Research in Transportation Economics 94 (2022) 101127

Contents lists available at ScienceDirect

Research in Transportation Economics

journal homepage: www.elsevier.com/locate/retrec

Examining COVID-19-triggered changes in spatial connectivity patterns in the European air transport network up to June 2021

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ARTICLE INFO

JEL classification:
R40

Keywords:
European air transport network
COVID-19
Spatial connectivity changes
Airport susceptibility

ABSTRACT

The integrity of international supply chain operations heavily relies on air transport services to facilitate the movement of goods and enable human interactions between its stakeholders. With the outbreak of COVID-19 in Europe around March 2020, air transport networks have been subject to profound alterations. Although the link between variations in air transport service levels and changes in user costs for network-wide travel has been analysed extensively, few studies have examined the extent to which severe network shrinkage events lead to a reduction in network connectivity, which is therefore difficult to predict. This paper investigates how the COVID-19 pandemic has structurally altered the European air transport network in 2020/21 and how these changes have deteriorated users' ease when utilising network-wide air transport services. To do this, the paper estimates the change in average quickest path length at the airport level during different stages of this period. Results indicate there is strong heterogeneity in airports' susceptibility to pandemic-induced network changes, with both regional variations and variations in the airline type serving individual airports. Furthermore, topological features of individual airports are found to determine airport susceptibility. The findings are discussed in terms of their implications for locational decisions in supply chain designs.

1. Introduction

In response to the COVID-19 pandemic, which reached Europe in the winter of 2020, governments have implemented a range of measures, including movement restrictions and temporary border closures, to contain the spread of the virus. These measures have affected the way in which operations in transnational supply chains are coordinated, as indicated, for example, by the unprecedented increase in online business meetings. However, some supply chains cannot fully abstain from international connectivity, as they often rely on the timely accessibility of specialized services, expert staffing, and the rapid long-distance transportation of intermediate or finished products. Airlines, the primary providers of such transport services in Europe, markedly downscaled their operations in 2020 (EUROCONTROL (2021); IATA (2020)), bringing a long-term growth phase in inner-European connectivity (Burghouwt (2007); Dobruszkes (2014)) to an abrupt halt and shrinking the structure of the European air transport network (EATN) on an unprecedented scale. Consequently, the manner in which inner-European air transportation is organized may have changed fundamentally, bringing about wide-ranging implications related to human mobility, regional accessibility, and international supply chain operations reliant on the connectivity created by air transport services.

Applying concepts of complex network theory, this paper analyses how these structural network changes have affected regional and network-wide connectivity patterns in 2020 and 2021. Special emphasis is placed on (i) the analysis of spatial variations of connectivity outcomes among different regions in Europe, (ii) the differentiation of effects in regard to varying airline business models, and (iii) the explanation of effect size variations at the airport level. To this end, this study employs the concept of airport susceptibility, which is the change of an airport's average quickest path length (Malighetti et al., 2008), in 2020 and 2021 relative to corresponding values prior to the pandemic. The EATN is treated as a multi-layered network (Cardillo, Gómez-Gardeñes et al., 2013), and the definition of its spatial substructures is derived from modularity maximizing community detection (Newman & Girvan, 2004). This study adds to the literature by mapping structural network changes during a historically rare period of transport network shrinkage to explain the drivers behind the heterogeneity of the system's response and by discussing the implications of these changes with respect to locational supply chain design decisions.

The remainder of this paper is organized as follows. Section 2 outlines relevant literature and Section 3 discusses the network theoretical

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https://doi.org/10.1016/j.retrec.2021.101127
Received 22 February 2021; Received in revised form 23 July 2021; Accepted 7 September 2021
Available online 17 September 2021

methods applied in this paper. Section 4 presents the results of the analysis in three steps. First, the long-term evolution of the EATN between 2004 and 2019 is briefly discussed to provide a reference for the analysis; second, the structural changes that have occurred in 2020/21 are outlined; third, the corresponding connectivity effects are presented. Lastly, Section 5 concludes.

2. Literature review

Characteristics of air transport networks and their evolution over time have been studied at the global (Guimerà et al. (2005); Azzam, Klingauf, and Zock (2013); Verma et al. (2014); Woolley Meza et al. (2011)), regional (Dai et al. (2018); Lordan and Sallan (2019)) and domestic levels (e.g. Jia et al. (2014); Hossain and Alam (2017); Su et al. (2019)). This section considers the most relevant streams of literature to this study, beginning with the general evolution of the EATN and continuing to publications relevant in terms of methodological choice.

A number of contributions describe the general evolution of European air transport since the industry's deregulation at the end of the last century using supply statistics (e.g., Dennis (1994); Graham (1998); Dennis (2005)). A common finding of this literature is that network evolution in Europe was a two-stage process. Prior to 2000, primarily full-service carriers (FSC) drove network evolution by setting up radial systems to yield the benefits of hubbing operations (Burghouwt et al. (2003); Burghouwt and de Wit (2015)). In subsequent years, network development was dominated by low-cost carriers (LCC) scaling up their presence in Europe stepwise (Fan, 2006). Initially, LCCs focused their operations on north-south links connecting secondary airports within Western Europe (Dobruszkes, 2006), often bypassing major hub airports (Ramos-Pérez and Sánchez-Hernández 2014). They then diversified their operations to focus on connecting Western and Central-Eastern Europe (Dobruszkes (2009); Dobruszkes (2013)), and from 2010 on, they have increasingly also offered services from major hub airports (Dobruszkes et al., 2017). The continuous growth of LCC operations outside established FSC structures is thereby found to have led to a de-concentration of the EATN (Suau-Sanchez et al., 2016).

Another strand of the literature applies methods of complex network theory to study the topological structure of air transport networks and their evolution. Using network snapshots on specific dates, authors have analysed network properties of individual airlines (Han et al. (2009); Lange and Bier (2019)), domestic systems (Guida and Maria (2007); Papatheodorou and Arvanitis (2009); Jimenez, Claro, and Jorge Pinho de Sousa (2012)), or, more holistically, the European system (Paleari et al. (2010); Tranos (2012)). A frequent finding is that the networks studied show features similar to those of so-called "small-world" (Watts & Strogatz, 1998) and "scale-free" networks (Barabási and Albert 1999), with relatively small average topological distances between all network airports and a strong heterogeneity in connectivity pattern across these airports. Using a longitudinal perspective, S. Zhang, Derudder, and Witlox (2015) study the drivers behind the structural changes of the EATN between 2003 and 2009 and identify two counteracting network dynamics. While the growth of hub-and-spoke structures promoted by FSC airlines has led to a spatial concentration of flights in the network, the emergence of LCC airlines has formed triadic structures and thus contributed to network densification. Similarly, Wandelt et al. (2019) compare the evolution of the EATN with the growth in other air transport networks and suggest that the EATN is subject to a gentle but continuous densification process. Sun et al. (2015) investigate the temporal evolution of the European airport network by analysing regular variations in network properties over time. Their findings indicate that network properties vary substantially by season and day of the week, implying that a longitudinal analysis of network properties must consider such a pattern.

A different research grouping is concerned with the analysis of the extent to which air transport networks facilitate network-wide travel. Various approaches to measuring connectivity - here defined as the extent to which an airport is connected to the rest of the network and hence facilitates network-wide journeys - have been proposed in the literature (Burghouwt and Redondi (2013); ITF (2018)). A general finding in these studies is a strong heterogeneity in connectivity across different airports (Malighetti et al. (2008); Lee et al. (2014)). In the context of longitudinal data, research has focused on long-term connectivity evolution during stages of network growth (Allroggen et al. (2015); Cattaneo et al. (2017); Mueller and Aravazhi (2020)). This literature suggests that there has been substantial growth in network-wide connectivity in the decades prior to the outbreak of COVID-19. However, empirical literature that analyses connectivity effects during network shrinkages remains extremely sparse, with a notable exception being Woolley Meza et al. (2013). Computing the increase in a path length-based measure due to network shrinkage caused by the 2010 eruption of the Eyjafjallajökull volcano and September 11th, 2001, terrorist attacks, the authors find that such events have heterogeneous impacts on airports' connectivity that correlate with the topological characteristics of individual airports.

Methodically most relevant are several recent contributions that apply more advanced concepts of complex network theory. First, several studies have explored network topology based on the view that complex systems can be represented as multi-layered networks (see Aleta and Moreno (2019) for a recent review). As indicated by Cardillo, Gómez-Gardeñes et al. (2013), the topological properties of aggregated networks, in this case the EATN, are the consequence of progressively merging individual network layers (i.e., airline networks). Thus, studying the aggregated network without considering the special feature of its building blocks might disguise important relationships. Applying a multi-layer perspective to the European airport system in 2014, for example, Lordan and Sallan (2017) detect the existence of a hierarchical airport structure in the EATN. Second, with a special interest in a more fine-grained spatial partitioning of a network, a few contributions apply community detection algorithms to identify 'natural' subcomponents within the network. A general finding in this stream of literature is that the European airport network can be subdivided into multiple sub-modules, characterized by denser interactions (i.e., number of flights) among themselves than with the rest of the network. The demarcations of these airport communities are identified to typically follow national borders clustering together airports in close geographical vicinity into supra-national constructs (Malighetti et al. (2009); Gurtner et al. (2014)). This finding is significant as it allows researchers to derive geographically coherent segments of the network based on existing topological features rather than on arbitrary segmentation of the network and hence might provide a consistent approach to the study of network evolution in a spatial context.

Finally, a body of literature has started to emerge that covers several dimensions of the COVID-19 pandemic's link to the air transport system. Publications have analysed air transport's contribution to the virus spreading globally (Christidis and Christodoulou (2020); Y. Zhang et al. (2020)), related mitigation strategies (Chen et al., 2020), and potential recovery patterns (Gudmundsson et al. (2021); Serrano and Kazda (2020); Bauer et al. (2020)) and have conducted early assessments of changes in air transport geography due to the pandemic (Sun et al., 2020).

To summarize, the literature review indicates that the nature and evolution of the EATN have been studied predominantly in a cross-sectional context or during phases of network growth. Empirical studies on structural changes and their network-wide, as well as spatial connectivity implications during periods of network shrinkage remain widely absent. This paper provides such an analysis, using the network alterations that have occurred during the COVID-19 pandemic as a case study.

3. Methods

In this paper, the EATN is represented as a network with N nodes (airports) that takes the form of a weighted $N \times N$ adjacency matrix W, where its elements w_{ij} represent the number of weekly direct scheduled passenger flights x between any two airports i and j located within Europe. To analyse the structural evolution of the EATN through time, static snapshots W_t for the period between 2004 and 2021 are derived. Every snapshot W_t represents the network with only the set of airports and flights that appears in t as sourced from the 'SRS-Analyzer Flight Schedule Database' (SRS 2021). W_t is constructed as an asymmetric matrix with elements $w_{ij} = x$ if $x \geq 1$ and $w_{ij} = 0$ otherwise. Thresholding W_t yields the corresponding unweighted adjacency matrix A_t, with its elements $a_{ij} = 1$ in cases of $|w_{ij}| \geq 1$, and $a_{ij} = 0$ otherwise (da F. Costa et al., 2007). Various structural network characteristics can be derived from A and W (Boccaletti et al. (2006); da F. Costa et al. (2007); Barthélemy (2011)). An overview of the basic network theoretical metrics, their standardization (Zanin et al. (2018)) and other concepts applied in this paper is provided in Annex 1. To unveil the role that different airline types, play in the evolution of the aggregated EATN, this paper derives two additional subsets for each W_t. The first comprises only flights operated by LCCs (as classified by (SRS 2021)), in this paper termed the 'LCC layer', and the second contains all flights not operated by LCCs, called the 'FSC layer'.

The connectivity of an airport i in a certain network snapshot W_t is proxied by the quickest travel time approach proposed in Malighetti et al. (2008). For each network airport $j \neq i$, the specific travel path is identified for which the summation of in-vehicle travel time and eventual periods of waiting for connecting flights is minimal, termed the 'quickest path length' L_Q. To also measure the connectivity effects of weakly integrated airports, L_Q is derived based on weekly network snapshot W_t ranging from Mondays 00:00 to Fridays 24:00, and no bound is established on total maximum travel times. It is further assumed that indirect travel paths require in general a minimum connection time of 30 min. For remotely located airports, this minimum connection time is reduced to 10 min (EC 2019).

To assess connectivity changes at the nodal level, the concept of the airport's susceptibility (Woolley Meza et al., 2013) is used and defined in this paper as

$$\chi_i = m_i\left(L_Q^{t+n}\right) - m_i\left(L_Q^{t}\right), \tag{1}$$

Namely, it is the difference in typical quickest path length of an airport i between two periods, with m_i denoting the median across all values L_Q for a fixed origin airport i. Note that χ_i is derived using only those destination airports that are connected to the network in both periods.

To investigate the evolution of the EATN over time from a spatial perspective, a partition of the network into reasonable sub-components is needed, which is (i) non-arbitrary and (ii) sufficiently stable over time to foster longitudinal comparisons. As for the former condition, this paper analyses the community structure of the EATN resulting from the maximization of modularity (Newman and Girvan (2004); Blondel et al. (2008)) and hence is not biased by arbitrarily selected geographical bounds. Fig. 1 suggests that the resulting clusters are spatially coherent and hence are suitable to serve as geographical subdivisions of the network.

As for the necessary stability of network partitions over time, lines of community succession of 32 independently computed, seasonal[1] consensus community structures (Bassett et al. (2013); Lancichinetti and Fortunato (2012)) are established using the inclusion value method proposed in Bródka et al. (2013). Results suggest an inherent stability of the community structure, with the majority of the occurring evolutionary events referring to the temporary disconnect of individual airports from the network. Only a few structural effective evolutionary events (e.g., merging of French and Iberian clusters) can be found, but interestingly, such events embed or extract communities in their entirety into other clusters rather than breaking them into multiple subgroups. A detailed assessment of the similarity of the partitions over time, based on the information-theoretical measure of the variation of information (Meilă, 2007) also quantitatively confirms this longitudinal stability in community structure. Building on the aforementioned findings, the spatial analysis in this paper is grounded in the geographical demarcations of the network as defined by the airport communities presented in Fig. 1. To enrich the analysis, individual clusters (e.g., French, Turkish) are consistently treated as separate communities even in snapshots in which they are embedded in other clusters.[2]

4. Results

4.1. Long-term evolution of the EATN and its layers prior to the COVID-19 pandemic

The long-term evolution of the EATN can be traced to the interplay of opposing, evolutionary processes within its two layers. The substantial and continuous growth of the LCC layer accompanied the stagnation of the FSC layer (Fig. 2, Panels A–C). Especially after the global financial crises of 2007–2008, gains in the EATN's size are predominantly attributable to the advances in the LCC layer. Despite an overall network densification process, the EATN and its layers remain extremely sparse networks, with only 2%–6% of all city-pairs connected by a direct flight (Table 1). Density in the FSC layer is thereby considerably lower than in the LCC layer, with flights being more concentrated on individual city-pairs in the former than in the latter. Regardless of this low density, a journey in 2019 between two randomly picked airports requires only 2.5 to 3.0 connecting flight segments, emphasizing the highly organized nature of the layers. Considering the existing dissimilarities in network sizes, these differences in the directness of travel between the EATN and its layers are only minor (i.e., z-scores). The diverting clustering values (both absolute and standardized) between the two layers are indicative of different structural network organizations. Applying the concept of clustering in weighted graphs (Barrat et al., 2004) yields that triplets in the EATN and especially the FSC layer are often formed by high-frequency links, which is typical for networks where many spoke airports are simultaneously linked to at least two interconnected (hub-) airports.

Beyond aggregated network size statistics, Panel D maps changes in the distributional form of link flux (w), degree (k), and strength (s) for the EATN. As mentioned by others (e.g., Woolley Meza et al. (2011)), the tailing distributions reflect the strong structural heterogeneity in the network, with a few high-connectivity observations and a majority of nodes/links with weaker network integration. A comparison with randomly organized networks (i.e., networks of equal size but unpreserved degree structure) manifests this high grade of network organization. However, in contrast to earlier reporting, statistical testing (Gillespie (2015); Clauset et al. (2009)) does not yield evidence that any of the distributions (including layer-specific distributions) follow a power-law over multiple orders of magnitude. Instead, decay at particularly high-spectrum airports is faster than linear. In an evolutionary context, differences in distributions over time in the EATN are statistically significant (Kolmogorov-Smirnov test), as a general shift towards higher degree/strength airports occurred. For a comparison of layer-specific distributions, the reader is referred to Annex 3.

Panel E maps the corresponding evolution of the network-wide connectivity based on the changes in the average quickest path statistic (L_Q) over time. Accordingly, in the period from 2004 to 2019, the average minimum travel times between pairs of airports in the EATN

[1] Network snapshots 2004–2019 in line with IATA-seasons (IATA (2019)).

[2] For supplementary information about the diversity in communities' structural properties, flow volumes and airline dominance, the interested reader is referred to Annex 2.

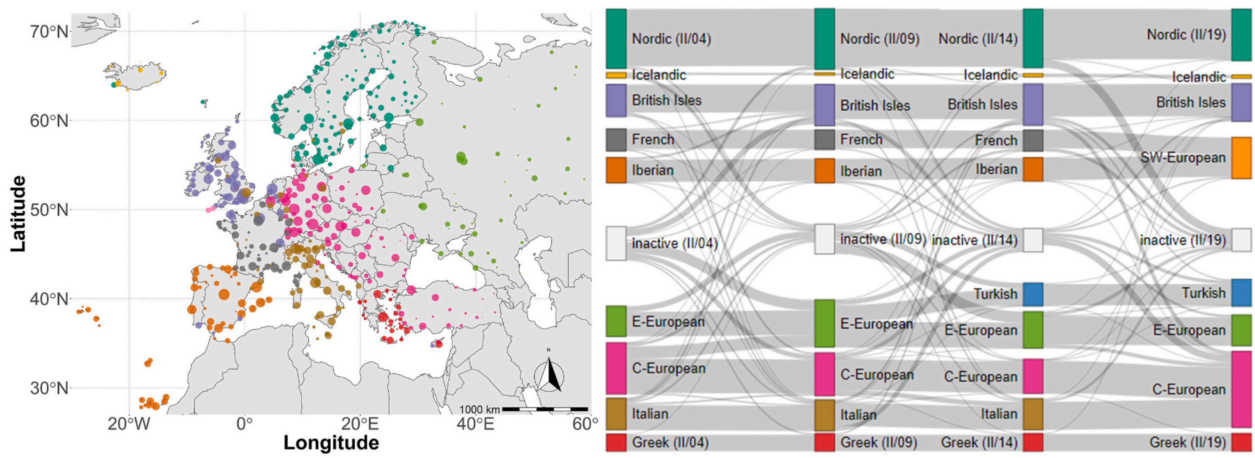

Fig. 1. Consensus community structure EATN and community succession over time.

Note: The consensus community structure is derived based on 1000 randomized community realizations per snapshot. The map to the left shows the network snapshot of the summer season of 2004. Airports are represented by circles whereby the radius of the circle is proportional to airport strength (log). Airport colouring indicates community membership and is consistently applied in visualizations throughout this paper. The alluvial diagram to the right represents community membership of airports as flows over time. Vertical bars are proportional to the number of airports affected. Notation of communities is done according to the geographical location in Europe. The 'inactive' bar denotes airports disconnected from the network in a specific snapshot. Communities $|G| < 5$ are omitted to increase perceptibility.

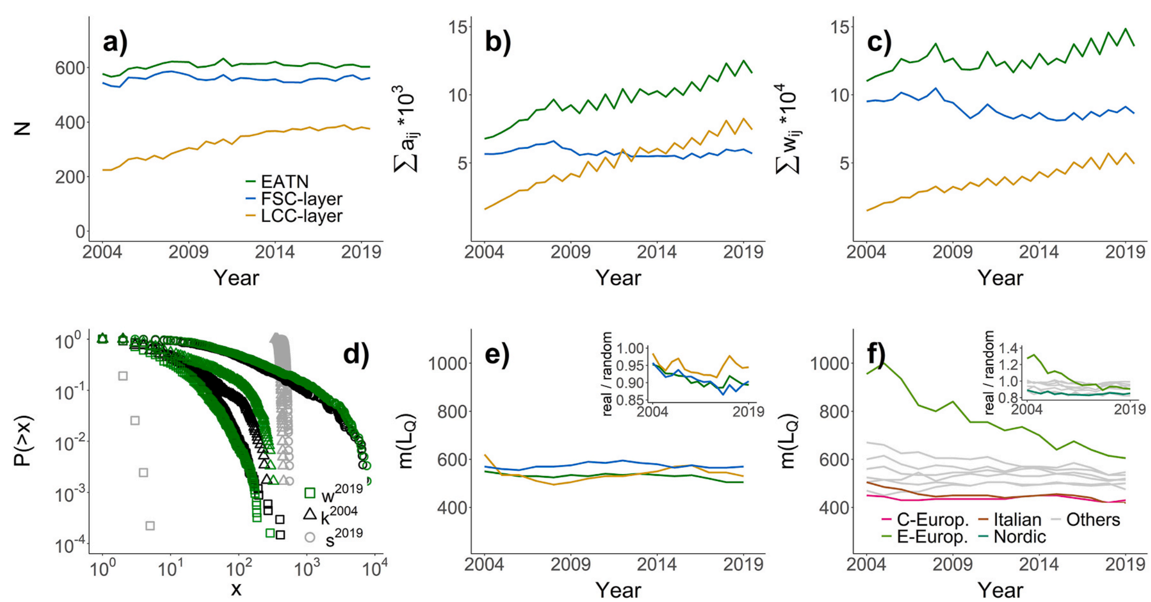

Fig. 2. Network evolution 2004–2019.

Note: Panels a) - c) depict the evolution of network size statistics (airports, links, and flights) in the EATN and its layer. Based on snapshots of the first calendar week in April and November each year. Panel d) depicts distributions of link weights (w), airport degree (k), and airport strength (s) based on April 2004 and 2019 for the EATN. Distributions for random network realizations with size statistics equal to empirical networks of April 2019 but with unpreserved degree sequence (Bernoulli-type) as a reference in grey. Panels e)-f) depict evolution in average quickest path length over time for EATN, layers and communities. The insets provide the ratio between the empirical networks and the median values source for random network realizations with preserved degree and strength sequence. Departure times remain thereby unchanged but arrival times at the 'randomized' destination nodes are adjusted according to the corresponding flight distance between the nodes.

decreased by approximately 10% from 550 to 500 min (Panel E), with a strong variation of values at the individual airport level. This connectivity increase is robust even if potential effects induced by network size alterations are considered (inset Panel E). In fact, such a perspective yields that connectivity gains in the EATN are primarily driven by improvements in the FSC layer. Note that a ratio of 1 between the observed and randomized measures as such indicates that the temporal coordination between flights has not been an intended design feature in the planning process of the network. It can therefore be concluded that temporal coordination is of minor concern in the LCC layer and that variations in absolute values in this layer (main panel) are largely attributable to network size effects and related alterations in spatial coverage.

Regarding variations in connectivity across different regional parts of the EATN, Panel F allows for several observations. First, minimum travel times from different parts of the network vary substantially. Average journeys across Europe from the best-connected community in 2019, the Italian cluster, involve a travel time of on average 430 min, whereas trips from the average Eastern-European airport last a minimum of 605 min. As travel time-based measures are sensitive to the geographical location of airports in the network, it is not surprising that more centrally located communities achieve better values. However, a

Table 1
Comparison network properties of 2004 vs. 2019.

Network	Network metrics									
	$\langle k \rangle$	$\langle s \rangle$	$\langle w \rangle$	D	$\langle C \rangle$			L		
					W_t	W_t^{rand}	z-score	W_t	W_t^{rand}	z-score
$EATN_{04}$	12	382	15.9	0.019	0.45	0.16 ± 0.007	39.3	3.1	2.9 ± 0.012	13.9
$EATN_{19}$	21	493	11.8	0.034	0.48	0.21 ± 0.009	30.5	2.7	2.7 ± 0.008	6.5
LCC_{04}	7	134	8.9	0.012	0.28	0.12 ± 0.012	13.3	2.8	3.0 ± 0.026	−7.5
LCC_{19}	21	300	6.9	0.057	0.39	0.22 ± 0.009	18.5	2.5	2.6 ± 0.009	−8.2
FSC_{04}	10	350	16.4	0.019	0.45	0.15 ± 0.012	33.7	3.2	3.0 ± 0.014	14.3
FSC_{19}	11	328	15.1	0.019	0.47	0.16 ± 0.012	33.3	3.0	3.0 ± 0.013	1.0

Note: Network snapshots are based on the first week of April in both years. Average link weights calculated for one-directional city-pairs and densities in 2004 derived based on airport count in 2019. Columns 'W_t' are calculated for the original network/layer, Columns 'W_t^{rand}' report the mean and standard deviation of the metric obtained from 1000 random network realizations with preserved degree sequence. For definition and interpretation of z-scores see Zanin et al. (2018).

comparison with the results sourced for random network realizations shows that this effect is somewhat offset by the apparently better temporal coordination of flights in communities such as the Greek or Nordic cluster. Further, the majority of clusters are found to have improved connectivity over time in line with the development on the aggregated network level. The extraordinary development for the Eastern-European cluster highlights the progressive integration of its airports with the rest of the EATN over time.

4.1.1. *Structural network changes during 2020-21*

The impacts of the pandemic on the structural evolution of the EATN in 2020 and 2021 were pronounced. Mapping network size statistics for 2020/21 relative to the values for the corresponding snapshots of 2019 (Fig. 3, Panels A–C) indicates the existence of distinct stages of network evolution in 2020/21. In a first phase, lasting until the beginning of March 2020, the network largely resembled a standard seasonal pattern. This was followed by a period of rapid and extensive network shrinkage until mid-April 2020, as airlines first adjusted to the outbreak of COVID-19 in Europe. At the peak, the number of daily flights operated in the EATN was 90% below the normal levels, serving around 85% fewer direct city-pairs and leaving approximately 270 airports, about 50% of the 2019 network nodes, temporarily disconnected from the EATN. The airports abandoned at this stage were already characterized by relatively low network integration prior to the pandemic. Their airport degree and strength in 2019 was approximately 50% below the network-wide median. This finding is consistent for both layers, suggesting that airlines constrained their operations to their core networks and over proportionally abandoned 'peripheral' airports. Businesses reliant on such airports to engage in physical interactions with other supply chain stakeholders were literally disconnected from them at this stage.

From mid-April to mid-July 2020, a phase of partial network recovery followed, in which the EATN reconnected around 90% of all network nodes and hence at least theoretically enabled supply chains to physically interact across Europe. This recovery of essential network connectivity was accompanied by a less pronounced increase of city pairs connected by direct flights (65% of 2019) and an even weaker recovery in overall flight volumes (45%). In the subsequent phase, between August and the first weeks of November 2020, the network remained at these activity levels and followed the standard seasonal pattern. The network density in this period approaches approximately 0.02 for the EATN (0.03 LCC; 0.01 FSC) and is thereby approximately 35% below the corresponding 2019 values. The matching reduction in

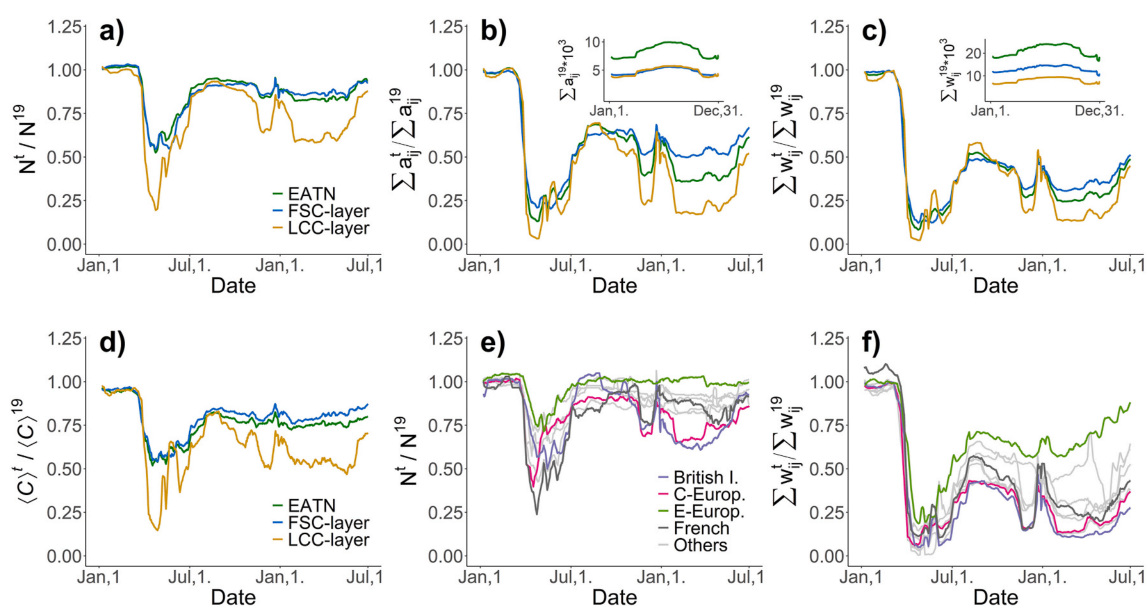

Fig. 3. Evolution of network size and nodal distributions in 2020/21.
Note: Panels a) - f) show network size statistics as a ratio between the 2020/21 and corresponding 2019 daily network snapshots and thereby free from seasonal alterations in network size. Insets in Panel b) - c) depict the underlying seasonality in 2019 as reference values. Panels e) - f) depict spatial perspective with the colouring of selected communities suppressed to increase perceptibility.

average clustering (Panel D), however, is found to be attributable to alterations in network size (i.e., z-score) and hence not to an extensive structural reorganization of local embeddedness in the EATN and its layers. The average shortest path length (L) increases in the LCC layer by 0.3 and in the EATN/FSC layer by 0.5. Even corrected for size effects, there is a sizeable reduction in the directness of travel as compared to 2019. Further, at the nodal level, network shrinkage has not markedly changed the hierarchical pattern of nodal network integration. That is, airports that were characterized by a low average shortest path length, high degree, and high strength prior to the pandemic are typically those that remain the most closely connected to the network during the pandemic. This signals in sum for businesses dependent on passenger and cargo transport with scheduled air services, that enterprises located at non-hub airports might have experienced the strongest negative implications.

Starting in mid-November 2020, a second distinct contraction period occurred in which the network temporarily and substantially shrunk. This network shrinkage coincided with lockdown periods in several Western European countries (see Table 2). Reductions in network density and service frequencies were distinct, while the number of disconnected airports increased modestly, suggesting higher indirectness of travel, especially for customers travelling between non-hub airports. Apart from a temporary comeback between December 2020 and January 2021, this network stage persisted until early May 2021, when network properties started to approach the levels of fall 2020 again.

Concerning the two layers in the network, the LCC layer seems to have adjusted more dynamically in 2020/21 than the FSC layer in both phases of shrinkage. The most striking difference between the two layers is (1) the extent to which airports became disconnected from the layers during shrinkage in general and (2) the magnitude in link and frequency removal in the LCC-layer during the second period of shrinkage. LCCs appear much more willing and able to downsize and adjust network structures (Panel A). Travellers dependent on airports exclusively served by low-cost airlines are therefore more likely to be cut off from air transport services during extensive network shrinkage than those dependent on airports with FSCs. Further, Panels B and C suggest that alterations in the LCC layer in terms of links and flows occurred approximately proportionally to each other. In contrast, the structure of the FSC layer appears consistently closer to normal in a topological (i.e., links) than a weighted (i.e., flights) perspective. This signals the tendency of FSCs to preserve topological network structures during phases of shrinkage, which is indicative of the continuation of hub-and-spoke operations in this layer.

Assessed in a spatial context, network size fluctuations in 2020/21 are found to vary strongly across regions, which is symptomatic of the regionally different approaches to dealing with the COVID-19 pandemic. For example, while more than 50% of all French cluster airports lost service for an extended period between April and June 2020, other communities, such as the Eastern-European cluster, remained much more intact, ensuring basic accessibility by air for 75% of its network nodes (Panel E). Furthermore, the second incident of network shrinkage from November 2020 appears to be primarily linked to airports served by LCCs located in the British, French, and Central-European clusters. As for the changes in flows to and from airports of different communities, Panel F indicates that the British and Central-European clusters have been particularly affected throughout the pandemic. For instance, while the number of flights from Eastern-European airports in the second half of 2020 reached around 70% of 2019 levels and approached 90% towards July 2021, the corresponding values for British cluster airports remained below 50%.

Table 2 provides a selection of major 2020/21 European regulations and policy initiatives that are relevant to air travel, such as the types of lockdowns and different forms of travel restrictions. One can note that this timeline of policies correlates with the measured alterations in the network properties shown in Fig. 3. In particular, Panels E and F suggest that the policies have different timings, strategies, and stringencies in the different areas of Europe. For example, the distinct network shrinkages in the British, C-European, and French airport communities at the end of 2020 coincide with the re-imposition of lockdown measures in multiple Western European countries. Instead, no nationwide lockdowns were reported in this period in Russia (i.e., the E-European cluster). In this context, network alterations in the case of the pandemic are consequential to the decision-making processes of national governments. Hence, the governments' individual strategies, but also their overall attitudes towards the pandemic, have directly determined the degree to which the COVID-19 pandemic has affected air freight transport and passengers' air travel ease.

A supplementary analysis on the community pair level (Annex 4) indicates that link structures (i.e., the number of direct city pairs) and their flows within a community appear generally less affected by network shrinkage than links between different airport clusters. This phenomenon is especially pronounced in the Eastern-European, the Greek and the Nordic airport community. This might reflect airlines' general tendencies to focus during crises on operations in their individual 'core-geographies' and might be further enhanced by national governments ensuring basic levels of connectivity within the bounds of their jurisdictions (Abate et al., 2020).

4.1.2. *Connectivity analysis*

The question remains of how the network changes described above have affected network-wide connectivity. To assess this, Fig. 4 (Panel A) compares the typical quickest path length in 2020/21 with the corresponding values from 2019 (weekly perspective) and maps the resulting network-wide airport susceptibility (Eq. (1)) over time. According to

Table 2
Selection of travel restrictive policies/actions affecting major European countries in 2020.

Week	Policy action	Country
6	Advise against unessential travel to mainland China	France, UK
11	Declaration of nation-wide lockdown	Italy
	Declaration of partial lock-down measures	Several
	Advise against all but essential travel to Italy	UK
	Suspension of all flights to Italy	Spain, Portugal
	Border closing for non-citizens/residents	Denmark, Poland, Czech Rep.
	Suspension of entry from selected European countries	US
12–13	Suspension of all civil flights	Italy
	Border closing for non-citizens/residents	Germany, France, Russia
	Announcement of ban of non-essential travel	European Union
	Declaration of nation-wide lockdown	Several
23–27	Reopening of borders for European tourists	Italy, Spain
	Announcement of lifting travel restrictions within EU	Germany, France, UK
40–44	Reimposition partial and nation-wide lockdowns	Spain, UK, Italy, France, Belgium
51	Imposition of travel restrictions on United Kingdom	Several

Note: Adapted from Kantis, Kiernan, and Bardi (2021).

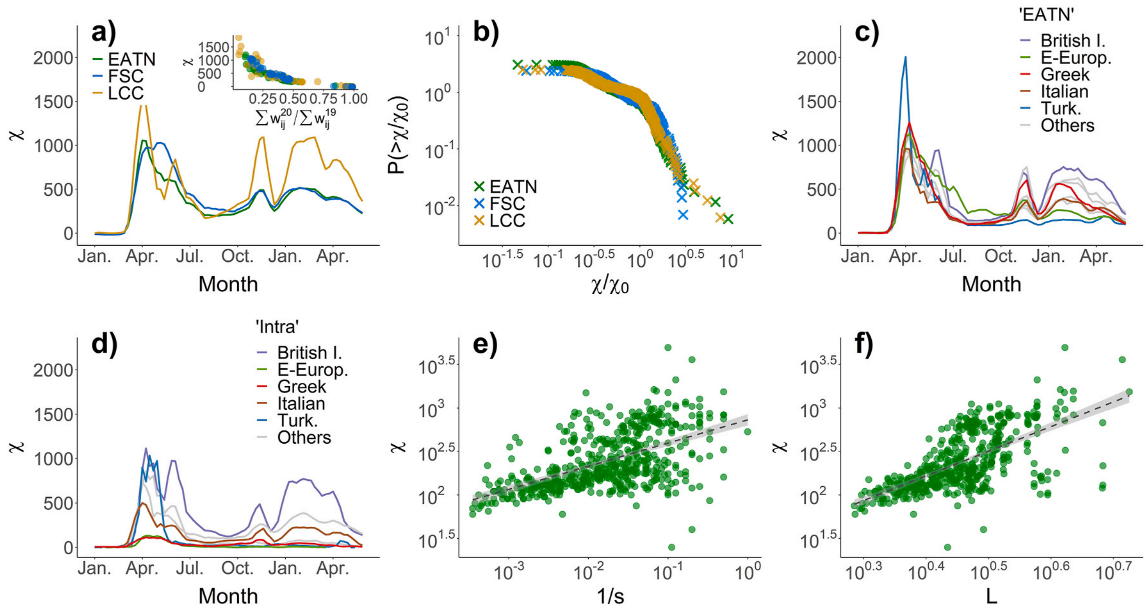

Fig. 4. Evolution of network connectivity in 2020/21 and dependency structures.
Note: All panels covering only airports present in both 2020/21 and 2019 snapshots. Panel a) depicts the evolution of median airport susceptibility from January 2020 to June 2021 relative to 2019 and the inset shows the functional relationship with network flux. Panel b) depicts the cumulative probability distributions of airport susceptibility for July 17th, 2020 and Panels c)-d) map the evolution of airport susceptibility in a spatial context (Panel c) and for intra-community flows only (Panel d). Panels e)-f) depict airport susceptibility as a function of inverse airport strength and average shortest path length based on the network snapshot corresponding to July 17th, 2020.

that, airport susceptibility in the EATN and the FSC layer between April and June 2020 reached values of $\chi \approx 1000$. This implies that the travel time required for a journey between two randomly picked network airports in 2020, was on average 17 h longer than in the previous year. Hence, the total average travel time necessary more than tripled, and most airport pairs still connected to the network at this stage could not be reached without at least one overnight transfer. This highlights the substantial level of network deterioration and that network-wide air travel at this stage was infeasible. After partial network recovery in July 2020, average susceptibility values declined to $\chi \approx 240$, indicating that inner-European air connectivity was still substantially weakened.

Panel A further hints that the deterioration in connectivity in the LCC layer from April to May 2020 and again starting at the end of the year is much more pronounced than in the FSC layer. This corresponds to the disproportionate shrinkage of the layer at these times (Fig. 3). Apart from these scale effects, susceptibility appears qualitatively similarly distributed in the EATN and its layers within the same time snapshot (Panel B). This suggests that despite their different structural properties, both layers and, in their aggregation, the EATN underwent shrinkage processes according to fundamentally similar processes.

Assessing in more detail the association between airport susceptibility and the extent of network shrinkage, the inset of Panel A suggests the existence of an exponential relationship for the EATN and both layers. As long as the reduction in the number of flights and direct links during network shrinkage does not exceed a critical level, demand can be rerouted over the remaining links and frequencies such that there are only minor implications on average travel times. However, the more flights are eliminated from the network, the greater the impact of time lost due to greater indirectness and/or deterioration of temporal coordination in the network and the more dynamic airport susceptibility grows.

Panel C maps the evolution of susceptibility in a spatial context per community over time, and Panel D supplements an *intra*-community perspective (i.e., only the flow between airports within the same community are considered). Even though following a common trend, susceptibility does vary across geographies. For instance, the Italian cluster appears on average to be less susceptible, whereas the Turkish cluster in April 2020, the Eastern European cluster during the fall 2020 and the British cluster in 2021 seem exceptionally affected. Detailed analysis reveals that case specifics explain these particularities. The relatively centric location of Italian airports on the European continent translates into relatively short topological travel distances to other network nodes and hence limits their general susceptibility. For the Turkish community, a far-reaching cutback of domestic and international services in April coinciding with the Easter holiday period in many European countries, during which flows to the Turkish community in 2019 were relatively high, dramatically increased susceptibility. Susceptibility values indicate that the Turkish cluster at that stage was largely isolated from the rest of the network. The driver behind the Eastern-European results relates to a change in international connectivity at many cluster airports during 2020. Some 18 airports (30% of the total) lost all direct flights to airports outside their cluster, leaving only 20% of all Eastern Europe airports with such links. This increased average travel times from many community airports and hence substantially increased susceptibility.

On the contrary, the Eastern-European airports performed considerably well from a purely regional, intra-community perspective (Panel D). As for the Greek cluster, susceptibility values do not exceed a maximum of $\chi \approx 160$ for any period in 2020. This is substantially below the value of, for example, the British cluster, suggesting the existence of distinct spatial differences in the distribution susceptibility. These heterogeneities are found to correspond well with the divergences in structures and flows of different clusters. As noted earlier, intra-community structures of the Greek and Eastern-European clusters, for example, have been relatively modestly affected through 2020/21, whereas flows within the British cluster have more deteriorated (Annex 4).

Susceptibility is further found to vary significantly at the airport level. Based on a range of high and low connectivity airports in 2019 and their corresponding susceptibility values for selected dates in 2020, Table 3 demonstrates several aspects. First, airport susceptibility of major hub-airports, such as Munich or Amsterdam, is relatively limited.

Table 3
Susceptibility values 2020 and airport characteristics.

Airport			χ_i			Airport characteristics			
	Country	L_Q^{2019}	(1)	(2)	(3)	s^{2019}	s^{2020}	L^{2019}	L^{2020}
Munich	Germany	245	0	380	80	2645	770	1.8	2.1
Frankfurt	Germany	250	−5	320	60	2840	850	1.8	1.9
Amsterdam	Netherlands	255	−2.5	265	70	2840	855	1.8	2.0
Copenhagen	Denmark	255	0	320	110	1554	490	1.9	2.1
(…)									
London City	UK	335	10	–	185	652	35	2.6	2.8
Leipzig	Germany	335	15	–	890	148	3	2.4	3.0
(…)									
Vilhelmina	Sweden	528	−30	760	1503	10	8	2.9	4.2
(…)									
Båtsfjord	Norway	1460	−5	244	130	20	20	4.5	4.8

Note: Column 3 depicts average quickest path as of period July 15th - 19th, 2019 as reference. Columns 4–5 map 2020′- airport susceptibility based on weekly snapshots: (1) March 9th –13th, (2) April 20th - 24th, (3) July 13th - 17th. The remaining columns depict airport strength and average shortest path statistics based on July 15th - 19th, 2019 and July 13th - 17th, 2020.

While the network-wide mean approached 240 min, susceptibility values for the best integrated European airports (i.e., overall lowest L_Q in 2019) in July 2020 stayed below 120 min (Column 6). Second, the geographical location of an airport might not be a sufficient determinant of airport susceptibility. For example, while the susceptibility of Frankfurt July 2020 was at a modest 60 min, the geographically close Leipzig/Halle airport reached a value of 890 min. On the other hand, the extremely remotely located Norwegian airport of Båtsfjord achieved values comparable to those of Copenhagen. Existing contractual agreements between airlines and national governments to supply subsidized air transportation (i.e., Public Service Obligations) kept service levels stable during crises and dampened susceptibility. As compared to the much larger airports of London City or Leipzig, existing PSO-arrangements at Båtsfjord and Vilhelmina airport prevented them from becoming disconnected even through the extreme stages of network shrinkage (Column 5).

As suggested by Woolley Meza et al. (2013), airport susceptibility might instead adhere to a pattern of nodal network integration. For instance, the higher the strength of an airport during the COVID-19 pandemic, the more alternative travel paths exist over which flows could be redirected and hence the lower the airport's susceptibility. A fixed-effects estimation is employed to rate the associations between airport susceptibility and nodal characteristics in 2020, considering changing activity levels in the network. The relationship is modelled as follows:

$$\chi_{it} = \beta_0 + \beta_1 s_{it} + \beta_2 l_{it} + \beta_3 w_t + u_{it}, \tag{2}$$

where i indexes an airport and t captures a certain network snapshot; χ_{it} is the log of susceptibility, s_{it} denotes log of the nodal strength, and l_{it} the log of average shortest path length; w_t is the log of the total of all flights in the network to account for overall changes of activities in the network, and u_{it} reflects the idiosyncratic error term. The analysis uses all weekly network snapshots from 2020 and covers all airports that were continuously connected to the network in this period. The dependent variable is the airport-specific susceptibility values as calculated in this paper (Eq. (1)). The independent variables are the nodal characteristics for the individual airports and the corresponding network snapshot (see Annex 5 for descriptive statistics).

The parameters of interest are estimated as $\beta_1 = -0.19$ and $\beta_2 = +1.93$, confirming that airports with high strength and/or those located topologically close to the gravity of the network are typically less susceptible (Annex 5). Further tests on individual cross-sections reveal that β_1 varies $(-0.4 \le \beta_1 \le 0)$ over the year. The negative correlation between node strength and airport susceptibility weakens (i.e., $\beta_1 \rightarrow 0$) the more the network deteriorates. During minor stages of network shrinkages (e.g., fall 2020), the number of airports connected to the system is high and the reduction in density and link weights appears to have relatively more effect on weakly integrated airports. As shrinkage progresses, however, the network reduces to a 'core system' in which characteristics of the remaining airports and their susceptibility converge.

Individual panels for both network layers (Annex 5) confirm the correlations found for the EATN. The sensitivity of airport susceptibility to average shortest path length in the LCC layer is more pronounced, but the dependency on the overall number of network flights is less distinct than in the FSC layer. This finding is consistent with the difference mentioned above in the temporal coordination between both layers. Reducing the number of flights decreases the temporal coordination in the FSC layer and thereby increases journey times. In contrast, the sheer existence of temporal coordination diminishes the effect of increased path length. In the absence of coordinated transfers (i.e., in the LCC layer), no such effects can occur.

5. Discussion and conclusion

This paper has analysed the evolution of the EATN during the COVID-19 pandemic in 2020/21 using network-theoretical concepts. It has emphasised the examination of changes in network connectivity relative to long-term evolutionary processes from a spatial and multi-layer perspective. This multi-perspective approach contributes towards a better understanding of how dynamics in different sub-entities account for changes in structural features of the aggregated network. Consequently, the paper identifies simple indicators that inform a location's sensitivity to air transport network alterations and provides insights into how the exposure of supply chains to future network shrinkage events could be reduced. For example, the results suggest that weakly integrated airports are over-proportionally susceptible to network shrinkage. The distribution of susceptibility is unequal across airports and appears to follow exponential patterns. Therefore, rather than using airport existence as a binary assessment criterion, businesses reliant on air transport that are evaluating a location's potential for future business activities might give more weight to the actual level of services available at nearby airports.

This analysis focuses on air passenger transport networks. Their alterations are relevant to the management of supply chains in at least two ways. First, scheduled passenger flights have transported approximately 50% of the global air cargo in the pre-COVID-19 era in the belly cargo (Statista.com, 2021). Therefore, this paper's discussion of the network shrinkage and its implications for a loss of network connectivity is relevant to other pandemic-related phenomena associated to supply chains, such as rising lead times (UNICEF, 2020) and increasing air freight rates due to temporary capacity shortage in the air freight market (IATA, 2021). Second, corporate air travel has historically constituted a substantial share of the aggregated air passenger demand. This is because many businesses in manufacturing (e.g., after-market services) or the service industry (e.g., finance, engineering) rely on the availability of timely, long-distance transportation. For example, in 2019, the share of business-related, international air travel from Norway accounted for approximately 30 percent of the total air travel (Avinor, 2020). Depending on the definition of the term 'supply chain' and whether the reader finds it appropriate to include the end-customer in the definition, a significant share of this business-related travel can be directly attributed to supply chain activities. Passenger air transport services can thus be considered highly important for value creation across industries. This is suggested by the number of domestic and interregional air trips in 2019 – more than 500 million in the EU member states (Eurostat, 2020) – and a conservative assumption (that is substantially lower than Norway's) of the share of these trips related to business activities. The airport susceptibility values reported in this paper are therefore reflective of the challenges the pandemic has posed for the coordination of supply chain activities in such industries.

The present analysis of the long-term network evolution prior to the pandemic complements earlier research (e.g., Cardillo, Zanin, et al. (2013)) on the existence of structural differences between the FSC and LCC layers and thus provides evidence that diverse underlying principles promote evolution in both layers. Structural changes in the aggregated EATN between 2004 and 2019 are predominantly attributable to development in the LCC layer. By contrast, an increase in network connectivity, as measured by a change in the average quickest path length, appears to be predominately linked to stronger temporal coordination in the FSC layer. The temporal coordination of flights is not particularly pronounced in the LCC layer. Commercial entities dependent on the timely accessibility of a large set of inner-European destinations could consider this distinction when making locational decisions and in turn give more weight to locations that provide access to the FSC layer rather than the LCC layer.

The evolution of the EATN after the COVID-19 outbreak in Europe is a process that has occurred in distinct stages. Despite prior knowledge of the emergence of COVID-19 in Europe and other parts of the world, initial network size adjustments seemed abrupt rather than governed by a gradual downscaling of operations. The major network shrinkage event coincided with national lockdowns in several European countries and the transition from the 2019 winter schedule to the 2020 summer season. The more-than-proportional network adjustments in the LCC layer during this and the second shrinkage stages may partially reflect the lower temporal dependencies of operations and higher flexibility with respect to abundant routes. For businesses located at sites with access to predominantly LCC-based services, this finding signals a higher probability to lose network connectivity during shrinkage events.

The findings further suggest that during the partial recovery process, airlines in both layers re-established networks of considerably smaller size but that these networks largely resemble the normal hierarchical structures. This indicates the tendency to scale up operations along known paths rather than apply a radical reorganization of the networks in response to the pandemic. However, results hint that network pruning also leads to a more heterogeneous spatial concentration of traffic in the network. This relates to airlines over-proportionally focusing their operations on their home markets during a crisis. City pairs within fixed geographical areas are relatively unlikely to be abandoned during network shrinkage events compared with links that reach outside these core areas. Detailed analyses of the airport community structure during 2020 and 2021 reveal that the clustering shown in Fig. 1 has remained relatively unchanged during the pandemic. This relates to the dominance of individual FSC-airlines in the specific clusters, which drive the network density within the clusters upwards, while the operations of LCC-airlines are less attributable to individual clusters. This inherent stability in community structure suggests that intra-cluster air travel remains relatively less affected during network shrinkage events.

In the context of supply chain vulnerability, this finding suggests that supply chains distributed across multiple geographical areas are more prone to suffering negative implications than those concentrated within one region. Therefore, the geographical demarcations derived in this paper might be considered during supply chain design processes to reduce the risk of supply chain disintegration due to large-scale disruptions in air transport systems.

The existence of substitutional frequencies combined with airlines' tendency to primarily abandon non-hub city-pairs in periods of minor-to-modest network shrinkage limits the size of average airport susceptibility during such phases and hence the disutility occurring to the average traveller. Once shrinkage reaches critical levels, though, the network-wide connectivity disintegrates dramatically. Variations in network size in different geographical parts of the EATN and at different points in time, therefore, lead to substantial spatial differences in airport susceptibility across Europe, which are hardly predictable based on geographical location alone. However, the extent to which an airport's network-wide connectivity declines due to network shrinkage is found to correlate with nodal characteristics. Topologically weaker integrated and peripherally located airports are more susceptible to network shrinkage than airports that are strongly and centrally embedded in the network; this is because the rerouting flexibility of the former class of airports is generally lower, and a decline of temporal network coordination is more significant with every transfer necessary. Since nodal characteristics during the COVID-19 pandemic period have been found to correlate with nodal properties prior to network shrinkage, strength, and the average shortest path length of an airport in the undisturbed network stages can be used as indicators for the assessment of supply chain vulnerability. That is, supply chains that are highly dependent on human mobility and the movement of goods by air should concentrate their activities close to high-frequency and centrally-located airports. On a regional level, the impact of centrality suggests that, all else being equal, business activities located in more central airport clusters are less prone to network disruptions than businesses in more remotely located clusters. The results presented in this paper support this claim as we find comparably modest susceptibility values for inter-community travel starting from the Italian and the C-European airport communities.

Concerning the limitations of this study, future work might benefit from implementing connectivity measures that can map a broader set of factors that impact customer disutility due to pandemic-induced network alterations. For example, as the quickest-path-based method applied here does not pick up the value of all lost frequencies which do not directly contribute to the quickest path, this paper might have underestimated airport susceptibility from the traveller's and shipper's perspectives. Future work could include airfare changes and the significance of frequency reduction in the context of a scheduled delay. Moreover, a valuable future contribution could address network alterations in the corresponding designated air cargo network, thereby complementing the passenger and belly-cargo centric perspective applied in this paper. Furthermore, empirical research on the extent to which organizations have altered their strategies and business relationships to increase resilience in the post-pandemic era could yield interesting insights on the importance of European air transport services for the organization of value chains. Finally, as this paper has only covered network evolution only until June 2021, a further natural step would be to investigate whether permanent changes in network structure and connectivity patterns persist after the pandemic is over.

CRediT authorship contribution statement

Falko Mueller: Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing – original draft.

Declaration of competing interest

None.

Annex 1.

Table A1
Network metrics and concepts applied

Measure/concept	Notation	Description
Airport degree	$k_i = \sum_j a_{ij}$	The number of airports an airport i is connected to by direct flight. Then, $\langle k \rangle = \frac{1}{N}\sum_i k_i$ gives the average degree in the network.
Airport strength	$s_i = \sum_j w_{ij}$	The number of flights operated at airport i. Then, $\langle s \rangle = \frac{1}{N}\sum_i s_i$ denotes the average airport strength in the network.
Average link weight	$\langle w \rangle = \sum w_{ij} / \sum a_{ij}$	The average number of flights per city-pair.
Clustering coefficient	$C_i = \frac{2a_i}{k_i(k_i - 1)}$	The ratio of the number of links a_i between the neighbors of i and the number of triplets centered on the airport. Averaged over the network, $\langle C \rangle = \frac{1}{N}\sum_i C_i$ measures the average fraction of an airport's destination airports that are also connected by direct flight.
Density	$D = \frac{\sum_i a_{ij}}{N(N-1)}$	The proportion of existing links between airports and the total number of potential links.
Average Shortest Path Length	$L = \frac{1}{N(N-1)}\sum d_{ij}$	The average number of flights along all shortest paths d_{ij} between two airports in the network.
Normalization of network metric (z-score)	$z_L = \frac{L - \langle L^{random} \rangle}{\sigma_{L^{random}}}$	The normalization of network metrics to facilitate comparison over time exemplified for L (Zanin et al., 2018). The z-score z_L is the number of standard deviations $\sigma_{L^{random}}$ that the mean shortest path length $\langle L^{random} \rangle$, derived for 1000 random network realizations, deviates from the empirical metric.
Modularity	$Q = \frac{1}{2m}\sum_{ij}(w_{ij} - P_{ij})\delta(c_i, c_j)$	The modularity of a weighted network, where m is the total number of flights in the network, P_{ij} denotes the ij th element of the null-model matrix, c_i represents the community that contains node i, and the Kronecker delta δ is 1 if $c_i = c_j$ and 0 if $c_i \neq c_j$ (Newman et al., 2004). The value of Q is maximized to derive the community structure of a network.
Null-model matrix	$P_{ij}^{NG} = \frac{s_i s_j}{2m}$	The non-spatial null model applied for modularity maximization, with s_i being the strength of an airport i and m denoting the total number of network flights (Newman & Girvan, 2004).
Inclusion value for community matching	$I(G_1, G_2) = \frac{\lvert G_1 \cap G_2 \rvert}{\lvert G_1 \rvert} * \frac{\sum_{i \in (G_1 \cap G_2)} s_{G1}(i)}{\sum_{i \in (G_1)} s_{G1}(i)}$	The agreement of airports co-occurrence in communities G_1 in period n and G_2 in period n+1, considering the strength of the involved airports (Bródka et al., 2013).

Annex 2.

Table A2
Derived airport communities-characteristics April 2019

Community	Network metrics*			Intra-community flows			Inter-community flows		
	$\lvert N_C \rvert$	$\langle k \rangle$	$\langle s \rangle$	'top 3'-airlines	'top 3' (in %)	'LCC' (in %)	'top 3'-airlines	'top 3' (in %)	'LCC' (in %)
British	64 (+12)	44 (+42)	583 (−3)	FlyBE British A. easyJet	56	52	EasyJet British A. KLM	46	45
C-Europ.	78 (+4)	57 (+58)	670 (+20)	Lufthansa Eurowings Austrian	60	27	Lufthansa Ryanair Wizzair	34	39
E-Europ.	61 (+24)	21 (+62)	292 (+170)	Aeroflot JSC Siberia Utair	64	8	Aeroflot Lufthansa JSC Siberia	61	11
French	36 (−14)	33 (+77)	377 (+10)	Air France HOP! easyJet	78	20	easyjet Ryanair Vueling	37	57
Greek	37 (+6)	22 (+67)	175 (+10)	Olympic Sky Express Astra	88	7	Ryanair Aegean easyJet	51	49
Iber.	45 (+10)	44 (+79)	577 (+34)	Vueling Iberia Binter C.	52	33	Ryanair Vueling TAP	41	56
Italian	47 (−20)	69 (+170)	630 (+50)	Ryanair Alitalia easyJet	82	59	Ryanair easyJet Lufthansa	49	63
Nordic	105 (−12)	20 (+54)	315 (+33)	SAS Wideroe Norwegian	70	19	SAS Norwegian Finnair	36	40
Turk.	50 (+79)	22 (+73)	327 (+170)	Turkish Airl. Pegasus SunExpress	96	31	Turkish Airl. Pegasus SunExpress	54	28

Note: * Values in parentheses indicate percentage change compared to 2004 value. Information provided in Columns 5–10 are separated for flows within and flows to/from a community. 'Top 3' airlines based on market share in number of flights. Columns 6, 7 and 9, 10 provide accumulated market shares of 'Top 3' airlines and airlines classified as LCC.

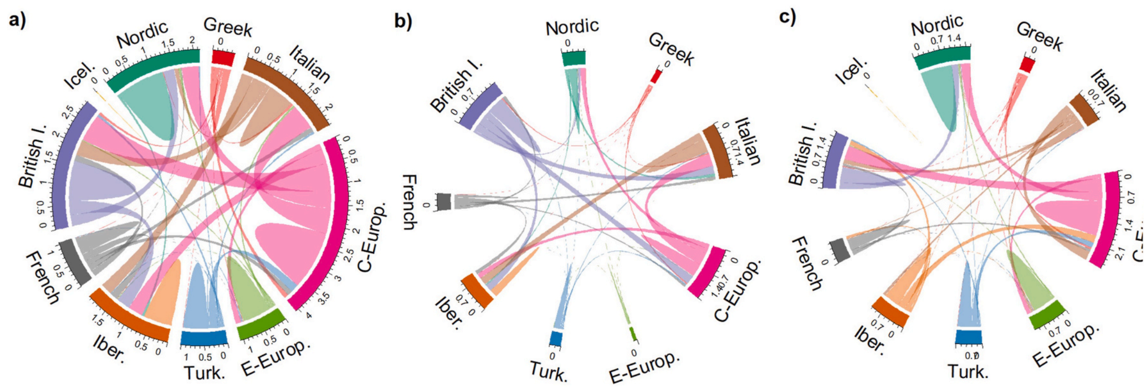

Fig. A2. Number of weekly flights (*10^4) between communities - a) EATN, b) LCC layer, c) FSC layer.
Note: Weekly flows between any two communities based on network snapshots of the first week of April 2019. Colour-coding corresponds with Fig. 1. Intra-community flows mapped as arcs with source and endpoint in the same community.

Annex 3.

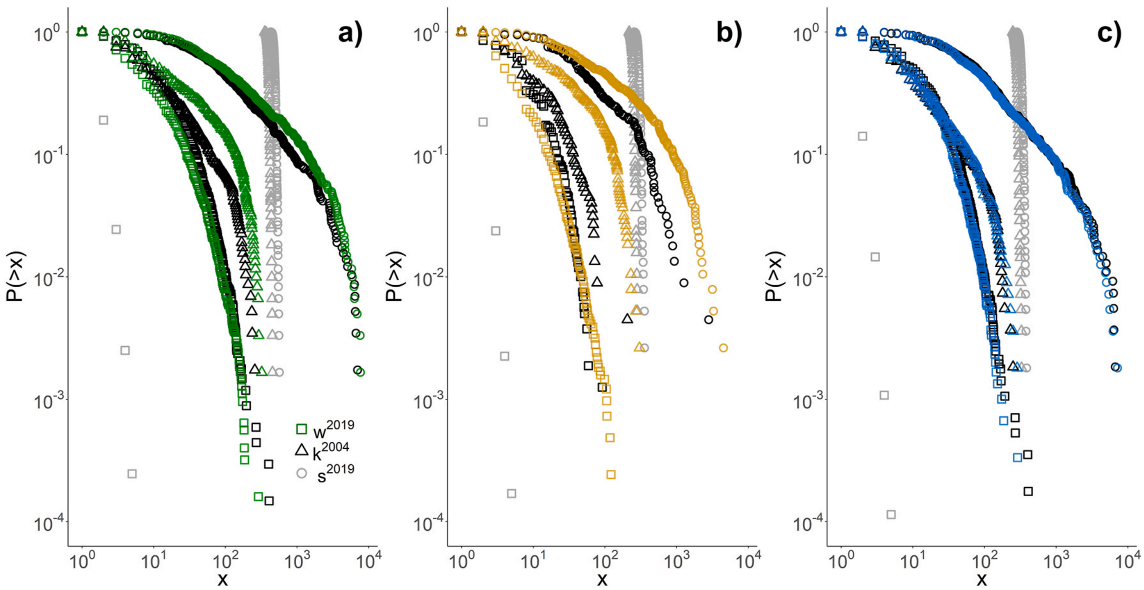

Fig. A3. Comparison of changes in distributions EATN (a), LCC-layer (b) and FSC-layer (c).
Note: Panels depict distributions of link weights (w), airport degree (k), and airport strength (s) based on April 2004 and 2019 for the EATN. Distributions for random network realizations with size statistics equal to empirical networks of April 2019 but with unpreserved degree sequence (Bernoulli-type) as a reference in grey. The properties of the depicted distributions reflect diverting forms of network organizations, and one sees that the LCC layer has evolved most dynamically. In 2004, the LCC-network structure was more homogenous in terms of degree and strength distribution than the FSC-layer, indicating a lower dependency on hub-operations in the former. The 'right shift' of the distributions for airports in the higher spectrum in 2019 suggests that the LCC network has become more heterogeneous in terms of node properties and that some airports approach connectivity stages like the hub airports in the FSC layer. Comparing the layer distributions with Panel a) yields that high connectivity airports in both layers are typically not identical, suggesting, e.g., that the presence of LCC-airlines at classical hub-airports in 2019 is still rather low, and hence their choice of routes is different from those of FSC-airlines. These routes are further found to show a more heterogeneous pattern in terms of link weights.

Annex 4.

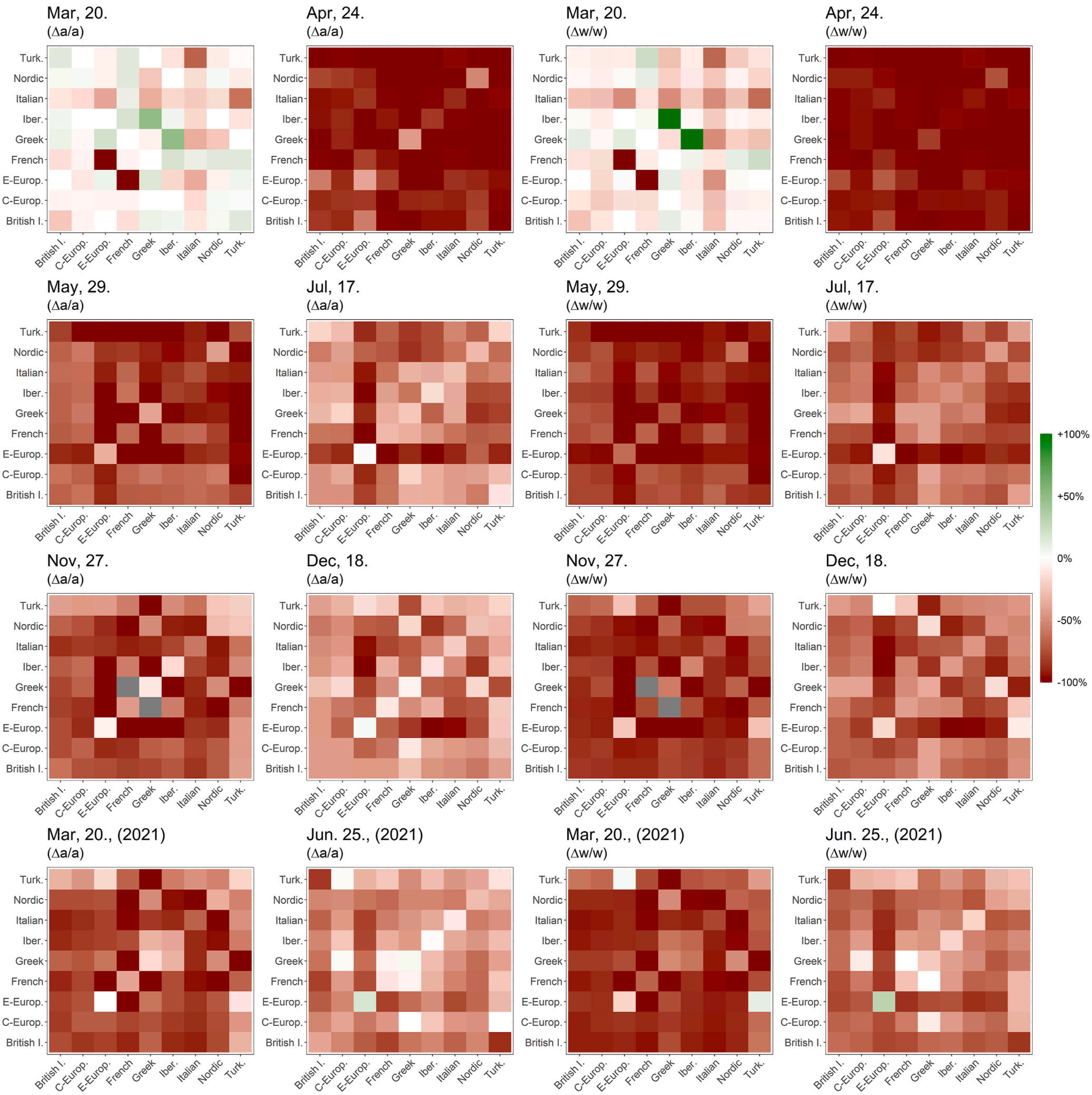

Fig. A4. Comparison number of direct city pairs and flights 2020 (2021) vs. 2019-community pair perspective.
Note: Panels show the percentage change in the number of links (Columns 1 and 2) and number of flights (Columns 3 and 4) between each pair of airport communities (i.e. $\Delta a/a = \left(\sum a^{t}_{G_iG_j} - \sum a^{2019}_{G_iG_j}\right) / \sum a^{2019}_{G_iG_j}$) for selected network snapshot in 2019 vs. 2020/21. 2019 dates are adjusted to reflect the corresponding day of the week 2020. Grey cells indicate observations with missing data.

Annex 5.

Table A5.1
Descriptive statistics panel data

Variable	*Network*		
	EATN	LCC-layer	FSC-Layer
Susceptibility			
Mean	423	486	522
SD.	481	535	514
Nodal strength			
Mean	73	46	51
SD	148	78	10
Av. Shortest path length			
Mean	3.1	2.7	3.3
SD	0.59	0.49	0.59
Sum flights in network			
Mean	39 000	15 035	24 545
SD	17 300	7244	8957

Table A5.2
Estimation results panel regression susceptibility

	Dependent variable:		
	Airport Susceptibility (log)		
	EATN	LCC layer	FSC layer
Airport strength (log)	−0.19***	−0.19***	−0.20***
	(0.022)	(0.013)	(0.002)
Average shortest path length (log)	1.93***	2.47***	2.15***
	(0.165)	(0.091)	(0.173)
Number of flights in network (log)	−0.78*** (0.027)	−0.51*** (0.015)	−0.89*** (0.031)
Observations	17399	9567	15672
Adjusted R^2	0.64	0.57	0.58
F Statistic	10299***	9221***	7508***

Note: ***$p < 0.001$; robust SE in parentheses.

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