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Citation for published version:
Voltes-Dorta, A, Rodríguez-Déniz, H & Suau-Sanchez, P 2017, 'Vulnerability of the European air transport network to major airport closures from the perspective of passenger delays: Ranking the most critical airports', *Transportation Research Part A: Policy and Practice*, vol. 96, pp. 119-145. https://doi.org/10.1016/j.tra.2016.12.009

Digital Object Identifier (DOI):
10.1016/j.tra.2016.12.009

Published In:
Transportation Research Part A: Policy and Practice

VULNERABILITY OF THE EUROPEAN AIR TRANSPORT NETWORK TO MAJOR AIRPORT CLOSURES FROM THE PERSPECTIVE OF PASSENGER DELAYS: RANKING THE MOST CRITICAL AIRPORTS

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ABSTRACT

This paper analyzes the vulnerability of the European air transport network to major airport closures from the perspective of the delays imposed to disrupted airline passengers. Using an MIDT dataset on passenger itineraries flown during February 2013, full-day individual closures of the 25 busiest European airports are simulated and disrupted passengers then relocated to minimum-delay itineraries. Aggregate delays are used to rank the criticality of each airport to the network, with the possibility of disaggregating the impact across geographical markets. The results provide useful reference values for the development of policies aimed at improving the resilience of air transport networks.

Keywords: Air transport networks, resilience, criticality, passenger recovery.

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1. INTRODUCTION

Air transport networks are vulnerable to external events, even those that only have a local impact. For example, a single airport closure due to poor weather conditions or an industrial action may affect the network's overall performance. The final impact can range from a few delays and missed connections to significant economic losses (Mazzocchi et al., 2010). One of the possible reasons behind this vulnerability is that ensuring resilient operations has been secondary to profit maximization and other geopolitical factors in airline network development during the last decades (Lordan et al., 2014b). On top of that, predicted rates of growth in air transport demand (ICAO, 2013) in combination with large shocks such as 9/11, or the 2010 Volcanic Ash Cloud, can reduce the ability to cope with such disturbances and put additional pressures on air transport networks (Cardillo et al., 2013). Within this context, reducing the vulnerability and improving the resilience of transport networks has been recognized by the European Commission as a high level goal for 2050 (EC, 2014a).

There is a decent body of literature on the resilience of air transport that largely employs complex network theory to analyse the topological properties of airline networks and their implications in terms of vulnerability to airport failures or the closure of air corridors. There is a disconnection, however, between these analyses and the actual impact of air transport disruptions on the final users (i.e. the passengers that experience travel delays). Indeed, only few of these studies consider the important aspect of how airlines relocate disrupted passengers and, to the best of our knowledge, no previous paper uses actual passenger demand data to that end. This situation contrasts with a richer literature in other modes, such as rail or road, where the analysis of resilience and vulnerability is more developed, and the implications in terms of direct cost to the user (e.g. travel delays) in the event of a disruption in service have been modelled in more detail (e.g. Jenelius et al., 2006).

Thus, this paper builds upon the concepts developed in previous studies with the objective to develop a new method to incorporate demand data into the assessment of vulnerability of the European air transport network to major airport closures. Using a Market Information Data Transfer dataset (commonly known as MIDT) on passenger itineraries during February 2013, full-day individual closures of the 25 busiest European airports are simulated and disrupted passengers are relocated to delay-minimizing itineraries where seat capacity is available. A multi-layered network is constructed, where airlines are only able to relocate passengers within their own alliances' flight networks. Vulnerability is measured by the aggregate delays imposed to the disrupted passengers. This allows us to rank the most critical airports in the European network. In addition, we can disaggregate the impact on geographical markets (with special focus on passengers travelling in routes within the European Economic Area, from now on "intra-EEA" routes). Information on how the traffic is redistributed under each scenario is provided as well, leading to an exploratory discussion on the main drivers of airport criticality. The results aim to complement the stream of literature that employs complex network theory to the same end and also provide useful reference values for the development of policies aimed to reduce the vulnerability and improve the resilience of air transport networks.

The rest of this paper is structured as follows: Section 2 provides a literature review on the analysis of resilience and vulnerability of air transport networks and discusses our contribution. Section 3 describes the supply and demand datasets. Then, the methodological process is explained, with particular focus on the passenger relocation algorithm. Section 4 presents the results and discusses their main implications. Finally, Section 5 summarizes our findings, addresses the limitations of our model, and proposes new paths for future research.

2. LITERATURE REVIEW AND CONTRIBUTION

2.1 Basic definitions

Vulnerability is a concept that is complementary to the ideas of resilience, robustness, or reliability. Rose (2007) defined resilience as the ability of a system to maintain functionality when disrupted, with particular focus on the speed at which the system returns to normal. Vulnerability was defined by Berdica (2002) as the "susceptibility of a system to experience disruptions that can affect its functionality". In the context of a transportation network, functionality can be understood as operability or serviceability, i.e. the possibility of using any node of link of the network during a given period. As noted by Jenelius et al., (2006), this definition of vulnerability can be linked to the general concept of risk and thus disaggregated in two components: 1) the probability of the disruptive event occurring, and 2) the consequences of the disruptive event (system damage). Given the difficulties in estimating the probabilities of extreme events, such as natural disasters or terrorist attacks, authors like Berdica (2002) or D'Este and Taylor (2003) argue that measuring the magnitude of consequences should be the primary focus of vulnerability studies. This leads to the concept of "conditional vulnerability", defined as the measurement of system damage given that the disruptive event occurs.

It is also possible to measure the criticality of a certain component of the system, such as any particular nodes or links. A critical component has a high probability of failure and creates a large amount of damage if removed. In parallel to above, ignoring the probability of failure in the analysis gives rise to the concept of "conditional criticality" defined by Jenelius et al., (2006), as the measurement of the damage caused by the failure of the relevant component.

2.2 Previous studies

The resilience and vulnerability of network systems have been areas of great interest because strategic economic sectors such as energy, utilities, transport, or telecommunications are dependent on networks to function. In regards to transport networks, Faturechi and Miller-Hooks, (2015) list approximately 200 published works on a wide range of modes, including metro/subway systems (e.g. Derrible and Kennedy, 2010; Li and Kim, 2014; D'Lima and Medda, 2015); maritime transport (e.g. Berle et al., 2011; Thekdi and Santos, 2015: port operations; Ducruet et al., 2010: liner shipping; DiPietro et al., 2014: inland waterways); rail (e.g. De los Santos et al., 2012; Cacchiani et al., 2014; Rodríguez-Núñez and García-Palomares, 2014); road (e.g. Chen et al., 2002; Jenelius et al., 2006; Jenelius and Mattsson, 2012; El-Rashidy and Grant-Muller, 2014; Cats and Jenelius, 2015); air transport (covered below); and finally, there have also been attempts at developing models for intermodal resilient operations (e.g. Chen and Miller-Hooks, 2012).

After a comprehensive review of studies, Mattsson and Jenelius (2015) described two main approaches to measure vulnerability of transport networks: a) topological vulnerability, and b) system-based vulnerability.

In the topological vulnerability approach, the network is represented as an abstract graph and the researcher measures system damage as a result of changes in network topology after a disruption affects one or more nodes or links. This type of approach typically uses only supply data on available infrastructure and service frequencies. The topological properties of networks are characterised by indicators such as average shortest path or degree distribution, which determine how the network will be classified within a number of generic structures. The study of Zhang et al. (2015) analyses of 17 different network structures, concluding that factors such as a higher average degree (i.e. more well-connected nodes), structural redundancies[1], and excess capacity reduce the vulnerability of transport networks.

In the system-based vulnerability approach, the network graph is complemented with information on actual or predicted traffic flows, and the interaction between supply and demand under disruptions is modelled, for example, with a user re-routing algorithm. Examples of this system-based approach can be found in Jenelius et al. (2006), De los Santos et al. (2012), or Rodríguez-Núñez and García-Palomares (2014), where road and rail network vulnerability under a variety of disrupting scenarios is measured according to the total delays experienced by the users, who need to alter their original itineraries, as well as the amount of unsatisfied demand. This second approach is the one we prefer. The reason is that it allows us to obtain a more detailed measurement of "conditional vulnerability" and "conditional criticality", as defined in the previous subsection, since the consequences for the users (in terms of travel costs) are now directly quantified.

Most of the studies on vulnerability and resilience of air transport networks employ a supply-based topological approach (e.g., Zanin and Lillo, 2013; Lordan et al., 2014a). By using a network characterisation of airports as nodes and air corridors as links (either weighted or unweighted by capacity), airline networks can be classified according to their topological properties. In an air transport context, hub-and-spoke networks are generally considered to have "scale-free" properties (i.e. concentrated around large nodes) while point-to-point networks lean more towards to the "small-world" class (Zanin and Lillo, 2013). Studies such

[1] The concept of structural redundancy is linked to the network's cyclicity. For example, a circular subway network can maintain functionality even if one station closes (Derrible and Kennedy, 2010).

as Guimerà et al. (2005), Guida and Maria (2007), Reggiani et al. (2010), Wang et al. (2011) and Zeng et al. (2011) apply these methods to identify the respective network's most relevant airports, which are generally those with highest degree centrality (i.e., largest number of destinations), closeness (i.e. shortest average distance to all other airports) or betweenness centrality (i.e., lying in the largest number of shortest-paths between other airport pairs).

By analysing the evolution of these indicators in the Brazilian network over 12 years, Rocha (2009) found that large airports gain importance over time as airlines move capacity to the most profitable routes. However, as network concentration around pivotal nodes increases so does the network's vulnerability, mainly as a result of the lack of structural redundancies that support recovery of traffic flows via alternative routings (Zhang et al., 2015). Hence, while "scale-free" networks are considered to be more resilient to random failures, this comes at the cost of higher vulnerability to targeted attacks to their most central nodes (Albert et al., 2000). In this regard, the recent years have seen a growing interest in measuring the damage caused by the removal of nodes (i.e. airport closures) and/or links (i.e. air corridors) in order to determine the network's vulnerability to these events.

The purely topological approach to assess this damage in air transport networks does not explicitly take into account the need to redistribute the disrupted traffic. The study by Chi and Cai (2004) for the US airport network analyses how the main topological indicators change after nodes or links are removed. They found that removing the top 10% most connected airports would reduce network efficiency by 25%. Lordan et al. (2014a) modeled the global airport network with unweighted links and developed a measure of the damage produced by both random failures and targeted attacks based on the number of disconnected airports that result from them. Betweenness centrality is used as one of the selection criteria for targeted attacks. Results are similar to those obtained by Guimerà et al. (2005) in which the most critical airports turn out to be the largest and best connected (e.g. Frankfurt, Paris, or Amsterdam) as well as the main gateways to isolated areas (e.g. Anchorage, Tahiti). Janic (2015) relied on disconnected flights as a measure of network damage, also leading to the aforementioned conclusion that larger airports (i.e. Atlanta in the case of 2012 Hurricane Sandy) tend to be the most critical. More recently, Lordan et al. (2015) analysed the resilience of the global airline alliance networks using similar topological indicators, concluding that Star Alliance is the most resilient, followed by SkyTeam and Oneworld. One of the main reasons is that the Star Alliance network has a more continuous distribution of degree and betweenness centrality among its constituent airports, while the other alliances are dominated by few large hubs. In that regard, the degree of vulnerability of the dominating alliance is expected to be one of the main predictors of airport criticality.

A system-based approach to assess network resilience incorporates information on passenger flows in order to model the disruption costs from the user's perspective. To that end, any relevant model would need to replicate the challenges arising from irregular airline operations, with particular focus on the recovery of aircraft, crews, and passengers in an optimal (i.e. cost-minimizing) fashion. As noted by Barnhart (2009), there are a number of strategies that airlines can use to adjust schedule operations, including delaying and cancelling flights, reassigning aircraft or crews to different routes, and relocating disrupted passengers. All these adjustments are subject to a number of restrictions, including crew work rules, maintenance schedules, and aircraft and passenger positioning. On top of that, there is the issue of modelling delay propagation (See e.g. Fleurquin et al., 2014; Kafle and Zhou, 2016) since a delayed aircraft may have a cascading effect on flight operations at other airports that are directly or indirectly connected to it. In this context, there is a large body of literature devoted to providing efficient methods to solve these optimization problems under different scenarios (e.g., Yan and Lin, 1997; Lettovsky et al., 2000; Abdelghany et al. 2008;

Bratu and Barnhart, 2006; Petersen et al., 2012; Zhu et al., 2015; and Maher, 2015) as well as measuring the costs of these disruptions for airlines and passengers (e.g., Schavell, 2000; Allan et al., 2001; Schaefer and Millner, 2001; Janic, 2005; Khol et al., 2007; Janic, 2015).

From the passenger perspective, there are different cost measures, including the number of passengers affected (missed connections and cancellations), the proportion of those relocated, and the total delay experienced, measured by the difference in travel times between the original and rescheduled itineraries (Bratu and Barnhart, 2006). These measures of user costs are, in essence, the same ones defined by Jenelius et al., (2006) to represent system damage in their road network study.

In the intersection between the topological and the system-based approach, there is a relatively recent stream of literature that focuses on measuring the changes in network topology as a result of passenger rescheduling. However, none of the published studies so far use detailed demand data and, instead, passenger flows are either inferred from the existing capacity, or they are only available at a flight sector level (without knowing the passengers' full itineraries). For simplicity, these studies retain a view of air transport networks as isolated components of overall transport networks. The goal is to determine how vulnerable the provision of air transport is in a particular country or region without considering the possibility of switching to other transport modes in case of an external shock. Cardillo et al. (2013), working with the European network, developed a passenger rescheduling algorithm and determined the change in the network's topological indicators after simulating random failures and assigning the disrupted passengers to alternative itineraries. They define a multi-layered network, with each layer representing an individual airline's flight network. In order to make the rescheduling more realistic, passenger recovery options within the same layer are given priority. Results show that the definition of a multi-layered structure negatively affects the measures of network resilience as it effectively restricts the options for passenger relocation. Also relevant is the contribution by Hossain et al. (2013) for Australian airports, where variables such as airport capacity and ground transfers between airports were included in the rescheduling algorithm. They estimated the unit cost of relocation associated to each airport closure as a measure of airport criticality and then ranked the airports according to that dimension. They found a high correlation (78%+) between the relocation costs and the indicators of degree and betweenness centrality. In spite of that, the impact of a closure can be mitigated by having close surrogate airports to serve the stranded passengers.

2.3 A new method using demand data

Our paper builds on the last two contributions (i.e., Cardillo et al., 2013; and Hossain et al., 2013) in which a system-based approach to measure network vulnerability is undertaken, though with a much stronger methodological focus on passenger relocation than on the analysis of network topology. In addition, we adapt Jenelius et al. (2006) concepts to an air transport context by measuring system vulnerability and node criticality according to passenger delays and unsatisfied demand conditional to different disruption scenarios. Furthermore, we maintain the simplifying view of air transport networks as an isolated component, meaning that the passengers in our model will not fully substitute air travel by road or rail. Nevertheless, we do consider ground transport for broadening the set of alternatives available to disrupted passengers and aspects like intermodal integration can help to explain how vulnerable airline operations are at a particular airport.

The present study adds to the literature in four key areas. The first and most important is the development of an enhanced relocation algorithm where disrupted passengers are offered options that cover their entire journey. This is only possible because we use demand data to characterise traffic flows within the European Air Transport Network. In addition, it is possible, for the first time, to disaggregate the network impact according to different origin/destination markets, with particular focus on the intra-European market which is of great interest for EU policy-makers. The second novelty is the use of a multi-layered network defined at an alliance/partnership level (as recommended by Cardillo et al., 2013; and Zanin, 2015). The reason is that a significant proportion of bookings in our dataset are operated by two or more airline partners and, hence, the individual airlines' flight networks may not be able to provide relocation alternatives. Thirdly, we provide the first ranking of airport criticality within the European network based on non-topological measures of network damage. Finally, we also aim to explore the main drivers of airport criticality under our new approach and discuss how the main conclusions from the existing body of research on topological vulnerability of air transport networks relate to our results.

3. DATA AND METHODOLOGY

3.1 Scope of analysis and methodological stages

In this paper, "European airports" are defined as those located in any country that is totally or partially in Europe. European airports can be split between European Economic Area (EEA) and non-EEA members. Switzerland is included in the EEA group. The European air transport network is characterised by all worldwide passenger itineraries that include at least one European airport during a certain period. These concepts, along with the datasets described below, delimit the geographical and temporal dimensions of this study.

In regards to methodology, the whole process can be split in three stages. First, we generate a baseline scenario by assigning a flight combination with a minimum travel time for each observed passenger itinerary. Second, we simulate the closure of one major airport and the affected passengers are sequentially relocated in delay-minimizing alternative itineraries within a predefined network, taking into account capacity constraints and allowing for ground transfers between airports. Third, the aggregate delay is used as measure of network damage generated by the particular airport closure.

3.2 Datasets

The proposed method combines supply (schedules and seats) and demand data (passenger itineraries). The supply side is covered by a dataset of worldwide flight schedules during the first week of February 2013, for which the primary source is the OAG Schedules dataset. This time period was chosen as major airport closures in Europe are typically linked to adverse weather conditions during the North Hemisphere winter season[2]. After simple data processing, the supply dataset comprises 558,503 unique records of scheduled passenger flight departures for 755 airlines that offered 74.2 million seats across a network of 2,101 commercial airports (this includes all airports in Europe as well as those in other regions connected directly or indirectly to them). Each record indicates the operating airline, alliance membership (if applicable), flight number, origin and destination airport codes, aircraft type, number of seats, flight distance, and Universal Time Coordinated (UTC) departure and arrival times.

The demand side is covered by a Marketing Information Data Transfer (MIDT) dataset containing air passenger itineraries flown during February 2013. Each record contains information on the published airline, as well as the points of origin and destination, the connecting airports (up to two intermediate stops), and the number of passengers. The airports of origin and destination determine the market to which the passengers belong. Most markets can be served via different itineraries, depending on the points of connection. In

[2] An additional simulation was run for August 2013 in order to discuss the robustness of our results.

total, the MIDT dataset contains 424,155 different itineraries in 135,078 directed markets, involving 47.1 million passengers, 441 airlines, and 2,150 airports (454 from the European Economic Area). Table 1 shows the distribution of this passenger demand by geographical markets. The largest market served by the European airport network is the intra-EEA, which amounts to 56.4% of its total passenger traffic. When non-EEA countries are also considered, the total share of intra-European traffic rises to 70.3%. Of the remaining network traffic, 28,6% is devoted to linking Europe with the rest of the world, with the most important destinations being Asia-Pacific and North America. The remaining 1.1% of passengers make use of European airports as gateways during their journeys between other continents. Note that Europe has a small presence in each continent pair, except the intra-American ones.

Table 1. Distribution of passenger demand by geographical markets (February 2013)

(passengers travelling between)	*EEA*	*Rest of Europe (non-EEA)*	*Africa*	*Asia-Pacific*	*Latin America and Caribbean*	*Middle East*	*North America*
EEA	26,585,156	2,593,487	2,268,371	3,201,116	1,406,508	1,704,083	2,494,909
Rest of Europe (non-EEA)		3,949,195	137,187	1,323,383	83,527	672,892	204,223
Africa			5,401	20,580	7,783	20,833	79,903
Asia-Pacific				11,892	36,349	19,526	134,450
Latin America and Caribbean					0	26,243	0
Middle East						1,698	108,486
North America							0

Source: MIDT, own elaboration. Note: EEA: European Economic Area.

The original sources of information for the MIDT dataset are Global Distributions Systems (GDSs) such as Galileo, Sabre, or Amadeus, among others. According to ARG (2013), 44% of all bookings of major airlines were done through GDSs in 2012. The proportion increases to 55% for network airlines, while low-cost carriers (LCCs), that prefer direct sales, only get 16% of their bookings via GDSs. This imbalance is an important limitation of the original dataset, as low-cost carriers may be underrepresented. In order to correct that, the provider of our data (OAG Traffic Analyser) adjusted the market figures using mathematical algorithms based on frequencies and supplied seats in each flight sector. The reliability of these adjustments, in terms of LCC representation, can be judged by calculating the airline market shares in the intra-EEA market that result from our adjusted data. The combined market share of LCCs is approximately 44%, which is similar to the estimate provided by the European Commission for the common market in 2013 (EC, 2014b). Other past studies have also used this dataset for connectivity purposes (e.g, Suau-Sánchez et al., 2014, 2015).

Finally, the proposed method requires of three additional datasets: 1) a full list of alliance, codeshare, and interline partners for each published airline in the MIDT file. Alliance membership is broadly defined to include subsidiaries of member airlines that are not specifically named as affiliate members. This information was obtained both from OAG and the airlines' websites; 2) Airport-specific minimum connecting times for the 250 busiest airports in terms of connecting traffic, including around 68,000 airline-specific exceptions. This was obtained from the OAG Connections Analyser; and 3) Minimum ground transfer times between the 50 largest airports in the European network and their potential surrogates. The surrogates are defined as the airports located less than 130 min of uncongested road/rail transfer from a given airport. This represents the best road/rail travel time corresponding to the shortest scheduled flights at Europe's largest airports. The goal is to prevent road/rail transport to become a full alternative to air travel within the context of this paper. The travel times were easily obtained by using Google Maps.

3.3 Creating the baseline scenario

Although the MIDT dataset provides information on passenger itineraries, it does not indicate the actual flights taken by the passengers nor their travel times. Therefore, there is need to match each MIDT record with flight schedules from the OAG dataset in order to create a baseline scenario. Due to the difference in time spans (demand data is for a month and schedules are for a week), the first step is to adjust the MIDT data in order to account for one week's traffic (dividing passengers by four).

Table 2. Sample MIDT record (1st week of February 2013)

Published Airline	***Origin***	***Gateway 1***	***Gateway 2***	***Destination***	***Passengers***
IB (Iberia)	LPA (Gran Canaria)	MAD (Madrid)	-	LHR (Heathrow)	70

For each adjusted MIDT record (Table 2), a search is made in the OAG file for all relevant flights (i.e. LPA to MAD and MAD to LHR) that were operated by either the published airline or any of its partners during the sample week. In case the airline filters do not return any matches, the search is broadened to include all airlines. If there are no scheduled flights for any of the relevant sectors, the MIDT record is discarded.

If the itinerary involves more than one sector, flight connections are built on the following restrictions, adapted from Grosche (2009): a) the published minimum connecting times must be met, b) the maximum connecting time is arbitrarily set at one hour above the shortest valid connection time[3], c) passengers on each first-leg flight always prefer the alternative with the shortest travel time, and d) passengers on each final-leg flight also prefer the shortest travel times. The process is illustrated in Table 3 below. The four shortest connections are discarded because they do not meet the minimum connecting times set by Madrid airport for Domestic-International transfers between the sample airlines. As a result, the shortest valid connection time is 65 min and the maximum connecting time is set as 125 min. The third condition discards all the underlined connections because a shorter alternative is available for the first-leg passengers. Finally, we also discard the connection in italics (18:05-20:10) because the second-leg flight can be reached by a later arrival.

Table 3. Selected flight connections for the sample MIDT record (only Monday flights)

Connecting times (min)		MAD-LHR												
	arrival\departure	10:45	12:40	13:35	14:20	14:55	15:00	15:55	16:50	17:10	18:30	20:10	20:45	06:45+1
LPA-MAD	10:30	~~15~~	130	185	230	265	270	325	380	400	480	580	615	1,215
	14:50					~~5~~	~~10~~	**65**	120	140	220	320	355	955
	18:05										~~35~~	*125*	170	770
	19:00											**70**	105	705
	22:25													500

Notes: Minimum Connecting Time= 45-55 min (depending on arrival and departure terminals). Bold indicates selected connections.

The outcome of this selection process will be a baseline scenario in which passengers take the best connections available, leading to minimum travel times. We acknowledge that this is somewhat unrealistic in the sense that passengers may trade off longer connection times for cheaper fares or more convenient flight times, thus spending more time at the hub airport than the minimum necessary to complete their trip. On the other hand, these "inflated" connection times may compromise the measures of network damage by introducing a substantial element of travel time savings as a result of passenger rescheduling (i.e., a passenger with a 6-hour extended connection at a closed hub may be given a 1-hour connection in an alternate airport instead). Hence, while a more complex modelling of passenger flight choice is slated for future research, for this initial application a "minimum travel time" baseline scenario is considered an appropriate benchmark to provide measures that can be easily interpreted.

Once the suitable flights (or flight combinations) are identified, the number of passenger bookings in the MIDT record is distributed among them according to seat capacity, which is

[3] This is meant to allow for some variability in connection times across the sample week. The goal is to prevent all passengers being allocated to the best weekly connection, which, in early simulations, usually led to capacity problems and important computational costs. Changing this window to 2 hours increases the sample-wide average connecting time only in 2.5% (approx. 3-4 min) due to the effect of other restrictions.

determined by the minimum number of seats across all sectors (see column *seat capacity* in Table 4). The proportion of passengers allocated to each travel option is equal to the proportion of its seat capacity to total capacity. In order not to gain or lose passengers due to rounding, the passenger allocations for each flight combination are rounded up or down randomly until all passengers in the MIDT record are allocated (see column *pax* in Table 4). The information on the individual flights and the total travel time for each flight combination that has received at least one passenger are added to the baseline scenario. Then, the next MIDT record is selected and the process starts again from the top of this section.

Table 4. Allocation of demand to flight combinations and generation of travel times for the baseline scenario

ID	Day	*Flight 1: LPA-MAD*					*Flight 2: MAD-LHR*					*Full itinerary*		
		Airline	*Flight No.*	*Dep.*	*Arr.*	*Seats*	*Airline*	*Flight No.*	*Dep.*	*Arr.*	*Seats*	*Seat capacity*	*Pax.*	*Travel Time (min)*
1	Mon	I2	3925	11:15	14:50	150	IB	3166	15:55	17:20	200	150	4	365
2	Mon	IB	823	15:10	19:00	200	BA	463	20:10	21:30	254	200	5	380
3	Tue	I2	3925	11:15	14:50	150	IB	3166	15:55	17:20	342	150	4	365
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
17	Sun	IB	823	15:10	19:00	200	BA	463	20:10	21:30	254	200	5	380
											Total	**2,875**	**70**	

After all itineraries in MIDT file have been processed, the records in the baseline scenario are aggregated by flight number and departure date in order to check whether the number of passengers in all origin/destination markets assigned to each individual flight does not exceed the seat capacity of the aircraft. Passenger numbers in those records involving flights over capacity are scaled down in the proportion needed to bring the aircraft to full capacity. New MIDT records with excess passengers are created and then brought into new rounds of processing with the same rules as the first stage. The main difference is that seat capacities in the OAG file are updated with the passenger numbers from the first stage (i.e. flight records only indicate remaining seats and full flights are removed). For this paper, three sequential rounds were enough to ensure that 95.8% of all passengers were allocated.

Table 5. Outcome of the passenger allocation process

Status	*Passengers*	*Share*
Allocated-first round	10,915,521	92.70%
Allocated-second round	313,914	2.67%
Allocated-third round	56,344	0.48%
Total Allocated	11,285,779	95.85%
No Schedules	318,840	2.71%
No valid Connections	59,609	0.51%
Over Capacity	110,683	0.94%
Total Passengers	11,774,911	100.00%
Allocated passengers only		
Non-stop trips	8,883,646	78.72%
Connecting trips	2,402,133	21.28%
1-stop	2,326,103	96.83%
2-stops	76,030	3.17%
Inline	1,487,645	61.93%
Intra-alliance	563,978	23.48%
Inter-alliance	67,413	2.81%
Other interline	283,097	11.79%

The remainder of passenger bookings (4.2%) had to be discarded for different reasons (See Table 5): 2.7% did not have any schedules for at least one of its sectors, 0.9% were over capacity, and 0.5% of the proposed itineraries did not match to any valid connections. These lost records can be explained by the fact that, while OAG schedules belong to the actual week under study, MIDT traffic represents an average week in February. Therefore, it may include itineraries flown in any of the other weeks. Further exploration of the data indicates that 85% of connecting trips in our sample are predicted to have been served entirely within the respective alliances, with the remaining 15% relying upon individual interlining and codeshare agreements signed by the carriers, regardless of their alliance membership.

In order to assess the reliability of this stage, we check the predicted load factors in intra-European flights, calculated after the final update of the OAG file, and compare them with the actual ones reported for February 2013 by the Association of European Airlines (AEA) and the largest individual carriers. These are presented in Table 6. Despite the limitations of our algorithm in distributing the passenger traffic across weekdays, the predicted load factors are roughly similar to the actual ones for the entire month, and successfully discriminate between carriers, with LCCs having larger load factors than network airlines.

Table 6. Predicted load factors in intra-European routes (1st week of February 2013)

Association of European Airlines (AEA) Members	*ASK (million)*	*RPK (million)*	*Load Factor*	
			Predicted	*Reported Feb-2013*
Europe Domestic	1,236.3	757.8	61.3%	66.6%
Europe Cross-border	4,633.7	3,126.8	67.5%	69.3%
Europe Total	5,870.0	3,884.7	66.2%	68.7%
Major Carriers				
Ryanair	1,475.3	1,097.0	74.4%	77.0%
Easyjet	1,083.9	939.4	86.7%	90.5%
Air France-KLM Group	1,132.6	775.8	68.5%	68.6%
Lufthansa Passenger Airlines	1,036.6	685.1	66.1%	66.0%
SAS group	456.4	288.0	63.1%	66.9%
International Airlines Group	853.4	569.4	66.7%	69.5%
Norwegian Air Shuttle	436.5	330.2	75.6%	78.3%
Air Berlin	488.1	402.7	82.5%	85.3%

Sources: Airlines' and AEA websites. Own elaboration. ASK: Availble seat-kilometers, RPK: Revenue passenger kilometers

The datasets with the baseline scenario and the updated OAG file with the predicted load factors for all individual flights (renamed "Matrix of Flight Sectors" - MFS) are brought forward to the next stage.

3.4 Airport closures and passenger rescheduling

The next steps in the algorithm are the following: 1) identify the disrupted passengers from a given airport closure and compile that information in a rescheduling matrix, 2) build a distance matrix with the available flights, 3) relocate the disrupted passengers in alternative travel itineraries using a shortest-path-length algorithm.

3.4.1 Creating the rescheduling matrix

An airport closure is characterised by a vector including the airport code and the times of beginning and end of the closure. The passenger itineraries from the baseline scenario are checked against the parameters of the airport closure. Using a similar approach than Janic (2015), all flights scheduled to arrive at[4] or depart from a closed airport are labelled as "OFF". Of all remaining flights, those already at full capacity are labelled as "FULL" and the rest are "ON". For each record in the baseline scenario, the itineraries to be considered for rescheduling include: 1) all "OFF" flights, 2) all "ON" or "FULL" flights departing after an "OFF" flight (i.e. passengers are rescheduled to the end of their trip), 3) all "ON" or "FULL" flights preceding an "OFF" flight but still departing within the period of closure. For example, if the itinerary in the baseline scenario is A→B→C→D and airport C is closed, the passengers will be rescheduled for their full A→D itinerary if the closure is already known at the time of their A→B departure. This gives the airline the opportunity to look for an alternative routing as soon as possible in order to minimize delay (note that this optimal routing may end up including the A→B flight anyway). If the A→B flight departs before the beginning of the closure of C, then the passengers will be rescheduled for the B→D itinerary. Responsibility for relocation is given to the airline that operates the first flight in the affected sequence.

[4] For simplicity, we do not consider the implications of being caught by the closure mid-flight. However, since the closures used in this paper start at midnight, the number of flights affected by this is relatively small.

Every record from the baseline scenario that has been disrupted by the closure is compiled in a new rescheduling dataset (RES) that indicates the number of passengers, the first flight in their itinerary to be rescheduled (according to the rules above), and the final destination of their trip. This matrix is sorted by the departure time of the disrupted flight in order to establish the sequence in which passengers will be relocated.

3.4.2 Creating the time-distance matrix

The MFS dataset is also cross-referenced against the parameters of the airport closure. Flights are labelled as “ON”, “OFF” or “FULL” using the same criteria explained above. From the perspective of the airlines, two different passenger recovery options are considered to deal with “OFF” flights: 1) relocation via the remaining flights in the affected airline’s own network, including alliance or interline partners where applicable, and 2) unrestricted relocation (passengers can be relocated in suitable flights operated by all airlines). For simplicity, only remaining “ON” flights can be used for passenger recovery and all retain their original schedules. In addition, there is the possibility of transferring to other airports by ground transport with the objective to make flight connections or end the journey. The model, however, does not contemplate the option of entirely substituting air travel by ground travel. This is consistent with the current goal of measuring how well the European air transport network, taken as an isolated component of the overall European transport network, is able to absorb major shocks.

The search for alternative routings for passenger recovery will be governed by the objective of delay-minimization as it is common under irregular airline operations (Barnhart, 2009). To that end, a shortest-path-length algorithm will be adapted to our case study and applied on a directed distance matrix where the distance between origin nodes (rows) and destination nodes (columns) is expressed in time units (Time Distance Matrix - TDM). The origin and destination nodes of this matrix will be all flights in the MFS dataset that depart between the time of the earliest flight in the RES matrix and an arbitrary period of 24 hours after the end of the airport closure[5]. Origin flight nodes indicate points in time where passengers are expected to make a flight departure. One additional origin node is added for every airport in the network labelled “GRT (ground transfer)”, which represents a departure from an airport by road/rail in order to complete the last travel segment. Destination flight nodes indicate points in time where passengers have reached the next flight departure in their journey. Two additional destination nodes are added for every airport in the network labelled “GRT” and “END”. The first denotes a passenger arriving from a flight to immediately leave by road/rail in order to complete the last travel segment, and the second denotes a passenger that reaches the final destination in its journey.

The time distances within the TDM are calculated following the set of rules detailed in Table 7, which take into account the status of the origin and destination flight nodes. Published minimum connecting times are used to generate valid flight connections, including official inter-airport transfer times (e.g. Heathrow-Gatwick). Since there are no official inter-airport transfer times for all surrogate airport pairs in the sample, artificial values were constructed: we observed that, on average, inter-airport transfers allow for three times the length of the uncongested ground transfer plus the standard transfer time for the type of connection. No ground transfer time is added between surrogate airports in the same city.

Table 7. Rules for the calculation of time distances in the TDM

Origin	*Destination*	*Conditions*	*Time distance*

[5] This is set up for computational purposes (it restricts the size of the TDM). By setting this parameter at 24 hours after the closure ends, stranded passengers that cannot be relocated on the same day could potentially be assigned to the same original itinerary after the airport reopens the following day.

Node	*Node*		
ON or FULL flight	ON flight	The origin flight can connect to any future onward journey that departs from its destination airport or from a valid surrogate of the latter. In both cases, the recovery networks of both flights must be compatible (i.e. alliance or unrestricted), there must be enough connecting time, and the onward flight must not come back to the initial airport.	= Departure Time Destination flight - Departure Time Origin flight
ON or FULL flight	OFF or FULL flight	An "OFF" or "FULL" is not a valid onward journey for passengers that are being relocated from other flights.	Not defined
ON or FULL flight	GRT or END node	There is always a time distance if the END/GRT airport is the destination of the origin flight.	= Arrival Time Origin flight - Departure Time Origin flight
OFF flight	ON flight	The stranded passengers can connect to any future onward journey that departs from a valid surrogate of the closed airport or from the latter when it reopens, provided the recovery networks of both flights are compatible and there is enough connecting time.	= Departure Time Destination flight - Departure Time Origin flight
OFF flight	OFF or FULL flight	An "OFF" or "FULL" flight is not a valid onward journey for passengers that are being relocated from other flights.	Not defined
OFF flight	GRT or END node	Two consecutive ground transfers are not allowed. An END node can only be reached from an "ON" or "FULL" origin flight or by means of a ground transfer.	Not defined
GRT node	-	There is a time distance if and only if the destination node is an END node of a valid surrogate of the GRT airport.	= Ground Transfer Time between GRT and END airports (replaced by zero if both airports serve the same city)

3.4.3 Passenger rescheduling

Once the initial TDM has been constructed, a shortest-path-length algorithm finds the optimal alternative routing for the disrupted passengers in the RES matrix in a dynamic and iterative process (a step-by-step description is provided in Table 8). In summary, for each record in the RES matrix, a shortest-path alternative itinerary is found between the origin node of the disrupted flight and the END node of the passengers' ultimate destination. Capacity constraints are taken into account: if there is no spare capacity to allocate all disrupted passengers in their new itinerary, the excess passengers are taken aside and relocated in a new iteration using an updated TDM resulting from changing the status of the relevant flight/s from "ON" to "FULL". Any passenger that remains unallocated at the end of the iterative process (e.g. because of lack of seat capacity) is flagged as such. After all records in the RES matrix have been processed, the new itineraries are compiled in a relocation (REL) matrix.

Table 8. Algorithm for passenger rescheduling

Inputs: Time-directed distance matrix (TDM) containing origin and destination flights.
Rescheduling matrix (RES) created from the disrupted records in the baseline scenario.
Matrix of flight sectors (MFS) from OAG.
Output: Matrix with the new itineraries of the relocated passengers (REL).

```
for each entry of RES do
    lookup the disrupted flights in MFS
    subtract disrupted passengers and check for changes in status (i.e. "FULL" to "ON")
    if status has changed then update TDM using rules from Table 7
    while not all passengers are processed do
        SP ← shortest path in TDM between the first flight in RES and the END node of the final destination airport
        if SP algorithm does not converge then do
            discard passengers and lookup next entry in RES
        else
            create a new entry of REL
            for each flight segment in SP do
                if capacity of the flight is exceeded then do
                    add the segment to the current entry of REL allocating as many passengers as possible
                    change the status of the segment in MFS to "FULL" and update TDM
                    relocate the remaining passengers in further iterations
                else
                    add the segment to the current entry of REL allocating the disrupted passengers
                    if flight is full now then change the status of the segment in MFS to "FULL" and update TDM
```

```
                    end if
                end for
            end if
        end while
    end for
```

The calculation of shortest-path itineraries made use of the *iGraph* library in R. This employs the well-known Dijkstra algorithm, which performs an exhaustive search that ensures that, if anything, a shortest path is always returned.

3.5 Measuring vulnerability and airport criticality

In total, 125 individual airport closure scenarios are run, five for each of the 25 busiest European airports (Table 9). The closures last 24 hours (00:00-24:00 UTC) and happen either Monday or Friday, which are considered the most critical days in terms of "weekday" and "weekend" traffic. In the Monday case, running both alliance and unrestricted options allows us to assess how close the airline alliances that dominate the major European hubs come to offering the globally optimal solutions (exclusively in terms of travel time) to their disrupted passengers. An extra scenario without seat capacity constraints will also be run.

Table 9. Top 25 busiest European airports (estimated traffic for 1st Week of February 2013)

Airport	*Passengers (all markets)*			*Passengers (intra-EEA)*			*Distribution of passenger departures*				*% inter-alliance*
	OD	*Conn.*	*Total*	*OD*	*Conn.*	*Total*	*OneW*	*StarAll*	*Skyteam*	*Other*	
London Heathrow (LHR)	**903,181**	156,133	**1,059,314**	**397,387**	24,478	**421,865**	57.4%	20.2%	6.4%	16.0%	5.6%
Paris (CDG)	**600,521**	**172,802**	**773,323**	312,842	35,245	348,087	5.7%	11.3%	65.4%	17.5%	6.0%
Frankfurt (FRA)	422,106	**221,392**	**643,498**	211,358	**63,908**	275,266	6.3%	76.3%	5.5%	11.9%	7.2%
Istanbul Ataturk (IST)	423,722	**189,246**	612,968	0	1,208	1,208	1.4%	78.7%	4.4%	15.6%	2.5%
Madrid (MAD)	**475,918**	103,879	579,797	**368,823**	39,602	**408,425**	51.8%	8.6%	19.1%	20.6%	8.2%
Amsterdam (AMS)	414,963	157,518	572,481	272,269	**45,157**	317,426	5.4%	8.7%	70.3%	15.6%	6.4%
Munich (MUC)	371,358	118,599	489,957	269,747	**65,870**	335,617	13.1%	73.7%	4.4%	8.8%	3.6%
Barcelona (BCN)	442,452	14,819	457,271	**372,342**	12,313	**384,655**	40.6%	13.7%	11.6%	34.1%	2.4%
London Gatwick (LGW)	439,171	14,385	453,556	337,820	6,487	344,307	17.7%	2.6%	1.4%	78.3%	3.8%
Rome Fuimicino (FCO)	363,363	69,602	432,965	261,918	34,293	296,211	7.7%	11.4%	55.6%	25.3%	6.0%
Paris Orly (ORY)	393,225	20,315	413,540	293,045	15,917	308,962	9.5%	3.2%	47.7%	39.6%	2.3%
Moscow Dom. (DME)	348,163	40,473	388,636	0	6	6	35.4%	7.2%	2.1%	55.2%	3.9%
Moscow Sher. (SVO)	276,968	75,973	352,941	0	319	319	0.4%	1.5%	90.9%	7.2%	3.9%
Oslo (OSL)	293,093	38,861	331,954	264,922	36,591	301,513	4.4%	46.6%	3.2%	45.8%	4.9%
Copenhagen (CPH)	270,369	48,908	319,277	213,933	39,527	253,460	8.3%	56.7%	4.9%	30.2%	7.1%
Zurich (ZRH)	246,771	66,517	313,288	165,353	27,967	193,320	12.4%	75.1%	4.9%	7.6%	9.6%
Stockholm (ARN)	275,928	26,408	302,336	229,491	23,853	253,344	9.1%	56.3%	5.2%	29.3%	5.3%
Geneva (GVA)	278,612	4,638	283,250	222,724	2,982	225,706	8.8%	30.6%	11.1%	49.6%	3.8%
Dusseldorf (DUS)	266,593	16,546	283,139	198,081	9,525	207,606	35.7%	44.3%	6.9%	13.0%	3.1%
Milano Malpensa (MXP)	267,615	4,070	271,685	172,583	1,201	173,784	10.8%	25.3%	12.3%	51.6%	3.3%
Dublin (DUB)	255,230	9,504	264,734	220,012	5,556	225,568	5.2%	5.2%	4.8%	84.8%	8.4%
Brussels (BRU)	238,806	23,881	262,687	158,662	10,150	168,812	8.7%	59.1%	8.3%	23.9%	6.9%
Vienna (VIE)	209,851	52,360	262,211	144,021	20,321	164,342	18.6%	67.5%	5.7%	8.3%	4.7%
London Stansted (STN)	258,752	623	259,375	249,679	523	250,202	0.9%	2.9%	0.0%	96.2%	1.8%
Manchester (MAN)	251,335	5,293	256,628	171,173	3,734	174,907	10.0%	14.6%	5.8%	69.6%	5.3%

Source: MIDT, own elaboration. Note: OD = Origin/destination passengers; Conn.= Connecting passengers.

Due to the fact that all the disruptions modelled affect only one component of the network (the closed airport), the measure of "conditional criticality" under each closure scenario will be used also as a measure of "conditional vulnerability" of the entire network. Moreover, from now on, "conditional vulnerability" and "conditional criticality" will be simply referred as vulnerability and criticality, respectively. In our case study, these are measured by the relocation rate (the proportion of passengers for which an alternative itinerary was found within the relocation window – 24 hours after the closure ends) and, also, by the accumulated delay experienced by the disrupted passengers. For those relocated, the total delay is made of two components: the departure delay generated by the original disruption, and the difference between the journey times of the baseline and rescheduled itineraries. For non-relocated passengers, the total delay is measured as the difference between their baseline departure time and the end of the relocation window. Separate measures of airport criticality will be provided for the intra-EEA markets and we will also report the airports that serve the largest amounts of relocated traffic in each closure scenario.

Finally, the resulting ranking of airport criticality will be compared with three well-known topological indicators − degree centrality, closeness, and betweenness centrality − in order to establish a link between our results and the previous literature. Degree centrality (D_i) is calculated as the total number of destinations served by airport i. Closeness (C_i) is the inverse of the sum of the distances between airport i and all other airports in the network:

(1) $$C_i = \frac{1}{\sum_j distance(i,j)}.$$

Betweeness centrality (B_i) is calculated as follows:

(2) $$B_i = \sum_{j \neq i \neq k} \frac{\sigma_{jk(i)}}{\sigma_{jk}},$$

where σ_{jk} are the total number of shortest paths (measured in graph distance – number of links between two nodes) from airport j to airport k and $\sigma_{jk(i)}$ is the number of those paths that pass through airport i. Both C_i and B_i will be calculated over unweighted networks and normalized between [0,1]. The lack of degrees of freedom prevents us from carrying out a regression analysis, so our conclusions will be based on correlation coefficients. Further discussion of any drivers of airport criticality beyond network topology will be mostly exploratory and rely on ad-hoc indicators based on the simulation results.

4. RESULTS AND DISCUSSION

The simulation results are provided in Appendices A-E alongside a glossary of airport codes in Appendix F.

4.1 Airport criticality vs. network topology

Table 10 summarizes the simulation results for the Monday closure, under alliance recovery, and considering all markets (Appendix A). Airports are sorted according to the accumulated delay experienced by both relocated and non-relocated passengers (*aggdel'*). This measurement indicates that the most critical airports in the European network during the sample period were Heathrow, Istanbul, and Barcelona with total delays ranging from 81 to 115 thousand passenger-days. Highest delays per passenger, nevertheless, are experienced in Moscow-DME, Barcelona, and Stockholm[6]. While the limited temporal scope of the measures provided (February 4-5, 2013) must always be borne in mind, it is possible to obtain interesting conclusions by ranking the airports according to other dimensions. For example, according to the number of disrupted passengers (*dpax*), the ranking is topped by major airports: Heathrow, Paris-CDG, and Istanbul (it is estimated to surpass Frankfurt in terms of passenger traffic on the sample day). From the point of view of passenger recovery, however, important differences can be found within the largest European hubs. The airlines affected by the closure of Istanbul Ataturk are able to relocate 61% of disrupted passengers within their own alliances (*%reloc*). The relocation rate increases to around 72% for Heathrow and Paris, while Frankfurt stands out with the highest relocation rate in the entire sample at 86.9%. Amsterdam is marginally below 60% and other major airports such as Domodedovo (39.5%), Milano Malpensa (43.5%), Gatwick (38.9%), or Barcelona (46.2%) are among the worst-ranked. Of course, relocation rates are capped by the amount of inter-alliance traffic, which cannot be relocated as per the model restrictions. However, by comparing these relocation rates with the inter-alliance traffic shares reported in Table 9 – all below 10% – , it is clear that the performance of the latter airports is very poor. The quality of

[6] Note that long-distance rail travel from Stockholm to Copenhagen is not contemplated by the model.

the alternative itineraries is a further concern in Barcelona, as relocated passengers would experience, on average, increases of more than 400% in travel times over the best available itineraries from the baseline scenario (Δ*avt%*). A similar effect is predicted for Stansted Airport, which suggests that low-cost dominance may have a negative influence on the quality of relocation due to the lack of alliance partners to provide alternative itineraries (see Section 4.2). On the contrary, the (predominantly) full-service network carriers operating at Frankfurt can provide the best alternative itineraries within their own alliances, with an average delay of only 69.5% over the baseline travel times. In addition, Frankfurt also benefits from the availability of local surrogates to achieve an average departure delay (*avddel*) under 12 h (third best in the sample after Zurich and Dusseldorf). This helps the main German hub to achieve the lowest average delays per disrupted passenger.

Table 10. Simulation results: Monday closure; alliance passenger recovery; all markets.

Closed Airport	***All markets***												
	dpax	***reloc***	***%reloc***	***avddel (min)***	***avt0 (min)***	***avt1 (min)***	***Δavt%***	***non-reloc***	***aggdel' (pax-days)***	***aggdel'/dpax (days)***	***Di***	***Ci***	***Bi***
Heathrow	**108,197**	78,267	72.30%	940	348	805	131.50%	**29,930**	**115,937**	1.072	140	**0.482**	0.056
Istanbul	**75,410**	46,346	61.50%	912	300	807	168.50%	29,064	**87,185**	1.156	**174**	0.453	0.054
Barcelona	64,825	29,954	46.20%	881	174	884	**408.80%**	**34,871**	**81,050**	**1.250**	107	0.42	0.016
Madrid	68,386	42,442	62.10%	894	239	807	237.20%	25,944	79,032	1.156	126	0.448	0.031
Paris CDG	**78,532**	56,417	71.80%	837	322	687	113.20%	22,115	77,549	0.987	**178**	**0.488**	**0.087**
Gatwick	59,929	23,329	**38.90%**	817	162	385	137.80%	**36,600**	69,049	1.152	107	0.416	0.017
Amsterdam	63,250	37,744	59.70%	795	319	765	139.80%	25,506	68,196	1.078	170	0.475	**0.057**
Moscow DME	46,649	18,428	**39.50%**	**1,270**	235	502	114.10%	28,221	63,207	**1.355**	112	0.416	0.055
Rome Fiumicino	55,017	36,396	66.20%	848	231	815	252.90%	18,621	62,287	1.132	110	0.444	0.019
Paris Orly	55,448	32,541	58.70%	**998**	131	425	224.40%	22,907	60,983	1.100	82	0.387	0.019
Munich	63,479	53,656	84.50%	702	210	625	197.70%	9,823	55,495	0.874	134	0.454	0.024
Oslo	47,340	29,695	62.70%	956	133	601	**353.30%**	17,645	54,623	1.154	70	0.396	0.022
Frankfurt	69,499	60,412	86.90%	689	363	616	69.50%	9,087	52,649	0.758	**177**	**0.495**	**0.081**
Stockholm	41,818	23,159	55.40%	**1,026**	174	742	326.70%	18,659	52,090	**1.246**	78	0.407	0.028
Moscow SVO	40,299	23,099	57.30%	994	353	848	140.40%	17,200	49,402	1.226	112	0.42	0.02
Copenhagen	43,467	27,055	62.20%	786	207	787	279.80%	16,412	48,637	1.119	91	0.424	0.025
Milano Malpensa	36,894	16,050	**43.50%**	868	229	551	141.00%	20,844	44,054	1.194	78	0.424	0.008
Stansted	35,871	16,065	44.80%	851	119	614	**416.20%**	19,806	43,278	1.206	81	0.362	0.008
Geneva	34,319	15,416	44.90%	750	184	771	318.20%	18,903	41,766	1.217	69	0.407	0.004
Dublin	34,389	15,114	44.00%	941	158	499	215.00%	19,275	39,584	1.151	75	0.401	0.008
Vienna	35,217	29,197	82.90%	719	210	840	300.60%	6,020	35,518	1.009	94	0.418	0.007
Manchester	31,747	16,972	53.50%	759	199	583	192.50%	14,775	34,265	1.079	86	0.408	0.011
Dusseldorf	40,820	31,309	76.70%	659	164	420	156.50%	9,511	33,484	0.820	86	0.419	0.007
Zurich	34,432	26,912	78.20%	679	269	662	146.50%	7,520	30,233	0.878	98	0.447	0.014
Brussels	33,536	25,485	76.00%	719	197	488	148.00%	8,051	29,383	0.876	93	0.431	0.011

Notes: dpax: disrupted passengers, reloc: relocated passengers; avddel: average departure delay for relocated passengers (min); avt0: average baseline travel time (min) – relocated passengers; avt1: average relocated travel time (min); non-reloc: passengers not relocated; aggdel': aggregate delay for all passengers 24h after re-aperture; Di: degree centrality; Ci: closeness; Bi: Betweeness centrality.

Table 11. Simulation results: Monday closure; alliance passenger recovery; intra-EEA markets.

Closed Airport	***Intra-EEA markets***												
	dpax	***reloc***	***%reloc***	***avddel (min)***	***avt0 (min)***	***avt1 (min)***	***Δavt%***	***non-reloc***	***aggdel' (pax-days)***	***aggdel'/dpax (days)***	***Di***	***Ci***	***Bi***
Barcelona	**58,220**	26,749	45.90%	865	127	876	**587.80%**	**31,471**	**73,011**	**1.254**	**89**	**0.513**	0.055
Madrid	**57,085**	35,395	62.00%	904	146	743	410.00%	**21,690**	**66,786**	1.170	84	0.493	0.03
Heathrow	**59,333**	43,877	74.00%	922	143	746	421.00%	15,456	**66,540**	1.121	62	0.482	0.011
Gatwick	50,351	20,759	**41.20%**	819	119	357	199.40%	**29,592**	57,010	1.132	82	0.5	0.045
Amsterdam	45,988	25,950	56.40%	822	161	685	325.30%	20,038	51,770	1.126	**99**	**0.515**	0.039
Oslo	44,455	28,110	63.20%	**954**	105	581	455.30%	16,345	50,044	1.126	63	0.475	**0.087**
Rome Fiumicino	42,482	27,818	65.50%	868	130	773	493.80%	14,664	49,424	1.163	73	0.486	0.025
Paris Orly	44,972	28,796	64.00%	**973**	119	417	248.80%	16,176	47,395	1.054	63	0.441	**0.067**
Paris CDG	47,663	35,019	73.50%	827	162	575	254.00%	12,644	47,138	0.989	**89**	0.496	0.031
Stockholm Arlanda	37,390	20,604	55.10%	**1,033**	125	710	467.80%	16,786	47,112	**1.260**	67	0.465	**0.104**
Munich	48,422	41,132	84.90%	714	130	588	353.80%	7,290	43,700	0.902	86	0.503	0.028
Copenhagen	37,531	23,269	62.00%	785	139	767	451.80%	14,262	42,548	1.134	72	**0.507**	0.058
Stansted	35,357	15,845	44.80%	849	115	607	425.40%	19,512	41,154	1.164	80	0.463	0.064
Dublin	31,656	13,811	43.60%	912	114	478	317.20%	17,845	38,005	1.201	65	0.479	0.025
Geneva	28,670	12,246	**42.70%**	723	124	787	**534.50%**	16,424	34,690	**1.210**	51	0.488	0.014
Milano Malpensa	27,932	10,954	**39.20%**	817	128	545	325.10%	16,978	32,137	1.151	51	0.47	0.009
Frankfurt	39,798	35,556	89.30%	717	171	434	153.80%	4,242	30,086	0.756	84	0.495	0.023

Dusseldorf	33,240	26,091	78.50%	656	114	386	239.20%	7,149	26,665	0.802	64	0.474	0.014
Vienna	24,659	21,212	86.00%	731	136	850	**524.70%**	3,447	26,239	1.064	61	0.468	0.018
Manchester	24,657	14,560	59.10%	727	131	566	330.90%	10,097	25,789	1.046	65	0.489	0.035
Zurich	24,579	18,929	77.00%	667	147	626	327.20%	5,650	22,694	0.923	59	0.478	0.009
Brussels	25,995	21,005	80.80%	703	139	451	225.00%	4,990	21,651	0.833	63	0.478	0.01
Moscow SVO	38	12	31.60%	285	474	967	103.90%	26	51	1.352	40	-	-
Istanbul Ataturk	165	155	93.90%	233	423	452	6.80%	10	46	0.279	53	-	-
Moscow DME	0	0	-	-	-	-	-	0	-	-	18	-	-

Notes: dpax: disrupted passengers, reloc: relocated passengers; avddel: average departure delay for relocated passengers (min); avt0: average baseline travel time (min) – relocated passengers; avt1: average relocated travel time (min); non-reloc: passengers not relocated; aggdel': aggregate delay for all passengers 24h after re-aperture; Di: degree centrality; Ci: closeness; Bi: Betweeness centrality.

Table 11 presents the results for the intra-EEA disrupted passengers, ranked again by *aggdel'*. While there are many similarities with the overall results (intra-EEA is the largest market in the European airport network, see Table 1), the differences highlight the importance of using detailed demand data to assess airport criticality. On top of the geographical coverage of airline alliances and other restrictions that prevent relocation in particular routes, airports themselves play different roles in different markets. While Heathrow, Paris-CDG or Frankfurt devote a substantial share of their traffic to intercontinental routes, airports like Barcelona, Madrid, and Gatwick are mainly focused on intra-EEA traffic (Table 9). These three end up being among the ones whose closure would cause the largest aggregate delays within the EEA internal markets (Heathrow surpasses Gatwick in aggregate delays because of the scale of operations). It is also worth highlighting the difference between Heathrow and Paris-CDG, which, despite similar relocation rates, sharply differ in the quality of the alternative itineraries. Again, Frankfurt stands out as the least critical among the top European hubs, though its share of intra-EEA traffic is lower than all of the airports mentioned above.

The first port of call when searching for the main drivers of airport criticality is network topology. As explained in Section 2, the existing literature has established a link between network damage and the topological properties of both the network and the individual airports. Table 12 shows the linear correlation and rank correlation coefficients between four of our demand-based indicators (average departure delay: *avddel*, increase in average travel time: $\Delta avt\%$, aggregate delay: *aggdel'*, and aggregate delay per passenger) and three supply-based topological measures (degree, closeness, and betweenness centrality). When all markets are considered, the topological indicators present a positive and significant correlation to aggregate delays yet a negative correlation with average increase in travel time and aggregate delay per passenger. The first result is capturing an "airport size" effect and is in line with the previous literature, which generally agrees that airports with the highest number of connections and lying in the highest proportion of shortest-paths between other airports would also generate the highest network damage when closed. In regards to the negative correlations, Hossain et al. (2013) notes that the most central an airport is, the easier is to find good surrogates to handle the disrupted traffic, thus potentially improving the quality of relocations. However, the correlation between centrality and network damage was expected to be positive. The negative and significant effects are not present in the EEA markets, where we find airports that serve as sole gateways to remote destinations (Oslo, Stockholm) and hence, they score high in both betweenness centrality and travel time increase as the remote regions become disconnected. Overall, the sign and magnitude of these correlations is different from the supply-based measures by Hossain et al. (2013) in the range of 78%-90%. These results challenge the traditional views on the relationship between airport centrality and network damage from the perspective of passenger recovery, and a more comprehensive search for explanatory factors is warranted.

Table 12. Linear correlation and rank correlation coefficients: criticality vs. topological indicators

	All markets			*Intra-EEA markets*		
	Degree	*Closeness*	*Betweenness*	*Degree*	*Closeness*	*Betweenness*

avddel						
linear correlation	-0.081	-0.270	0.198	0.078	-0.276	0.678*
rank correlation	-0.103	-0.351	0.295	0.163	-0.200	0.594*
Δavt%						
linear correlation	-0.541*	-0.633*	-0.507*	-0.131	0.073	0.259
rank correlation	-0.616*	-0.588*	-0.479*	-0.069	-0.008	0.246
aggdel'						
linear correlation	0.595*	0.475*	0.597*	0.506*	0.345	0.381
rank correlation	0.615*	0.378	0.711*	0.542*	0.378	0.521*
aggdel'/dpax						
linear correlation	-0.308	-0.495*	-0.162	-0.028	0.022	0.449*
rank correlation	-0.295	-0.490*	-0.068	0.090	-0.002	0.370

*Notes: * indicates that the coefficient is significant at 95% confidence.*

4.2 Drivers of airport criticality: originating vs. connecting traffic

Understanding how passenger traffic is redistributed when a large airport closes can help identify the drivers of airport criticality. On the one hand, passengers starting or terminating their journey in a closed airport (i.e., *od* traffic) will be able to find an alternative itinerary if a local surrogate, that can be reached by ground transport, offers a compatible flight. Otherwise, *od* passengers will be "captive" in the closed airport until it reopens and hence they will experience longer departure delays. Connecting traffic, on the other hand, is not dependent on local surrogates, but on finding a compatible connection elsewhere. Adapting the argument of structural network redundancy discussed in Zhang et al. (2015), the quality of relocation in our case study is expected to reflect how the respective alliances overlap in their coverage of the affected markets.

In order to illustrate the impact of the above factors, Table 13 provides the top ten alternative airports for the ten largest closures in terms of disrupted passengers. The top alternative airports are the ones that experience the highest increase in passenger departures with respect to the baseline scenario. In addition, we also report the proportion of relocated passengers that have to wait for the affected airport to reopen. As expected, the top alternative airports in most cases match the dominant alliance of the closure airport (e.g., Heathrow and Madrid are both dominated by Oneworld – See Table 9). For Frankfurt and Paris-CDG, in what seems the most advantageous situation, the top alternative airports are alliance-matching surrogates (Dusseldorf and Orly, respectively), thus improving the chances of finding minimum-delay itineraries that can be completed via a road/rail transfer. This can explain the very low departure delays for the Frankfurt closure, as only 55% of disrupted passengers have to wait for the airport to reopen[7]. On the other end, the lack of local surrogates among the top alternates for Madrid or Barcelona is bound to translate into longer departure delays.

Table 13. Top alternative airports: Monday closure; alliance passenger recovery; all markets.

Closure	***Heathrow***		***Paris-CDG***		***Frankfurt***		***Istanbul Ataturk***		***Amsterdam***	
	reloc	***non-reloc***	***reloc***	***non-reloc***	***reloc***	***non-reloc***	***reloc***	***non-reloc***	***reloc***	***non-reloc***
Total pax	78,267	29,930	56,417	22,115	60,412	9,087	46,346	29,064	37,744	25,506
od pax	64,573	23,488	41,294	18,070	35,756	5,691	31,442	19,631	25,128	20,318
Connecting pax	13,694	6,442	15,123	4,045	24,656	3,396	14,904	9,433	12,616	5,188
top alternative airports (passenger departures)	alt.	Δpax	alt.	Δpax	alt.	Δpax	alt.	Δpax	alt.	Δpax
	MAD	6,097	ORY	9,246	DUS	9,970	FRA	8,123	CDG	8,870
	FRA	5,956	AMS	6,881	MUC	8,462	MUC	6,834	BRU	6,590
	MUC	5,071	FCO	4,941	STR	4,434	ESB	4,280	LHR	1,995
	LGW	4,416	SVO	2,503	CGN	4,009	VIE	3,097	SVO	1,919
	TXL	3,612	FRA	2,484	VIE	3,762	DUS	2,971	ORY	1,733
	BCN	3,595	BRU	2,257	IST	3,156	CAI	2,605	FCO	1,681
	DUS	3,194	LIN	2,166	ZRH	2,468	BRU	2,097	LCY	1,540
	HEL	2,592	LYS	2,146	BRU	2,358	SAW	2,006	MAD	1,375
	BRU	2,582	TLS	1,914	HAM	2,318	ZRH	1,984	FRA	1,249
	VIE	2,523	NCE	1,843	LHR	2,313	HAM	1,963	LIN	1,228

[7] We ran the Frankfurt closure without the ground transport link to Dusseldorf in order to check the consistency of that estimate. The relocation rate would remain virtually the same (86.7%), as well as the proportion of passengers after reopening (55.8%). Only the "average travel time increase" indicator would suffer (a 15% increase to 84.5%) as Munich, Cologne, and Stuttgart airports absorbed the additional traffic.

% After reopening	LHR	83.4%	CDG	72.9%	FRA	55.6%	IST	70.4%	AMS	66.3%
Closure	***Madrid***		***Munich***		***Barcelona***		***Gatwick***		***Rome Fuimicino***	
	reloc	***non-reloc***	***reloc***	***non-reloc***	***reloc***	***non-reloc***	***reloc***	***non-reloc***	***reloc***	***non-reloc***
Total pax	42,442	25,944	53,656	9,823	29,954	34,871	23,329	36,600	36,396	18,621
od pax	33,086	22,312	37,749	7,352	25,623	32,305	21,846	34,938	26,370	15,837
Connecting pax	9,356	3,632	15,907	2,471	4,331	2,566	1,483	1,662	10,026	2,784
top alternative airports (passenger departures)	alt.	Δpax	alt.	Δpax	alt.	Δpax	alt.	Δpax	alt.	Δpax
	BCN	8,529	FRA	9,202	MAD	8,819	LHR	4,464	CDG	7,213
	LHR	6,240	STR	6,821	LHR	3,897	STN	2,064	LIN	5,944
	CDG	2,685	DUS	5,633	FRA	1,963	BRS	1,883	AMS	2,756
	PMI	1,971	VIE	4,506	DUS	1,614	LTN	1,609	MXP	2,447
	AMS	1,909	BRU	3,480	MUC	1,595	BHX	1,316	FRA	1,811
	MUC	1,855	TXL	3,272	CDG	1,560	BFS	978	ORY	1,799
	ORY	1,813	HAM	3,196	PMI	1,523	MAD	883	LHR	1,689
	TXL	1,574	NUE	3,129	TXL	1,444	GVA	766	SVO	1,347
	SVQ	1,538	IST	2,464	BRU	1,162	CDG	754	MAD	1,310
	DUS	1,513	CGN	2,392	ORY	1,102	AMS	697	CTA	1,303
% After reopening	MAD	78.9%	MUC	62.6%	BCN	87.2%	LGW	92.3%	FCO	70.0%

Notes: reloc: relocated passengers; non-reloc: passengers not relocated.

Table 14 presents the shares of connecting and *od* traffic, alongside two new indicators. First, we calculate the proportion of overlapping seat capacity offered by the airport's local surrogates (*% overlap surrogates*). This indicates the proportion of a given airport's seat capacity that could be substituted by an alternative seat from the same airline (or alliance partner), to the same destination, and that departs from at least one of the surrogates. It ranges from 77.1% at Dusseldorf –whose passengers could potentially reach alliance-matching Frankfurt Airport within the set time limit of 130 minutes–, down to 0% for the relatively isolated Madrid and Rome airports. Second, we determine the proportion of connecting traffic for which the respective alliance networks offer at least one alternative connection point (*% overlap alliance*). The values are strongly influenced by the distribution of traffic across alliance and non-alliance airlines. On one end, we find the 95.6% coverage of Zurich hub connections – mainly by Star Alliance –. On the other end, there is an 8.4% coverage for Dublin – dominated by low-cost carrier Ryanair and Aer Lingus –, an airport with a very low share of connections. In order to account for these differences in traffic split, the two types of overlap can be combined to estimate the overall proportion of the airport's traffic that is not covered by any other alliance service either locally on in connection *(% non-overlap*).

Table 14. Capacity overlap provided by airline alliances and surrogate airports

Airport	***%conn***	***overlap alliance***	***%od***	***overlap surrogates***	***% non-overlap***	***Potential surrogates (airports <130 min uncongested road/rail transfer)***
Heathrow	12.8%	43.0%	87.2%	13.1%	83.1%	BHX BOH BRS LCY LGW LTN SEN SOU STN
Barcelona	3.6%	82.0%	96.4%	1.8%	95.3%	GRO ILD REU
Istanbul	28.0%	51.1%	72.0%	5.4%	81.8%	SAW TEQ
Gatwick	2.7%	39.4%	97.3%	39.2%	60.8%	BOH LCY LHR LTN MSF OXF SEN SOU STN
Madrid	13.8%	51.7%	86.2%	0.0%	92.9%	SLM VLL
Amsterdam	19.9%	59.9%	80.1%	20.2%	71.9%	BRU EIN GRQ MST NRN RTM
Moscow Domodedovo	10.0%	12.1%	90.0%	6.9%	92.6%	BKA SVO VKO
Paris CDG	17.2%	65.5%	82.8%	10.7%	79.9%	BVA DOL LEH LIL LTQ ORY XCR
Rome Fuimicino	15.4%	55.6%	84.6%	0.0%	91.4%	CIA
Paris Orly	3.6%	64.4%	96.4%	20.9%	77.5%	BVA CDG DOL LEH TUF XCR
Oslo	12.4%	46.9%	87.6%	2.9%	91.6%	RYG TRF
Milano Malpensa	1.3%	82.6%	98.7%	20.0%	79.2%	BGY GOA LYN LUG PMF TRN VRN
Copenhagen	15.3%	70.8%	84.7%	5.1%	84.8%	AGH HAD KID MMX RKE
Stockholm Arlanda	9.2%	32.8%	90.8%	1.2%	95.9%	BMA NRK NYO VST
Moscow Sheremetyevo	20.9%	42.7%	79.1%	3.5%	88.3%	BKA DME VKO
Stansted	0.1%	29.4%	99.9%	35.7%	64.3%	BHX EMA LCY LGW LHR LTN NWI OXF SEN
Geneva	1.1%	88.1%	98.9%	26.5%	72.8%	BRN DLE LYS NCY
Dublin	3.1%	8.4%	96.9%	16.5%	83.7%	BFS BHD WAT
Munich	23.0%	85.2%	77.0%	26.9%	59.7%	AGB PDH FMM INN NUE STR SZG
Manchester	2.2%	55.1%	97.8%	44.1%	55.7%	BHX BLK DSA EMA GLO HUY LBA LPL VLY
Frankfurt	31.6%	73.0%	68.4%	38.6%	50.5%	CGN DUS FKB HHN NUE SCN STR
Vienna	21.3%	84.1%	78.7%	2.9%	79.8%	BRQ BTS GRZ
Dusseldorf	6.8%	87.7%	93.2%	77.1%	22.2%	BRU CGN CRL DTM EIN FMO FRA MST NRN PAD
Zurich	18.3%	95.6%	81.7%	29.4%	58.5%	ACH BRN BSL FDH FMM MLH STR SXB
Brussels	7.7%	71.8%	92.3%	66.0%	33.5%	AMS CGN CRL DUS EIN LIL LUX MST NRN OST RTM

Similarly to the previous section, Table 15 presents the linear and rank correlation coefficients between our measures of airport criticality, the alliance non-overlap, the share of *od* traffic, and the market shares of alliance and non-alliance airlines. Results confirm the intuition that the alliance non-overlap presents a positive correlation to airport criticality, a positive and statistically significant relationship also exists between the share of *od* traffic and the aggregate delay per passenger. Among the market shares, the proportion of non-alliance traffic has the strongest positive correlation to aggregate delay per passenger. Clearly, non-alliance airlines (such as low-cost carriers) will have a harder time in finding alternative itineraries for their disrupted passengers exclusively through their own flight networks. On the contrary, there is a negative and significant correlation between delays per passenger and the market share of Star Alliance. While it is beyond the scope of this paper to establish causal relationships between alliance market shares and airport criticality, these correlations are in line with the results from Lordan et al. (2015) which point at Star Alliance as the most resilient of the three major alliances.[8]

Table 15. Linear correlation and rank correlation: criticality vs. traffic and network overlap indicators

	All markets					
	%non-overlap	***%od***	***%oneworld***	***%staralliance***	***%skyteam***	***%non-alliance***
avddel						
linear correlation	0.697*	0.180	0.162	-0.474*	0.140	0.275
rank correlation	0.776*	0.169	-0.151	-0.514*	0.004	0.371
Δavt%						
linear correlation	0.368	0.382	-0.043	-0.059	-0.238	0.324
rank correlation	0.345	0.321	-0.070	-0.047	-0.186	0.302
aggdel'						
linear correlation	0.481*	-0.216	0.494*	-0.260	0.171	-0.188
rank correlation	0.509*	-0.265	0.128	-0.247	0.112	-0.022
aggdel'/dpax						
linear correlation	0.759*	0.433*	0.057	-0.571*	0.085	0.498*
rank correlation	0.699*	0.405*	-0.106	-0.444*	-0.078	0.505*

*Notes: * indicates that the coefficient is significant at 95% confidence.*

In relation to the topological indicators, it is worth noting that neither degree nor betweenness centrality have been defined to capture the existence of local surrogates or the degree of alliance coverage. As a result, there is no statistically significant correlation between degree, betweenness, or closeness centrality and any of the capacity overlap indicators. This is not to say that our variables are the best predictors, but we argue that the positive correlations found, within the exploratory nature of this section, are grounds to support further research in this area. A graphical representation of how the relationship between these variables could be interpreted is shown in Figure 1.

[8] Indeed, a quick inspection of the MIDT dataset reveals that Star Alliance network offers an average of 1.81 routings per origin/destination market. This is followed by Skyteam with 1.51 and finally Oneworld with 1.45. The intuition is that a higher network redundancy makes passenger recovery easier in case of airport failure.

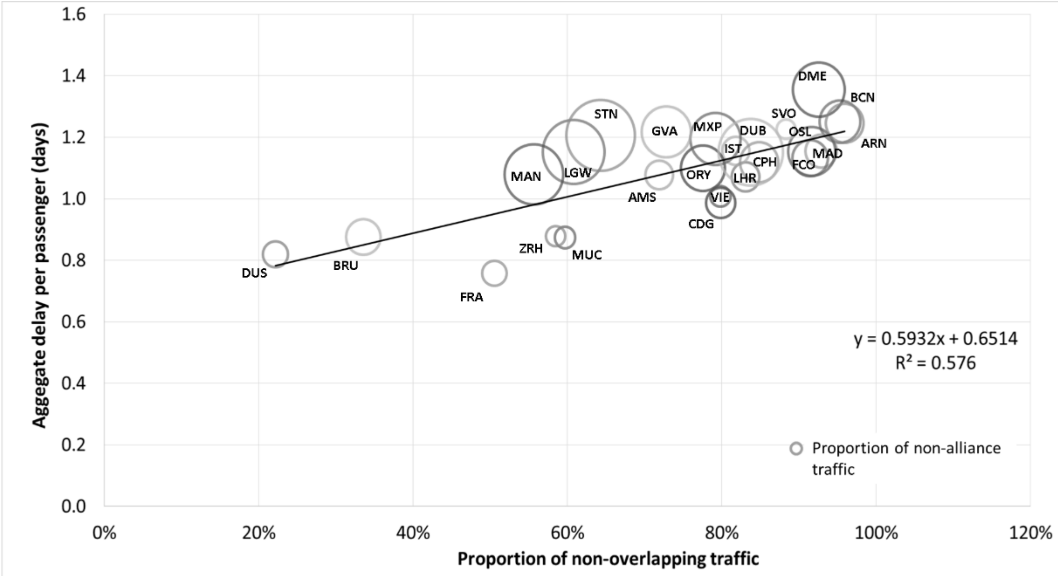

Figure 1. Aggregate delays per passenger vs proportions of non-overlapping and non-alliance traffic

In general, for the same level of non-overlapping traffic, airports with a higher share of alliance traffic tend to experience lower delays per passenger. Dual hub operations by major carriers can benefit relocation further by providing mutual hub alternatives for connecting markets. The prime examples of that are Frankfurt and Munich within Lufthansa's network (Star Alliance). There is also the coupling of Paris-CDG and Amsterdam within the network of Air France-KLM (Sky Team). Low-cost and other non-alliance dominated airports, on the other hand, are among the most critical in terms of delays per passenger, regardless of the amount of traffic overlap provided by the local surrogates. In particular, it is worth mentioning the case of London Gatwick, which achieves the poorest relocation rate in the sample despite its passengers having access to many surrogate airports in South East England with low-cost capacity on offer.

We now explore the impact of the model restrictions in order to determine the limitations of the previous factors in explaining airport criticality. One of the most important of these restrictions is alliance recovery, implemented via the definition of a multi-layered network where relocation across layers is not possible. In order to quantify the negative impact of that restriction (as predicted by Cardillo et al., 2013), Table 16 provides a summary of the simulation results for the unrestricted recovery scenario. When all markets are considered, results show that inter-alliance cooperation can potentially increase relocation rates from 1.7% (Barcelona) up to 31.2% (Moscow-DME), with an average of 15.5%. This leads to a reduction in aggregate delays between 1.3% (Dublin) and 29.6% (Moscow-SVO), with an average of 17.1%. Since the increase in relocation rates clearly exceeds the proportion of inter-alliance traffic in most cases (Table 9), it is clear that the benefits of alliance cooperation extend to intra-alliance traffic due to cross-alliance network overlap. Interestingly, this impact can be different even between alliance-matching airports, such as Amsterdam and Paris-CDG. Due to the geography of Sky Team's network, the passenger connections at Amsterdam would benefit more from cross-alliance relocation than those connecting in Paris during the sample day[9]. However, the main effect of removing the alliance restriction is that it gives Amsterdam's *od* passengers access to the Star Alliance frequencies at Brussels, which then becomes main alternate airport under that closure scenario (See Appendix B).

[9] The MIDT reveals that 26.2% of Sky Team's connecting passengers at Amsterdam could only be relocated in other alliances, while the same indicator for Paris is 21%.

Table 16. Simulation results: Monday closure; unrestricted passenger recovery.

Closed Airport	*all markets* %reloc	*diff.*	*aggdel'*	*diff.*	*intra-EEA markets* %reloc	*diff.*	*aggdel'*	*diff.*
Heathrow	83.6%	11.3%	**85,417**	-26.3%	82.1%	8.2%	**50,676**	-23.8%
Barcelona	47.9%	1.7%	**79,620**	-1.8%	46.6%	0.7%	**72,379**	-0.9%
Madrid	75.3%	13.3%	**72,380**	-8.4%	73.4%	11.4%	**63,225**	-5.3%
Istanbul	82.8%	21.3%	69,637	-20.1%	98.8%	4.8%	9	-80.5%
Paris CDG	85.2%	13.3%	59,195	-23.7%	84.3%	10.8%	38,284	-18.8%
Fiumicino	83.3%	17.2%	53,838	-13.6%	82.3%	16.8%	44,350	-10.3%
Oslo	74.7%	12.0%	51,487	-5.7%	75.2%	11.9%	48,481	-3.1%
Amsterdam	81.0%	21.3%	50,915	-25.3%	78.5%	22.1%	40,339	-22.1%
Gatwick	62.7%	23.8%	50,606	-26.7%	65.2%	23.9%	41,255	-27.6%
Paris Orly	72.6%	13.9%	50,196	-17.7%	73.8%	9.8%	40,490	-14.6%
Munich	93.3%	8.8%	47,427	-14.5%	93.4%	8.5%	38,612	-11.6%
Moscow Domodedovo	70.7%	31.2%	46,838	-25.9%	-	-	-	-
Stockholm Arlanda	69.4%	14.0%	45,543	-12.6%	69.3%	14.2%	41,246	-12.5%
Copenhagen	73.5%	11.3%	44,149	-9.2%	73.4%	11.4%	38,967	-8.4%
Frankfurt	95.4%	8.5%	40,542	-23.0%	95.9%	6.6%	25,276	-16.0%
Dublin	71.9%	28.0%	39,064	-1.3%	72.4%	28.8%	36,964	-2.7%
Geneva	67.1%	22.1%	36,543	-12.5%	68.6%	25.9%	31,626	-8.8%
Moscow Sheremetyevo	80.0%	22.7%	34,756	-29.6%	100.0%	68.4%	2	-95.4%
Stansted	62.1%	17.3%	33,359	-22.9%	62.0%	17.2%	34,942	-15.1%
Milano Malpensa	67.2%	23.7%	32,050	-27.2%	68.0%	28.8%	23,270	-27.6%
Vienna	93.9%	11.0%	31,581	-11.1%	93.0%	7.0%	24,462	-6.8%
Manchester	71.8%	18.4%	28,956	-15.5%	74.2%	15.2%	22,423	-13.1%
Dusseldorf	79.6%	2.9%	27,323	-18.4%	80.5%	2.0%	22,280	-16.4%
Zurich	89.6%	11.4%	24,874	-17.7%	88.9%	11.9%	19,127	-15.7%
Brussels	83.6%	7.6%	24,398	-17.0%	85.9%	5.1%	18,453	-14.8%

Notes: diff indicates the difference with respect to the restricted scenarios from Tables 10 and 11.

Low-cost dominated airports like Gatwick, Stansted, and Dublin particularly benefit from the relocation opportunities brought by the alliances' flight networks, but in the first two cases, the unrestricted relocation rates remain below 70%. The case of Barcelona is also noteworthy, since its performance barely changes with respect to the alliance recovery scenario. What keeps passengers from being relocated is seat capacity. If we run the original model with unlimited seat capacity (Appendix C), relocation rates rise above 90% in 22 out of the 25 closures, with individual improvements that range from 10% to 45%. Therefore, the final methodological implication of this section is that ignoring seat capacity in the analysis of network vulnerability and airport criticality, as it is common in previous studies, will introduce a major distortion in the results.

Finally, the robustness of these results is discussed by changing the temporal scope of the simulations. All the rankings of airport criticality presented above refer to Monday closures. The results from the Friday simulation (shown in Appendix D) lead to slightly different rankings, but are fully consistent with all the conclusions in this section. More relevant is the expected variability in traffic across the year. Airports that experience strong seasonality will become more critical to the European network in the summer period. In order to illustrate that, Appendix E shows the results for a new simulation carried out using data from August 2013. We find that relocation rates are generally much lower in August than in February, which we attribute to the same factors discussed in the paper: increased *od* traffic in summer, increased non-alliance traffic (from 43.2% in February to 48.5% in August), and reduction in spare capacity (load factor in intra-European flights increases from 67.2% in February to 74.6% in August). A particularly interesting case is Palma de Mallorca (PMI) airport, which stands out as one of the most critical airports in August, despite not appearing in the February ranking. PMI airport shows the lowest relocation rate in the sample (29.9%), which, besides of the above factors, can be attributed to the lack of road/rail surrogates for an island airport which may impose additional constraints to passenger relocation in the event of a closure.

4.3 Policy and management implications

From a policy perspective, the proposed method provides useful reference values for the development of strategies aimed at improving the resilience of the European transport network. The identification of critical airports for particular origin and destination markets can help directing investment to achieve high-level strategic objectives. One of these objectives is to ensure robust gate-to-gate travel times within the EEA. From the point of view of air transport, the intra-EEA is mainly a point-to-point market (approx. 10% connecting traffic). Thus, resilience rests mainly on the ability of airlines to find local surrogate airports −the issues of accessibility and intermodality take center stage here−, as well as the available capacity of the affected airports to absorb the increased traffic after reopening. Unsurprisingly, the most critical airports in intra-EEA markets are: a) geographically isolated (e.g., Madrid), which prevents them to have local surrogates that can be reached by ground transport; b) located in airport systems in which the local surrogate has a low level of network overlapping with the closed airport or there is a high proportion of low-cost traffic (e.g., Barcelona); or c) part of an airport system in which the main surrogate is severely congested (e.g., London Gatwick).

Another high-level objective could be to reinforce the air transport links with emerging economies. With enough data, the proposed method can help determine how important foreign airports and airlines are to the worldwide connectivity of the EEA. In relation to that, the fact that Istanbul Ataturk is one of the most critical airports for the transportation of air passengers in the European continent, as well as the key player in facilitating air transport between EEA and non-EEA European countries is indeed relevant.

From an airport management and tactical perspective, quantifying the impact on passengers during airport closures can be used to justify pre-emptive investments in facilities, equipment, personnel, and intermodal connectivity, as well as emergency planning and the enactment of additional policies to guarantee the resilience of the network. One may argue that these results should be combined with models of climate risk in order to identify the places where there is a coincidence of bad weather conditions and high airport criticality. London airports could be used as example. After the extended closure of London Heathrow airport due to snow in December 2010, a resilience enquiry determined that additional investments in "an enhanced snow plan" were needed (Heathrow Airport, 2010). As a result, the airport operator invested £36 million in related staff and equipment (BBC, 2013) and have been investing more in resilience ever since.

Climate risk notwithstanding, airport criticality is affected by other factors. For example, the extreme criticality of Istanbul airport is a warning sign of the potential for massive delays that actions like the recent terror attacks or military occupation of the airport (in Summer 2016) can have on the European air transport network, particularly in connecting European passengers to non-European destinations. Our results for Barcelona airport are a close reminder of the effects of the so-called "wildcat strike" by ground handling workers in late July 2006 (19 months before the high-speed rail line with Madrid was inaugurated). The industrial action culminated with a runway incursion that paralyzed airport operations for 11 hours, affecting approximately 100,000 passengers (El País, 2006). The airport took four days to recover while the disrupted passengers camped across the entire terminal concourse in the absence of alternative means of transportation. Iberia, the dominant airline at the time, brought 100 staff members from other airports and provided additional seat capacity in critical routes. A similar situation occurred in late 2010, amidst a nationwide strike of Air Traffic Controllers (ATC), the national railway operator increased capacity in 4,800 seats on the high-speed train between Barcelona and Madrid (this would represent approximately 3.6% of the disrupted passengers in our case study). Normality was recovered after five days (El País, 2010). By combining these past experiences with our estimates of airport criticality, and the prospects of an ongoing conflict with the ATC unions in Spain, a clear policy recommendation is the enactment of regulatory measures to ensure the continuous provision of ATC at least in the country's main airports.

From the perspective of airline operations and network development, results provide estimates of how demand would be geographically redistributed under a minimum-delay criterion, as well as the points in which adding capacity would help speeding up the return to normal after the shock. They also highlight the importance of inter-alliance cooperation, which could become a required procedure in emergency situations. In addition, the model provides a framework to quantify the benefits for airlines (and their main hubs) to either join an alliance or support the integration of other carriers. To illustrate this point, we ran the Monday simulation for the Heathrow closure adding Qatar Airways' seat capacity to the Oneworld network (the Middle Eastern airline joined the alliance in October 2013). The relocation rate at Heathrow would increase 2.3% and Doha airport would experience the highest increase in relocated traffic from Heathrow in non-EEA markets (11.7% of the disrupted non-EEA passengers). This indicates that Qatar Airways is able to provide minimum-delay alternative itineraries in those routes against other options for passenger recovery within the alliance network. This type of evidence could also be valuable within the current debate about the increasingly dominant role of Middle Eastern airlines and airports in worldwide international markets and their relationships with other network carriers both in Europe and the US.

5. SUMMARY, LIMITATIONS, AND FUTURE RESEARCH

This paper undertakes an exploratory analysis of the vulnerability of the European air transport network to major airport closures from the perspective of the delays imposed to disrupted airline passengers. Using an MIDT dataset on passenger itineraries flown during February 2013, full-day individual closures of the 25 busiest European airports are simulated and disrupted passengers then relocated to minimum-delay itineraries within the respective alliances' networks where seat capacity is available.

From a methodological perspective, our results illustrate the added value of employing demand data and modelling passenger recovery for a true system-based assessment of the vulnerability of air transport networks. The traditional topological indicators of degree and betweenness centrality, used by previous air transport studies, are not able to capture important drivers of structural network redundancy that the broad literature on transport networks identifies as relevant as well. In our case study, these factors include both the capacity provided by local surrogate airports and the specific network overlap from the respective airline alliances, which are shown to have an impact on passenger relocation delays. As a consequence, the proportion of non-alliance traffic is a strong predictor of aggregate delay per passenger. Airports dominated by non-alliance airlines (e.g. low-cost carriers) will be less successful in finding alternative itineraries for their disrupted passengers exclusively through their own flight networks. When alliance restrictions are removed, the benefits in terms of passenger recovery extend to intra-alliance traffic due to cross-alliance network overlap. Finally, it is worth noting the importance of accounting for seat capacity restrictions, which can prevent early recovery of up to 45% of disrupted passengers.

An additional contribution is the ability to disaggregate the impact according to geographical market. Our rankings point at Heathrow airport as the most critical in the European air transport network in terms of aggregated delays, while Barcelona would take that spot for the intra-EEA markets. The latter airport is affected by the lack of compatible surrogates and significant capacity constraints to handle the amount of disrupted traffic generated by a 24-hour closure. Within the largest European hubs, Frankfurt stands out as the most resilient overall due to its relatively low share of non-alliance traffic, the good network coverage of connecting routes (supported by Lufthansa's dual-hub strategy), and the availability of alliance-matching surrogate airports.

From a policy and managerial perspective, the proposed method provides useful reference values for the development of strategies aimed at improving the resilience of the European transport network. The identification of critical airports for particular origin and destination markets can help directing investment to suit high-level strategic objectives, such as ensuring robust gate-to-gate travel times within the European Union, or reinforcing the air transport links with emerging economies. The quantification of the short-term passenger delays resulting from airport closures (especially those in geographical isolation), can be used to support additional investments in equipment, personnel, and intermodal connectivity to mitigate the impact on the system. From the perspective of airline operations and network development, results highlight the importance of inter-alliance cooperation and provide a framework to quantify the benefits for airlines (and their main hubs) to either join an alliance or support the integration of other carriers.

Our results, however, are conditioned to the limited post-reopening search period (24 hours) and the 130 min uncongested road/rail transfer. The first constraint is imposed by the available computational capacity. Expanding the search period will increase the relocation rate but at the same time also increase the aggregate delays. Taking into account that i) most closure scenarios see the majority of their passengers relocated within the set time, and ii) poorly performing airports face important capacity constraints, no significant variation of the airport rankings is expected. Increasing the time limit for surrogate airports will require modifying the model to allow for ground transport modes (such as high-speed rail) to substitute air travel in short-haul trips, thus expanding the scope of this research to analyse the resilience of the integrated European transport network. This could lead to interesting estimates, e.g. what is the contribution of Eurostar trains or the Madrid/Barcelona high-speed rail line to passenger recovery when any of the relevant airports fails?

Expanding the temporal scope of analysis to capture additional sources of airport criticality is a straightforward extension of our paper, but the proposed model has many other applications. In its current form, it can also be used to simulate extended airport closures of single airports, city-wide multi-airport systems, or even nationwide networks. One aspect that the current approach ignores (simply because of computational limitations) is the possibility of a high correlation between multiple airport closures in the same geographical region due to, for example, weather conditions. In that context, it is not realistic to assume that ground transfer links between airports in the same affected area will remain a valid alternative to stranded passengers, thus also creating more delays and relocation costs. With enough depth of computation, determining the number of days it takes the system to fully absorb the shock is an alternative way to approach the analysis of network vulnerability and airport criticality. Additional applications include airline failures at their main bases or even entire shutdowns due to e.g. industrial actions. Another objective is to model airspace closures linked to weather conditions or armed conflicts. The geographical scope of analysis can also be expanded to include the worldwide airport network, with particular attention to the Middle East hubs and their increasingly dominant role in connecting markets.

We conclude by proposing three main avenues for further research in order to overcome the many limitations of our current methodology:

i) Introduce a set of criteria to prioritize different options of passenger recovery across layers (e.g. airline, alliance, interline partners, other airlines) in order to model the passenger rescheduling process in a more realistic fashion. This can be achieved by incorporating the published IROPS (Irregular Operations) guidelines for the major carriers into the rescheduling algorithm.

ii) Introducing aircraft and crew recovery decisions by the affected airlines. Due to the European-wide scale of our case study, a sequential approach would reduce the complexity of the model. Given a particular airport closure, airlines would first relocate their crews and aircraft following an objective of cost minimization (Barnhart, 2009). The updated flight schedules could then be used in the passenger recovery stage as described in this paper. This model would have to consider aspects that our simplified simulation ignores, such as the constraints imposed by crew work rules, maintenance schedules, airport capacity and airside congestion, the impact of flight diversions, and the propagation of delays across the flight network to other airports. In addition, the use of airline costs as objective function in this optimization process will lead to useful estimates for airline managers and policymakers.

iii) Combining flight and rail schedules in the distance matrix and introducing a passenger choice model. Potentiating intermodal connections between air and rail transport modes in order to reduce gate-to-gate travel times and improve the resilience of the European transportation network is one of the high-level objectives of the European Commission for 2050 (EC, 2014a). In that regard, the introduction of rail schedules would allow for a more realistic picture of the travel options available to each disrupted passenger. The potential of these new travel alternatives will only be fully exploited with an econometric model of passenger choice. This would require the collecting information on variables such as: air and rail fares, competition, access and travel times, and booking classes. A Multinomial Logit model of travel itinerary selection has been employed by many authors in this context and could be applied to that end (See Grosche, 2009).

ACKNOWLEDGEMENTS

This research project has been partly funded by the University of Edinburgh Business School through the Early Venture Fund program. The authors would also like to thank the support of the Business School IT department.

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Appendix A. Simulation results: Airport closure on Monday, February 4th 2013 between from 00:00 to 23:59 UTC; passenger recovery via alliance network.

Closed	*All markets*														*intra-EEA markets*													
Airport	*dpax*	*conn*	*%conn*	*reloc*	*%reloc*	*avddel*	*avt0*	*avt1*	*Δavt%*	*aggdel*	*aggdel'*	*alt.*	*Δpax*	*%reloc*	*dpax*	*conn*	*%conn*	*reloc*	*%reloc*	*avddel*	*avt0*	*avt1*	*Δ%*	*aggdel*	*aggdel'*	*alt.*	*Δpax*	*%reloc*
LHR	108,197	13,896	12.8%	78,267	72.3%	940	348	805	131.5%	75,955	115,937	FRA	6,160	7.9%	59,333	3,604	6.1%	43,877	74.0%	922	143	746	421.0%	46,459	66,540	FRA	4,594	10.5%
CDG	78,532	13,472	17.2%	56,417	71.8%	837	322	687	113.2%	47,090	77,549	ORY	9,246	16.4%	47,663	4,701	9.9%	35,019	73.5%	827	162	575	254.0%	30,153	47,138	ORY	6,791	19.4%
FRA	69,499	21,971	31.6%	60,412	86.9%	689	363	616	69.5%	39,488	52,649	DUS	9,970	16.5%	39,798	8,970	22.5%	35,556	89.3%	717	171	434	153.8%	24,200	30,086	DUS	7,155	20.1%
IST	75,410	21,130	28.0%	46,346	61.5%	912	300	807	168.5%	45,634	87,185	FRA	8,123	17.5%	165	165	100.0%	155	93.9%	233	423	452	6.8%	28	46	MUC	74	47.7%
AMS	63,250	12,595	19.9%	37,744	59.7%	795	319	765	139.8%	32,521	68,196	CDG	8,870	23.5%	45,988	5,408	11.8%	25,950	56.4%	822	161	685	325.3%	24,260	51,770	CDG	5,837	22.5%
MAD	68,386	9,419	13.8%	42,442	62.1%	894	239	807	237.2%	43,088	79,032	BCN	8,529	20.1%	57,085	5,148	9.0%	35,395	62.0%	904	146	743	410.0%	36,907	66,786	BCN	7,654	21.6%
MUC	63,479	14,606	23.0%	53,656	84.5%	702	210	625	197.7%	41,627	55,495	FRA	9,202	17.1%	48,422	8,721	18.0%	41,132	84.9%	714	130	588	353.8%	33,500	43,700	FRA	6,711	16.3%
FCO	55,017	8,474	15.4%	36,396	66.2%	848	231	815	252.9%	36,191	62,287	CDG	7,213	19.8%	42,482	4,692	11.0%	27,818	65.5%	868	130	773	493.8%	29,191	49,424	LIN	5,243	18.8%
LGW	59,929	1,611	2.7%	23,329	38.9%	817	162	385	137.8%	16,843	69,049	LHR	4,464	19.1%	50,351	963	1.9%	20,759	41.2%	819	119	357	199.4%	15,230	57,010	LHR	3,641	17.5%
BCN	64,825	2,360	3.6%	29,954	46.2%	881	174	884	408.8%	33,102	81,050	MAD	8,819	29.4%	58,220	1,957	3.4%	26,749	45.9%	865	127	876	587.8%	29,978	73,011	MAD	8,371	31.3%
DME	46,649	4,658	10.0%	18,428	39.5%	1,270	235	502	114.1%	19,681	63,207	SVO	1,051	5.7%	0	0	-	0	-	-	-	-	-	-	-	-	0	0.0%
SVO	40,299	8,422	20.9%	23,099	57.3%	994	353	848	140.4%	23,887	49,402	CDG	5,410	23.4%	38	38	100.0%	12	31.6%	285	474	967	103.9%	6	51	AMS	9	75.0%
ORY	55,448	2,013	3.6%	32,541	58.7%	998	131	425	224.4%	29,192	60,983	CDG	9,990	30.7%	44,972	1,770	3.9%	28,796	64.0%	973	119	417	248.8%	25,408	47,395	CDG	9,398	32.6%
CPH	43,467	6,672	15.3%	27,055	62.2%	786	207	787	279.8%	25,663	48,637	FRA	5,017	18.5%	37,531	5,477	14.6%	23,269	62.0%	785	139	767	451.8%	22,836	42,548	FRA	4,582	19.7%
ZRH	34,432	6,287	18.3%	26,912	78.2%	679	269	662	146.5%	20,050	30,233	STR	5,524	20.5%	24,579	3,181	12.9%	18,929	77.0%	667	147	626	327.2%	15,078	22,694	STR	4,445	23.5%
GVA	34,319	393	1.1%	15,416	44.9%	750	184	771	318.2%	14,309	41,766	LYS	4,419	28.7%	28,670	256	0.9%	12,246	42.7%	723	124	787	534.5%	11,782	34,690	LYS	3,156	25.8%
MXP	36,894	463	1.3%	16,050	43.5%	868	229	551	141.0%	13,268	44,054	LIN	2,675	16.7%	27,932	209	0.7%	10,954	39.2%	817	128	545	325.1%	9,385	32,137	LIN	1,626	14.8%
STN	35,871	47	0.1%	16,065	44.8%	851	119	614	416.2%	15,019	43,278	BRS	1,600	10.0%	35,357	43	0.1%	15,845	44.8%	849	115	607	425.4%	14,752	41,154	BRS	1,600	10.1%
DUB	34,389	1,051	3.1%	15,114	44.0%	941	158	499	215.0%	13,450	39,584	LHR	1,607	10.6%	31,656	789	2.5%	13,811	43.6%	912	114	478	317.2%	12,230	38,005	LHR	1,526	11.0%
DUS	40,820	2,759	6.8%	31,309	76.7%	659	164	420	156.5%	19,914	33,484	FRA	7,907	25.3%	33,240	2,001	6.0%	26,091	78.5%	656	114	386	239.2%	16,825	26,665	FRA	6,555	25.1%
MAN	31,747	701	2.2%	16,972	53.5%	759	199	583	192.5%	13,465	34,265	BHX	3,379	19.9%	24,657	481	2.0%	14,560	59.1%	727	131	566	330.9%	11,747	25,789	BHX	2,895	19.9%
BRU	33,536	2,573	7.7%	25,485	76.0%	719	197	488	148.0%	17,865	29,383	DUS	5,805	22.8%	25,995	1,800	6.9%	21,005	80.8%	703	139	451	225.0%	14,805	21,651	DUS	5,013	23.9%
VIE	35,217	7,509	21.3%	29,197	82.9%	719	210	840	300.6%	27,348	35,518	FRA	7,115	24.4%	24,659	3,232	13.1%	21,212	86.0%	731	136	850	524.7%	21,291	26,239	MUC	5,600	26.4%
ARN	41,818	3,867	9.2%	23,159	55.4%	1,026	174	742	326.7%	25,631	52,090	FRA	4,461	19.3%	37,390	3,484	9.3%	20,604	55.1%	1,033	125	710	467.8%	23,143	47,112	CPH	3,834	18.6%
OSL	47,340	5,854	12.4%	29,695	62.7%	956	133	601	353.3%	29,377	54,623	CPH	3,460	11.7%	44,455	5,603	12.6%	28,110	63.2%	954	105	581	455.3%	27,918	50,044	BGO	3,212	11.4%

Appendix B. Simulation results: Airport closure on Monday, February 4th 2013 between from 00:00 to 23:59 UTC; unrestricted passenger recovery.

Closed	*All markets*														*intra-EEA markets*													
Airport	*dpax*	*conn*	*%conn*	*reloc*	*%reloc*	*avddel*	*avt0*	*avt1*	*Δavt%*	*aggdel*	*aggdel'*	*alt.*	*Δpax*	*%reloc*	*dpax*	*conn*	*%conn*	*reloc*	*%reloc*	*avddel*	*avt0*	*avt1*	*Δ%*	*aggdel*	*aggdel'*	*alt.*	*Δpax*	*%reloc*
LHR	108,197	13,896	12.8%	90,504	83.6%	703	368	676	83.9%	63,593	85,417	LGW	10,124	11.2%	59,333	3,604	6.1%	48,724	82.1%	683	149	571	284.2%	37,394	50,676	LGW	7,319	15.0%
CDG	78,532	13,472	17.2%	66,891	85.2%	656	330	631	90.9%	44,416	59,195	ORY	15,966	23.9%	47,663	4,701	9.9%	40,188	84.3%	630	161	568	251.8%	28,916	38,284	ORY	10,900	27.1%
FRA	69,499	21,971	31.6%	66,306	95.4%	598	369	563	52.6%	36,468	40,542	DUS	10,208	15.4%	39,798	8,970	22.5%	38,186	95.9%	642	176	412	133.6%	23,279	25,276	DUS	7,072	18.5%
IST	75,410	21,130	28.0%	62,428	82.8%	721	306	794	159.1%	52,397	69,637	SAW	9,634	15.4%	165	165	100.0%	163	98.8%	88	428	384	-10.2%	5	9	MUC	54	33.1%
AMS	63,250	12,595	19.9%	51,214	81.0%	592	307	711	131.4%	35,394	50,915	BRU	13,953	27.2%	45,988	5,408	11.8%	36,111	78.5%	597	161	673	317.8%	27,792	40,339	BRU	11,536	31.9%
MAD	68,386	9,419	13.8%	51,507	75.3%	737	247	930	277.2%	50,803	72,380	BCN	9,669	18.8%	57,085	5,148	9.0%	41,925	73.4%	750	152	912	501.5%	43,982	63,225	BCN	8,734	20.8%
MUC	63,479	14,606	23.0%	59,241	93.3%	612	217	633	191.4%	42,289	47,427	STR	7,135	12.0%	48,422	8,721	18.0%	45,230	93.4%	632	136	610	349.4%	34,761	38,612	STR	5,672	12.5%
FCO	55,017	8,474	15.4%	45,856	83.3%	664	227	891	293.2%	42,309	53,838	LIN	5,995	13.1%	42,482	4,692	11.0%	34,967	82.3%	679	132	894	579.5%	34,986	44,350	LIN	5,368	15.4%
LGW	59,929	1,611	2.7%	37,580	62.7%	513	174	382	119.2%	18,810	50,606	LHR	15,044	40.0%	50,351	963	1.9%	32,818	65.2%	514	134	352	162.4%	16,683	41,255	LHR	12,996	39.6%
BCN	64,825	2,360	3.6%	31,064	47.9%	818	180	972	438.7%	34,725	79,620	MAD	9,077	29.2%	58,220	1,957	3.4%	27,143	46.6%	812	134	976	628.7%	31,166	72,379	MAD	8,072	29.7%
DME	46,649	4,658	10.0%	32,967	70.7%	826	267	642	140.1%	27,493	46,838	SVO	10,660	32.3%	0	0	-	0	-	-	-	-	-	-	-	-	0	0.0%
SVO	40,299	8,422	20.9%	32,242	80.0%	676	357	741	107.4%	23,719	34,756	DME	9,576	29.7%	38	38	100.0%	38	100.0%	90	457	473	3.5%	2	2	BCN	6	15.8%
ORY	55,448	2,013	3.6%	40,230	72.6%	790	139	415	199.2%	29,798	50,196	CDG	17,511	43.5%	44,972	1,770	3.9%	33,185	73.8%	806	124	401	222.4%	24,960	40,490	CDG	14,040	42.3%
CPH	43,467	6,672	15.3%	31,965	73.5%	695	214	842	293.8%	29,379	44,149	FRA	5,209	16.3%	37,531	5,477	14.6%	27,566	73.4%	686	147	840	471.2%	26,388	38,967	FRA	4,919	17.8%
ZRH	34,432	6,287	18.3%	30,849	89.6%	652	274	575	110.2%	20,419	24,874	STR	5,386	17.5%	24,579	3,181	12.9%	21,850	88.9%	659	151	527	249.9%	15,708	19,127	STR	4,311	19.7%
GVA	34,319	393	1.1%	23,014	67.1%	627	158	963	508.2%	22,871	36,543	LYS	8,241	35.8%	28,670	256	0.9%	19,663	68.6%	605	117	972	731.9%	19,942	31,626	LYS	6,753	34.3%
MXP	36,894	463	1.3%	24,805	67.2%	658	192	478	148.4%	16,251	32,050	LIN	8,002	32.3%	27,932	209	0.7%	19,004	68.0%	623	119	442	271.6%	12,483	23,270	LIN	6,609	34.8%
STN	35,871	47	0.1%	22,281	62.1%	730	121	454	274.4%	16,449	33,359	LHR	8,026	36.0%	35,357	43	0.1%	21,935	62.0%	729	118	453	284.8%	16,221	34,942	LHR	7,849	35.8%
DUB	34,389	1,051	3.1%	24,735	71.9%	739	167	947	467.1%	26,086	39,064	LHR	5,720	23.1%	31,656	789	2.5%	22,918	72.4%	760	127	965	660.0%	25,435	36,964	LHR	5,852	25.5%
DUS	40,820	2,746	6.7%	32,504	79.6%	554	174	364	109.2%	16,801	27,323	FRA	7,973	24.5%	33,345	2,001	6.0%	26,845	80.5%	534	124	328	164.0%	13,751	22,280	FRA	6,335	23.6%
MAN	31,747	701	2.2%	22,803	71.8%	630	224	712	218.5%	17,713	28,956	BHX	5,292	23.2%	24,657	481	2.0%	18,299	74.2%	616	148	695	368.4%	14,765	22,423	BHX	4,348	23.8%
BRU	33,536	2,573	7.7%	28,044	83.6%	645	212	454	114.7%	17,289	24,398	DUS	5,516	19.7%	25,995	1,800	6.9%	22,338	85.9%	638	144	405	181.2%	13,947	18,453	DUS	4,387	19.6%
VIE	35,217	7,509	21.3%	33,060	93.9%	637	220	838	281.7%	28,832	31,581	FRA	7,121	21.5%	24,659	3,232	13.1%	22,926	93.0%	670	139	868	526.1%	22,270	24,462	FRA	5,736	25.0%
ARN	41,818	3,867	9.2%	29,010	69.4%	827	175	780	344.6%	28,850	45,543	CPH	4,319	14.9%	37,390	3,484	9.3%	25,924	69.3%	832	130	769	491.6%	26,467	41,246	CPH	3,940	15.2%
OSL	47,340	5,854	12.4%	35,386	74.7%	914	143	707	393.6%	36,320	51,487	CPH	5,143	14.5%	44,455	5,603	12.6%	33,421	75.2%	915	118	694	490.2%	34,622	48,481	BGO	4,904	14.7%

*Notes: dpax: disrupted passengers, conn: connecting passengers; reloc: relocated passengers; avddel: average departure delay (min); avt0: average original travel time (min); avt1: average relocated travel time (min); aggdel: aggregate delay in pax-days [last 4 measures for relocated passengers only]; aggdel'***:** *aggregate delay in pax-days for all passengers 24h after re-aperture; alt: main alternate airport; Δpax: relocated passenger departures at the alternate airport.*

Appendix C. Simulation results: Airport closure on Monday, February 4th 2013 between from 00:00 to 23:59 UTC; passenger recovery via alliance network; unlimited capacity.

All markets

Closed Airport	*dpax*	*conn*	*%conn*	*reloc*	*%reloc*	*avddel*	*avt0*	*avt1*	*Δavt%*	*aggdel*	*aggdel'*	*alt.*	*Δpax*	*%reloc*
LHR	108,197	13,896	12.8%	104,390	96.5%	709	344	566	64.4%	67,506	72,430	LGW	10,013	9.6%
CDG	78,532	13,472	17.2%	73,342	93.4%	613	308	551	78.9%	43,569	50,960	ORY	17,302	23.6%
IST	75,410	21,130	28.0%	70,555	93.6%	677	287	533	85.6%	45,228	51,990	FRA	18,048	25.6%
FRA	69,499	21,971	31.6%	65,357	94.0%	500	361	575	59.4%	32,414	38,407	DUS	11,331	17.3%
MAD	68,386	9,419	13.8%	64,186	93.9%	634	225	622	176.0%	45,949	51,859	BCN	8,923	13.9%
BCN	64,825	2,360	3.6%	59,562	91.9%	649	161	567	251.3%	43,627	51,117	MAD	11,203	18.8%
MUC	63,479	14,606	23.0%	60,486	95.3%	534	213	456	114.1%	32,621	36,486	FRA	9361	15.5%
AMS	63,250	12,595	19.9%	59,361	93.9%	623	269	562	108.7%	37,767	43,453	BRU	12,081	20.4%
LGW	59,929	1,611	2.7%	49,401	82.4%	746	160	333	108.4%	31,535	46,998	LHR	5,124	10.4%
ORY	55,448	2,013	3.6%	51,275	92.5%	724	145	319	119.3%	31,956	37,998	CDG	13,819	27.0%
FCO	55,017	8,474	15.4%	51,040	92.8%	634	214	606	182.8%	36,349	41,975	CDG	10,763	21.1%
OSL	47,340	5,854	12.4%	42,906	90.6%	683	136	463	239.7%	30,077	36,311	SVG	6,962	16.2%
DME	46,649	4,658	10.0%	35,804	76.8%	1,030	237	374	57.9%	29,017	45,501	LHR	1914	5.3%
CPH	43,467	6,672	15.3%	40,545	93.3%	639	195	463	137.8%	25,551	29,578	ARN	7,675	18.9%
ARN	41,818	3,867	9.2%	39,287	93.9%	756	166	397	138.8%	26,930	30,274	CPH	6,849	17.4%
DUS	40,820	2,746	6.7%	38,401	94.1%	561	169	355	110.2%	19,942	23,245	FRA	8,127	21.2%
SVO	40,299	8,422	20.9%	37,883	94.0%	728	336	588	75.0%	25,798	29,383	AMS	6,528	17.2%
MXP	36,894	463	1.3%	34,129	92.5%	691	185	412	122.7%	21,761	25,632	LIN	4,596	13.5%
STN	35,871	47	0.1%	33,452	93.3%	739	120	338	182.1%	22,236	25,641	DUB	3,260	9.7%
VIE	35,217	7,509	21.3%	33,457	95.0%	575	214	497	131.8%	19,932	22,305	GRZ	7,358	22.0%
ZRH	34,432	6,287	18.3%	32,433	94.2%	598	261	449	71.9%	17,698	20,444	STR	6,481	20.0%
DUB	34,389	1,051	3.1%	31,262	90.9%	849	148	420	183.9%	24,333	28,926	BHX	3,225	10.3%
GVA	34,319	393	1.1%	32,267	94.0%	644	165	417	152.6%	20,068	22,774	LYS	10,414	32.3%
BRU	33,536	2,573	7.7%	31,230	93.1%	601	202	422	108.8%	17,811	20,764	DUS	6,473	20.7%
MAN	31,747	701	2.2%	24,493	77.2%	708	209	415	98.7%	15,547	25,908	BHX	5,230	21.4%

intra-EEA markets

Closed Airport	*dpax*	*conn*	*%conn*	*reloc*	*%reloc*	*avddel*	*avt0*	*avt1*	*Δ%*	*aggdel*	*aggdel'*	*alt.*	*Δpax*	*%reloc*
LHR	59,333	3,604	6.1%	58,693	98.9%	661	143	346	143%	35,242	36,078	LGW	7,815	13.3%
CDG	47,663	4,701	9.9%	46,285	97.1%	577	153	379	148%	25,804	27,626	ORY	13,844	29.9%
IST	165	165	100.0%	155	93.9%	102	423	407	-4%	11	27	MUC	59	38.1%
FRA	39,798	8,970	22.5%	38,638	97.1%	503	171	369	116%	18,808	20,434	DUS	8,154	21.1%
MAD	57,085	5,148	9.0%	54,454	95.4%	623	144	542	275%	38,601	42,220	BCN	7,382	13.6%
BCN	58,220	1,957	3.4%	54,043	92.8%	628	123	540	341%	39,252	44,937	MAD	10,395	19.2%
MUC	48,422	8,721	18.0%	46,504	96.0%	532	130	381	193%	17,171	19,635	STR	8019	17.2%
AMS	45,988	5,408	11.8%	44,430	96.6%	618	145	454	213%	28,583	30,755	BRU	10,129	22.8%
LGW	50,351	963	1.9%	44,315	88.0%	726	124	300	143%	27,771	36,311	LTN	4,891	11.0%
ORY	44,972	1,770	3.9%	44,238	98.4%	681	129	292	125%	25,908	26,904	CDG	13,143	29.7%
FCO	42,482	4,692	11.0%	40,442	95.2%	618	125	540	331%	28,985	31,736	CDG	7,481	18.5%
OSL	44,455	5,603	12.6%	40,640	91.4%	671	108	440	307%	28,287	33,721	SVG	6,685	16.4%
DME	0	0	-	0	-	-	0	0	-	-	-	-	0	0
CPH	37,531	5,477	14.6%	35,379	94.3%	619	130	411	216%	22,129	24,992	ARN	6,834	19.3%
ARN	37,390	3,484	9.3%	35,399	94.7%	750	119	347	191%	24,027	26,966	CPH	6,065	17.1%
DUS	33,345	2,001	6.0%	31,926	95.7%	540	114	306	169%	16,247	18,203	FRA	6,580	20.6%
SVO	38	38	100.0%	29	76.3%	480	461	903	96%	19	35	CDG	12	41.4%
MXP	27,932	209	0.7%	26,730	95.7%	664	117	367	214%	16,962	18,634	LGW	4,107	15.4%
STN	35,357	43	0.1%	32,971	93.3%	735	116	334	187%	21,819	25,256	DUB	3,260	9.9%
VIE	24,659	3,232	13.1%	23,821	96.6%	566	135	422	213%	14,100	15,240	GRZ	6,424	27.0%
ZRH	24,579	3,181	12.9%	23,438	95.4%	589	143	342	140%	12,826	14,322	STR	4,850	20.7%
DUB	31,656	789	2.5%	29,303	92.6%	830	116	397	243%	22,613	25,807	BHX	3,224	11.0%
GVA	28,670	256	0.9%	27,204	94.9%	623	114	372	228%	16,665	18,600	LYS	8,974	33.0%
BRU	25,995	1,800	6.9%	25,537	98.2%	570	137	368	169%	14,210	14,837	DUS	5,454	21.4%
MAN	24,657	481	2.0%	20,854	84.6%	684	136	355	161%	13,075	18,282	BHX	4,615	22.1%

Appendix D. Simulation results: Airport closure on Friday, February 8th 2013 between from 00:00 to 23:59 UTC; passenger recovery via airline network.

All markets

Closed Airport	*dpax*	*conn*	*%conn*	*reloc*	*%reloc*	*avddel*	*avt0*	*avt1*	*Δavt%*	*aggdel*	*aggdel'*	*alt.*	*Δpax*	*%reloc*
LHR	127,326	16,206	12.7%	94,258	74.0%	882	423	951	125.0%	92,298	136,414	MAD	6,097	6.4%
CDG	95,364	14,287	15.0%	66,798	70.0%	827	416	817	96.2%	56,958	97,347	ORY	10,763	16.1%
FRA	78,412	21,040	26.8%	66,813	85.2%	677	420	691	64.8%	44,024	60,572	DUS	11,429	17.1%
IST	76,768	18,925	24.7%	53,038	69.1%	908	312	789	152.9%	51,021	84,413	FRA	10,495	19.8%
AMS	70,289	12,583	17.9%	43,454	61.8%	772	393	832	111.6%	36,555	74,647	CDG	11,203	25.8%
MAD	75,761	9,690	12.8%	39,274	51.8%	890	330	931	182.1%	40,680	90,671	LHR	6,305	16.1%
MUC	65,926	13,205	20.0%	53,014	80.4%	633	244	731	199.7%	41,236	58,404	FRA	11,093	20.9%
FCO	58,250	7,410	12.7%	33,968	58.3%	763	279	960	244.3%	34,062	67,645	CDG	7,546	22.2%
LGW	67,330	1,405	2.1%	27,127	40.3%	810	198	413	108.9%	19,307	76,759	LHR	5,466	20.1%
BCN	68,834	2,145	3.1%	23,603	34.3%	879	222	900	306.0%	25,522	87,911	MAD	5,476	23.2%
DME	52,709	4,291	8.1%	21,034	39.9%	1,234	280	532	89.8%	21,695	69,767	SVO	1,390	6.6%
SVO	43,188	7,811	18.1%	28,176	65.2%	970	346	835	141.1%	28,536	50,140	CDG	6,168	21.9%
ORY	61,476	1,768	2.9%	31,314	50.9%	921	183	505	175.5%	27,020	69,891	CDG	11,434	36.5%
CPH	44,940	6,047	13.5%	20,152	44.8%	735	275	867	215.3%	18,575	53,044	FRA	4,689	23.3%
ZRH	37,770	6,128	16.2%	30,089	79.7%	664	297	723	143.3%	22,775	33,171	STR	6,377	21.2%
GVA	38,192	303	0.8%	19,833	51.9%	745	208	813	290.0%	18,586	43,055	LYS	4,600	23.2%
MXP	40,622	530	1.3%	16,973	41.8%	695	276	632	129.2%	12,387	45,102	LIN	2,816	16.6%
STN	37,801	56	0.1%	16,835	44.5%	827	123	583	374.4%	15,051	45,393	BRS	1,868	11.1%
DUB	38,814	976	2.5%	16,175	41.7%	897	197	553	179.9%	14,066	46,606	LHR	1,335	8.3%
DUS	42,594	2,132	5.0%	27,148	63.7%	480	194	507	161.8%	14,950	35,391	FRA	8,828	32.5%
MAN	35,096	585	1.7%	17,928	51.1%	704	250	671	168.7%	14,017	38,755	BHX	3,799	21.2%
BRU	34,566	2,039	5.9%	22,262	64.4%	626	242	575	137.4%	14,820	30,896	DUS	6,434	28.9%
VIE	36,249	6,637	18.3%	26,376	72.8%	673	250	913	266.0%	24,477	37,811	FRA	6,920	26.2%
ARN	41,560	3,247	7.8%	12,022	28.9%	999	240	937	291.2%	14,163	53,515	FRA	2,764	23.0%
OSL	48,274	5,465	11.3%	15,015	31.1%	930	187	875	367.7%	16,869	63,618	FRA	2,948	19.6%

intra-EEA markets

Closed Airport	*dpax*	*conn*	*%conn*	*reloc*	*%reloc*	*avddel*	*avt0*	*avt1*	*Δ%*	*aggdel*	*aggdel'*	*alt.*	*Δpax*	*%reloc*
LHR	61,934	3,015	4.9%	43,429	70.1%	918	187	837	347.4%	47,276	71,076	FRA	4,875	11.2%
CDG	52,129	3,594	6.9%	35,443	68.0%	843	221	685	209.4%	32,172	54,906	ORY	5,646	15.9%
FRA	42,217	7,928	18.8%	36,516	86.5%	739	222	507	128.7%	25,976	33,708	DUS	7,127	19.5%
IST	120	120	100.0%	115	95.8%	158	413	397	-3.9%	12	20	MUC	55	47.8%
AMS	48,116	4,516	9.4%	27,192	56.5%	801	202	736	263.7%	25,205	54,172	CDG	6,879	25.3%
MAD	60,417	4,349	7.2%	29,096	48.2%	917	196	856	336.2%	31,853	74,134	BCN	5,451	18.7%
MUC	49,991	7,795	15.6%	39,425	78.9%	645	151	707	366.9%	32,879	46,802	FRA	8,781	22.3%
FCO	44,553	4,087	9.2%	24,157	54.2%	763	159	949	498.0%	26,067	53,874	CDG	5,120	21.2%
LGW	55,198	835	1.5%	22,234	40.3%	777	124	346	179.1%	15,430	61,439	LHR	3,780	17.0%
BCN	62,033	1,885	3.0%	19,876	32.0%	878	151	878	480.9%	22,152	79,983	MAD	5,067	25.5%
DME	0	0	-	0	-	-	-	-	-	-	-	-	0	0.0%
SVO	32	32	100.0%	13	40.6%	467	538	684	27.1%	5	39	CDG	6	46.2%
ORY	48,369	1,617	3.3%	25,970	53.7%	863	169	513	203.9%	21,776	52,809	CDG	10,714	41.3%
CPH	38,182	4,936	12.9%	15,797	41.4%	740	173	842	388.2%	15,469	46,359	FRA	4,159	26.3%
ZRH	25,948	2,815	10.8%	19,918	76.8%	641	154	711	360.4%	16,566	24,616	STR	4,645	23.3%
GVA	31,928	171	0.5%	15,365	48.1%	726	135	829	516.2%	15,156	37,482	LYS	3,022	19.7%
MXP	29,959	153	0.5%	10,636	35.5%	589	148	668	352.3%	8,197	34,979	LIN	1,652	15.5%
STN	37,299	51	0.1%	16,548	44.4%	825	119	576	385.5%	14,733	44,231	BRS	1,868	11.3%
DUB	35,343	658	1.9%	14,122	40.0%	877	135	523	288.2%	12,412	40,502	STN	1,265	9.0%
DUS	33,985	1,480	4.4%	22,067	64.9%	460	131	481	267.7%	12,421	29,230	FRA	7,326	33.2%
MAN	27,394	443	1.6%	14,277	52.1%	633	151	648	328.3%	11,206	28,954	BHX	3,040	21.3%
BRU	26,628	1,336	5.0%	17,443	65.5%	596	168	518	208.7%	11,458	24,366	DUS	5,248	30.1%
VIE	24,943	2,731	10.9%	17,440	69.9%	662	166	958	476.2%	17,610	27,815	FRA	5,039	28.9%
ARN	37,636	3,028	8.0%	10,063	26.7%	1,028	164	928	465.6%	12,520	53,296	FRA	2,579	25.6%
OSL	45,277	5,250	11.6%	13,463	29.7%	943	133	851	538.7%	15,526	62,280	FRA	2,798	20.8%

*Notes: dpax: disrupted passengers, conn: connecting passengers; reloc: relocated passengers; avddel: average departure delay (min); avt0: average original travel time (min); avt1: average relocated travel time (min); aggdel: aggregate delay in pax-days [last 4 measures for relocated passengers only]; aggdel'***:** *aggregate delay in pax-days for all passengers 24h after re-aperture; alt: main alternate airport; Δpax: relocated passenger departures at the alternate airport.*

Appendix E. Simulation results: Airport closure on Monday, August 5th 2013 between from 00:00 to 23:59 UTC; passenger recovery via airline network.

All markets

Closed Airport	*dpax*	*conn*	*%conn*	*reloc*	*%reloc*	*avddel*	*avt0*	*avt1*	*Δavt%*	*aggdel*	*aggdel'*	*alt.*	*Δpax*	*%reloc*
LHR	104,870	15,089	14.4%	53,634	51.1%	1,261	328	513	56.4%	53,877	123,556	LGW	3,064	5.7%
BCN	99,922	4,951	5.0%	34,891	34.9%	1,102	163	734	349.7%	40,534	130,999	FCO	2,950	8.5%
IST	96,342	30,295	31.4%	38,984	40.5%	1,198	214	457	113.3%	38,993	120,307	SAW	7,992	20.5%
LGW	95,763	1,755	1.8%	40,348	42.1%	1,016	165	406	146.8%	35,238	114,490	LHR	4,451	11.0%
CDG	91,878	13,781	15.0%	44,804	48.8%	1,163	311	558	79.2%	43,861	109,515	ORY	5,618	12.5%
FRA	81,803	27,826	34.0%	50,380	61.6%	915	324	711	119.4%	45,550	88,852	MUC	12,158	24.1%
PMI	78,869	1,856	2.4%	23,621	29.9%	1,038	141	846	498.6%	28,577	105,908	TXL	2,816	11.9%
FCO	78,560	13,998	17.8%	34,651	44.1%	1,127	189	582	208.6%	36,572	98,886	LIN	2,790	8.1%
AMS	76,670	15,854	20.7%	32,120	41.9%	1,134	234	497	111.9%	31,152	94,347	BRU	5,137	16.0%
MUC	69,552	17,502	25.2%	46,468	66.8%	863	223	658	194.9%	41,898	72,967	FRA	14,589	31.4%
MAD	67,401	9,092	13.5%	27,103	40.2%	1,163	248	672	170.7%	29,865	83,487	BCN	1,560	5.8%
ORY	65,673	2,287	3.5%	29,942	45.6%	1,134	158	491	210.1%	30,501	82,140	CDG	7,352	24.6%
DME	63,570	5,793	9.1%	22,597	35.5%	1,322	239	469	96.4%	24,356	87,960	VKO	1,345	6.0%
STN	60,119	35	0.1%	14,077	23.4%	773	137	641	367.2%	12,476	76,916	LGW	2,173	15.4%
SVO	51,568	14,429	28.0%	18,394	35.7%	1,333	299	517	72.7%	19,811	68,966	LED	2,526	13.7%
DUS	50,463	3532	7.0%	30,756	60.9%	783	179	515	187.2%	23,889	49,351	FRA	7,558	24.6%
MAN	50,133	935	1.9%	25,398	50.7%	788	196	579	195.1%	20,644	56,352	BHX	4,789	18.9%
DUB	49,935	1719	3.4%	16,835	33.7%	1,227	159	603	279.2%	19,533	66,818	STN	1,371	8.1%
BRU	47,864	3909	8.2%	22,958	48.0%	884	203	567	178.8%	19,892	53,548	AMS	4,578	19.9%
CPH	47,648	6,188	13.0%	17,576	36.9%	1,011	197	745	278.8%	19,032	61,118	OSL	1,891	10.8%
ZRH	46,231	7645	16.5%	25,070	54.2%	1,020	206	463	124.7%	22,230	50,456	STR	4,215	16.8%
OSL	45,568	5,990	13.1%	15,148	33.2%	1,087	175	728	315.8%	17,252	59,575	CPH	2,306	15.2%
MXP	44,969	546	1.2%	16,923	37.6%	927	249	532	113.6%	14,215	54,215	NCE	1,823	10.8%
VIE	41,088	9,736	23.7%	20,440	49.7%	1,196	189	469	147.8%	20,941	47,866	FRA	1,815	8.9%
ARN	40,453	3,358	8.3%	12,721	31.4%	1,043	195	832	327.1%	14,846	52,574	CPH	2,729	21.5%

intra-EEA markets

Closed Airport	*dpax*	*conn*	*%conn*	*reloc*	*%reloc*	*avddel*	*avt0*	*avt1*	*Δ%*	*aggdel*	*aggdel'*	*alt.*	*Δpax*	*%reloc*
LHR	56,060	3,389	6.0%	30,213	53.9%	1,285	140	368	162.7%	31,730	64,476	LGW	2,397	7.9%
BCN	89,620	4,201	4.7%	30,893	34.5%	1,091	127	743	483.4%	36,606	115,215	FCO	2,875	9.3%
IST	314	314	100.0%	43	13.7%	688	374	794	112.4%	34	467	ESB	5	11.6%
LGW	80849	1141	1.4%	35368	43.7%	1,027	135	386	186.0%	31,390	93,006	LTN	3881	11.0%
CDG	51,579	3,623	7.0%	27,093	52.5%	1,137	164	449	173.1%	26,741	59,020	ORY	4,092	15.1%
FRA	45,852	13,248	28.9%	30,705	67.0%	967	185	546	195.2%	28,321	49,597	MUC	8,123	26.5%
PMI	78,489	1,854	2.4%	23,573	30.0%	1,037	141	846	501.5%	28,526	104,867	TXL	2,807	11.9%
FCO	60,576	8,227	13.6%	29,464	48.6%	1,115	139	565	307.6%	31,535	74,107	LIN	2,568	8.7%
AMS	54,946	7437	13.5%	24,609	44.8%	1,142	155	441	184.8%	24,402	65,561	BRU	3,694	15.0%
MUC	49,344	10,344	21.0%	34,572	70.1%	879	148	614	315.8%	32,313	52,317	FRA	10,506	30.4%
MAD	52753	4238	8.0%	21680	41.1%	1,170	154	620	302.8%	24,628	65,590	BCN	1480	6.8%
ORY	52069	1971	3.8%	23910	45.9%	1,152	146	457	212.5%	24,287	64,095	CDG	5889	24.6%
DME	5	5	100.0%	0	0.0%	1,060	-	-	-	-	-	-	0	0.0%
STN	57,828	32	0.1%	13,084	22.6%	788	127	640	405.6%	11,822	74,613	DUB	1,972	15.1%
SVO	42	42	100.0%	13	31.0%	1,059	456	503	10.4%	10	61	MUC	3	23.1%
DUS	37,252	2166	5.8%	24,267	65.1%	781	129	468	263.8%	18,882	37,466	FRA	5,611	23.1%
MAN	40,555	600	1.5%	22,244	54.8%	758	151	569	277.9%	18,180	43,394	BHX	4,397	19.8%
DUB	45,112	902	2.0%	15,327	34.0%	1,223	119	602	405.0%	18,153	56,627	STN	1,371	8.9%
BRU	36,118	2614	7.2%	17,577	48.7%	881	154	561	263.8%	15,727	41,331	AMS	3,653	20.8%
CPH	39,425	4,385	11.1%	15,162	38.5%	1,010	150	737	390.9%	16,816	49,782	ARN	1,720	11.3%
ZRH	33,407	4059	12.2%	19,474	58.3%	993	140	443	215.6%	17,519	36,547	STR	3,566	18.3%
OSL	41,232	5,457	13.2%	14,130	34.3%	1,076	150	722	381.9%	16,168	55,780	CPH	2,276	16.1%
MXP	32,353	145	0.4%	10,584	32.7%	820	139	493	253.6%	8,625	38,896	NCE	1,477	14.0%
VIE	28,250	4,227	15.0%	15,869	56.2%	1,201	140	433	209.6%	16,464	33,258	FRA	1,405	8.9%
ARN	35,061	2,726	7.8%	11,143	31.8%	1,056	155	819	428.6%	13,307	47,522	CPH	2,453	22.0%

*Notes: dpax: disrupted passengers, conn: connecting passengers; reloc: relocated passengers; avddel: average departure delay (min); avt0: average original travel time (min); avt1: average relocated travel time (min); aggdel: aggregate delay in pax-days [last 4 measures for relocated passengers only]; aggdel'**:** aggregate delay in pax-days for all passengers 24h after re-aperture; alt: main alternate airport; Δpax: relocated passenger departures at the alternate airport.*

Appendix F. IATA Airport codes

Code	*Airport*	*Code*	*Airport*	*Code*	*Airport*	*Code*	*Airport*	*Code*	*Airport*
ACH	Altenrhein (Switzerland)	CPH	Copenhagen Kastrup (Denmark)	HAD	Halmstad (Sweden)	MLH	Mulhouse (France)	SCN	Saarbruecken (Germany)
AGB	Munich Augsburg (Germany)	CRL	Brussels S. Charleroi (Belgium)	HAM	Hamburg (Germany)	MMX	Malmo (Sweden)	SEN	London Southend (UK)
AMS	Amsterdam (Netherlands)	CTA	Catania (Italy)	HEL	Helsinki (Finland)	MST	Maastricht/Aachen (Netherlands)	SLM	Salamanca (Spain)
ARN	Stockholm Arlanda (Sweden)	DLE	Dole (France)	HHN	Frankfurt Hahn (Germany)	MUC	Munich International (Germany)	SOU	Southampton (UK)
BCN	Barcelona (Spain)	DME	Moscow Domodedovo (Russia)	HUY	Humberside (UK)	MXP	Milan Malpensa (Italy)	STN	London Stansted (UK)
BFS	Belfast International (UK)	DOL	Deauville (France)	ILD	Lleida (Spain)	NCE	Nice (France)	STR	Stuttgart (Germany)
BGY	Milan Bergamo/Orio al Serio (Italy)	DSA	Doncaster/Sheffield (UK)	INN	Innsbruck (Austria)	NCY	Annecy (France)	SVO	Moscow Sheremetyevo (Russia)
BHD	Belfast George Best City (UK)	DUB	Dublin (Ireland)	IST	Istanbul Ataturk (Turkey)	NRK	Norrkoping (Sweden)	SVQ	Sevilla (Spain)
BHX	Birmingham (UK)	DUS	Duesseldorf International (Germany)	KID	Kristianstad (Sweden)	NRN	Duesseldorf Weeze (Germany)	SXB	Strasbourg (France)
BKA	Moscow Bykovo (Russia)	EIN	Eindhoven (Netherlands)	LBA	Leeds Bradford (UK)	NUE	Nuremberg (Germany)	SZG	Salzburg (Austria)
BLK	Blackpool (UK)	EMA	Nottingham East Midlands (UK)	LCY	London City (UK)	NWI	Norwich (UK)	TEQ	Tekirdag (Turkey)
BMA	Stockholm Bromma (Sweden)	ESB	Ankara Esenboga (Turkey)	LEH	Le Havre (France)	NYO	Stockholm Skavsta (Sweden)	TLS	Toulouse (France)
BOH	Bournemouth (UK)	FCO	Rome Fiumicino (Italy)	LGW	London Gatwick (UK)	ORY	Paris Orly (France)	TRF	Oslo Sandefjord-Torp Arpt (Norway)
BRN	Berne Belp (Switzerland)	FDH	Friedrichshafen (Germany)	LHR	London Heathrow (UK)	OSL	Oslo Gardermoen (Norway)	TRN	Turin Caselle (Italy)
BRQ	Brno (Czech Republic)	FKB	Karlsruhe/Baden-Baden (Germany)	LIL	Lille Lesquin (France)	OST	Oostende/Brugge (Belgium)	TUF	Tours Val de Loire (France)
BRS	Bristol (UK)	FMM	Memmingen (Germany)	LIN	Milan Linate (Italy)	OXF	Oxford (UK)	TXL	Berlin Tegel (Germany)
BRU	Brussels (Belgium)	FMO	Muenster/Osnabrueck (Germany)	LPL	Liverpool (UK)	PAD	Paderborn/Lippstadt (Germany)	VIE	Vienna (Austria)
BSL	Basel (Switzerland)	FRA	Frankfurt International (Germany)	LTN	London Luton (UK)	PMF	Milan Parma (Italy)	VKO	Moscow Vnukovo (Russia)
BTS	Bratislava (Slovakia)	GLO	Gloucester/Cheltenham (UK)	LTQ	Le Touquet-Paris-Plage (France)	PMI	Palma de Mallorca (Spain)	VLY	Anglesey (UK)
BVA	Paris Beauvais-Tille (France)	GOA	Genoa (Italy)	LUG	Lugano (Switzerland)	REU	Reus (Spain)	VRN	Verona Villafranca (Italy)
CAI	Cairo (Egypt)	GRO	Girona (Spain)	LUX	Luxembourg (Luxembourg)	RKE	Copenhagen Roskilde (Denmark)	VST	Stockholm Vasteras (Sweden)
CDG	Paris Charles de Gaulle (France)	GRQ	Groningen (Netherlands)	LYS	Lyon St-exupery (France)	RTM	Rotterdam (Netherlands)	WAT	Waterford (Ireland)
CGN	Cologne/Bonn (Germany)	GRZ	Graz (Austria)	MAD	Madrid Barajas (Spain)	RYG	Oslo Moss-rygge (Norway)	XCR	Paris Chalons-Vatry (France)
CIA	Rome Ciampino (Italy)	GVA	Geneva (Switzerland)	MAN	Manchester (GB) (UK)	SAW	Istanbul Sabiha Gokcen (Turkey)	ZRH	Zurich (Switzerland)