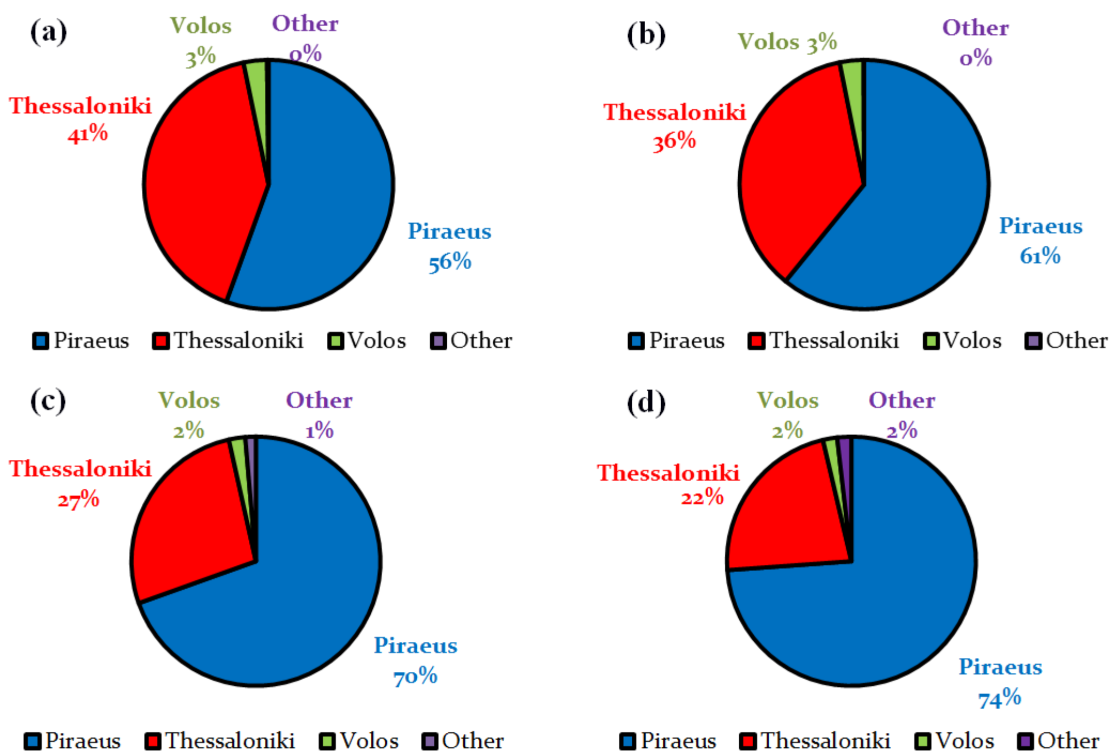


FIGURE 2 - DOMESTIC MARKET SHARES OF MARITIME CONTAINER TRAFFIC FROM GREEK TO NON-EU PORTS (***A***) BEFORE (2017-2019) AND (***B***) DURING (2020-2022) THE PANDEMIC; AND FROM NON-EU TO GREEK PORTS (***C***) BEFORE AND (***D***) DURING THE PANDEMIC.

The significant amount of foreign container traffic in Greece can be mainly attributed to the commercial activities of the Piraeus seaport, which has remarkably improved its throughput and the corresponding domestic market share since 2009, strengthening its position as a major transshipment hub in the region. The container vessel arrivals at and departures from the Greek seaports present a directional imbalance, which depicts the more intense flow of goods from East Asia to Europe along the international maritime trade corridor traversing the Suez Canal, compared to the flow from the opposite direction. Fig.2 clearly shows that Greece is a two-hub market for the global container shipping industry, as Piraeus and Thessaloniki cover the largest (>95%) share of the domestic market. Regarding both directions of containership flows, the market was further concentrated in favour of the Piraeus port after the pandemic outbreak. Specifically, from Greek to non-EU ports, Piraeus increased its market share from 55.5% to 61%, while from non-EU to Greek ports, Piraeus increased its dominant market share from 70% to 74%. The unpaired Welch's two-sample t-test analysis indicates that the mean of the containership flows from/to the Piraeus port ($\mu_{PIRAEUS}$) is significantly larger than the mean of containership flows from/to the other Greek ports (μ_{OTHER}), i.e., $\mu_{PIRAEUS} > \mu_{OTHER}$, both before and during the pandemic, with values t = 54.318 and t = 90.572, both having $\Pr(T > t) = 0.000$.

3.2. Graph Modeling

This analysis builds on the graph modeling of the network of containership movements, namely, the container vessel departures from the ports of loading and the container vessel arrivals to the ports of discharge. This modeling aims to examine the changes induced in its topological characteristics between the periods before (2017–2019) and during (2020–2022) the COVID-19 pandemic, by applying complex network analysis. We assume that each vessel movement (departure or arrival) configures a complete subgraph. Namely, a graph in which all ports servicing the same vessel are mutually connected and represent the graph models in space-P (Barthelemy, 2011), in line with the modeling approach adopted in the studies of Hu and Zhu (2009) and Ducruet (2022). The set of subgraphs configured from the containership movements based on the ConTraffic database is aggregated at the national level (NUTS0) to construct the overall maritime network, i.e., the International Container Shipping Network (ICSN), whose nodes represent countries (national port groups) and edges represent the number of container vessel trips between countries. In general, in the space-P representation, links represent at least one path connecting two network nodes (Barthelemy, 2011), regardless of whether this connection is direct or not. For example, in space-P, a shipping line with three successive port departures/arrivals at A, B, and C is represented by a (complete) graph, in which all possible pairs of the three nodes are interconnected. This approach differs from most representations where network consists of direct port-to-port connections (space-L), as in the studies of Bartholdi et al. (2016), Wang et al. (2016), Huang et al. (2018), and Pan et al. (2019).

Indicatively, in the example of a shipping line with three successive departures/arrivals (A, B, and C), a space-L representation would include only the links AB and BC. Therefore, constructing a graph model in space-P emphasizes on access (the potential of connectivity) rather than directedness (as in the case of a space-L model) between nodes, without accounting for the intermediate stops along the route connecting them. Space-P is called as the “space of changes” (Barthelemy, 2011), because the topology it imposes on a graph captures state changes through two successive links, that is, the (trans)shipment character (e.g., transshipment from route A to route B) for the case of ICSN. This representation is considered an effective approach for modeling networks subject to logistical distances (Rodrigue et al., 2013), as is the container shipping network case, where research interest is primarily focused on access rather than communication immediacy. Furthermore, the ICSN’s space-P modeling undertaken in this paper allows interpreting this network beyond its Greek-centered configuration as a global maritime trade market, through linking all nodes included along every generated path.

More specifically, we construct four (4) directed weighted graphs represented in the space-P, defined by the vessel movement directionality (from Greece ≡ buyers’ network, to Greece ≡ sellers’ network) and by the time reference to the COVID-19 pandemic condition (before and after 2020). Within this framework, differences observed in network metrics between the temporal layer classifications (2017–2019≡17-19 and 2020–2022≡20-22) can be associated with the emergence of the COVID-19 pandemic, whereas differences between the sellers' (S) and buyers' (B) layers can be attributed to the structural characteristics of the ICSN related to trade flow directionality. From a network perspective, this collection composes a multilayer network denoted as $\mathcal{M}(\mathcal{G}, \mathcal{C} = \emptyset)$ (De Domenico et al., 2013; Boccaletti et al., 2014; Kivela et al., 2014), where $\mathcal{G} = \{B_{17\text{-}19}, B_{20\text{-}22}, S_{17\text{-}19}, S_{20\text{-}22}\}$ expresses the set of graph layers and $\mathcal{C}$ represents the (null, in the case of the ICSN) set of interlayer connections. The first two layers, $B_{17\text{-}19}$ and $B_{20\text{-}22}$, represent the container vessel movements in the buyers' network, whereas the latter two layers, $S_{17\text{-}19}$ and $S_{20\text{-}22}$, represent the container vessel movements in the sellers' networks, for the periods 2017–2019 and 2020–2022, respectively.

The purpose of distinguishing between the buyers' and sellers' cases is to examine the role of directionality in the ICSN, arguing that, in this maritime logistics network, directionality (incoming vs. outgoing flows) matters and can provide insights in the trade direction and balance (Capello, 2016; Krugman and Wells, 2021). That is, origin countries (or the providers of intermediate trade countries) with a significantly higher relative volume of outgoing flows exhibit a production surplus and export capacity, implying that they can support their economic and development mechanisms through exports and experience the advantages of multiplier effects (Tsiotas, 2022), according to the Keynesian multiplier approach (Krugman and Wells, 2021) and the export base theory (Tiebout, 1956; North, 1955). Conversely, countries with a higher relative volume of incoming flows exhibit import-oriented economic profile, contributing to the diffusion of demand (Tsiotas, 2022), income leakages and foreign economic dependencies. In this framework, the direction-specific ICSN's configuration provides differentiated insights into the global distribution of production and consumption, while, from a geopolitical perspective, it may reveal dependencies and influence relationships among the countries comprising each network layer (buyers vs. sellers).

3.3. Network Analysis

3.3.1. Global network measures' analysis

Following the multilayer graph modeling, we examine the topological features of the four ICSN layers to detect changes in the network topology after the pandemic outbreak. In conceptual terms, we conceive the network topology as the prevailing rule describing the arrangement of network elements (nodes and edges) within a relational layout (Tsiotas and Polyzos, 2018), namely, as the organization of a graph's elements in a non-metric (topological) space. Relevant theoretical and empirical research (Koschutzki et al., 2005; Newman, 2010; Barabasi, 2013; Barthelemy, 2011; Tsiotas, 2019) has shown so far that networks of different topologies (such as random, lattice, small-world, hub-and-spoke, etc.) exhibit distinct properties in terms of connectivity, path accessibility, density, and related features. In this context, network topology is widely regarded in the literature as a comprehensive and defining state of a network's structure, functionality, and growth dynamics.

In general, computing a wide range of metrics for studying network topology is not a methodological luxury but rather a necessity inherent in the nature of networks themselves. This is because real-world networks are typically complex (Boccaletti et al., 2006; Barthelemy, 2011; Tsekeris, 2017; Tsiotas and Ducruet, 2021), thus, each metric captures a different facet of their topology. That is, since no single measure can adequately represent all the universal properties of a network, multiple measures must be examined simultaneously. This multi-measure approach allows depicting different aspects of network complexity and formulating a research question (**Q_1**) whether the COVID-19 pandemic induced significant changes in the ICSN's topology.

The conceptual framework underpinning this approach builds on the assumption that, although it is a maritime trade network centered on Greece, the reconstruction of the ICSN in space-P allows inferring to broader information on global maritime trade flows than solely to Greece's direct trading activity. In this context, despite the fact that network nodes $n(t)$ at each time t (t=17-19, 20-22) provide census-type information (namely, they encompass the entire countries' set participating in containership routes encompassing Greece), their number $n(t)$ may be regarded as a sample of the broader network set of $N(t)$ nodes composing the overall global container shipping market. Based on this assumption, the analysis seeks to provide inferential insights into the impact of COVID-19 on container shipping connectivity, rather than a narrow focus on Greece, from which the underlying database originates. Given that the limited availability of time data in this study (six years) hinders the application of inferential tests based on long timeseries means or differences (allowing interval estimation and inferences under given levels of certainty), we adopt an inferential statistical approach based on binomial distribution (Norusis, 2011; Walpole et al., 2012), providing a direct analogy to the estimation of proportions in electoral polling. In particular, in a network of n nodes, we assume that the relative change $\frac{\Delta X}{X_o} = \frac{X_t - X_o}{X_o}$ of a topological quantity X (e.g., number of nodes, edges, average degree, etc.) can be treated as an estimator of an unknown population proportion p drawn from n population units (Walpole et al., 2012). This assumption rests on the standard conditions outlined by Norusis (2011) and Walpole et al. (2012), namely: (*i*) independence (i.e., each of the n population units –nodes– is considered statistically independent with respect to the formation of X); (*ii*) equal contribution (i.e., each population unit contributes equally to the formation of X); and (*iii*) asymptotic normality, meaning that the $\hat{p}$ estimator's distribution is approximated by the Central Limit Theorem (i.e., by the normal distribution), thereby allowing the construction of confidence intervals of the form:

$$CI_{(1-a)}(p) = \hat{p} \pm z_{1-a/2} \cdot SE(\hat{p}) = \hat{p} \pm z_{1-a/2} \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n}} \quad (1)$$

where $\hat{p} = \frac{\Delta X}{X_o} = \frac{X_t - X_o}{X_o}$, $z_{1-a/2}$ is the *z*-score of confidence level 1−α, and *n* is the sample size (i.e., the number of nodes).

However, given that the network nodes do not constitute independent statistical units (since each node is interdependent – connected with its neighbors), using the full sample size in equation (1) may lead to an underestimation of the uncertainty associated with $\hat{p}$. To account for the correlation due to network connectivity, we conduct the analysis under the conservative assumption of a reduced effective sample size n_{eff}, which –due to network size– cannot be estimated asymptotically (Kolaczyk and Krivitsky, 2015) but approximately, by taking into account the local average neighbor degree, following the approach proposed by Chen and Su (2023). Within this framework, we estimate n_{eff} at the level of blocks (hypernodes) comprising connected neighbors, rather than at the individual network node level. Specifically, we assume that the structural entities satisfying the independence condition are hypernodes of size $\langle k \rangle$+1, consisting of a node itself (i.e., including a self-connection) along with its neighborhood, therefore estimating the effective sample size as follows:

$$n_{eff} = \frac{n}{\langle k \rangle + 1} \quad (2)$$

where *n* is the number of network nodes. For the sake of methodological conservatism, we estimate the effective sample size (n_{eff}) by using the minimum network size and the maximum average degree across the available layers $\mathcal{G}$={$B_{17\text{-}19}$, $B_{20\text{-}22}$, $S_{17\text{-}19}$, $S_{20\text{-}22}$}, as follows:

$$\begin{aligned} & n_{eff}\ s.t. \\ & n = min\{n_{B_{17-19}}, n_{B_{20-22}}, n_{S_{17-19}}, n_{S_{20-22}}\} \\ & \langle k \rangle = max\{\langle k \rangle_{B_{17-19}}, \langle k \rangle_{B_{20-22}}, \langle k \rangle_{S_{17-19}}, \langle k \rangle_{S_{20-22}}\} \end{aligned} \quad (3)$$

where n_j stands for the number of nodes of set *j*. For the empirical data used in this analysis, the effective sample size n_{eff} results in 23 units, corresponding to approximately 17% of the total network size.

In general, network science (Albert and Barabasi, 2002; Barabasi, 2013) provides a broad range of metrics and measures for complex network analysis, capturing multiple aspects of network structure and functionality (Newman, 2010; Tsiotas and Polyzos, 2018), connectivity (Newman, 2010; Barthelemy, 2011), accessibility (Barthelemy, 2011), efficiency (Newman, 2010), centrality (Koschutzki et al., 2005), similarity (Tsiotas, 2019), and divisibility or community structure (Blondel et al., 2008; Fortunato, 2010). In this paper, we argue that the joint assessment of these dimensions approximates the concept of network topology and –for the purposes of this study– we select a representative compact set. Specifically, in a maritime trade network, the number of nodes n (Newman, 2010; Barthelemy, 2011) generally represents the number of physical or organizational locations (entry, exit, storage, transfer, etc.) comprising the logistics chain of trade flows. In the case of the ICSN, nodes represent the countries participating in the network of international containership flows, collectively expressing the size and degree of complexity of the network.

Correspondingly, the number of edges m (Newman, 2010; Barthelemy, 2011) in the ICSN reflects the number of functional relationships developed along trade routes between countries. At the local level, degree k generally denotes the number of edges incident to a node (Albert and Barabasi, 2002; Barthelemy, 2011) and, for the ICSN, represents the set of countries that are functionally related to a given country-node through maritime trade routes. To the extent that trade flows between countries are shaped within the framework of neoclassical market equilibrium (Krugman and Wells, 2021; Capello, 2016), the node degree k may express a country's level of integration into the global trade network, while the average degree $\langle k \rangle$ denotes the expected level of integration of a country within the ICSN (i.e., the number of trade routes shared by a randomly selected node). When edge weights are taken into account, the weighted degree k_w (Albert and Barabasi, 2002; Barthelemy, 2011) –or node strength s– in the ICSN captures the total volume of trade activity linking a specific country-node to the rest of the network (thereby complementing the unweighted degree by incorporating the intensity of functional international trade relationships in terms of shipment frequency and time-distance). Analogously, the average node strength $\langle s \rangle$ reflects the expected frequency of trade activity connecting a country to others, delineating the intensity of node integration within global maritime trade flows. Furthermore, by incorporating directionality into degree and strength measures, we define in-degree (negative flow sign) and out-degree (positive flow sign), as well as in-strength and out-strength (Barthelemy, 2011), accounting for the intensity of incident edges. In the ICSN, the out-degree and out-strength (k+, s+) indicate the importance of a country-node as a source of export or outbound container flows, whereas the in-degree and in-strength (k–, s–) indicate its importance as a destination of imports or inbound container flows.

Graph density ρ generally expresses the share of existing edges to the network's potential connectivity (Newman, 2010); in the case of the ICSN, it describes the degree of mutual integration of countries within the trade network. The network diameter (dG) represents the longest of the shortest paths connecting any two nodes in a network (Koschutzki et al., 2005); for the ICSN, it corresponds to the longest trip chain of international containership flows, thus capturing the spatial extent of the network's global market dispersion. In addition, modularity (Q) measures the degree to which a network can be divided into communities (Blondel et al., 2008; Fortunato, 2010); for the ICSN, it reflects the number of local markets emerging within the international trade network. The local clustering coefficient $C(i)$ expresses the share of mutual connections among a node's neighbors (Newman, 2010) and can attain a weighted $C_w(i)$ expression when considering in addition the edge weights; in the context of the ICSN, it captures the degree of integration of local maritime trade markets along the network's trade routes. Finally, the average path length $\langle l \rangle$ generally denotes the expected distance between two randomly selected nodes in a network (Barthelemy, 2011); for the ICSN, it represents the expected number of shipments per trade route. These measures are selected so as to shape, as comprehensively as possible, an overall picture of network topology, in terms of connectivity (degree, strength, clustering, and density measures), access and accessibility efficiency (path-based measures), and modularity. The network measures considered in this analysis do not exhaust the full set available in the network science literature (Koschutzki et al., 2005; Newman, 2010; Barthelemy, 2011). Although the topological analysis in this paper should not be regarded as exhaustive, it builds upon a solid methodological framework based on interlayer comparisons, which suffices to yield meaningful and insightful empirical results for the ICSN.

Subsequently, we apply two complementary approaches to probe the degree of differentiation of the prevailing ICSN's topological patterns: the examination of the degree distribution (Albert and Barabasi, 2002; Newman, 2010; Barthelemy, 2011) and the computation of the small-world (SW) approximation omega (ω) index (Telesford et al., 2011). By and large, the study of emergent patterns in complex network topology is a particularly important element of network analysis (Albert and Barabasi, 2002; Barthelemy, 2011), providing insights into the underlying growth network mechanisms, as well as their development potentials and constraints (Rodrigue et al., 2013; Tsiotas, 2019). In general, in spatial networks (Barthelemy, 2011; Rodrigue et al., 2013) –and, particularly, for the ICSN– meaningful topological configurations are the hub-and-spoke, lattice, and random patterns. The hub-and-spoke topology (Albert and Barabasi, 2002; Barthelemy, 2011) implies the existence of economies of scale (see Krugman and Wells, 2021) and spatial agglomeration (see Capello, 2016), as hubs accumulate a large number of connections and high volumes of trade at specific geographical locations.

In the context of regional economics and economic geography (Krugman, 1991; Capello, 2016; Fratesi et al., 2024), a hub-and-spoke topology may provide evidence of a composite Core-Periphery model stimulating growth through centripetal forces between a hub and its associated spokes. From a technical perspective, this topology is associated with the scale-free (SF) property (Tsiotas, 2019) and is empirically identified by examining whether the degree distribution –computed from the frequency of nodes exhibiting a given degree– follows a power-law (PL) pattern with an exponent lying within the interval 2<γ<4 (Albert and Barabasi, 2002). The lattice topology (Barthelemy, 2011; Telesford et al., 2011; Tsiotas, 2019), in turn, indicates the presence of strong geographical constraints in spatial networks and an underlying mechanism of spatial competition among equivalent spatial units, whose coexistence in geographical space either does not favor the emergence of spatial concentrations (Rodrigue et al., 2013; Tsiotas, 2019; Tsoulias and Tsiotas, 2024) or has led to functional (economic) differentiation and complementarity. The random (Erdos-Renyi) topology is associated with the absence of causal forms of spatial organization in networks (Barthelemy, 2011; Rodrigue et al., 2013). From a technical viewpoint, we compute the omega (ω) index of Telesford et al. (2011) to detect random and lattice topologies. The omega index is calculated by comparing the clustering and the path length of the empirical network to those of an equivalent lattice network and an equivalent random network, respectively, using the Maslov and Sneppen's (2002) 'randomization' algorithm and the Rubinov and Sporns' (2010) 'latticization' algorithm. Values of $\omega \approx 0$ indicate small-world properties, positive values ($\omega > 0$) indicate random-like (RL) characteristics, whereas negative values ($\omega < 0$) indicate lattice-like (LL) characteristics. Since the computation of the ω index relies on heuristic algorithms, we perform iterative calculations, conducting 30 repetitions and constructing confidence intervals at varying confidence levels (90%, 95%, and 99%) for the mean the ω index in each case.

3.3.2. Community detection analysis

In the final stage of the analysis, we implement community detection techniques based on the modularity optimization algorithm of Blondel et al. (2008) to uncover the ICSN's community structure. In general, community detection in spatial networks (Fortunato, 2010; Barthelemy, 2011) contributes to the understanding of the internal structure of complex spatial systems, through identifying groups of nodes that are more densely connected to each other than to the rest of the network. The algorithm we apply in this paper (Blondel et al., 2008) provides results of group membership for each node by assigning them to communities and examining iteratively the overall score of the modularity function (Q), which expresses the network's divisibility. The modularity function is defined by the difference between observed and expected connectivity within network communities. Zero scores (Q=0) describe concrete, non-modular networks (such as star graphs), those approaching one ($Q \to 1$) describe highly divisible networks (Fortunato, 2010), whereas asymptotically infinite values ($Q \to \infty$) correspond to disconnected networks. The algorithm is greedy in nature, as it seeks to maximize intra-community connectivity while minimizing inter-community connectivity (Blondel et al., 2008). Within this context, the resulting network communities have dense internal connectivity and sparse inter-community connectivity (Blondel et al., 2008; Fortunato, 2010). The modularity algorithm we apply operates in two stages. In the first stage, nodes are initially assigned to separate communities and then are sequentially merged into common ones whenever the gain in the weighted modularity function Q_w –accounting for weighted instead of

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

binary connectivity– increases. In the second stage, the resulting communities are treated as nodes, and the procedure is repeated iteratively until convergence is achieved.

Given the heuristic nature of this algorithm (Fortunato, 2010), we subsequently apply a non-parametric chi-square test (McHugh, 2013; Sharpe, 2015) to examine whether a statistically significant association exists between the community structures identified in the periods 2017-2019 and 2020-2022. From a methodological perspective, the criterion employed by the algorithm (Blondel et al., 2008) to divide the ICSN into communities with strong intra-community (i.e., within communities) and weaker inter-community (i.e., between communities) connections enables the detection of latent structures within the network. These structures correspond to functional regions (Tsiotas and Kallioras, 2025) rather than strictly separated components (such as connected components, which in economic systems correspond to closed economies). In the case of the ICSN –which is assumed in this paper as a proxy for the global market of maritime trade flows– community detection is expected to provide insights into the formation of the network's 'local markets', that is, zones or regions with functional coherence in their maritime trade activities. More specifically, in the space-P representation, communities correspond to compact zones of maritime trade corridors, emerging from mutual containership paths along countries participating as nodes in the network.

In this context, community detection in the ICSN is an approach of critical importance for the research objectives of this paper, as it is expected to address the research question (**Q_2**): whether the COVID-19 pandemic induced significant changes in the internal organization –namely, the community structure– of zones within the global container shipping network. To address this question, we distinguish among two aspects of the ICSN's internal organization, i.e., the community composition (membership) and the spatial contingency (proximity), guiding subsequent analyses and statistical tests aimed at detecting changes in the community structure during the pandemic. In the ICSN's community detection analysis, the effective sample size (n_{eff}) correction discussed in equations (2) and (3) is not adopted. This methodological approach implies that the node degree –which affects grouping and, hence, inter-community configuration– and the heuristic nature of the algorithm itself apply a repairing mechanism to inter-community independence.

Within this framework, we adopt a threefold approach to examine changes in the group membership composition. First, we apply chi-square (χ^2) tests to determine whether there is a significant association between the composition of communities before and during the pandemic. In general, a chi-square test is applied to a cross-tabulation matrix constructed from two categorical variables to measure the asymmetry in group frequencies between the examined pair of variables relative to the case in which they are unrelated (McHugh, 2013; Sharpe, 2015). The null hypothesis (H_0) assumes no association (i.e., the ICSN's community composition before and during the pandemic is uncorrelated), whereas the alternative hypothesis (H_1) assumes an association. The test is conducted by calculating the χ^2 statistic, with p-values ≤0.05 (or, more loosely, ≤0.10) typically leading to rejection of the null hypothesis. Alongside the χ^2 statistic, we compute symmetric measures (Phi, Cramer's V, and symmetric Lambda; Norusis, 2011) to gain insights into the strength of the association. Lambda (λ) measures proportional reduction in error, assessing the asymmetry of the relationship between the paired variables in the contingency matrix (Norusis, 2011). Significant cases ($p \leq 0.05$ or $p \leq 0.10$) indicate that row and column variables are asymmetrically distributed in a statistically meaningful way. The Phi (φ) coefficient evaluates the strength of the pairwise correlation between the examined categorical variables, where, for binary cases, it ranges within [-1, 1] (with $\varphi = 0$ indicating no correlation), whereas for variables with more than two categories, it has no theoretical upper bound (Norusis, 2011). Finally, Cramer's V generalizes the φ coefficient, considering the number of categories in each variable to yield an upper bound of 1. This approach addresses the research question (**$Q_{2.1}$**) of whether the pandemic led to structural changes related to the initial network's community configuration (or induced structural reconfiguration of the containership flow map).

The second part of the membership composition analysis concerns the detection of statistically significant changes in the relative size of communities before and during the pandemic. This analysis aims to address the research questions: (**$Q_{2.2}$**) whether the share of communities in the global container shipping network changed significantly and (**$Q_{2.3}$**) which communities contributed to these changes. For this purpose, cross-tabulation and confidence intervals at variable levels (90%, 95%, 99%) are used to measure the relative (percentage) size of communities and the stable community members before and during the pandemic, based on the method of estimating an unknown population proportion p, as shown in Equation (1). The third examination of the ICSN membership composition focuses on detecting stable (fixed) intra-community relationships, and it addresses the question (**$Q_{2.4}$**) of whether the pandemic destabilized maritime trade cooperation relationships (**$Q_{2.4.1}$**) for each continent and (**$Q_{2.4.2}$**) along trade directions (for buyers and for sellers).

Finally, as regards the communities' spatial contingency, the analysis relies on the calculation of physical (kilometric) distances among the countries comprising the ICSN communities to detect changes in their geographical composition. This analysis comes into alignment with the theories of regional economics and economic geography (Krugman, 1991; Capello, 2016; Fratesi et al., 2024), which posits that geographical distance provides a friction in spatial economies, typically hindering the emergence of agglomeration economies and the integration of regional markets. In this theoretical framework, the spatial contingency of communities is examined through two approaches: first, by constructing confidence intervals at variable (90%, 95%, 99%) levels for the mean intra-community distances (i.e., kilometric distances between pairs of countries within the same community) before and during the pandemic, assuming a Student's t-distribution (Norusis, 2011; Walpole et al., 2012); second, by applying the Theil index decomposition method (Akita, 2003), which is a widely used entropy-based approach for the study of spatial inequalities (Tsiotas and Polyzos, 2013), to estimate the share of intra-community and inter-community inequalities in shaping spatial disparities across the ICSN communities. The latter approach addresses the research question (**$Q_{2.5}$**) whether observed spatial changes in community composition are attributable to intra-community or inter-community heterogeneity. In this case, confidence intervals are constructed under the assumption that the within-community (T_w) and between-community (T_b) Theil index's components can be treated as averages instead of point values and are computed using the standard error of the entire set of inter-country distances available for the ICSN.

4. RESULTS AND DISCUSSION

4.1. Global network analysis

Starting the ICSN analysis at a global scale, we show the composition of the network core consisting of the 15 countries with the highest node strength (i.e., the largest total volume of serviced shipments per country) (Table 1). In this part of the analysis, we focus on countries located within the core defined by the 10th percentile ($CoreP_{10}$) of network participants and others below (e.g. $CoreP_{7.5}$, $CoreP_5$, $CoreP_{2.5}$, $CoreP_1$), noting that the number of nodes per ICSN level is average, i.e., (136, 140, 150, 156) ≈ 146 nodes. The results reveal notable differences in the functional role of countries during the pandemic crisis, from both the buyers' and the sellers' network perspectives, compared to the pre-pandemic period. Within the buyers' network, countries such as China, Cyprus, the United States, and Turkey maintained their dominant positions, consistently occupying the top four ranks. However, the volume of containership flows for the subset of the four strongest core countries ($CoreP_{2.5}$) shows substantial losses (ranging between 15% and 50%), reflecting the generalized shrinkage of containership flows within this functional core during the pandemic. Furthermore, the countries occupying the top eight positions (i.e., forming the $CoreP_5$) retained their relative ranking with minor reshuffling, suggesting the existence of a stable structural core with a strategic role in the global container shipping network. Across the full set of countries forming the $CoreP_{10}$ in the buyers' network, 14 out of 17 unique cases remained within the core during the pandemic. This ratio provides a raw indication of the core cohesion at approximately ~75% (with a 95% Student's t-statistic confidence interval ranging from 54% to 98%, as described in Equation (1)). Nevertheless, notable reshuffling is observed within the $CoreP_{10}$: Indonesia and Italy are functionally downgraded and exit the core, while Lebanon and Russia are upgraded and enter the core. Geographically, this entry-exit pattern in the $CoreP_{10}$ indicates an eastward shift of the functional center of the buyers' ICSN core.

Similarly, in the sellers' network, China, Belgium, and Turkey maintained their dominant roles and hierarchy as the three strongest nodes (forming the $CoreP_2$), albeit they experienced functional strength losses of 10%–22%. Additionally, the countries occupying the top eleven positions (forming the $CoreP_{7.5}$) remained within the core, with no substantial reshuffling, suggesting the presence of a structural core in the sellers' network with greater stability compared to the buyers' network. Across the $CoreP_{10}$ of the sellers' network, 14 out of 16 unique cases remained within the core, yielding an approximately core cohesion of ~88% (with a 95% Student t-statistic confidence interval of 75%–100%, as described in Equation (1)). Observed reshuffling within the $CoreP_{10}$ includes the exit of Finland and the entry of Israel, indicating a more distinguished eastward shift of the functional center of the sellers' network core. Overall, considering both directions within the ICSN, we observe that the pandemic primarily affected the intensity of containership flows rather than the structural network's architecture.

Next, the topological measures of the ICSN (Table 2) provide a macroscopic overview of its structural changes across directions (buyers vs. sellers). Within the buyers' network, we initially observe that 64% (9/14) of the network measures exhibit statistically significant changes, of which 43% (6/14) reach 1% significance. The measures showing significant change in the buyers' ICSN include the number of edges m, the average degree $\langle k \rangle$, the average strength $\langle s \rangle$, the network density ρ, the weighted-by-arrival-days modularity Q_t, and all aspects of the average clustering coefficient $\langle C \rangle$. In contrast, the number of nodes n, the network diameter dG, the number of connected components (comp) and average path length $\langle l \rangle$ do not show statistically significant changes. Considering that n and dG capture network size and length, comp reflects network cohesion, and $\langle l \rangle$ accessibility, whereas the remaining measures pertain to connectivity (Barthelemy, 2011; Tsiotas and Polyzos, 2018), the results of Table 2 suggest that the buyers' network underwent internal restructuring in response to the COVID-19 pandemic. Specifically, the connectivity and neighborhood-level clustering increased, along with modularity and density at the global level, while functional service duration ($\langle s_t \rangle$, t=arrival days) also tended to increase, but without significant changes in other structural characteristics or overall efficiency $\langle l \rangle$. These results jointly imply that, during the pandemic, connectivity and distance-related challenges in the buyers' network were mitigated through internal reorganization, fostering a more regionalized structure with localized concentrations.

Conversely, the network measures analysis in the sellers' network reveals slightly different yet related dynamics. Numerically, 36% (5/14) of the network measures show statistically significant changes, of which only 14% (2/14) reach 1% significance. The measures exhibiting significant changes (decreases) include average strength $\langle s \rangle$, diameter dG, the weighted-by-arrival-days average clustering coefficient $\langle C_t \rangle$, and the average path length $\langle l \rangle$. Compared with the buyers' network, the sellers' network demonstrates a pattern of structural reconfiguration, with reductions in diameter and improvements in

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

efficiency ⟨*l*⟩, without significant changes in connectivity measures except for the decrease in weighted functional clustering. These results indicate the emergence of a process of 'forced rationalization' within the sellers' network in response to the pandemic, characterized by a shrinkage of container shipping lines (d*G*) alongside the development of local concentrations (as suggested by decreases in $\langle C_w \rangle$ components) and accessibility improvements ⟨*l*⟩, rendering the network both more compact (reduced complexity) and more efficient (enhanced spatial concentration). Overall, the joint consideration of both network directions in Table 2 indicates that, although the COVID-19 pandemic induced noticeable changes, it simultaneously triggered adaptive strategies, accelerating internal restructuring to enhance local cohesion and functional efficiency, without dismantling the network as a whole.

TABLE 1 - THE STRENGTH-CORE-P10 (TOP-15 IN STRENGTH COUNTRIES) OF THE ICSN IN THE PRE-PANDEMIC AND DURING-PANDEMIC PERIODS AND PER NETWORK DIRECTIONALITY (BUYERS VS. SELLERS)[(A)]

Rank	CoreP$_i$, i=…	Pre-pandemic (2017-19)		Change Rate (%)	During-pandemic (2020-22)	
		Country	Strength[(b)]		Country	Strength[(b)]
BUYERS NETWORK						
1	1	**China**[(c)]	95,989	-50.39	**China**	47,620
2		**Cyprus**	44,080	-23.82	**Cyprus**	33,582
3		**United States**	35,169	-15.31	**United States**	29,786
4	2.5	**Turkey**	31,761	-19.56	**Turkey**	25,548
5		United Kingdom	25,072	-20.33	Egypt	22,045
6		Egypt	20,139	9.46	United Kingdom	19,974
7		**Israel**	18,161	-5.85	**Israel**	17,099
8	5	**India**	12,480	0.98	**India**	12,602
9		*Indonesia*[(d)]	12,127	n/a[(e)]	Belgium	9,272
10		United Arab Emirates	11,745	-29.74	Spain	8,581
11	7.5	*Italy*	11,506	n/a	Saudi Arabia	8,568
12		Spain	11,137	-22.95	*Lebanon*	8,548
13		Belgium	10,497	-11.67	United Arab Emirates	8,252
14		Saudi Arabia	9,301	-7.88	Canada	6,989
15	10	Canada	8,230	-15.08	*Russia*	6,445
SELLERS NETWORK						
1	1	**China**	192,822	-13.48	**China**	166,835
2		**Belgium**	63,597	-21.45	**Belgium**	49,957
3		**Turkey**	33,829	-10.83	**Turkey**	30,165
4	2.5	India	26,618	-4.60	Spain	27,128
5		Spain	25,850	4.94	India	25,393
6		**Ecuador**	23,801	-14.26	**Ecuador**	20,406
7		Netherlands	22,014	-27.72	United States	17,480
8	5	United States	18,408	-5.04	Netherlands	15,912
9		**Rep. of Korea**	17,966	-18.08	**Rep. of Korea**	14,717
10		**Germany**	17,354	-18.40	**Germany**	14,161
11	7.5	**United Kingdom**)	15,423	-24.98	**United Kingdom**	11,570
12		Saudi Arabia	13,449	-28.23	*Israel*	11,487
13		*Finland*	12,029	-20.58	Italy	9,877
14		Egypt	11,353	n/a	Saudi Arabia	9,652
15	10	Italy	11,339	-12.89	Egypt	9,553

a. Excluding Greece
b. Movements (departures/arrivals)
c. Cases that retained their ranking are shown in **bold**
d. Unique cases per column are shown in *italics*
e. Not available

TABLE 2 - ICSN NETWORK MEASURES FOR THE PRE-PANDEMIC AND DURING-PANDEMIC PERIODS AND PER NETWORK DIRECTIONALITY (BUYERS VS. SELLERS)[(A)]

Metric	$Layer_{2017\text{-}2019}$	$Layer_{2020\text{-}2022}$	Change Rate (99% Normal Distr. Confidence Interval)		
			Lower Bound (%)	Mean (%)	Upper Bound (%)
BUYERS NETWORK					
n	156	150	–15.16	–3.85	7.46
m	532	671	**0.31**[(b)]	**26.13**	**51.95**
$\langle k\rangle$	3.41	4.473	**3.95**	**31.17**	**58.39**
$\langle s\rangle^{(c,1)}$	3385.077	2532.34	–50.70	–25.19	0.32
$\langle s_t\rangle^{(d)}$	90.457	116.375	**2.08**	**28.65**	**55.22**
dG	4	4	0	0	0
ρ	0.022	0.03	**8.09**	**36.36**	**64.63**
$Q_w^{(c)}$	0	0	–	–	–
$Q_t^{(d,2)}$	0.273	0.314	–5.98	15.02	36.02
Comp	1	1	0	0	0
$\langle C\rangle$	0.29	0.377	**3.07**	**30.00**	**56.93**
$\langle C_w\rangle^{(c,1)}$	0.356	0.444	–0.63	24.72	50.07
$\langle C_t\rangle^{(d)}$	0.265	0.335	**0.51**	**26.42**	**52.33**
$\langle l\rangle$	2.665	2.472	–22.47	–7.24	7.99
SELLERS NETWORK					
n	140	136	–12.66	–2.86	6.94
m	442	437	–7.34	–1.13	5.08
$\langle k\rangle$	3.157	3.213	–9.52	1.77	5.98
$\langle s\rangle^{(c,2)}$	5094.586	4474.625	–31.39	–12.17	7.05
$\langle s_t\rangle^{(d,2)}$	73.166	84.396	–5.84	15.35	36.54
dG	6	4	**–53.71**	**–33.33**	**–12.95**
ρ	0.023	0.024	–7.64	4.35	16.34
$Q_w^{(c)}$	0	0	–	–	–
$Q_t^{(d)}$	0.356	0.347	–11.76	–2.53	6.70
Comp	1	1	0	0	0
$\langle C\rangle^{(2)}$	0.247	0.214	–33.36	–13.36	6.64
$\langle C_w\rangle^{(c)}$	0.386	0.35	–26.42	–9.33	7.76
$\langle C_t\rangle^{(d,2)}$	0.222	0.187	–37.19	-15.77	5.65
$\langle l\rangle$	3.44	2.446	**–55.54**	**–28.90**	**–2.26**

a. Computations are based on Equation (1)-(3), normal distribution z-scores, and n_{eff}=23

b. Cases with significant changes are shown in **bold**

c. Weighted by vessel trip frequency

d. Weighted by arrival days

1. Significant at the 5% level

2. Significant at the 10% level

At the next stage of the analysis, the ICSN topology is further examined using pattern recognition methods. For the buyers' network, the degree distribution results (Fig.3) demonstrate a slight decrease in the power-law exponent in the network during the pandemic, although this difference is not statistically significant. This outcome reflects a mild weakening of the hierarchical organization and centrality features of the ICSN, without implying a fundamental disruption of the network structure, as also evidenced in the network measures analyzed in Table 2. This trend also provides an indication of the regionalization of trade flows, with markets adapting to greater geographical dispersion and diversification of containership routes. This pattern is more pronounced in the sellers' network, where

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

the decrease in the power-law exponent of the degree distribution during the pandemic period is statistically significant, reflecting a relaxation of the scale-free network characteristics and a departure from the hub-and-spoke model. In brief, these changes correspond to a restructuring of the container shipping market, with reduced dependence on hubs and a decreased concentration of strength, alongside an enhanced role of regional routes. Such changes support a transition from a network model structured around economies of scale and concentration toward a more distributed system.

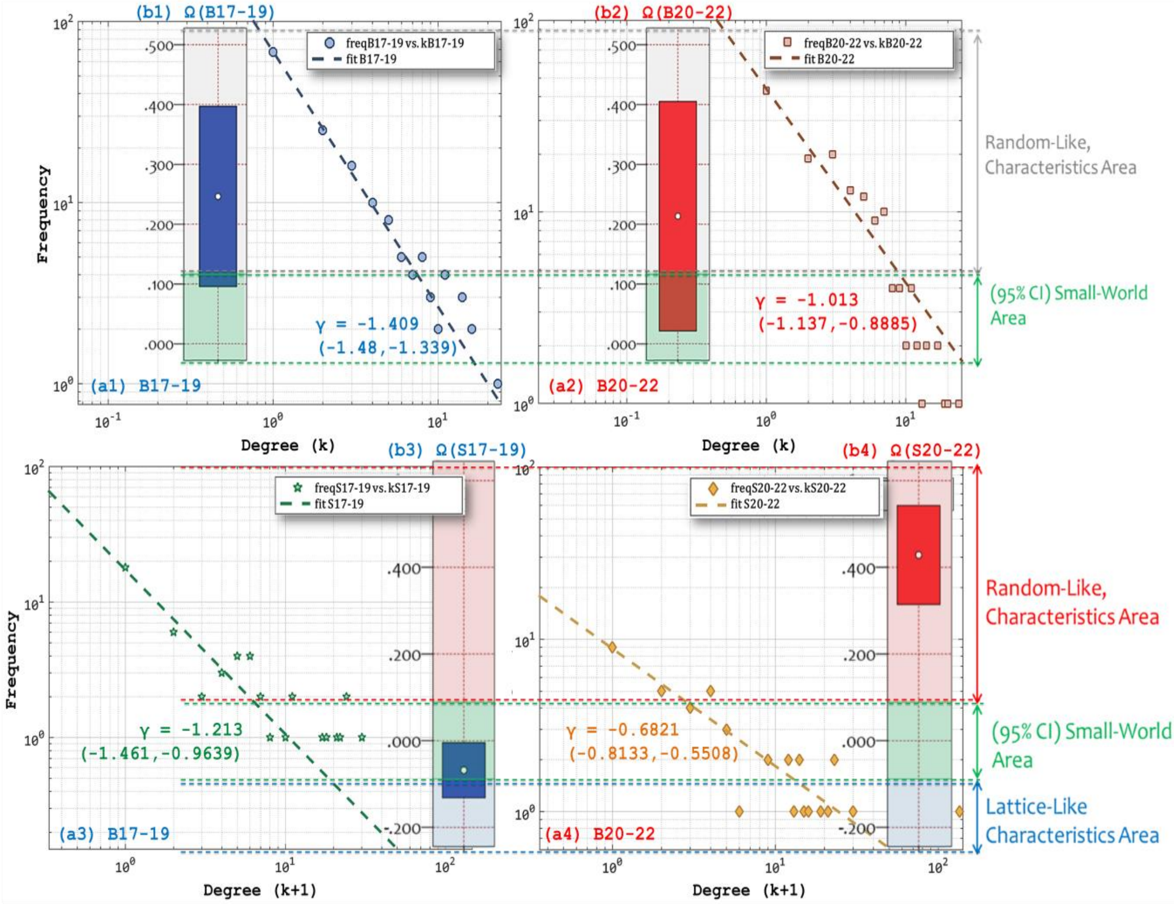


FIGURE 3- (a) THE DEGREE DISTRIBUTION AND (b) COMPARISON OF THE OMEGA INDEX'S MEAN VALUES AT THE 95% (NORMAL DISTRIBUTION) CONFIDENCE INTERVALS (CI) OF THE BUYERS' AND SELLERS' ICSN, DURING THE PERIODS 2017-2019 (17-19) AND 2020-2022 (20-22).

The results of the approximate small-world detection index were estimated using mean values over 30 successive computations and 95% confidence intervals (due to the heuristic nature of the measure). In the buyers' network, the mean ω-value decreases from 0.246 to 0.213 (from 2017–2019 to 2020–2022), although this change is not statistically significant (as the confidence intervals overlap). Nevertheless, the numerical difference in mean values, combined with the elongation of the error bars during 2020–2022 towards the small-world (SW) zone, suggests that the pandemic has increased heterogeneity in the ICSN's topological mix. Given that small-world topology describes the emergence of 'bridges' or shortcuts facilitating communication between functionally distant nodes, the latter finding implies that the pandemic is associated with the creation of new long-range interconnections within the buyers' ICSN, thereby enhancing alternative and potentially less traditional container shipping markets. In contrast, in the sellers' network, the omega index exhibits a statistically significant increase in its average value (from -0.068 to 0.4283), suggesting a topological shift toward more 'random' characteristics.

Concisely, this increase in randomness corresponds to an absence of deterministic growth, that is, a network expansion not guided by a deterministic pattern. Given the ω-index's degrees of freedom across the LL–SW–RL ranges, this transition toward greater randomness aligns with the 'forced rationalization' process observed in the analysis of network metrics, structured around the balance between spatial concentration and optimization. In other words, the ω-index results further suggest that the sellers' network adapted to the pandemic primarily through a defensive and stabilizing mechanism, rather than a targeted reorganization toward a more efficient or hierarchically improved structure. Consequently, while the buyers' network exhibits signs of adaptive diversification and new connections, the sellers' network reflects a more restrictive and shrunk response, reinforcing asymmetries in the functioning and economic dynamics of the container shipping market during the pandemic.

4.2. Community detection analysis

In this section, a community detection analysis is undertaken to probe the restructuring of the network's functional regions before and during the pandemic. Initially, the results of the Chi-Square (χ^2) test (Table 3) for the buyers' network confirm that community composition across the two periods is statistically significantly associated. This outcome suggests that the ICSN's restructuring in response to the pandemic was not radical, an observation that is consistent with the findings from the global-level analysis. However, the Cramer's V value indicates that the association's strength is 49.6% ≈ 50%, implying that, beyond the observed cohesion in the core structure, approximately half of the buyers' ICSN community composition after the pandemic outbreak. This finding highlights a substantial –but not fully disconnected– restructuring of the network. From the sellers' network's side, the χ^2 test results similarly show that community structure between the two periods is statistically associated. In this case, the Cramer's V value is slightly lower than that of the buyers' network (approximately 44.5% ≈ 45%), indicating that structural changes in the sellers' network community composition reaches around 55%. This result reinforces the observation that the sellers' ICSN underwent deeper structural changes during the pandemic compared with the buyers' network, confirming the asymmetric impact of this external shock on the structure and functioning of the container shipping market.

Furthermore, the analysis shown in Table 4 examines the communities' relative sizes across network directions (buyers vs. sellers) and between the two periods, providing pairwise statistical tests to detect the inequalities direction. In terms of the community configuration, the buyers' network exhibits four

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

communities during 2017-2019, which decrease to three communities in 2020-2022. This finding further confirms a more divisible and regionalized structure of the buyers' network during the pandemic, as also evidenced in Table 1. Conversely, the sellers' network shows a different dynamic, with the four communities of the 2017-2019 period reducing to three in 2020-2022, further supporting the previous finding of topological 'shrinkage' within the sellers' network.

TABLE 3 - RESULTS OF THE CHI-SQUARE TEST FOR THE ASSOCIATION OF COMMUNITIES

(i) Chi-Square Tests

Statistic	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
BUYERS NETWORK					
Pearson Chi-Square	70.901[(a)]	6[(b)]	.000	.000	
Likelihood Ratio	75.982	6	.000	.000	
Fisher's Exact Test	73.254			.000	
Linear-by-Linear Association	44.186[(c)]	1[(d)]	.000	.000	.000
N of Valid Cases	144				
SELLERS NETWORK					
Pearson Chi-Square	51.452[(a)]	6	.000	.000	
Likelihood Ratio	55.958	6	.000	.000	
Fisher's Exact Test	54.823			.000	
Linear-by-Linear Association	21.034[(c)]	1	.000	.000	.000
N of Valid Cases	130				

a. 4 cells (33,3%) have expected count less than 5. The minimum expected count is 1,02.
b. For $n_{B17\text{-}19}$=4 and $n_{B20\text{-}22}$=3 communities is computed as follows: df = $(n_{B17\text{-}19} - 1)\cdot(n_{B20\text{-}22} - 1) = 3\cdot 2 = 6$.
c. The standardized statistic is -4,586.
d. For $n_{S17\text{-}19}$=3 and $n_{S20\text{-}22}$=4 communities is computed as follows: df = $(n_{B17\text{-}19} - 1)\cdot(n_{B20\text{-}22} - 1) = 2\cdot 3 = 6$.

(ii) Symmetric Measures[(e,f)]

	Statistic	Value	Approx. Sig.	Exact Sig.
BUYERS NETWORK				
Nominal by Nominal	Phi	.702	.000	.000
	Cramer's *V*	.496	.000	.000
N of Valid Cases	144			
SELLERS NETWORK				
Nominal by Nominal	Phi	.629	.000	.000
	Cramer's *V*	.445	.000	.000
N of Valid Cases	130			

e. Not assuming the null hypothesis (no association).
f. Using the asymptotic standard error assuming the null hypothesis.

The sub-tables of the pairwise tests' results in Table 4 provide information regarding the direction of changes in community sizes. Specifically, sub-tables 4ii indicate that the pandemic led the buyers' network toward a more isotropic configuration. Amongst the four detected communities (Q_1, Q_2, Q_3, Q_4) during the pandemic, only one (Q_4) exhibits a statistically significantly larger size than any pre-pandemic community (in particular, Q_1), whereas three of these communities (Q_1, Q_2, Q_3) are found to be statistically smaller than at least one pre-pandemic community (Q_4). Considering that the weighted average confidence level index in Table 4ii suffices measuring the intensity of these dispersed changes, we observe in the buyers' network a smaller proportion of community growth (8.25%), compared to the reduction (24.75%) in community size. This finding points to a convergence trend in the number of participating countries within the maritime trade zones of the buyers' ICSN, consistent with the previously observed network regionalization. Conversely, sub-tables 4iii reveal the opposite pattern for the sellers' network, where the pandemic induced a more anisotropic configuration, with a larger proportion of community growth (49.17%) than reduction (23.67%) in size. This outcome suggests divergent trends in the number of participating countries within the maritime trade zones of the sellers' ICSN, which, together with the previously observed topological 'shrinkage' of this network, indicates signs of economies of scale and concentration mechanisms within the sellers' network.

TABLE 4 - RELATIVE SIZES OF THE ICSN COMMUNITIES PER PERIOD[1] AND DIRECTIONALITY (BUYERS VS. SELLERS)[2]

i. Descriptives table

Type		Q_{class}	Size	Total	Lower Bound (CI)(%) 99%	Lower Bound (CI)(%) 95%	Lower Bound (CI)(%) 90%	Relative Q Size	Upper Bound (CI)(%) 90%	Upper Bound (CI)(%) 95%	Upper Bound (CI)(%) 99%
Buyers	$B_{17\text{-}19}$(a)	1	28	156	10.04	11.93	12.90	17.95	23.00	23.97	25.86
		2	53		24.20	26.54	27.73	33.97	40.21	41.40	43.74
		3	75		37.78	40.24	41.50	48.08	54.66	55.92	58.38
	$B_{20\text{-}22}$(b)	1	31	150	12.15	14.19	15.23	20.67	26.11	27.15	29.19
		2	35		14.44	16.56	17.65	23.33	29.01	30.10	32.22
		3	27		9.92	11.85	12.84	18.00	23.16	24.15	26.08
		4	57		27.79	30.23	31.48	38.00	44.52	45.77	48.21
Sellers	$S_{17\text{-}19}$(c)	1	80	140	46.37	48.94	50.26	57.14	64.02	65.34	67.91
		2	22		7.79	9.68	10.65	15.71	20.77	21.74	23.63
		3	25		9.52	11.52	12.54	17.86	23.18	24.20	26.20
		4	13		2.97	4.48	5.25	9.29	13.33	14.10	15.61
	$S_{20\text{-}22}$(d)	1	11	136	2.07	3.51	4.24	8.09	11.94	12.67	14.11
		2	50		26.11	28.66	29.96	36.76	43.56	44.86	47.41
		3	75		44.16	46.79	48.14	55.15	62.16	63.51	66.14

ii. Pairwise tests' results of the buyer networks' community relative sizes

Test: $B_{17\text{-}19} < B_{20\text{-}22}$		$B_{20\text{-}22}$ Q_1	Q_2	Q_3	Q_4	Inequality Intensity(b) Directional	Undirectional
$B_{17\text{-}19}$	Q_1	-	-	-	99%(a)	8.25%	16.50%
	Q_2	-	-	-	-		
	Q_3	-	-	-	-		
Test: $B_{17\text{-}19} > B_{20\text{-}22}$		$B_{20\text{-}22}$ Q_1	Q_2	Q_3	Q_4	Directional	
$B_{17\text{-}19}$	Q_1	-	-	-	-	24.75%	
	Q_2	-	-	-	-		
	Q_3	99%	99%	99%	-		

iii. Pairwise tests' results of the seller networks' community relative sizes

Test: $S_{17\text{-}19} < S_{20\text{-}22}$		$S_{20\text{-}22}$ Q_1	Q_2	Q_3	Inequality Intensity Directional	Undirectional
$S_{17\text{-}19}$	Q_1	-	-	-	49.17%	36.42%
	Q_2	-	99%	99%		
	Q_3	-	95%(b)	99%		
	Q_4	-	99%	99%		
Test: $S_{17\text{-}19} > S_{20\text{-}22}$		$S_{20\text{-}22}$ Q_1	Q_2	Q_3	Directional	
$S_{17\text{-}19}$	Q_1	99%	95%	-	23.67%	
	Q_2	-	-	-		
	Q_3	90%(c)	-	-		
	Q_4	-	-	-		

1. Labels "17-19" correspond to period 2017-2019 and "20-22" to period 2020-2022.
2. CIs are computed based on equation (1), normal distribution z-scores, and for n=156, 150, 140, 136 respectively

a. The relative size of the first community (Q_1) in $B_{17\text{-}19}$ is statistically significantly lower than this of the fourth community (Q_4) in $B_{20\text{-}22}$ at the (100%-99%=) 1% significance level

b. Computed by the weighted average confidence level: $\langle CI_w \rangle = \Sigma_n((1-a)\%)/n$

c. The relative size of the third community (Q_3) in $S_{17\text{-}19}$ is statistically significantly higher than this of the second community (Q_2) in $S_{20\text{-}22}$ at the (100%-95%=) 5% significance level

d. The relative size of the third community (Q_3) in $S_{17\text{-}19}$ is statistically significantly higher than this of the second community (Q_2) in $S_{20\text{-}22}$ at the (100%-90%=) 10% significance level

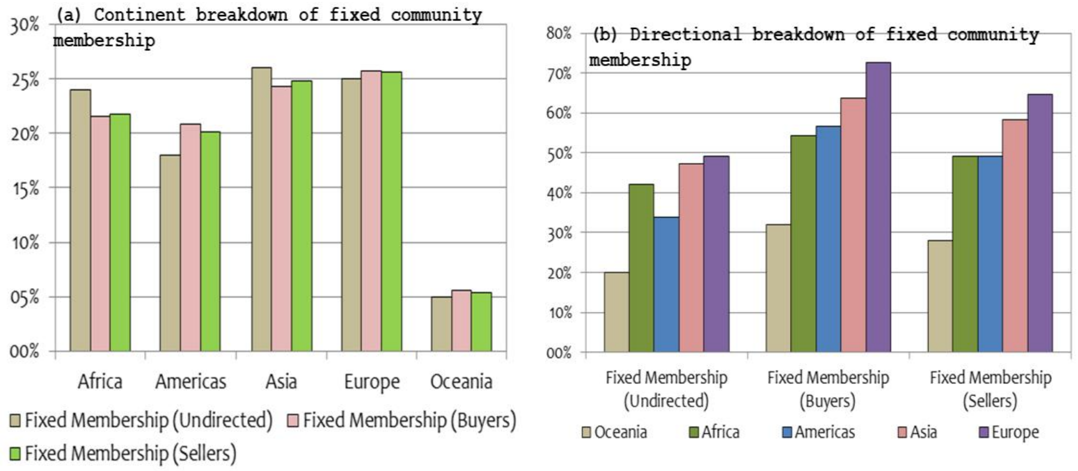
Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

Subsequently, the results in Fig.4 provide insights into the continent-level and the directional (undirected vs. buyers vs. sellers) breakdown of the cross-tabulation analysis applied to fixed-membership ICSN countries. In this part of the analysis, the term ‘fixed membership’ refers to countries (nodes) that remained in the same community before and during the pandemic. The undirected case is derived from examining and detecting mutual instances across both the pre-pandemic and during-pandemic directions. Fig.4a presents the continent-level breakdown of fixed membership by directionality (i.e., the share of stable memberships held by each continent across the total examined flows), while Fig.4b shows the directional breakdown of fixed membership within each continent (i.e., the share of fixed membership corresponding to each continent’s intra-continental flows).

According to Fig.4a, Europe and Asia emerge as cores with the highest stability in participation within the global ICSN flow network, followed by Africa, the Americas, and Oceania. This hierarchy is maintained in both directional networks (buyers and sellers), whereas in the undirected case, the order of the leading continents changes (from Europe, Asia, etc., to Asia, Europe, etc.), indicating a higher degree of overlap of the maritime trade zones along directions for Asia. Furthermore, this hierarchy appears consistent in Fig.4b, whose stability aligns with the χ^2 test findings, demonstrating association in the composition of the ICSN communities before and during the pandemic. This finding provides evidence that the distribution of global containership flow stability is non-random and is shaped according to the structural characteristics of each continent. For example, the bipolar north-south geographical configuration of the Americas appears to limit its degree of stability.

In terms of spatial differentiation, the results in Fig.5 provide information on the mean inter-membership kilometric distances of ICSN communities for both buyers’ and sellers’ networks before and during the pandemic. Initially, in relation to the average inter-membership distance (shown in the first column of the error bars for each confidence level), we observe that –across all confidence levels– communities during the pandemic in the buyers’ network are overall more geographically dispersed compared to the pre-pandemic communities. In contrast, for the sellers’ network, the communities during the pandemic appear generally closer to the mean distance compared to their pre-pandemic counterparts.

Pairwise comparisons, i.e., comparisons between each community before and during the pandemic, as shown in the pairwise tabulation matrices (Fig.5), further confirm that buyers’ communities during the pandemic are more spatially expanded than before the pandemic, with indicative total differentiation intensities ranging from 11% to 33%. Conversely, the sellers’ communities during the pandemic are less spatially extended, with indicative differentiation intensities from 0% to 25%. These findings align with earlier ones presented in this study regarding the regionalization of the buyers’ network structure and the topological ‘shrinkage’ of the sellers’ network during the pandemic, further reinforcing them by adding the spatial dimension. In other words, Fig.5 depicts both the structural and spatial dimensions of buyers' network regionalization: countries participating in the buyers' communities during the pandemic became more geographically dispersed, whereas countries in the sellers' network communities became less geographically dispersed.

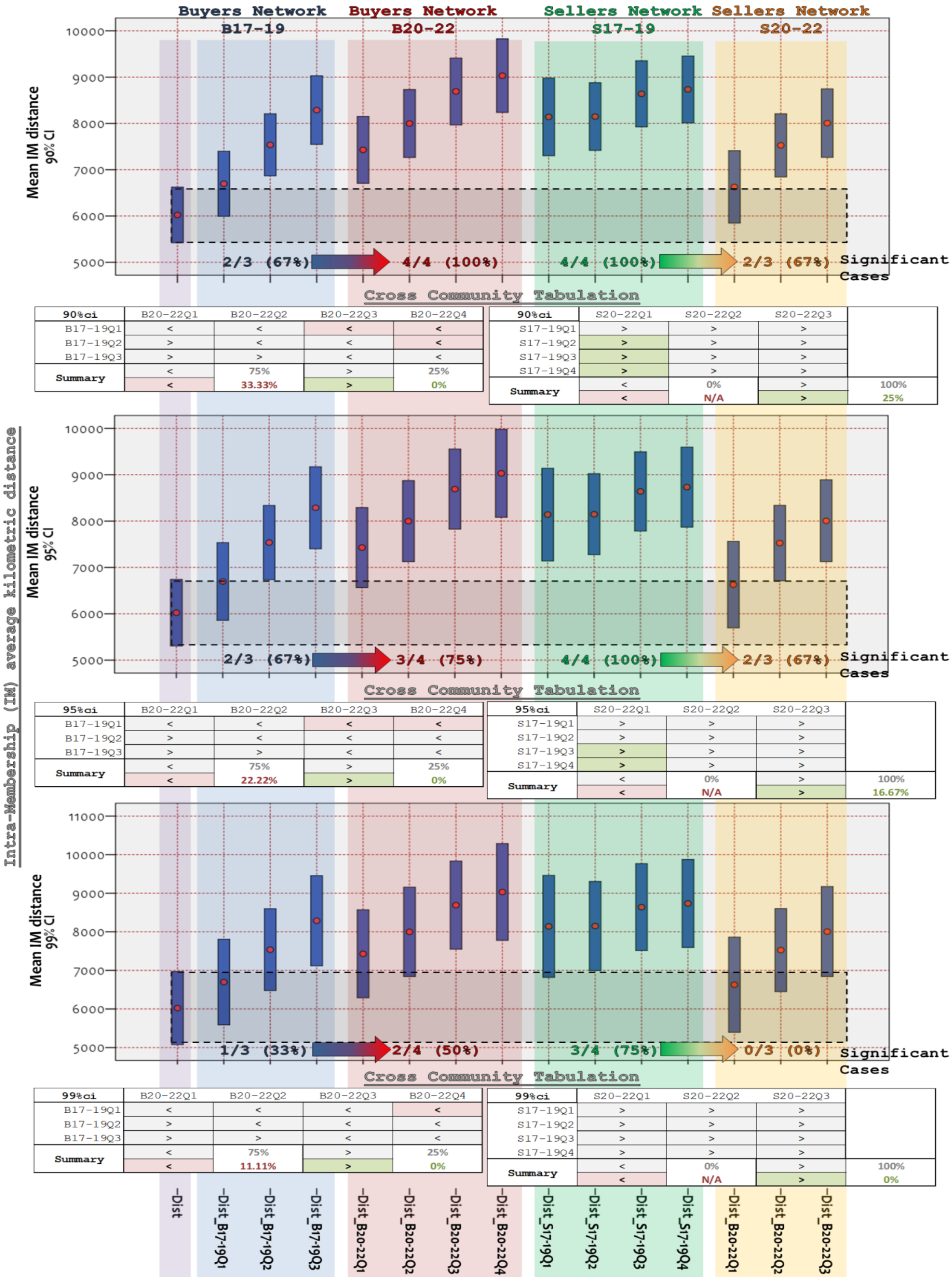


Continent		Fixed Membership (Undirected)	Fixed Membership (Buyers)	Fixed Membership (Sellers)
Africa	Sum	24	31	28
	% of Total (within continent)	42.1%	54.4%	49.1%
	90% CI	(31.16%,53.04%)	(43.37%,65.43%)	(38.03%,60.17%)
	95% CI	(29%,55.20%)	(41.18%,67.62%)	(35.84%,62.36%)
	99% CI	(24.66%,59.54%)	(36.38%,71.99%)	(31.44%,66.76%)
	% of Total (within category)	24.0%	21.5%	21.7%
	90% CI	(16.91%,31.09%)	(15.83%,27.17%)	(15.69%,27.71%)
	95% CI	(15.53%,32.47%)	(14.73%,28.27%)	(14.52%,28.88%)
	99% CI	(12.78%,35.22%)	(12.56%,30.44%)	(12.21%,31.19%)
Americas	Sum	18	30	26
	% of Total (within continent)	34.0%	56.6%	49.1%
	90% CI	(23.1%,44.9%)	(45.2%,68%)	(37.6%,60.6%)
	95% CI	(20.94%,47.06%)	(42.94%,70.26%)	(35.32%,62.88)
	99% CI	(16.6%,51.4%)	(38.4%,74.8%)	(30.74%,67.46%)
	% of Total (within category)	18.0%	20.8%	20.2%
	90% CI	(11.62%,24.38%)	(15.2%,26.4%)	(14.34%,26.06%)
	95% CI	(10.47%,25.53%)	(14.11%,27.49%)	(13.21%,27.19%)
	99% CI	(7.91%,28.09%)	(11.97%,29.63%)	(10.96%,29.44%)
Asia	Sum	26	35	32
	% of Total (within continent)	47.3%	63.6%	58.2%
	90% CI	(36.03%,58.57%)	(52.74%,74.46%)	(47.07%,69.33%)
	95% CI	(33.80%,60.80%)	(50.59%,76.61%)	(44.87%,71.53%)
	99% CI	(29.33%,65.27%)	(46.28%,80.92%)	(40.44%,75.96%)
	% of Total (within category)	26.0%	24.3%	24.8%
	90% CI	(18.72%,33.28%)	(18.38%,30.22%)	(18.5%,31.1%)
	95% CI	(17.4%,34.6%)	(17.24%,31.36%)	(17.28%,32.32%)
	99% CI	(14.48%,37.52%)	(14.97%,33.63%)	(14.86%,34.74%)

Continent		Fixed Membership (Undirected)	Fixed Membership (Buyers)	Fixed Membership (Sellers)
Europe	Sum	25	37	33
	% of Total (within continent)	49.0%	72.5%	64.7%
	90% CI	(37.27%,60.73%)	(62.02%,82.98%)	(53.48%,75.92%)
	95% CI	(34.94%,63.06%)	(59.94%,85.06%)	(51.26%,78.14)
	99% CI	(30.26%,67.74%)	(55.76%,89.24%)	(46.78%,82.62%)
	% of Total (within category)	25.0%	25.7%	25.6%
	90% CI	(17.81%,32.19%)	(19.67%,31.73%)	(19.23%,31.97%)
	95% CI	(16.51%,33.49%)	(18.5%,32.9%)	(18%,33.2%)
	99% CI	(13.63%,36.37%)	(16.19%,35.21%)	(15.55%,35.65%)
Oceania	Sum	5	8	7
	% of Total (within continent)	20.0%	32.0%	28.0%
	90% CI	(6.31%,33.69%)	(16.04%,47.96%)	(12.64%,43.36%)
	95% CI	(3.48%,36.51%)	(12.74%,51.25%)	(9.47%,46.53%)
	99% CI	(0%,42.38%)	(5.91%,58.09%)	(2.88%,53.12%)
	% of Total (within category)	5.0%	5.6%	5.4%
	90% CI	(1.38%,8.62%)	(2.43%,8.77%)	(2.1%,8.7%)
	95% CI	(0.7%,9.27%)	(1.81%,9.39%)	(1.46%,9.34%)
	99% CI	(0%,10.72%)	(0.6%,10.6%)	(0.2%,10.6%)
Total	Sum	100	144	129
	% of Total (within continent)	40.8%	58.8%	52.7%
	90% CI	(35.62%,45.98%)	(53.61%,63.99%)	(47.43%,57.97%)
	95% CI	(34.62%,46.98%)	(52.61%,64.99%)	(46.71%,58.98%)
	99% CI	(32.65%,48.95%)	(50.64%,66.96%)	(44.42%,60.98%)
	% of Total (within category)	100.0%	100.0%	100.0%

FIGURE 4 - CLUSTERED BAR-CHARTS AND CROSS-TABULATION MATRICES SHOWING (a) THE CONTINENT AND (b) THE DIRECTIONAL (TOTAL VS. BUYERS VS. SELLERS) BREAKDOWN OF THE CROSS-TABULATION ANALYSIS APPLIED TO FIXED MEMBERSHIP ICSN COUNTRIES (THOSE THAT WERE INCLUDED IN THE SAME COMMUNITY BEFORE AND DURING THE PANDEMIC). CIS COMPUTATIONS ARE BASED ON EQUATION (1) AND ON STUDENT'S DISTRIBUTION'S Z-SCORES. SAMPLE SIZES ARE CONSIDERED AS N=57, 53, 4, 55, 51, 25 FOR CONTINENT SIZES, AND N=100, 144, AND 129 FOR DIRECTIONAL NETWORK SIZES.

Finally, the results of the Theil decomposition analysis, which is applied to pairwise distances (Fig.6), provide insights into the extent to which the geographical differentiation of the ICSN communities can be attributed to intra- vs. inter-community configurations.



90%ci	B20-22Q1	B20-22Q2	B20-22Q3	B20-22Q4
B17-19Q1	<	<	<	<
B17-19Q2	>	<	<	<
B17-19Q3	>	>	<	<
Summary	<	75%	>	25%
	<	33.33%	>	0%

90%ci	S20-22Q1	S20-22Q2	S20-22Q3	
S17-19Q1	>	>	>	
S17-19Q2	>	>	>	
S17-19Q3	>	>	>	
S17-19Q4	>	>	>	
Summary	<	0%	>	100%
	<	N/A	>	25%

95%ci	B20-22Q1	B20-22Q2	B20-22Q3	B20-22Q4
B17-19Q1	<	<	<	<
B17-19Q2	>	<	<	<
B17-19Q3	>	>	<	<
Summary	<	75%	>	25%
	<	22.22%	>	0%

95%ci	S20-22Q1	S20-22Q2	S20-22Q3	
S17-19Q1	>	>	>	
S17-19Q2	>	>	>	
S17-19Q3	>	>	>	
S17-19Q4	>	>	>	
Summary	<	0%	>	100%
	<	N/A	>	16.67%

99%ci	B20-22Q1	B20-22Q2	B20-22Q3	B20-22Q4
B17-19Q1	<	<	<	<
B17-19Q2	>	<	<	<
B17-19Q3	>	>	<	<
Summary	<	75%	>	25%
	<	11.11%	>	0%

99%ci	S20-22Q1	S20-22Q2	S20-22Q3	
S17-19Q1	>	>	>	
S17-19Q2	>	>	>	
S17-19Q3	>	>	>	
S17-19Q4	>	>	>	
Summary	<	0%	>	100%
	<	N/A	>	0%

FIGURE 5 - ERROR BARS OF VARIABLE CONFIDENCE LEVELS (90%, 95%, 99%) AND PAIRWISE TABULATION MATRICES FOR THE MEAN INTER-MEMBERSHIP KILOMETRIC DISTANCES OF THE ICSN BUYER AND SELLER COMMUNITIES BEFORE AND DURING THE PANDEMIC. COMPUTATIONS ARE BASED ON THE CONSTRUCTION OF CONFIDENCE INTERVALS FOR THE MEAN AND NORMAL DISTRIBUTION'S Z-SCORES.

Although no statistically significant differences can be traced in any of the results in Fig.6, the similarity among the T and T_w patterns, and the numerical magnitude relationship of $T>0.9 \cdot T_w$, suggest that the inter-community geographical configuration of the ICSN is substantially more homogeneous than the intra-community configuration. In other words, container shipping communities (markets) appear to have been driven toward a state of geographical balance, approaching a theoretical condition akin to perfect competition, where no single zone is geographically dominant or more spatially extensive than the others. At this scale, the ICSN appears structured to minimize inequalities among container shipping communities (markets).

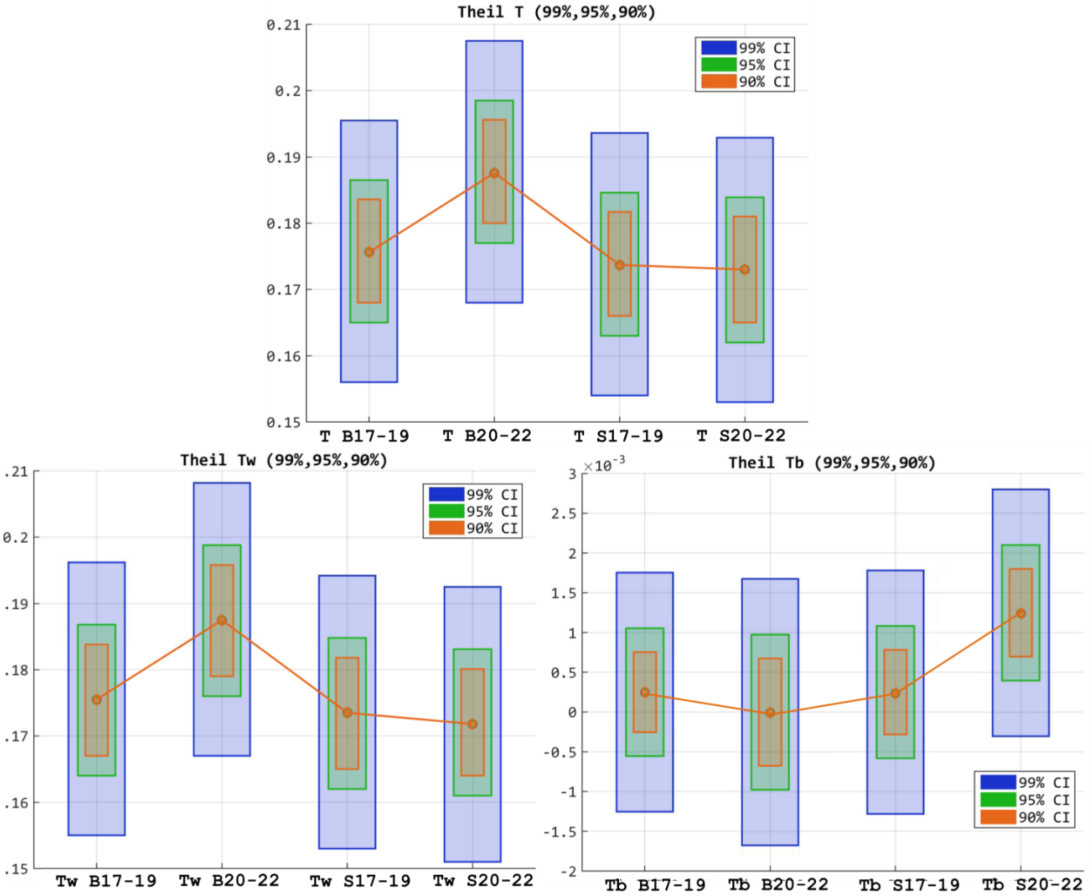


FIGURE 6 - ERROR BARS OF VARIABLE CONFIDENCE LEVELS (90%, 95%, 99%) FOR THE RESULTING MEAN VALUES OF THEIL'S DECOMPOSITION ANALYSIS (T=THEIL'S INDEX, TW=WITHIN GROUPS COMPONENT, TB=BETWEEN GROUPS COMPONENT), APPLIED TO PAIRWISE INTER-MEMBERSHIP COMMUNITY DISTANCES. COMPUTATIONS ARE BASED ON NORMAL DISTRIBUTION'S Z-SCORES.

Beyond the lack of statistically significant differences in the ICSN community changes before and during the pandemic, the Fig.6 plots indicate an increasing trend in the intra-community distances (i.e., geographical expansion or regionalization) for the buyers' communities during the pandemic, and conversely a decrease (i.e., geographical shrinkage) for the sellers' communities during the pandemic. Additionally, the results suggest a slight reduction in inter-community geographical differentiation for the

Theoretical and Empirical Researches in Urban Management
Volume 21 Issue 2 / May 2026

buyers' network and a corresponding increase for the sellers' network. These findings reinforce previous observations regarding the regionalization of the buyers' network and the shrinkage of the sellers' network following the pandemic outbreak.

5. CONCLUSIONS

This paper employed a spatial network analytics framework to examine the impact of the COVID-19 pandemic, through combining pattern recognition, community detection and decomposition methods, to unveil changes in the cross-country maritime shipping connectivity following the pandemic outbreak. The space-P network reconfiguration using the rich dataset of ConTraffic about the containership flows between the Greek ports and non-EU ports on the origin-destination level of countries revealed the complex structure of hub-and-spoke maritime operations and changes in connectivity patterns, the hierarchical structure and the geographical deconcentration or regionalization of the network following the pandemic outbreak.

On the one side, in the buyers' ICSN, it is found that, during the pandemic, connectivity and distancing problems were avoided through an internal reorganization and topological transformation towards a more spatially deconcentrated network structure and clustering. The pandemic also appears to have mostly affected the markets in the east of the network, creating a shift of activity to other markets, largely in the south of the globe. The hierarchical organization of the buyers' ICSN is found to be weakening and the network receives polycentric structure characteristics, i.e., it becomes more regionalized, through the emergence of regional markets. As far as the suppliers' ICSN is concerned, the pandemic is also found to have mostly affected the markets in the east of the network, forging a shift of activity to markets of the west and south of the globe. The network appears to be losing characteristics of a hierarchical organization and can be described by a mechanism of 'disordered defragmentation' rather than a rational redesign process, but it still retains the hierarchical structure of a small world.

The findings suggest the varying roles which different countries and mega-regions hit by the pandemic crisis played in (re)shaping the structure of the container shipping network and verify the hierarchical configuration of the global container shipping industry. The transformative process of the organization of the given network underlines the changing distributional asymmetries of the container traffic flows. It also stresses that inter-port relationships among countries must be evaluated not as isolated phenomena but within a multi-layer network structure perspective involving both geographical and time dimensions. Despite the relative stability of the maritime container trade communities (mega-regions), the identified regionalization and geographical diversification of the network, through broadening the spatial scope of origin-destination markets, can be considered as consistent with the response of other supply network formation strategies to crisis situations. More specifically, in such strategies, firms multisource inputs and strategically invest to make trade relationships stronger and less fragile during crises like the pandemic, where technological disruptions and congestion degraded connectivity and increased the uncertainty of supply link operations (Elliot et al., 2022).

The statistically significant association found between the community structures before and during the pandemic outbreak for both the buyers' and sellers' networks underscores that the impact of COVID-19 dynamics was not coincidental. Nonetheless, it should be noted that the observed changes in the container shipping network during the study period cannot be exclusively attributable to the pandemic itself. Other factors −overlapping with or triggered/accelerated by the pandemic− may have also influenced the supply chain diversification trends and the gradual structural transformation of the network. These factors may refer to geopolitical tensions and trade policy shifts, including new trade agreements, which led to regional cargo diversion. Shifts in vessel trip intensity, service frequencies and network design may also be attributed to the decarbonisation and carbon pricing strategies, which pushed carriers to upgrade container fleets and adjust schedules, and to mergers/acquisitions to share capacity, reduce costs and exploit scale economies. The digitalisation of the container shipping industry, including the development of automated ports and port community systems, has also improved vessel scheduling and network efficiency (OECD, 2021).

It should be also noted that the observed changes may depict the net outcome of different decisions of carriers ranging from tactical operational changes on skipping or switching their vessel calls to strategic decisions on establishing new inter-port connectivity and multi-port cooperations within and among countries, involving diverse connectivity patterns, such as with core ports, semi-core ports, and more peripheral ports to improve the end connectivity of the network (Liu et al., 2018). Long-term plans to strengthen connectivity and increase resilience could also involve increasing terminals' capacity and development of alternative combined (sea-rail) transportation options over the European hinterland to attract more long-haul services and strengthen supply chain smoothness during crisis situations.

The findings also underscore the need to strengthen the position of transshipment hub countries, such as Greece, which has increased dependence on a few major trade partner countries, to render them more flexible and resilient to risks and make their responses more robust to unexpected large-scale disruptions (e.g., Huang et al., 2022). In particular, the market concentration of the liner shipping companies and their vertical integration with the container port industry increases the sources of risk and vulnerability, especially when the sourcing countries are highly affected by network failures. Amongst others, suitable alternative liner shipping strategies which could be employed, even in combination with each other, encompass service cancelations and skipping ports (Zhou et al., 2024), rescheduling in routing, calling frequencies and chartering operations (Dirzka and Acciaro, 2022), and increasing the geographical diversity and sources of shipping liners, port call choices of carriers, and hinterland transportation connections. Regarding the container port industry, efforts should be focused on strengthening the port capacity, efficiency and hinterland connectivity (to dry ports, land transportation hubs and freight logistics centres), through developing intermodal (sea-rail) transportation operations, the digitization and establishment of smart logistics centers, preparation of contingency plans and foresight strategies, the diversification of operations and supply chain routes, and the coordination and collaboration with various government and supply chain stakeholders and with other ports in adjacent areas (Xu et al. 2024; Nguyen et al., 2024).

In the light of these transformative processes, national authorities and private container port operators aiming to upgrade the competitiveness of their port system facilities as main transshipment hub and sea gateways must encounter in their decision-making the multiple scaling impacts on the whole maritime transportation system. In Greece as well as the wider EU context, redundant barriers to maritime connectivity beyond EU should be addressed, through updating relevant legislation, agreements and regulatory rules. These efforts should aim to promote trade facilitation, coordination and intermodality with transportation networks of neighboring mega-regions (e.g., the Trans-African transportation corridors) while simultaneously supporting the needs for increased efficiency, geopolitical security and reduced carbon footprint. Finally, relevant authorities and operators must disentangle the potential impacts of interventions and shocks into different maritime trade communities and origin-destination markets, according to their particular topological, spatial and dynamic characteristics. An extended and more detailed study on the port throughputs and different types of commodity markets could provide a useful complement for a deeper understanding of the impacts of COVID-19 pandemic on the container port activity and the liner shipping industry.

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