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Identification of shipping schedule cancellations with AIS data: An application to the Europe-Far East route before and during the COVID-19 pandemic

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Abstract The COVID-19 pandemic caused severe disruptions throughout global supply chains. In response to this situation, container carriers had been cancelling services and port calls. The reasons behind the cancellations were diverse: restoring schedule reliability; coping with sudden demand decreases; or with severe port congestion. To fully understand the implications of this practice, it is crucial to have a robust measurement method. This paper presents a novel method to estimate the incidence of port call cancellations based on AIS data. A normal service is first defined, on the basis of the most frequent port call sequence, and deviations are measured subsequently. As a first glance at the unique value of this method, we apply it to the ports along the Europe-Far East route. A binomial logistic model expresses the probability a port is skipped, based on its own characteristics, the size of vessels, and the region in which the port is located. We find non-trivial effects related to vessel size. At the largest end of the vessel size scale, the ports attracting mega vessels (with a capacity above 15K TEUs) were less affected by cancellations in 2018-2019. This relationship reversed during the 2020-2021 period, and handling mega vessels seemed to have become a burden for ports during the pandemic. Another important result of this study is that, before the COVID-19 pandemic, the rate of cancellations was much more uneven between world regions than after the COVID-19 outbreak. This study provides useful operational insights to port authorities and governments, enabling them to anticipate the effects of future crises.

Keywords: Containerization, COVID-19 pandemic, AIS, disruption, vessel schedule cancellation.

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1. Introduction

The COVID-19 pandemic caused severe disruptions throughout global supply chains. Interruptions in port activity triggered by the lockdowns and their relaxation can be viewed as a Global Transport Networks experiment. This is a unique opportunity to identify the multiple effects of a global shock on transport systems. The insights gained from this natural experiment will therefore inform strategies to mitigate the effects of similar shocks on supply chains in the future. As a first step in this direction, this paper studies the incidence of service cancellations on ports. We show that the incidence is higher at certain ports and regions. This result will be useful for shippers, operators and policy makers, to identify the most vulnerable ports; anticipate the effects of disruptions; and develop suitable interventions to mitigate such disruptions in the future.

Vessel schedule cancellations are frequently used by carriers to cope with business cycles and with sudden changes in market conditions. They were used during the COVID-19 pandemic to reduce capacity, avoid delays, or restore schedule reliability. Two main types of vessel schedule cancellations exist: the cancellation of an entire string, or the cancellation of a port call within an operating string. The current work focuses on the latter.

One of the few studies to have analyzed the incidence of vessel schedule cancellation at ports used public notices provided by carriers and official shipping schedules (Dirzka and Acciaro 2022). Other works, based on AIS data, have compared the observed trajectory of a vessel to its average historical trajectory, in order to identify anomalies or to predict the destination (see, for example, Pallotta et al. 2013; Sheng and Yin 2018; Kim and Lee 2018; Zhang et al. 2022).

Our approach is a combination of the above methodologies. The AIS data we use have already undergone a first treatment by the data provider (VesselFinder 2021) to transform vessel trajectories into port-to-port sequences. Afterwards, we study the most recurrent port sequences and identify deviations from them. Such an approach overcomes the drawbacks associated with the use of official shipping schedules, which do not systematically reflect the real vessel calls. It also avoids the problems related to the lack of information on cancellations, which are not announced publicly by carriers (Dirzka and Acciaro 2022). On the other hand, compared to studies based on the average trajectory of vessels, this work exclusively focuses on the port call sequence, and not on the actual and precise trajectories followed by vessels, which may depend on a host of circumstances, such as weather conditions. Our focus is

rather on the commercial organization of carriers and not on the detailed routes followed by vessels between port pairs.

This paper proposes a data-driven method to measure vessel schedule cancellations at the level of ports using Automatic Identification System (AIS) data. It aims to understand how the COVID-19 pandemic affected vessel schedule cancellation patterns, vis à vis cancellations observed during the previous period. We focus on the Europe-Far East shipping route, where the largest vessels are deployed and where the incidence of vessel calls cancellation has been argued to be the highest (Notteboom et al., 2021). As a preview of the results, this research shows that during the COVID-19 pandemic, the incidence of call cancellations is higher at intermediate hubs and small gateways than in large Asian and European gateways at both ends of the pendulum routes.

This research adds to the extant literature in transport geography by analyzing the port call annulations separately, and not together with service annulations (Dirzka & Acciaro 2022). This distinction is useful since the two types of measures have different purposes: When a carrier cancels a full service, it reduces the maritime transport supply. This often happens at the start of the year when the demand is low after the Christmas peak, or when there is a sudden drop in demand. But when a port is skipped within a service, the transport supply changes only locally. Therefore the purpose of the carrier is completely different, and it is more related to avoiding delays and restoring reliability in vessel schedules. Another distinctive advantage of this paper, compared to previous studies, is to take into account a long time period that coincides with much of the pandemic, from January 2018 to August 2021, including most of the lockdowns. Therefore, it is possible to compare vessel cancellations before and during the COVID-19 pandemic, thus avoiding seasonal effects. This is particularly relevant for a better understanding of how the COVID-19 pandemic increased uncertainty for ports, as suggested by early studies (Notteboom & Haralambides 2020).

The remainder of the paper is organized as follows. Related work on the study of vessel route patterns and disruptions is presented in section 2. Section 3 describes the methodology for the vessel schedule cancellation prediction and the vessel cancellation metrics. The results and discussions can be found in Section 4. Section 5 presents the conclusions of this research.

2. Literature review

This study aims to contribute to two strands of research. The first is methodological and relates to the identification of regularities in vessel trajectories and of departures from these regularities. The second strand analyzes the effects of disruptions in maritime transport, from a transport geography perspective.

2.1. Vessel trajectory extraction and analysis

With the spread of AIS data, there has been a number of works in operations research that have proposed methods to convert large amounts of raw data into understandable information. Two main types of research have been implemented to recognize patterns and formulate predictions. Spiliopoulos et al. (2017) proposed a way to simplify vessel trajectories by grouping vessel positions displaying similar characteristics in terms of time and location. Further improvements included sailing speed and the introduction of thresholds for controlling variations in vessel course and speed (Wei et al., 2020). Another line of research in vessel trajectory analysis seeks to predict the destination of vessels and their expected time of arrival (Pallotta et al. 2013; Kim and Lee 2018; Alessandrini et al. 2018). Most of the works are based on the extraction of turning way points and various advanced methods (for instance, Neural networks, Bayes models) to predict destination. The latter provide good predictions but seem to require disproportionate computing capacities to be applied globally (Zhang et al. 2020). Alternatively, data mining techniques are used to extract trajectory data. Within the context of this work, a vessel trajectory is an ordered sequence of its geographical positions during a period of time. Stay-point detection, for example, extracts the point where the vessel engages in limited movement or remains stationary for a while. Another method is trajectory segmentation, to divide the historical trajectories of vessels in relevant sub-trajectory patterns based on time, turning-points, key-shape points or stay-points (Zhang et al. 2020). Once the trajectory of a vessel has been detected and simplified, there are techniques to measure the similarity between trajectories, based on their geometry (geographical setting) and the time stamps (Magdy et al., 2015). The main types include pure spatial similarity measures, purely temporal similarity measures, and spatiotemporal similarity measures.

Within the fields of transport geography and maritime economics, there are a few works studying vessel trajectories. One of the challenges in this area of study is the extraction of relevant economic information, such as decisions regarding maritime operations, from vessel movement data. A major advantage of this type of data is that they provide comprehensive and consistent information on vessel movements at the global scale, even in countries where the information on port throughput and

performance is scarce or unavailable. In a global analysis of the container network, Ducruet and Notteboom (2012) identified port regions and looked at the ways they have changed over time. As pointed out by these authors, one aspect of these changes is related to the deployment of larger vessels and the subsequent reorganization of services, resulting in a lower number of port calls in pendulum services. More detailed studies on individual vessel trajectories come from Li et al. (2020) and Charlier and McCalla (2006), highlighting the seasonal complementarities in cruise operations. Cruise ships can be moved seasonally from one cruising area to another, so as to enjoy best market opportunities throughout the year.

Beyond the studies focusing on cruise operations, there is a dearth of systematic analyses of the trajectories of liner vessels from a transport geography and maritime economics perspective. In fact, our analysis suggests that liner shipping is not always regular and punctual, and that departures from the norm may be useful to understand the behavior of carriers. This research seeks to provide a framework for studying the movements of individual vessels operating on fixed schedules.

2.2. Disruptions and resilience of maritime transport networks

In the literature of transport geography, several studies have assessed how major shocks have affected maritime transport networks. Rousset and Ducruet (2020) studied the effects of three major disruptions caused by hurricane Katrina in New Orleans, Louisiana, the World Trade Center terrorist attacks in New York City, and the Hanshin earthquake in Kobe, Japan. They showed that the time needed to recover from these disruptions was higher in the ports located nearby. Calatayud et al. (2017) explored the risks that maritime freight flows are exposed to as a function of the structure of liner shipping networks. Countries showed different levels of vulnerability to simulated attacks depending on the structure of the networks of the carriers providing services. For example, in their analysis, Calatayud et al. (2017) found that Jamaica, Argentina and Uruguay proved to be highly vulnerable to disruptions in Brazil. Wan et al. (2021) evaluated the resilience of ports in Asia with regard to typhoons and tropical cyclones. Their results suggest a higher resilience in South Asian ports as compared to East Asian ones, due to a lower recovery time and cost in case of disruption.

More recently, a number of studies have evaluated the effects of disruptions caused by the COVID-19 pandemic on port networks. Verschuur et al. (2021) estimated the effects of COVID-19 containment measures on port calls; their results demonstrate a strong geographical and sectoral heterogeneity. In their study on network dynamics during the initial phases of the COVID-19 pandemic, Dirzka and Acciaro (2022)

showed that suspended services were concentrated in East Asia, before rippling along main trade routes. Companies were able to prevent a rate collapse, despite deep declines in volumes — very much unlike the situation that unfolded more than a decade earlier during the financial crisis (Notteboom et al. 2021; Ferrari and Tei 2020). Guerrero et al. (2022) examined how port calls evolved during the first stages of the COVID-19 pandemic, compared to the later period. They showed that the mitigation policies implemented by governments affected regional port hierarchies differently, with a reduction in port concentration in Europe and Africa and an increase in Asia and North America. At the global level, their analysis shows that large ports or small but densely inter-connected ports were less affected by the crisis than small transshipment hubs.

Amongst the former studies, the only one analyzing specifically vessel schedule cancellation is Dirzka and Acciaro (2022). However, this study fails to distinguish between whole service cancellations and port call cancellations. To fill this void, this research proposes a novel methodology to detect vessel call cancellations on the basis of AIS data, which are widely available and increasingly used in port studies.

3. Data description and methodology

3.1. Data description

The initial dataset comprises 3,254,872 AIS positions of different containerships worldwide. The datetime ranges from January 2018 to October 2021. Vessels with some port outside the pendulum services, joining East Asia with the European Northern Range (Table 1, Figure 1) are not considered, yielding a final operational set of 96,645 AIS positions used in the present study.

Two levels of sample disaggregation are considered to fulfill two complementary research goals in this study: 1) to have inputs under alternative conditions for the design and implementation of the algorithm measuring the incidence of blank sailings; and 2) to find statistically significant results on operational conditions of shipping services that would be obscured without that dataset splitting. The first one is an obvious consideration of set partition according to the variable of arrival year of each vessel: before the COVID-19 outbreak ($\text{year} < 2020$) and after the COVID-19 outbreak ($\text{year} \geq 2020$).

The second one is to segment the data according to vessel size, expressed in twenty-foot equivalent units (TEUs); a meaningful criterion given the specific operational characteristics of vessels in each size group, and given the complexities of the pendulum services operated between Europe and East Asia (multiple regional sub-market coexisting with services spanning the entire range, mix of ports with diverse

nodal properties). Four size classes emerge from this splitting criterion: $\text{size} \geq 15,000$, $8,000 \leq \text{size} < 15,000$, $4,000 \leq \text{size} < 8,000$, and $\text{size} < 4,000$.

Table 1. Sample composition

| | year < 2020 (pre-COVID-19) | year \geq 2020 (COVID-19) | Total | Mean positions per vessel | Max positions per vessel |
|---|-------------------------------|--------------------------------|-----------|---------------------------|--------------------------|
| # {Positions} | 1,730,410 | 1,524,462 | 3,254,872 | | |
| # {Positions} _{pendulum} | 49,835 | 46,810 | 96,645 | | |
| # {Vessels} | | | 5,546 | 483 | 1,625 |
| # {Vessels} _{TEUs \geq 15000} | | | 175 | 316 | 964 |
| # {Vessels} _{8000 \leq TEUs < 15000} | | | 885 | 432 | 1,145 |
| # {Vessels} _{4000 \leq TEUs < 8000} | | | 1,162 | 519 | 1,177 |
| # {Vessels} _{TEUs < 4000} | | | 3,324 | 666 | 3,215 |
| # {Vessels} | | | 406 | 256 | 466 |
| # {Vessels} _{TEUs \geq 15000} | | | 138 | 163 | 279 |
| # {Vessels} _{8000 \leq TEUs < 15000} | | | 58 | 232 | 347 |
| # {Vessels} _{4000 \leq TEUs < 8000} | | | 77 | 316 | 595 |
| # {Vessels} _{TEUs < 4000} | | | 133 | 313 | 641 |

Source: Own elaboration

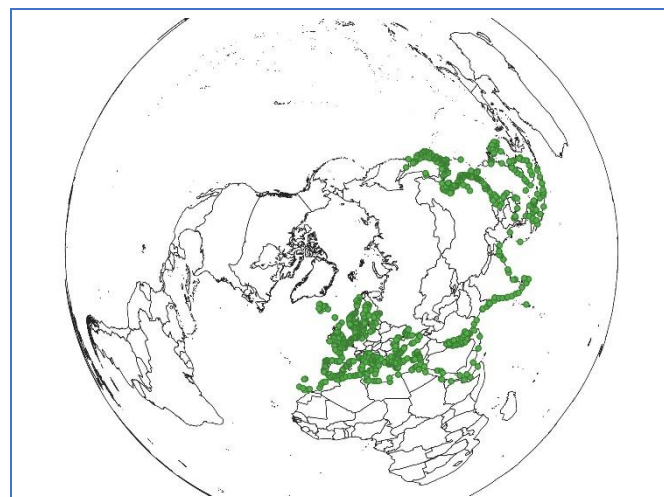


Figure 1. Operational dataset: geographical scope

Source: Own elaboration

3.2. Methodology

3.3.1 Schedule cancellation estimation

A new algorithm has been designed and implemented in pgSQL (postgresql.org)

2012) over the sequence of consecutive AIS positions of each vessel v (Figure 2), in order to estimate missing positions, if any. An example of vessel trajectory is depicted via the space-time diagram of Figure 3, where observed port calls and estimated ones are reported.

The basic idea of the embedded control iteration is to scan the path of each vessel and to test, for a given x_{i-1}^v port call, if $|x_i^v - X_i^v| < e$ where x_i^v is the actual next position of vessel v and X_i^v is the theoretical next position, estimated by the exploration of the statistical structure of the time frequency series for any given port within the complete path of this vessel. In the test above, e is a preset cutoff. If the test is not passed, then position i is marked as being skipped on the vessel's path and a new missed call is generated, along with an estimate of the timestamp.

The indicator that best captures the magnitude of blank sailings at the port level is the ratio (RBS) of blank sailings (B/S) between the (a) average number of B/S by vessel, and (b) the average number of effective calls by vessel. Naturally, the RBS ratio can theoretically take a minimum value of 0 and a maximum value of 1.

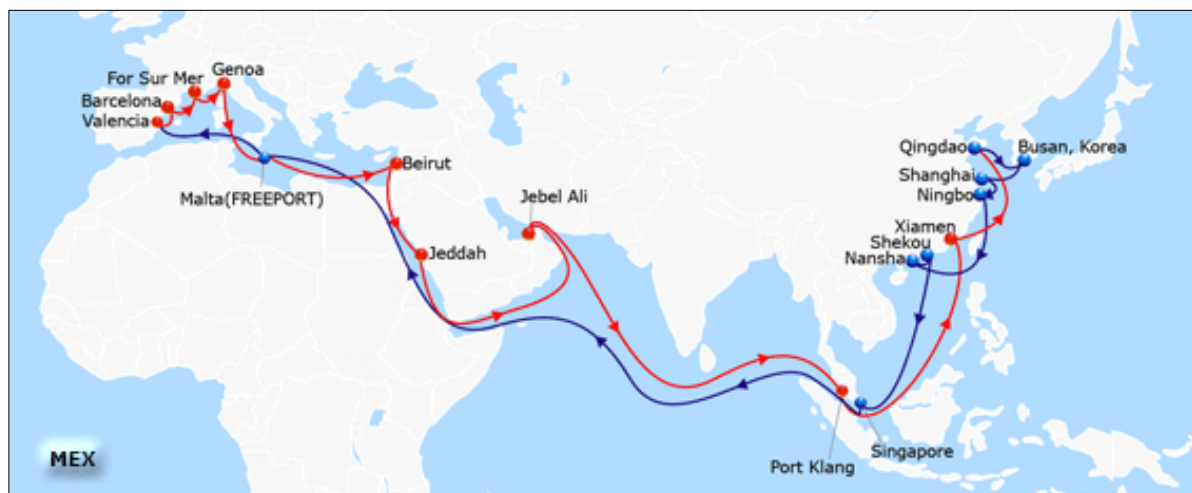


Figure 2. Mediterranean Club Express service (Example)

Source: CMA CGM. Retrieved on May 9, 2022 from the company's website

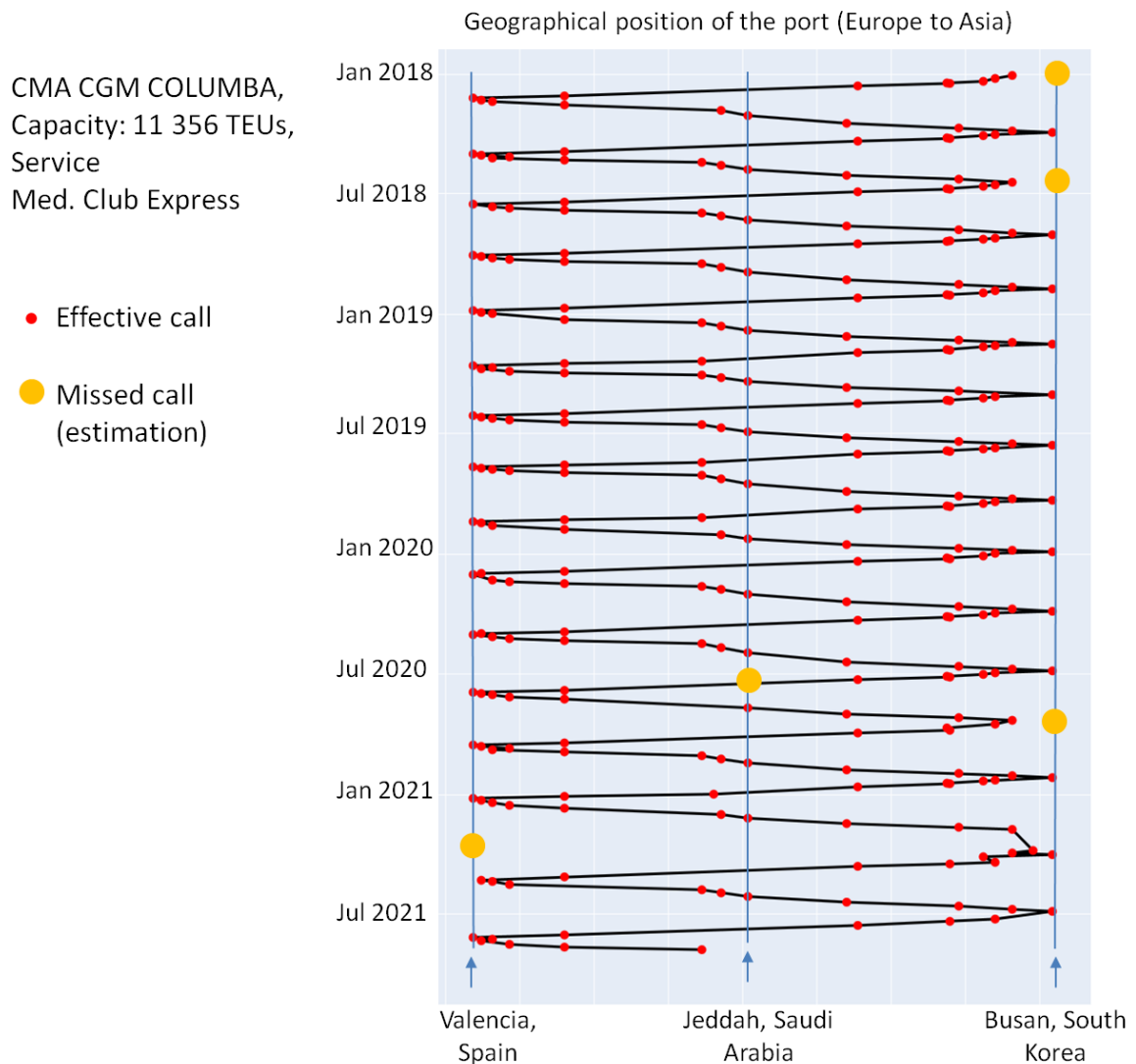


Figure 3. Space-time visualization of a sample vessel trajectory

Source: Own elaboration

3.3.2 Network description

According to the standard and currently accepted methods of complex networks construction (Ducruet & Notteboom 2012; Pais-Montes et al. 2012; Kang and Woo 2017), the whole sample of AIS positions has been grouped by the vessel's IMO number and by ascending order of positions between Europe and East Asia in each vessel grouping. This SQL query yields an array structure of consecutive positions. By splitting this array by ordered port arrival-departure pairs, a network, formed of a set of nodes (ports) and edges (consecutive positions), is produced for all vessels in the data sample. Other networks are derived from the two segmentations of the data indicated in Section 3.1. The network can be analyzed using a common software tool for directed graph analysis. Gephi, a classic, robust and continuously developing

environment for network analytics, was chosen for that purpose (Bastian et al. 2009).

A number of local, node-based measures of the containerized service network are computed. The purpose is to seek evidence of the possible dependence of the incidence of blank sailing (RBS) at the port level on their topological properties within the entire network of pendulum services. Table 2 comprises the complete list of calculated network estimators and of their meaning.

Table 2. Local network indicators

| | |
|-------------------------------|---|
| Indegree | Number of inward relational edges |
| Outdegree | Number of outward relational edges |
| Degree | Number of relations (edges) of each node |
| Weighted indegree | Number of inward links, weighted by edge weights |
| Weighted outdegree | Number of outward links, weighted by edge weights |
| Weighted degree | Number of relations (edges) of each node, weighted by the weight of each edge |
| Eccentricity | Maximum distance of one node from other nodes |
| Closeness centrality | Reciprocal of the sum of the length of the shortest paths between a given node and all other nodes in the graph (the more central a node is, the closer it is to all other nodes) |
| Harmonic closeness centrality | Reciprocal of closeness centrality: sum of the length of the shortest paths between a given node and all other nodes in the graph |
| Betweenness centrality | Number of shortest paths that pass through a node |
| Clustering coefficient | Ratio of the number of edges between the nodes within a node's neighborhood of immediately connected nodes to the number of edges that could possibly exist between them |

Source: Own elaboration

Table 3 presents the main global characteristics of the different networks, computed according to the two levels of segmentation; one graph is used to depict each time segment (before and after 2019). In a second level of disaggregation, we add an additional tier of disaggregation based on the class size of the vessels.

With the indicators computed, a first overview of the network topology of the

AIS sample can be obtained. The partitioning of data, based on the inception of the COVID-19 pandemic, does not point to great changes in degrees and weighted degrees (evidence supporting the robustness of the containerized transport network according to the direct connectivity parameter). On the other hand, Betweenness Centrality increases in a significant manner on average (evidence of a greater concentration of the supply lines after the emergence of the COVID-19 pandemic) and decreases in the maximum value (perhaps a signal of a clear loss of influence of all ports regarding the global transport pattern).

According to the vessel class, more significant differences can be seen, and some hypotheses that deserve further research can be outlined: a) do larger vessels tend to have higher direct connectivity? (According to the degree and weighted degree parameters); b) do ports serving larger vessels belong to more isolated supply sub-structures on the network? (Remarkably decreasing eccentricity parameter and increasing Closeness Centrality); c) is port competition stronger among smaller vessels? (Continuously decreasing Betweenness Centrality). All these preliminary intuitive elaborations will be put into context with the blank sailing structure of the vessels analyzed.

Table 3. Topology measures of networks

| | Pre COVID-19 | COVID-19 | TEUs < 4000 | 4000 ≤ TEUs < 8000 | 8000 ≤ TEUs < 15000 | TEUs ≥ 15000 |
|------------------------|--------------|----------|-------------|--------------------|---------------------|--------------|
| #Nodes | 1214 | 1214 | 1214 | 1214 | 1214 | 1214 |
| #Edges | 49331 | 46278 | 19732 | 9596 | 5928 | 11022 |
| Degree | | | | | | |
| avg | 25.48 | 25.55 | 21.07 | 19.03 | 21.16 | 24.10 |
| max | 137 | 130 | 85 | 72 | 84 | 71 |
| Weighted Degree | | | | | | |
| avg | 4.840E+6 | 4.497E+6 | 1.319E+6 | 2.062E+6 | 4.587E+6 | 1.552E+7 |
| max | 5.711E+7 | 6.060E+7 | 1.322E+7 | 1.543E+7 | 2.790E+7 | 7.511E+7 |
| Eccentricity | | | | | | |
| avg | 3.90 | 3.91 | 6.06 | 4.15 | 3.22 | 2.82 |
| max | 5 | 5 | 8 | 5 | 4 | 3 |
| Closeness Centrality | | | | | | |
| avg | 0.39 | 0.38 | 0.30 | 0.35 | 0.44 | 0.48 |
| max | 0.60 | 0.56 | 0.46 | 0.51 | 0.66 | 0.71 |
| Betweenness Centrality | | | | | | |
| avg | 386.27 | 437.43 | 560.23 | 346.07 | 144.76 | 86.76 |
| max | 8,208.54 | 7,810.11 | 7,114.23 | 4,522.34 | 1,751.89 | 679.94 |
| Clustering Coefficient | | | | | | |
| avg | 0.62 | 0.60 | 0.64 | 0.59 | 0.62 | 0.69 |
| max | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |

Source: Own elaboration based on AIS data

3.3.3 Logistic regression

To study the factors behind cancellation incidences at ports before and after the outbreak of the COVID-19 pandemic, we use a binomial logistic regression of the RBS measure on several intrinsic and extrinsic port attributes (port size, geographic location, position on the logistic networks, size of calling vessels). This type of model is appropriate for modeling proportions (Orelien, 2003), such as RBS. Technically, this is handled by considering possible port calls as trials and a cancellation as a binomial event. The logistic model can be used to determine if independent variables such as port size or the position of the port in the containerized shipping network affect the variation in the number of blank sailings at each port. We conduct the statistical analysis using the GENMOD procedure in the commercial statistical package SAS with a binomial specification of the response variable (SAS Inc. 2019).

To characterize the positions of ports within the containerized network we considered three specific indicators: weighted degree, betweenness centrality, and clustering coefficient. The weighted degree tallies shipping services calling at ports and weighs them by the number of vessels; it is used as a proxy for the capacity of the vessels deployed by carriers at ports. The betweenness centrality measures the number of possible shortest paths on which the port is positioned (Ducruet 2010). This is usually high at hubs and *en route* ports, and low for the ports served by few services, and generally located at the ends of shipping routes. The clustering coefficient of a port is a measure of the interconnectedness of its neighbors. This is particularly low for hub ports, because these are connected to many ports but the latter are poorly connected between themselves.

Figure 4 maps the network indicators for the ports under study before the outbreak of the COVID-19 pandemic. In both maps, the size of the circles is proportional to the ports' weighted degree. In Figure 4A, we show that the ports with higher betweenness centrality are large ports, located in East and Southeast Asia, as well as in intermediary locations such as Dubai, Piraeus and at both ends of the Suez Canal. On the other side of the range of values, ports with low levels of betweenness centrality (blue) are generally of smaller size, or they are located at the ends of the main East-West route, or in remote locations with regard to this line.

Figure 4B shows the level of clustering coefficient, which is generally high for small and medium-sized ports, many of which are located away from the main East-West shipping route. There are some complementarities between the two maps; for example large ports tend to have high levels of betweenness centrality and lower levels of clustering coefficient. However, there are a number of situations in which both indicators are positively

correlated (e.g., small ports at the ends of the Baltic Sea, Black Sea or in the Arabian Gulf). Therefore, these two indicators bring different information and potentially contribute to the explanation of the geographical distribution of cancellations. It is worth noting that although these maps reflect the situation of ports before the pandemic, they are similar to those obtained during the pandemic.

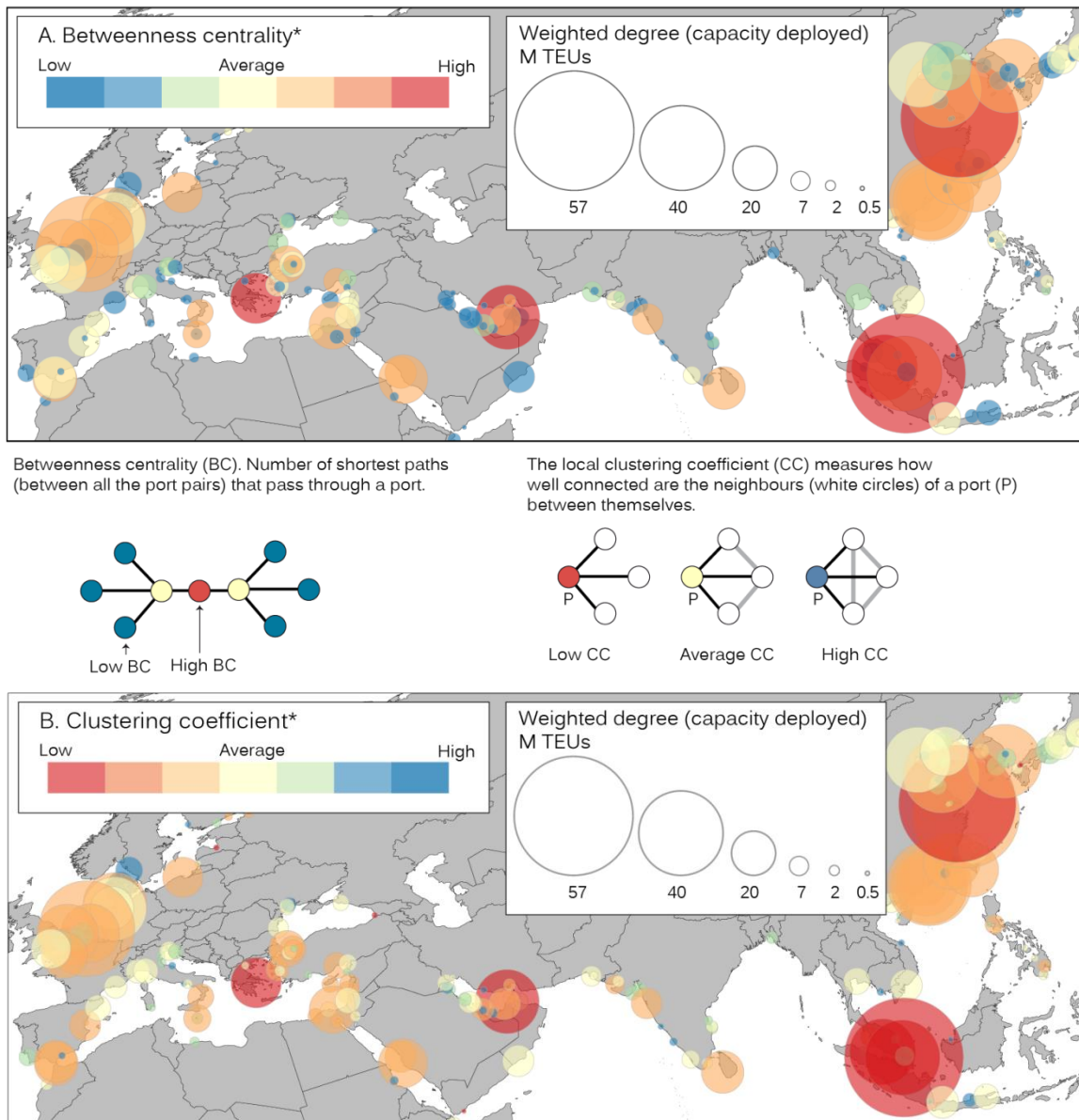


Figure 4. Network indicators for the ports under study (2018-2019)

Source: Own elaboration

To control for regional effects, we consider seven geographical groupings that are broadly consistent with the categories generally considered by maritime companies (AXS Marine 2022, p.28) (Table 4). To measure potential heterogeneity resulting from different sizes of vessels, we introduce the share of different sizes of vessels calling at the port: “XL”, for the vessels with a capacity greater than or equal to 15K TEUs, and “S” for the vessels with a capacity under 4K TEUs. Table 5 contains the descriptive statistics of the variables used in the logistic regression. The number of trials is given by RBS, which is the dependent variable of interest. Figure 5 shows the geographical distribution before and during the pandemic.

Table 4. Ratio of Blank Sailings (RBS) by region

| 2018-2019 | 2018-2019 | | | | | 2020-2021 | | | | |
|-----------|-----------|------|--------|-----|------|-----------|------|--------|-----|------|
| | N | Avg | StdDev | Min | Max | N | Avg | StdDev | Min | Max |
| ASEAN | 24 | 0.06 | 0.05 | 0 | 0.17 | 25 | 0.07 | 0.05 | 0 | 0.16 |
| FAR_EAST | 52 | 0.06 | 0.05 | 0 | 0.19 | 48 | 0.05 | 0.05 | 0 | 0.22 |
| IND_SUBC | 16 | 0.10 | 0.07 | 0 | 0.25 | 22 | 0.06 | 0.05 | 0 | 0.20 |
| MID_EAST | 29 | 0.06 | 0.05 | 0 | 0.19 | 35 | 0.06 | 0.06 | 0 | 0.33 |
| NORTH_EUR | 23 | 0.04 | 0.04 | 0 | 0.17 | 24 | 0.05 | 0.04 | 0 | 0.15 |
| NORTH_MED | 15 | 0.05 | 0.05 | 0 | 0.20 | 14 | 0.05 | 0.03 | 0 | 0.10 |
| SOUTH_MED | 34 | 0.06 | 0.05 | 0 | 0.25 | 37 | 0.04 | 0.04 | 0 | 0.14 |
| TOTAL | 193 | 0.06 | 0.05 | 0 | 0.25 | 205 | 0.06 | 0.05 | 0 | 0.33 |

Source: Own elaboration

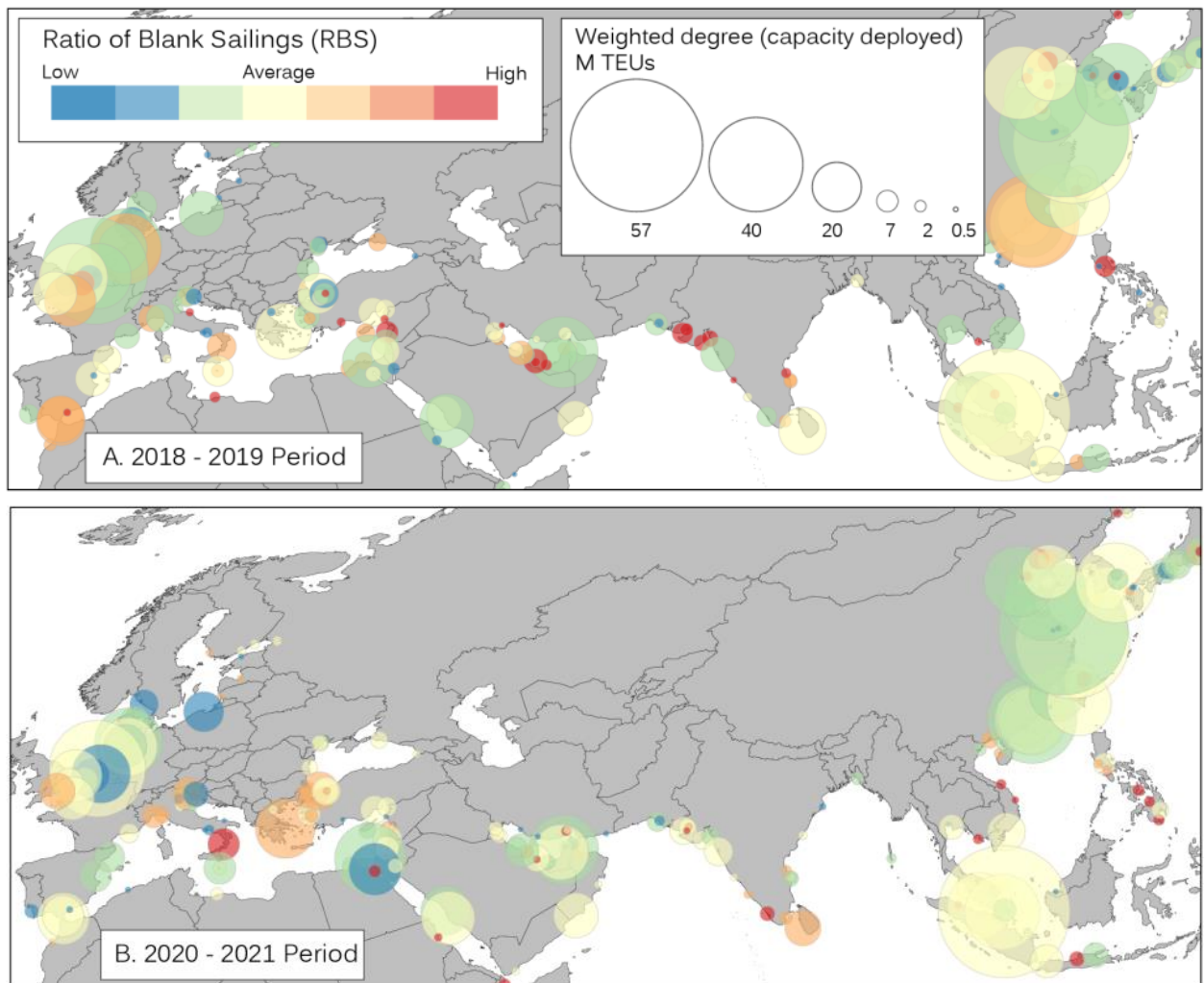


Figure 5 – Ratio of Blank Sailings (RBS)

Source: Own elaboration

Table 5. Descriptive statistics

| 2018-2019 period (n=193) | | Avg | Std Dev | Min | Max |
|---------------------------------|------------------------------|------------|----------------|------------|------------|
| RBS | Ratio of blank sailings | 0.06 | 0.05 | 0 | 0.25 |
| deg | Degree | 22.33 | 21.18 | 1.00 | 137.00 |
| ldeg | Degree (Log) | 2.70 | 0.94 | 0 | 4.92 |
| wdeg ('000) | Weighted degree | 4 128 | 8 754 | 2 | 57 111 |
| lwdeg | Weighted degree (Log) | 13.56 | 2.07 | 7.71 | 17.86 |
| clustc | Clustering coefficient | 0.62 | 0.23 | 0.00 | 1.00 |
| lclustc | Clustering coefficient (Log) | - 0.84 | 1.95 | - 11.51 | 0 |
| btwc | Betweenness centrality | 330.70 | 849.17 | 0.00 | 8 208.54 |
| lbtwc | Betweenness centrality (Log) | 2.27 | 5.21 | - 11.51 | 9.01 |
| wdeg_s_pct | % vessels of < 4K TEUs | 0.45 | 0.41 | 0 | 1.00 |
| wdeg_xl_pct | % vessels of > 15K TEUs | 0.16 | 0.28 | 0 | 1.00 |
| FAR_EAST | Regional dummy | 0.27 | 0.44 | 0 | 1 |
| NORTH_EUR | Regional dummy | 0.12 | 0.32 | 0 | 1 |
| SOUTH_MED | Regional dummy | 0.18 | 0.38 | 0 | 1 |
| NORTH_MED | Regional dummy | 0.08 | 0.27 | 0 | 1 |
| IND_SUBC | Regional dummy | 0.08 | 0.28 | 0 | 1 |
| ASEAN | Regional dummy | 0.12 | 0.33 | 0 | 1 |
| MID_EAST | Regional dummy | 0.15 | 0.36 | 0 | 1 |
| 2020-2021 period (n=205) | | | | | |
| RBS | Ratio of blank sailings | 0.06 | 0.05 | 0 | 0.33 |
| deg | Degree | 22.29 | 20.78 | 1.00 | 130.00 |
| ldeg | Degree (Log) | 2.70 | 0.95 | - | 4.87 |
| wdeg ('000) | Weighted degree | 3 793 | 8 188 | 4 | 60 598 |
| lwdeg | Weighted degree (Log) | 13.41 | 2.13 | 8.39 | 17.92 |
| clustc | Clustering coefficient | 0.62 | 0.23 | 0.00 | 1.00 |
| lclustc | Clustering coefficient (Log) | - 0.78 | 1.74 | - 11.51 | 0 |
| btwc | Betweenness centrality | 366.44 | 882.34 | 0.00 | 7 810.11 |
| lbtwc | Betweenness centrality (Log) | 2.17 | 5.60 | - 11.51 | 8.96 |
| wdeg_s_pct | % vessels of < 4K TEUs | 0.46 | 0.42 | 0 | 1.00 |
| wdeg_xl_pct | % vessels of > 15K TEUs | 0.17 | 0.30 | 0 | 0.96 |
| FAR_EAST | Regional dummy | 0.23 | 0.42 | 0 | 1.00 |
| NORTH_EUR | Regional dummy | 0.12 | 0.32 | 0 | 1 |
| SOUTH_MED | Regional dummy | 0.18 | 0.38 | 0 | 1 |
| NORTH_MED | Regional dummy | 0.07 | 0.25 | 0 | 1 |
| IND_SUBC | Regional dummy | 0.11 | 0.31 | 0 | 1 |
| ASEAN | Regional dummy | 0.12 | 0.33 | 0 | 1 |
| MID_EAST | Regional dummy | 0.17 | 0.38 | 0 | 1 |

Source: Own elaboration

4. Results

Table 6 reports the estimation results of the model, in which the coefficients have been standardized to enable comparisons and facilitate interpretation. Overall, its explanatory power, measured by the pseudo R^2 , is similar in the two periods (pseudo $R^2=0.64-0.65$). Both clustering coefficient and betweenness centrality contributed significantly to the model in both periods. This means that carriers cancel vessel calls at very central ports (ex. transshipment hubs which can be easily replaced by other hubs such as Gioia Tauro (Italy) or at ports that are more peripheral but also part of highly meshed networks such as Izmir in Turkey (hinterlands which can eventually be accessed through other ports)).

The results show that, in the period before the pandemic, the share of cancelled calls was clearly lower for ports attracting mega vessels. However, during the COVID-19 pandemic, the incidence of cancellations affected more the ports attracting a large share of mega vessels.

At the other end of the vessel size scale, ports attracting a high share of vessels of less than 4K TEUs were more severely hit by cancellations during the 2020-2021 period. This means that ports attracting a high share of vessels of “intermediate” size (4K-15K TEUs) proved to be more resilient to cancellations during the COVID-19 pandemic.

The results also show that cancellations have been less frequent in Northern Europe (reference category in the model) and in the Northern Mediterranean, than in the rest of the regions under study. En-route regions, such as ASEAN, South Med, Middle East and Indian Subcontinent, had particularly large coefficients in 2018-2019. These regions, where less cargo is sourced, appear less critical to carriers; they were therefore more likely than others to experience cancellations. During the 2020-2021 period, many of the ports of these regions have had substantially higher cancellation incidence. The smaller size of the coefficients and the lower statistical significance suggest that regional effects were less prominent during the COVID-19 pandemic.

Although the weighted degree, when considered alone, was not found to significantly affect the share of cancellations, it has indirect influence on results through other variables. Figure 5 shows the combined effects of weighted degree with other variables. The interactions with the clustering coefficient and with betweenness centrality show that the weighted degree substantially mitigates the effect of the former variables on the share of cancellations. This means that ports with high clustering coefficient or with high betweenness centrality only, have a high share of cancellations when their size is rather small. The interactions with the vessel size variables are more complex. In the case of large vessels (share of vessels with a capacity above 15K TEUs), in 2018-2019, the weighted degree mitigates the negative effect of vessel size on cancellations. Namely, the negative effect of mega vessels on cancellations, was less important in the largest ports

(high weighted degree). During the COVID-19 pandemic (2020-2021), we found the opposite effect: the positive impact of large vessel size on cancellations was largely mitigated by the size of the port (high weighted degree). Therefore, during the COVID-19 pandemic, large ports (high weighted degree) seem to be more affected by call cancellations than smaller ones. As it goes against former analyses based on port throughput (Fedi et al. 2022), this result appears to be counterintuitive; it calls for further investigation into alternative factors.

For ports attracting large shares of smaller vessels (below 4K TEUs), the weighted degree reduces the probability of being skipped, as shown by the negative interactions in both periods.

Table 6. Results of the logistic regression model

| Variable | Description | 2018-2019 | 2020-2021 |
|-----------------------|------------------------------|-----------|-----------|
| lwdeg | Weighted degree (log) | -1.34 | -1.03 |
| lclustc | Clustering coefficient (log) | 1.97 ** | 1.79 * |
| lbtwc | Betweenness centrality (log) | 2.31 ** | 2.48 ** |
| wdeg_xl_pct | Share of vessels >15K TEUs | -2.49 ** | 3.52 *** |
| wdeg_s_pct | Share of vessels <4K TEU | 1.49 | 3.05 *** |
| lwdeg*lclustc | Interactions | -1.85 * | -2.00 ** |
| lwdeg*lbtwc | Interactions | -2.64 *** | -1.95 * |
| lwdeg*wdeg_xl_pct | Interactions | 2.74 *** | -3.64 *** |
| lwdeg*wdeg_s_pct | Interactions | -1.97 ** | -3.27 *** |
| FAR_EAST | Regional dummy | 2.61 *** | 2.06 ** |
| ASEAN | Regional dummy | 4.19 *** | 3.12 *** |
| SOUTH_MED | Regional dummy | 3.71 *** | -0.45 |
| NORTH_MED | Regional dummy | -0.84 | -1.72 * |
| MID_EAST | Regional dummy | 3.24 *** | 0.71 |
| IND_SUBC | Regional dummy | 4.12 *** | 0.35 |
| N | | 193 | 205 |
| Pseudo R ² | | 0.65 | 0.64 |

Levels of significance: p-value<0.1 (*), p-value<0.05 (**), p-value<0.01 (***)

Source: Own elaboration

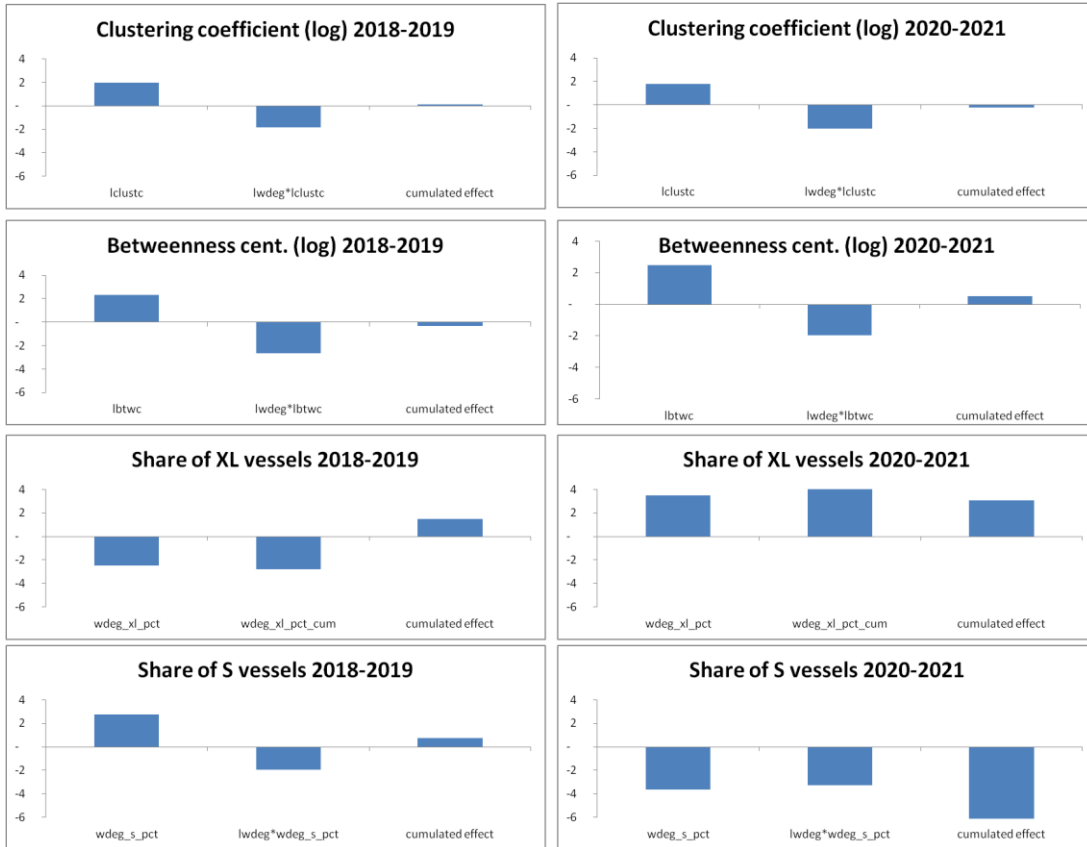


Figure 5 – Interactions with weighted degree (port size)

Source: Own elaboration

5. Conclusions

In this paper, we have proposed a novel method for identifying vessel schedule cancellations at ports. Compared to previous works (e.g., Dirzka and Acciaro 2022), the current approach has the advantage of being entirely based on the effective movements of vessels (AIS), instead of carrier notices and theoretical schedules. Moreover, our approach allows one to analyze call cancellations without the interference of service cancellations, whose purpose is different.

As an application of this method, we have analyzed the incidence of vessel schedule cancellations along the Europe–Far East route before and during the COVID-19 pandemic. Our results show that the incidence of vessel schedule cancellations was different before and during the COVID-19 pandemic, especially with regard to vessel size. In the period before the pandemic, the share of cancelled calls was clearly lower for ports attracting mega vessels. However, during the COVID-19 pandemic, the incidence of cancellations affected more the ports attracting a large share of mega vessels. Another important result of this study is that, before the COVID-19 pandemic, the rate of vessel schedule cancellations was much more uneven between world regions than after the COVID-19 outbreak. These regional effects diminished during the pandemic, with less differences in vessel cancellations between regions. It is worth noting that, in both periods, European ports were

significantly less affected than their counterparts in the other regions under study.

As an exploration on the determinants of high rates of cancellation at ports, we have looked at correlations with different network indicators. The share of cancellations is generally higher at central ports (betweenness centrality) such as Gioia Tauro (Italy) or in ports part of highly meshed networks (clustering degree), such as Semarang (Indonesia). This can be interpreted as higher vulnerability of hubs, which seem more easily substitutable in case of disruptions. This result is interesting and suggests that the centrality of ports for the carriers serving them may differ considerably from the theoretical centrality computed through classical network analysis.

The method proposed in this paper is just a first step in the identification of regularities/irregularities in sailing schedules. An avenue for further research could be the improvement of the algorithm for detecting cascading effects, such as same vessel shifting from one trade route to another. This may be eventually achieved by the automatic detection of highly irregular vessel schedule patterns. Also, the present work considered the COVID-19 pandemic period as a whole. A potential extension of this work could be the detailed analysis of the different waves of the pandemic to identify longitudinal changes in vessel call cancellation to operational conditions of the maritime logistics system.

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