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Analysis of the effect of extreme weather on the US domestic air network. A delay and cancellation propagation network approach

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ABSTRACT

Flight delays are one of the most discussed, yet not fully understood, topics in the aviation industry. In this paper, we shed more light into propagation of flight delays by providing a spatio-temporal analysis of flight departure delays of the US domestic air network for the year 2017. The analysis focuses on four US air carriers (full-service and low-cost) and two time events characterized by extreme weather conditions, in addition to a baseline case free of extreme weather conditions. We constructed a Delay Propagation Network (DPN) for each (time event, airline) pair detecting patterns of causality between hourly delays in airports using a Granger Causality approach. In addition, we identified four (time event, airline) pairs with a volume of cancellations large enough to construct a Cancellation Propagation Network (CPN), analogously to DPNs. For the baseline case, we observed that central nodes of the airport network (i.e., hubs) usually act as absorbers or intermediary nodes in the DPN. DPNs were more homogeneously distributed in space for point-to-point than for hub-and-spoke networks. For extreme weather events, we observed that the size of a DPN increases with the percentage of canceled flights as long as this stays below 10%. Conversely, it suddenly decreases when the percentage exceeds such tipping point because most causal relationships among delays are lost due to the volume of cancellations. We also observed that some airports located in the region of the extreme weather event were among the central nodes of the DPN. Those airports, together with the hub airports, acted as the top generators, absorbers, or intermediary nodes of the DPN. On the other hand, CPNs monotonously increased in size with the proportion of canceled flights. CPNs are less noisy and therefore easier to interpret than DPNs, as cancellations stem primarily from the extreme weather event only. In CPNs, hubs act as cancellation absorbers, due to the larger volume of resources that airlines allocate there.

1. Introduction

Flight delays represent a major problem for all the stakeholders in the air transport supply chain, as they affect passengers, airlines, airports, and air navigation service providers. They also result in huge economic losses, which were estimated by the Federal Aviation Administration (FAA) to be around $33 billion in 2019 (FAA, 2022), with roughly 55% attributable to passengers' discomfort. Delays in air transport networks can propagate in a snowball fashion because of connected resources related to an initially delayed flight. Such resources are the aircraft itself, passengers, crew, and the airport. As the same aircraft generally performs multiple flight legs in a day, delay of an earlier flight might have consequences on the subsequent flight legs. Flight crew might also switch between aircraft, causing the delay from one flight to propagate across multiple flights, similarly to connecting passengers.

The Bureau of Transportation Statistics (BTS) started collecting monthly numbers of flight delays from airlines in June 2003, with airlines reporting the causes of delays in five broad categories (BTS, 2022a). They are (i) air carrier, (ii) extreme weather, (iii) National

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Aviation System (NAS), (iv) late-arriving aircraft, and (v) security.[2] According to BTS (BTS, 2022b), before COVID-19 late-arriving flights were consistently the main cause of delay. For example, in July 2019 77% of flights were reported on-time, with late-arriving aircraft and air carrier the two major cause of delays (8 and 6% of flight, respectively). In this work, we decided to focus on category II, extreme weather, as we believe that delay generation and propagation that is concurrent with an extreme weather event is mostly attributable to the weather event itself and only secondarily to other causes. In addition, in the last decades there has been a staggering rise in extreme weather events, with their number almost doubling between the period 1980–1999 and 2000–2019 (YaleEnvironment360, 2022), as Fig. 1 highlights. As such, the impact of extreme weather on air transport is expected to increase in significance (Yahoo! News, 2022), justifying the focus of this paper on extreme weather-induced delays.

Due to an increased availability of flight data, research on flight delay propagation has intensified in the last decade. Techniques such as complex network theory (Zanin, 2015; Fleurquin et al., 2014), statistical analysis (Kafle and Zou, 2016; Tan et al., 2021), and machine learning (Wu and Law, 2019; Sismanidou et al., 2022) have been employed to mostly assess the role of airports in flight delay propagation. Airports represent the merging points where all the aforementioned resources interact and, hence, play a crucial role in delay management. Availability of flight data can be leveraged to compute flight delay patterns experienced by airports using reported scheduled and actual departure/arrival times. Such delays can be generally represented as time-series. Analyzing the magnitude of delays across airports can already provide insights into their propagation. Notwithstanding, from a methodological stand-point many research efforts have been devoted towards finding causal relationships between delays in airports (Du et al., 2018; Zanin, 2015, 2021). This approach entails considering the delay propagation problem from the perspective of delay time-series interdependence and assessing if a delay in one airport has some explanatory power with respect to a (future) delay in a different airport. Furthermore, flight data provide also information about canceled flights, so it is possible to examine the propagation of cancellations. To this avail, the objective of our research is to analyze patterns of propagation of disruptions in the context of extreme weather events. For that aim, 2017 is a fitting year as it was characterized by extreme storms and hurricane Irma (Wikipedia, 2022b). As those events usually lead to a significant volume not only of delays, but also of cancellations, we analyze those two types of disruptions separately. Propagation of flight delays is generally associated to a dis-utility for passengers and airports, but it does not necessarily imply an interruption of service. Cancellation of flights has more severe effects on the air transport network and the stakeholders involved. Our contribution to the literature is threefold. First, we focus on propagation of disruptions associated to specific events, instead of extracting time-series of disruptions of large periods of time. We believe that adopting this approach increases the explanatory power of the observed disruption propagation patterns. A better understanding of propagation of delays can help to better apply propagation mitigation strategies, like scheduled buffers (Brueckner et al., 2021) or integrated recovery models (Evler et al., 2022). Secondly, we examine not only Delay Propagation Networks (DPNs), but also Cancellation Propagation Networks (CPNs). Cancellations of flights occur when aircraft or crew of a canceled flight are not available for subsequent flights. The volume of canceled flights in extreme weather events can be large enough to make propagation of cancellations observable. Thirdly, we contribute to the examination of the behavior of airport networks regarding to delays and cancellations in the context of extreme events. As those events are likely to increase with climate change, we believe that this analysis is of increasing relevance. The rest of the paper is organized as follows. In Section 2 the most relevant academic literature on flight delay propagation is presented and the scientific gap is identified. Then, Section 3 describes the input data and how data was processed. Section 4 provides an overview of the methodological framework that was applied in the paper, while Section 5 presents results in terms of delay and cancellation propagation networks. Finally, in Section 6 a critical discussion of our results, conclusions, and future research avenues is provided.

2. Literature review

Flight delay propagation has been studied quite extensively in the last 15 years. In this section, we describe the relevant literature on the topic and provide a critical analysis of papers addressing causality relationships between delays at airports, identifying the research gap addressed by this paper in the process. Additionally, in Appendix A we summarize the reviewed references highlighting publication year, methodology, geographical focus, and main findings. One of the first approaches to model delay propagation was AhmadBeygi et al. (2008). The authors use a propagation tree approach to simulate how an initial delay can propagate through the network. Branching from a node (i.e., a specific flight) recognizes the fact that a single delay can generate multiple distinct delays downstream (due to the interconnected use of multiple resources). As an example, this occurs when the aircraft and the cockpit crew are scheduled to operate additional flights from a destination. The idea that shared resources across flights are the most relevant internal factors in spreading of flight delays is confirmed by Fleurquin et al. (2013) and Campanelli et al. (2016), with a focus on passenger and crew connectivity. Sismanidou et al. (2022) focused on the role of airports and used machine learning techniques to analyze the impact of connecting passengers on delay propagation for the twenty-one US airports with the most delays in July 2018. It was found that a correlation between arrival delays and carrier (departure) delays is stronger in airports featuring a single dominant carrier, as more resources are directly connected. Further research has explored other explanations for flight delays. In Zanin (2015), the author compares flight delay propagation patterns in a network comprising the fifty busiest European airports and the twenty largest airlines. Delay causality between airports is computed by analyzing flight delay time-series data using both Granger Causality (GC) and Transfer Entropy (TE). The research shows that aggregating networks of different airlines into a single one might lead to biased results. This is because airlines may share resources such as airspace and airports, but operate different business models and have different network structures. Hence delay propagation analysis needs to focus on each airline independently. Du et al. (2018) pair complex network theory with GC to analyze delay propagation patterns in domestic China using data covering the whole month of July 2012. It is found that large airports generally mitigate delays, while smaller airports propagate delays. GC is also used in Zanin (2021), where it is paired with agglomerative clustering techniques. That research sought *causality clusters*, which are groups of generators of delay and absorbers of delay, in contrast to more traditional approaches which group generators and absorbers of the same delay. This research introduces the concept of *intermediary* airports that act as delay brokers in the network. In follow-up work, Pastorino and Zanin (2021) analyze a dataset of sixteen non-continuous months between 2015 and 2018 for the fifty largest European airports, with the key finding that dissipation of delays is a process where all airports contribute, irrespective of their size. This last finding is at odds with other works such as (Du et al., 2018), creating an opening for further analysis. To the best of our knowledge, this is the first paper where the application of GC is utilized

[2] The five categories are briefly described as follows. (i) cancellation or delay due to circumstances within the airline's control, (ii) significant meteorological conditions that delays or prevents the operation of a flight, (iii) delays and cancellations attributable to NAS and related to a broad set of conditions, such as non-extreme weather conditions, airport operations, and air traffic control, (iv) delay due to the previous flight with the same aircraft arriving late, and (v) delays or cancellations caused by evacuation of a terminal or concourse, reboarding of aircraft because of security breach, etc.

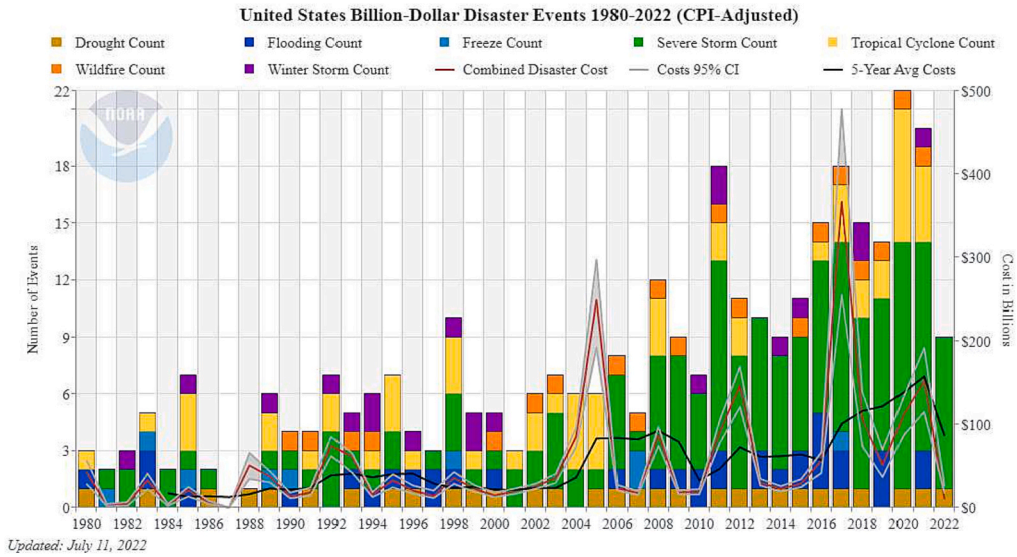


Fig. 1. Number of extreme weather events per year. From NCEI (2022).

with some methodological caveats to improve the quality of results. A key example is the use of an upper bound limiting the lags when comparing two time-series with a GC test. The particular example is the use of a six hours limit (which is the duration of the longest intra-European flight). This research also used a correction technique to reduce the false discovery rate by lowering the *p*-value threshold to limit type I errors. Another recent innovation involves data pre-processing techniques and the current paper follows that approach. It does so with some critical differences from the research done previously. First, most of the cited papers consider a single time-horizon and, hence, a single time-series when assessing delay causality between airports. Furthermore, some works (e.g., Zanin (2015); Pastorino and Zanin (2021)) use a de-trend process for each time-series by subtracting the average delay observed on the same day, in the two previous and posterior weeks, at the same hour. We argue this approach might conceal some delay propagation patterns, especially in the case of extreme weather events, where assessing the proper time-interval to study propagation effects due to the particular event itself is critical. Second, canceled flights seem to be overlooked in the literature. They are either omitted or artificially converted into delayed flights with an ad-hoc assigned delay (e.g., three hours in Du et al. (2018)). This array of research shows that the factors relevant to delay and its propagation between airports involves a complex array of factors. Airline operations and network configuration stand out as key factors, but their importance seems to vary from one study to another. One way to extend our understanding here is to explore the impact of the major delays associated to extreme weather events and to show how they are addressed by different airline networks. To pursue this goal and obtain unbiased results, it is paramount to study delay propagation within each identified weather event. In addition, extreme weather events cause canceled flights, whose effect is propagated through the transport network in a different manner to that of common delay propagation and creates different problems for airlines and passengers, so it should be assessed separately. Hence our goal is to study both DPNs and CPNs in air transport that emerge with extreme weather events and contribute to the current literature on the topic. That is the research agenda addressed in this paper.

3. Description of dataset

In our work, we assess delay propagation and causality relationships between airports by using as input hourly departure delays in each considered airport. To compute such departure delays, we processed the *Airline On-Time Performance and Causes of Flight Delays* dataset provided by the BTS (BTS, 2022a). The original dataset, which refers to the year 2017, contains information on each domestic commercial flight in the form of a row entry of the dataset. From the original columns of the dataset, we have retained the *carrier* operating the flight, the *origin* and *destination* airports, the *tail number* of the aircraft, and the flag indicating if the flight has been *canceled*. We have calculated the following features: the *departure delay* in minutes, as time difference between actual and planned departure time, the *planned flight time* in minutes, as the time difference between planned arrival and departure time, and the *planned departure hour* in UTC, including the date.

The resulting dataset includes 5,665,109 observations, representing the planned flights between US airports in 2017. These flights were operated by twelve airlines, namely American Airlines (AA), Alaska Airlines (AS), JetBlue Airways (B6), Delta Airlines (DL), ExpressJet (EV), Frontier Airlines (F9), Hawaiian Airlines (HA), Spirit Airlines (NK), SkyWest Airlines (OO), United Airlines (UA), Virgin America (VX), and Southwest Airlines (WN). Overall, 317 airports appeared in the filtered dataset (see Appendix B for a visual representation). As it concerns airport names, we will rely on their International Air Transport Association (IATA) codes both in the text and in all visualizations. For ease of understanding, in Appendix D we list all the airports that were mentioned at least once providing their full name, IATA code, geographical location, and passenger traffic.

4. Methodology

We divide this section into four parts as follows. First, in Section 4.1 we define how we detected the time-periods of interest for our analyses. Then, in Section 4.2 we describe how we processed the raw data presented in Section 3 to obtain time-series of hourly mean departure delays and number of cancellations. Then, in Section 4.3 we briefly outline the theory behind GC and how we determined causal relationships between airports using the aforementioned time-series. Finally, in Section 4.4 we provide an overview of the complex network theory indices and metrics we used to complement our analysis.

4.1. Time events detection and choice

In order to understand which time-periods to consider in our analysis, we studied the total number of daily domestic cancellations in the year 2017, to identify days or longer time-periods characterized by some form of disruption. We identified five time-periods with peaks of 1,500

daily canceled flights or more. Upon further analysis, each of those time-periods was characterized by an extreme weather event in the continental US. The five weather events, in chronological order, are (i) January 04–08, 2017 North American winter storm: major snow and ice storm that affected the conterminous US with winter weather (Wikipedia, 2022c); (ii) the February 09–11, 2017 North American blizzard: blizzard affecting the Northeastern US with winter weather and maximum snowfalls exceeding 60 *cm* (Wikipedia, 2022a); (iii) the March 09–18, 2017 North American blizzard: late-season blizzard affecting the Northeastern US and extending towards the Ohio Valley with maximum snowfalls exceeding 90 *cm* (Wikipedia, 2022d); (iv) an outbreak of severe thunderstorms: thunderstorms that pounded the Southwest from April 02, 2017, shifting into the mid-Atlantic region and moving towards East affecting the Northeast and Georgia (CNN Business, 2022; The Weather Channel, 2022), and (v) hurricane Irma: hurricane that, after causing havoc in the Caribbeans, moved to the Southeastern portion of the US, mostly affecting Florida and causing floods, widespread power outages, and more than 9,000 flight cancellations to or from Florida (Wikipedia, 2022b; The Points Guy, 2022).

We defined the aforementioned five time-periods Time Events (TEs) and added a numerical indicator (TE1,⋯,TE5) in chronological fashion. We fixed start and end times to encompass the abnormal rate of cancellations around the dates of each TE. On top of these five major disruptive events, we have added a baseline event TE6 which corresponds to a Business As Usual (BAU) situation. This event, spanning the week from May 27th to June 2nd, represents a period of time where the weekly number of flights and average delay were roughly equal to the mean for the whole year 2017. The start and end times selected for each TE are presented in Table 1, while Fig. 2 shows daily and weekly domestic flight cancellations in the US and the six TEs highlighted with different shades. It can be noted that while TE3 is the one with the highest impact on daily cancellations, TE5 has a longer impact spanning multiple weeks.

Given the TEs in Table 1, we computed for each airline of interest the percentage and number of canceled flights. We used these values as proxies to assess the severity of each extreme weather event. We report results in Fig. 3, where TE4 and TE5 appear as the events that caused the most damage to the US domestic air traffic. As a consequence, we chose these two events for further analysis, together with the baseline case TE6. As for airlines, we selected American Airlines (AA), Delta Airlines (DL), United Airlines (UA), and Southwest Airlines (WN). These are, respectively, the third, second, fifth and first airlines in the 2017 domestic US market by number of flights, representing the 65.78% of total flights. We excluded the fourth airline by number of flights, SkyWest (OO), as it was less affected by meteorological events than the other four according to our preliminary analysis. The four selected airlines represent two different business models (Klophaus et al., 2012): while WN is a low-cost carrier planning point-to-point flights, the other three are full-service carrier planning connecting flights within a (multi) hub-and-spoke networks. The set of three events and four airlines selected for in-depth analysis covered 206,419 flights and 167 distinct airports.

The impact of events TE4 and TE5 on airlines is heterogeneous. TE4 affects mainly DL, which has roughly the 23.09% of its flights canceled. TE5 has a higher impact on most airlines, higher than 30% in the case of NK. Among our sample of airlines, AA suffers the highest impact in relative values, followed by WN and DL.

Table 1
Start and end times for each event (times in UTC).

Time Event	start time	end time
January snowstorm (TE1)	2017-01-06 11:00:00	2017-01-10 11:00:00
February blizzard (TE2)	2017-02-06 00:00:00	2017-02-11 00:00:00
March blizzard (TE3)	2017-03-09 12:00:00	2017-03-16 12:00:00
April severe storms (TE4)	2017-04-05 08:00:00	2017-04-10 12:00:00
September hurricane Irma (TE5)	2017-09-07 08:00:00	2017-09-15 12:00:00
Business As Usual (TE6)	2017-05-27 00:00:00	2017-06-02 23:00:00

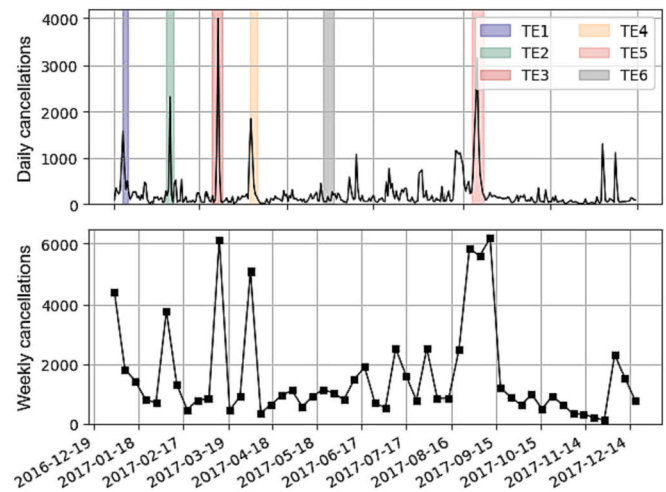


Fig. 2. Canceled flights (daily and weekly) in the US domestic air network in 2017.

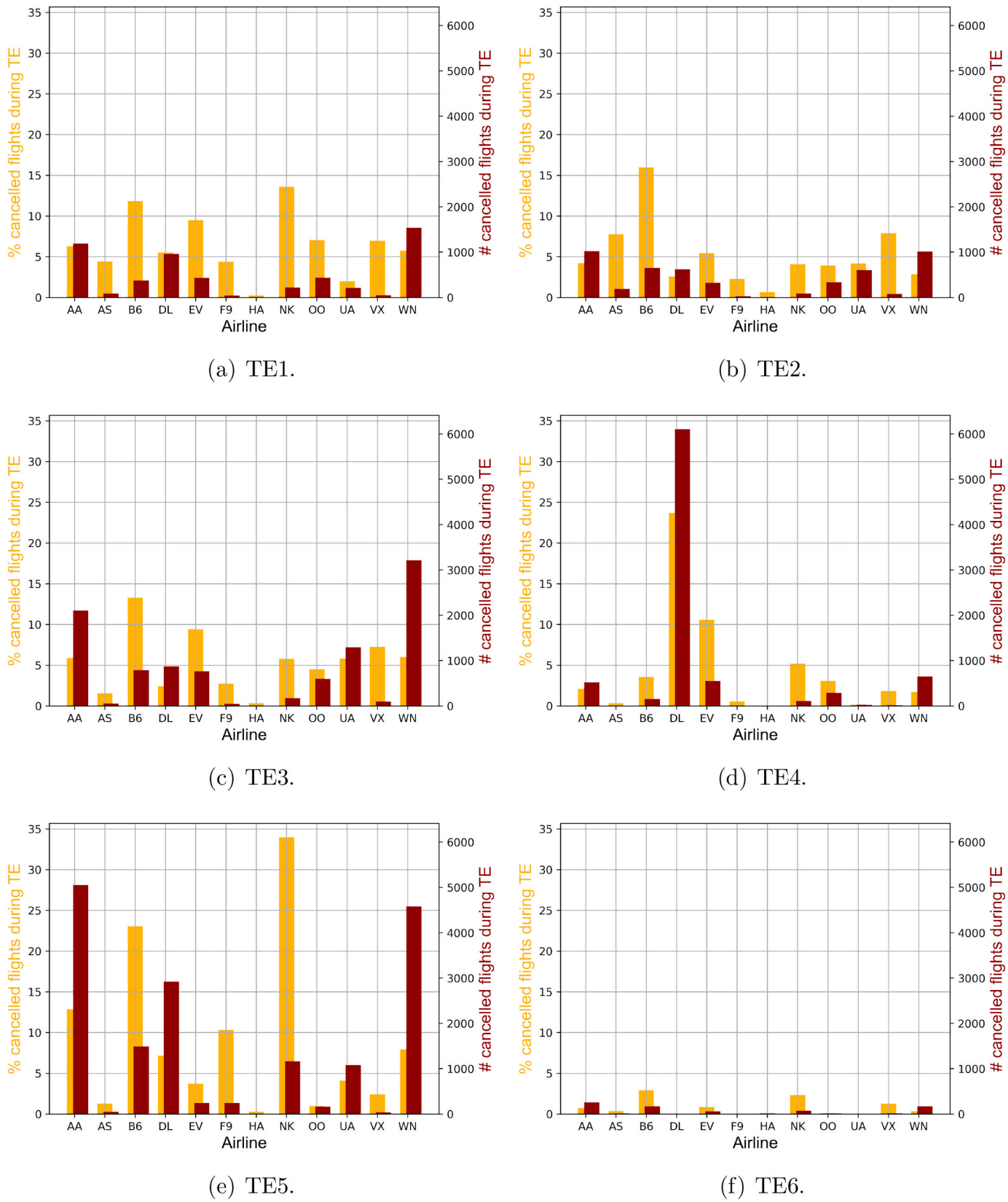
4.2. Flight delay and cancellations time-series extraction

To obtain a DPN through GC analysis, we need a time-series of average hourly delays for each origin airport, airline, and TE. A CPN requires an analogous set of time-series with hourly number of cancellations at the origin airport. We start building the time-series extracting from the dataset all flights included in the event time-window for each airline. Then, we are removing airports that have no departing flights in the time-window of interest (even if there may be flights arriving at these airports), as we assume they can play no role in delay or cancellation propagation due to our focus on departure delays/cancellations. Afterward, for each hour in the time-window and for each origin airport and airline we obtain the average departure delay (in minutes) and the total number of cancellations. Previous works on delay propagation have considered both arrival and departure delays as proxies to assess delay propagation (Fleurquin et al., 2014; Campanelli et al., 2016; Du et al., 2018). We have chosen departure delays as we consider that they better represent the nature of delay propagation: if an aircraft departs late, it is likely that the next flight in the rotation of that aircraft will also be delayed, irrespective of how airlines define time of arrival. In addition, arrival delays are harder to assess due to the common practice of schedule padding (BBC, 2022), i.e., the tendency of airlines to inflate flight times to increase on-time performances and conceal arrival delays. For hours and origin airports with no flights operated, we set average delay and number of canceled flights to zero.

In addition to the time-series for each airport, we obtain all Origin-Destination (OD) airport pairs (i,j) with at least one direct, non-canceled flight. All these pairs constitute the *airport network* for the set of flights considered after filtering by airline and time-window. For each OD pair, we evaluate the planned flight time t_{ij} as the average of all planned flight times.

4.3. Determining delay and cancellation propagation networks

To obtain each DPN, we use the hourly delay time-series and the OD pairs obtained in the previous section to evaluate if delays in destination airports are related to delays at origin airports using a GC test. This test requires establishing a hierarchical regression model for each OD pair, with the following two models. The first model, sometimes called unconstrained model, predicts hourly delays at destination airport j at time (hour) t using previous hourly delays in the same airport as shown in Eq. 1:



(a) TE1.

(b) TE2.

(c) TE3.

(d) TE4.

(e) TE5.

(f) TE6.

Fig. 3. Cancellations for each TE considered.

$$d_{jt} = \sum_{p=l}^{u} \alpha_p d_{j,t-p} + \varepsilon_t \quad (1)$$

The second model, sometimes called constrained model (Eq. 2), adds terms including prior delays at origin airport *i*:

$$d_{jt} = \sum_{p=l}^{u} \alpha_p d_{j,t-p} + \sum_{q=l_{ij}}^{u_{ij}} \beta_{iq} d_{i,t-q} + \varepsilon_t' \quad (2)$$

We have set $l = 1$ and $u = 3$ for all destination airports. With this choice, we hypothesize that hourly delays depend on hourly delays in the three previous hours. We assume this to take into account airport-specific events in previous hours (e.g., congestion or extreme weather) that can create delays in the considered hour. We have adopted values of l and u similar to previous GC analysis of delays (Du et al., 2018). The values of l_{ij} and u_{ij} are different for each (i,j) pair: we set $l_{ij} = t_{ij}$ and $u_{ij} = t_{ij} + 2$, where t_{ij} is the planned flight time in hours. By doing this, we assume that delays at airport j can appear because delayed flights coming from airport i bring resources (aircraft or crew) necessary for flights departing from j. Previous research (e.g, Zanin (2015)) has examined the relationship between delay time-series between pairs of airports with no direct flights. As there is no transference of crew and aircraft between those pairs of airports, we argue that there can be no direct causal effect between their respective delay time series. As an additional measure to avoid post hoc *ergo propter hoc* effects, we evaluate relationships between hourly delays time-series only for pairs of airports connected with direct flights. As a consequence, the delay propagation network will be a subset of the nodes and edges of the airport network that the GC test deemed statistically significant.

We evaluate the hierarchical regression models for delays with Ordinary Least Squares (OLS) regression. If the delays at destination j depend on delays at origin i, the constrained model will have more explanatory power than the unconstrained model. We assess the explanatory power by comparing both models with an ANOVA test. For each time event and set of airlines considered, we need to evaluate as many F-tests as the edges of the directed airport network. The evaluation of multiple statistical tests requires lowering the threshold of p-values to be considered significant, as the probability of committing Type-I errors increases with the number of comparisons. To avoid this inflation of probability of Type-I errors, we have adopted the false discovery rate controlling procedure described in Benjamini and Yekutieli (2001), estimating the false discovery rate with the method proposed by Dalmasso et al. (2005). The application of this procedure lowered the minimal p-value to discard null hypotheses from 0.05 to adjusted minimal p-values ranging from 2.61e-5 to 1.83e-3.

The set of significant relationships between delays at airport i and airport j allows us to construct the Delay Propagation Network, a network representation of propagation of flight delays for each (TE, airline) pair. This DPN is a graph $\mathscr{G}^D = (\mathscr{N}^D, \mathscr{E}^D)$, where $\mathscr{N}^D$ is the set of nodes and $\mathscr{E}^D$ is the set of edges. Each graph $\mathscr{G}^D$ is characterized by an adjacency matrix $\mathscr{A}^D_{|\mathscr{N}^D|\times|\mathscr{N}^D|}$, where element a^D_{ij} is unitary if airport i causes delays in airport j, and zero otherwise. Given the problem at hand, $\mathscr{G}^D$ is a directed graph and $\mathscr{A}^D$ is generally a non-symmetric matrix.

To obtain the CPNs, we define models analogous to the DPNs, replacing average departure delays with number of cancellations. The resulting hierarchical regression models are modelled with Poisson regression models, as the number of cancellations can be modelled as a Poisson distribution of counts. We evaluate the explanatory value of the constrained model over the unconstrained with a Chi-squared statistic of the difference of deviances. As with DPNs, the p-values threshold selected to include edges in the CPN were selected to control for false discovery rate. The obtained adjusted minimal p-values ranged from 1.70e-06 to 2.04e-03.

Analogously to DPNs, we define a CPN as a graph $\mathscr{G}^C = (\mathscr{N}^C, \mathscr{E}^C)$ with an adjacency matrix $\mathscr{A}^C$ with elements a^C_{ij} equal to one if cancellations in airport i are causing cancellations at airport j and zero otherwise.

4.4. Network metrics for propagation networks

For each DPN node $k \in \mathscr{N}^D$, we define the in- and out-degree as, respectively, $k^D_{in}(k) = \sum_{i\in\mathscr{N}^D} a^D_{ik}$ and $k^D_{out}(k) = \sum_{j\in\mathscr{N}^D} a^D_{kj}$. They do represent the number of nodes that are directly upstream (resp., downstream) of node k.

While in- and out-degree provide some indications of the centrality of a node in terms of connections within $\mathscr{G}^D$, they fail to identify how strong each connection is. To this avail, we can define an edge-specific measure, or *weight*, w^D_{ij}, that maps a certain key performance indicator or feature that is relevant for the problem at hand. In transport networks, examples of weights might range from distance, to travel time, travel cost, passenger flows, just to cite a few examples. We define edge weights for the DPN w^D_{ij} as the summation of all flight delays ≥15 min along arc (i,j). With this definition, we define the *net delay*[3] of node k as $\Delta d_k = \sum_{j\in\mathscr{N}^D} w^D_{kj} a^D_{kj} - \sum_{i\in\mathscr{N}^D} w^D_{ik} a^D_{ik}$. Intuitively, $\Delta d_k > 0$ means that airport k generates a net delay as outgoing flights have more delay than incoming flights, while $\Delta d_k < 0$ is associated to an absorption behavior.

We have used node unweighted betweenness b_i to find the most intermediary nodes in the network. It is defined as $b_i = \sum_{i\neq j\neq k} n(i)_{jk}/n_{jk}$, where n_{jk} is the number of shortest paths between any pair of nodes j and k and $n(i)_{jk}$ is the number of those paths including node i.

For cancellation propagation networks, in- and out-degree are defined in the same way as with delay propagation networks, and edge weights w^C_{ij} are the number of canceled flights departing from i and with destination in j. With those weights we can define *net cancellation* of a node $k \in \mathscr{N}^C$ as $\Delta c_k = \sum_{j\in\mathscr{N}^C} w^C_{kj} a^C_{kj} - \sum_{i\in\mathscr{N}^C} w^C_{ik} a^C_{ik}$. Nodes with $\Delta c_k > 0$ are generators of cancellations and nodes $\Delta c_k < 0$ act as absorbers of cancellations. We adopt a visualization code similar to the delay propagation networks, with node (airport) size proportional to the absolute value of its net cancellations. Intermediary nodes in a CPN are defined in the same way as in a DPN.

5. Results

5.1. Summary of the size of delay and cancellation propagation networks

In order to assess which DPNs and CPNs to consider in the analysis, we initially computed all DPNs and CPNs for the three TEs under scrutiny (TE4, TE5, and TE6). Table 2 summarizes the size of each network in terms of number of nodes $|\mathscr{N}|$ and edges $|\mathscr{E}|$.

As it concerns TE6, despite the lack of an extreme weather event, DPNs are non-negligible for all airlines. This is in line with the perspective of this paper. We expect extreme weather events to cause abnormal delays and/or cancellations, but flight delays in air transport are generated by a plethora of causes apart from the weather. On the other hand, all CPNs for TE6 are either not defined, or too limited in size to be significant. In absence of a major disruption (such as extreme weather or an operational one), we expect a very low cancellation rate.

For TE4 and TE5, most DPNs are significant in terms of $|\mathscr{N}|$ and $|\mathscr{E}|$. For TE4, the DPN of DL is the smallest, but its CPN is by far the largest. Hence, the size of the DPN is caused by the high cancellation rate. For the other three airlines, the cancellation rate appears to have been much lower as the associated CPNs are not significant. For TE5, both DPNs and CPNs seem significant, with UA being the least affected by hurricane Irma according to $|\mathscr{N}|$ and $|\mathscr{E}|$ values.

In terms of DPNs, we will analyze all twelve networks (three TEs,

[3] In the rest of the paper, we will drop the term *net* when describing net delay generators or absorbers.

Table 2
Size in terms of $|\mathscr{N}|$ and $|\mathscr{E}|$ for DPNs and CPNs related to TE4, TE5, and TE6. Values in bold are associated to networks that are analyzed further in this work.

	TE4				TE5				TE6			
	DPN		CPN		DPN		CPN		DPN		CPN	
Airline	$\lvert\mathscr{N}^D\rvert$	$\lvert\mathscr{E}^D\rvert$	$\lvert\mathscr{N}^C\rvert$	$\lvert\mathscr{E}^C\rvert$	$\lvert\mathscr{N}^D\rvert$	$\lvert\mathscr{E}^D\rvert$	$\lvert\mathscr{N}^C\rvert$	$\lvert\mathscr{E}^C\rvert$	$\lvert\mathscr{N}^D\rvert$	$\lvert\mathscr{E}^D\rvert$	$\lvert\mathscr{N}^C\rvert$	$\lvert\mathscr{E}^C\rvert$
AA	**47**	**66**	5	4	**31**	**54**	**37**	**86**	**19**	**15**	10	10
DL	**16**	**12**	**118**	**191**	**75**	**105**	**85**	**119**	**26**	**27**	0	0
UA	**28**	**29**	0	0	**11**	**9**	13	22	**23**	**20**	0	0
WN	**64**	**154**	6	4	**77**	**321**	**50**	**134**	**61**	**85**	2	1

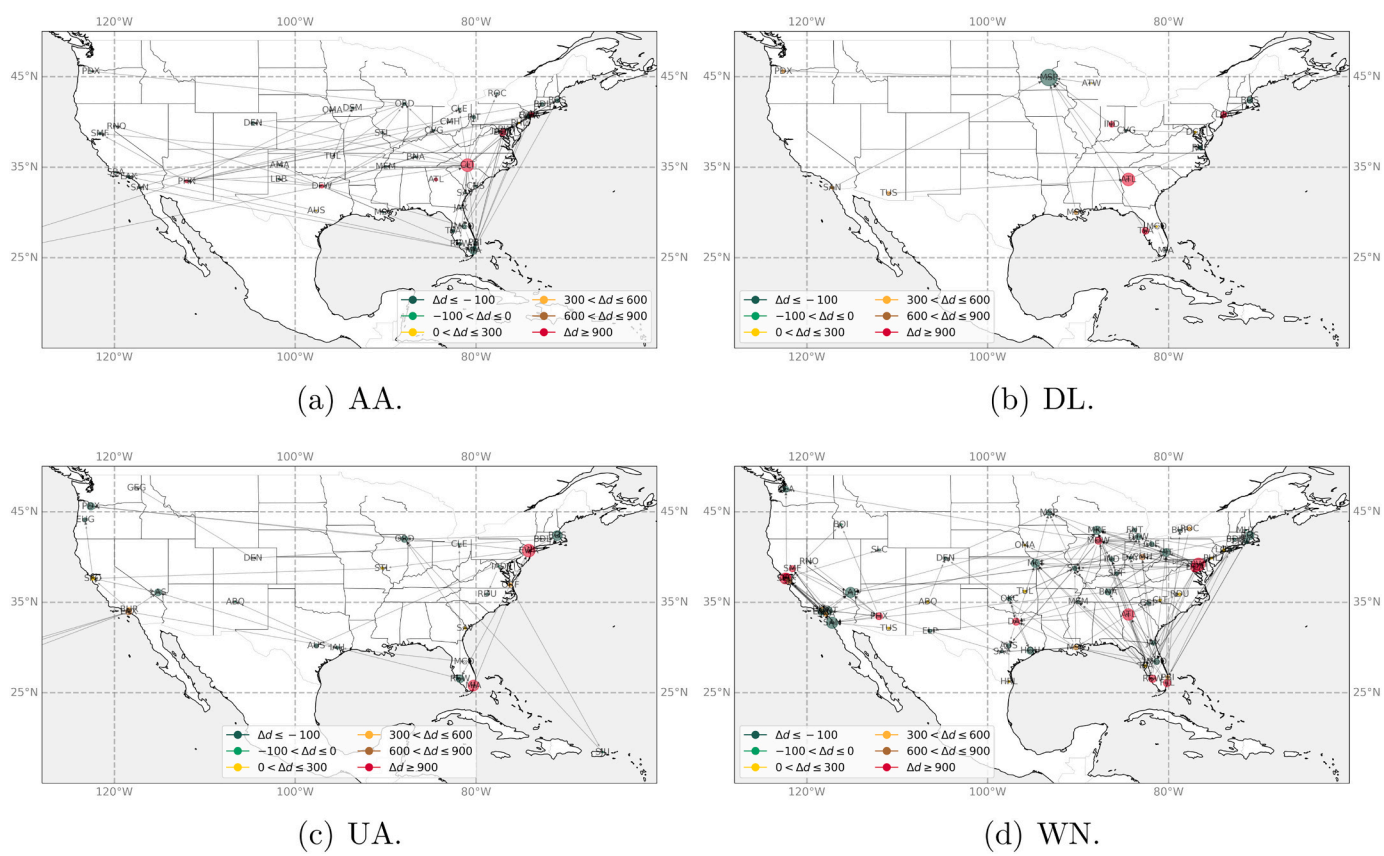
four airlines). A discussion of the DPNs of TE6, i.e., our baseline case not associated to an extreme weather event, is provided in Appendix C to show an example of how delays propagate in situations lacking an explicit disruption. The other two TEs are described in Section 5.2 instead. For CPNs, we will focus on the following four cases that we deemed significant: (TE4, DL), (TE5, AA), (TE5, DL), and (TE5, WN). The values of $|\mathscr{N}|$ and $|\mathscr{E}|$ for all combinations of (TE, airline) and type of network (DPN or CPN) that will be analyzed later in the section are highlighted in bold in Table 2.

5.2. Delay propagation networks in extreme weather events

In Figs. 4 and 5 we present the DPNs for the four analyzed airlines in events TE4 and TE5, respectively. In these plots we analyze in a graphical way some results obtained in the previous analysis. The DPNs of (TE4, UA) and (TE5, UA) are similar to the ones of a baseline event (see Appendix C), which is related with the low proportion of canceled flights. For events (TE4, AA) and (TE4, WN), related to a low proportion of canceled flights, we observe denser DPNs than in the baseline case. While in the case of (TE4, AA) the network seems to concentrate around the geographical location in the event, the spatial distribution of (TE4, WN) is similar to the baseline case, but denser. For events characterized by a medium percentage of canceled flights, we observe a similar pattern. The DPN of (TE5, DL) tends to concentrate in the immediate north of the geographical location of the event. TE5 is more localized than TE4, so the geographical effect is less salient in this case. On the other hand, the DPN of (TE5, WN) is evenly distributed across the US. For low and medium values of canceled flights, the DPNs of AA and DL tend to concentrate around the location of the event, while in the case of WN, as the proportion of cancellations increases (from TE6 to TE5), its DPN maintains the same spatial structure. Finally, for events (TE5, AA) and (TE4, DL), characterized by a high proportion of canceled flights, we observe smaller and geographically sparser DPNs.

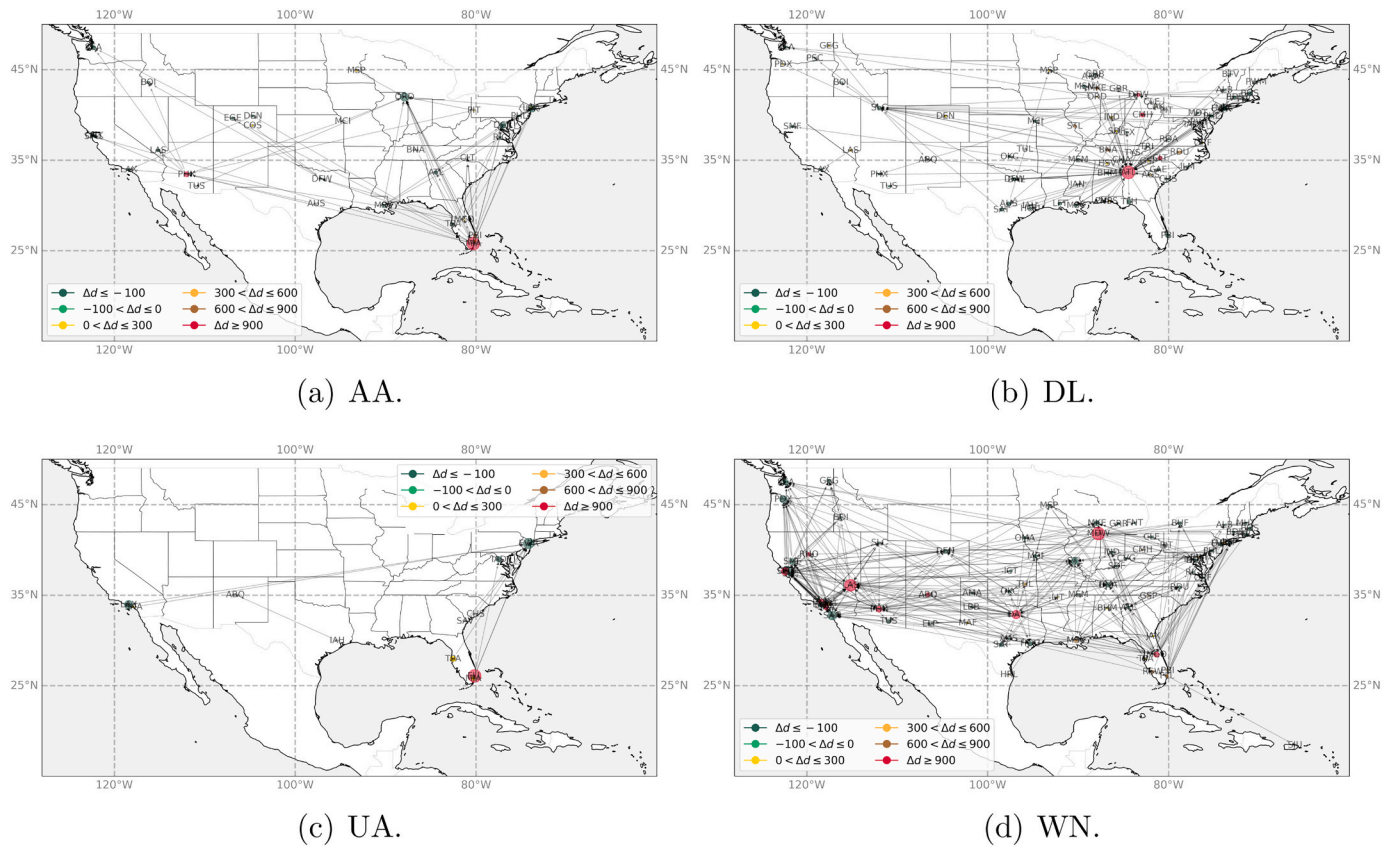
In Tables 3 and 4 we present the top-5 generators, absorbers, and intermediary nodes for TE4 and TE5. Generators are the nodes with highest Δd, absorbers the ones with most negative Δd, and intermediary nodes the ones with the highest betweenness. In addition to the main airports, we have also airports located in the specific geographical location of the event. In the cases of (TE4, DL) and (TE5, UA) there were no nodes (airports) with betweenness different from zero due to the lack of paths longer than two nodes in the resulting graph. This is due to the high sparsity and low density of such graphs. Hence, we left the columns mapping intermediary airports blank for those cases.

The results of these tables are harder to interpret than in the TE6



(a) AA. (b) DL. (c) UA. (d) WN.

Fig. 4. DPNs for TE4. Node size is proportional to absolute value of delay.



(a) AA. (b) DL.

(c) UA. (d) WN.

Fig. 5. DPNs for TE5. Node size is proportional to absolute value of delay.

Table 3
Top-5 delay generators (𝔾), absorbers (𝔸), and intermediary (𝕀) airports for TE4. In italics, airports located in the zone of event. In bold, main hubs of the airline. In bold and italics, main hubs of the airline that are also located in zone of event.

AA			DL			UA			WN		
𝔾	𝔸	𝕀	𝔾	𝔸	𝕀	𝔾	𝔸	𝕀	𝔾	𝔸	𝕀
MCO	***CLT***	***CLT***	*MSY*	***ATL***	–	**ORD**	**EWR**	**EWR**	**BWI**	PHX	*ATL*
FLL	*MIA*	**PHL**	BOS	JFK	–	BOS	**DEN**	***IAH***	*TPA*	**MDW**	*TPA*
RDU	***DFW***	*JAX*	LAS	MSP	–	***IAH***	SAN	**ORD**	MCI	**DEN**	**MDW**
PBI	**PHL**	**ORD**	DEN	SLC	–	*TPA*	**SFO**	LAX	SNA	*DAL*	STL
ATL	JFK	STL	CVG	*MCO*	–	LGA	PHX	IAD	DCA	*HOU*	BWI

Table 4
Top-5 delay generators (𝔾), absorbers (𝔸), and intermediary (𝕀) airports for TE5. In italics, airports located in the zone of event. In bold, main hubs of the airline. In bold and italics, main hubs of the airline that are also located in zone of event.

AA			DL			UA			WN		
𝔾	𝔸	𝕀	𝔾	𝔸	𝕀	𝔾	𝔸	𝕀	𝔾	𝔸	𝕀
MCO	**CLT**	**CLT**	***ATL***	EWR	***ATL***	**SFO**	LAS	–	SAN	PHX	DAL
BNA	**DFW**	*TPA*	CMH	MSN	LAS	DFW	**EWR**	–	**MDW**	OAK	**DEN**
RSW	*MIA*	SFO	DTW	RDU	LAX	AVL	PHL	–	SNA	DAL	BWI
PHL	LGA	*MIA*	MCI	SAT	*MCO*	*PBI*	CLE	–	LAX	**LAS**	*ATL*
PBI	**PHX**	**PHL**	*MCO*	BWI	DTW	*MCO*	RDU	–	*TPA*	SJC	**MDW**

case. While in TE6 there was a common pattern for the role of the main airports, here each airline displays a different behavior regarding the role of airports located in the event and main airports, which also depends on the evolution of the canceled flights. Many relevant airports of the DPNs of AA are located in the event, acting in all roles although mainly as generators. The presence of airports located in the event in (TE5, AA) is smaller than in (TE4, AA) case as cancellations increase. In the case of DL, the role of ATL is highly relevant. Note that ATL is the main hub of DL and that it is located where both TE4 and TE5 take place. In TE5, ATL acts as both a generator and intermediary airport. As WN has a more homogeneous network, both spatially and in terms of connections between airports (network density), airports located in the event are less relevant regarding generation, while hubs keep having an important role. The different business model operating a point-to-point network is evident as delay propagation occurs in a much denser DPN, as Fig. 4 and Fig. 5 suggest. UA is less affected by the considered events,

except for its hub IAH in TE4. As a result, the DPNs of UA have more hubs than other airports located in the geographical area of the event among the top-5 generators, absorbers, and intermediary nodes.

5.3. Cancellation propagation networks

In Fig. 6 we show the four significant CPNs that were identified in Table 2. Unlike DPNs, where the magnitude of delays across the different airports was comparable, the role of hubs is much more dominant in all CPNs. A clear hierarchical structure can be identified where hubs are strong cancellation absorbers. The most prominent example is DL with its main hub ATL. In both (TE4, DL) (Fig. 6(a)) and (TE5, DL) (Fig. 6(c)), ATL is on the receiving end of several cancellation edges, albeit with different geographical features. In (TE4, DL), cancellations are scattered around the whole continental US from the Midwest to the East Coast. In (TE5, DL), cancellations stem from Florida and closely follow the dynamics of hurricane Irma.

In (TE4, DL), ATL features a Δc of $-1{,}137$ (with the second-ranked absorber being DTW with a Δc of -95). In (TE5, DL), ATL features a Δc of -428 (with the second-ranked absorber being, again, DTW with Δc of -16). In both cases, the strong imbalance between outbound/inbound flights from/to ATL is remarkable. Note that outbound cancellations are still non-negligible in both (TE, airline) pairs, as Fig. 7 suggests. (TE4, DL) features a more widespread effect on cancellations that spans more than three days, while cancellations for (TE5, DL) are more localized on September 11th.

As it concerns ATL-inbound canceled flights for the two (TE, airline) pairs, in Fig. 8 we report the origin airports belonging to the CPNs that satisfied both conditions: (i) percentage of canceled flights vs. scheduled flights within the TE greater or equal to 20%, and (ii) number of canceled flights greater or equal to ten. The spatial patterns of the interested origins mimic closely the patterns of Fig. 6. The combined analysis of Figs. 7–8 suggests that the effect of hurricane Irma (TE5) on DL operations in ATL was much more localized than the effect of the extreme thunderstorms (TE4). While the geographical extension of the two extreme weather events might have hinted at this, our outcome extends beyond the geographical aspect as it is based on causal relationships.

For the two remaining CPNs, i.e., (TE5, AA) and (TE5, WN), the initial effect of hurricane Irma on Puerto Rico is still appreciable, as well as the high concentration of cancellation generators in Florida. Some airports that were generators for DL are now absorbers, such as MIA for AA and FLL for WN. They are, respectively, a main hub and operating base for the two airlines. If we extend our analysis beyond Florida, the same trend occurs for the AA hubs CLT and DFW and for the WN operating bases ATL, FLL, and HOU.

The four CPNs presented in Fig. 6 are easier to interpret than the DPNs for the same (TE, airline) pair. We observe delay propagation patterns even in periods of time with no extreme events, like TE6. On the contrary, we can appreciate significant cancellation patterns only in specific contexts, like extreme weather events that affect airline operations significantly. As a result, DPNs are denser, but also noisier, than CPNs. In a DPN we observe propagation patterns that can be attributed to a number of causes different from weather (e.g., airline operations, late-arriving aircraft, or security). What we observe in CPNs can be attributed to extreme weather events only. If we consider the four CPNs, a common pattern is identifiable. Main hubs for flag carriers (and, equivalently, operating bases for WN) function as cancellation absorbers regardless of their geographical location with respect to the extreme weather event causing cancellations. We believe this characteristic is, at least partially, attributable to the higher number of resources that airlines concentrate in those airports and that can be leveraged to still provide a minimum number of outbound operations as compared to inbound ones.

We provide an alternative representation of delay and cancellation propagation for all DPNs and CPNs with Sankey diagrams (Plotly, 2022)

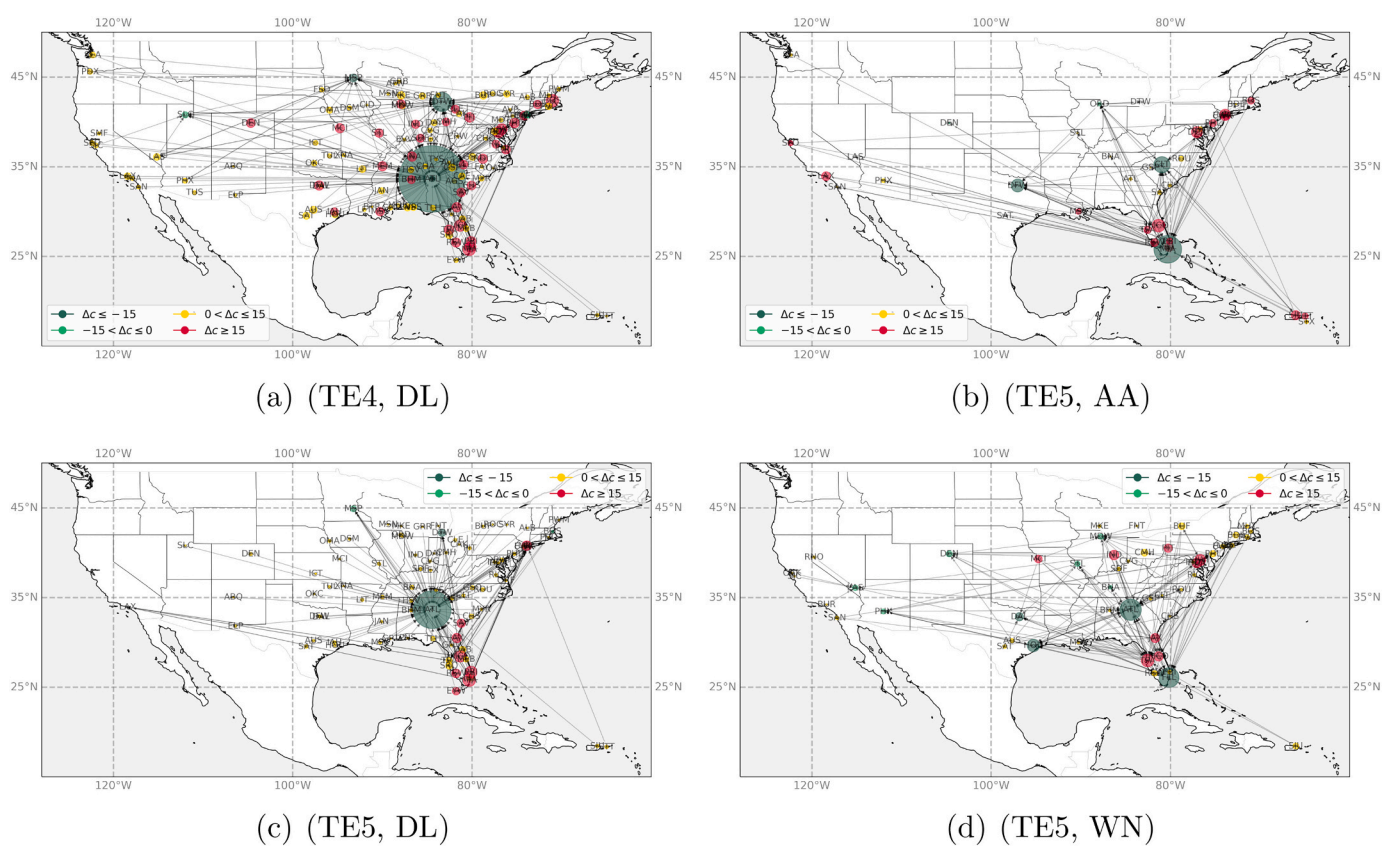
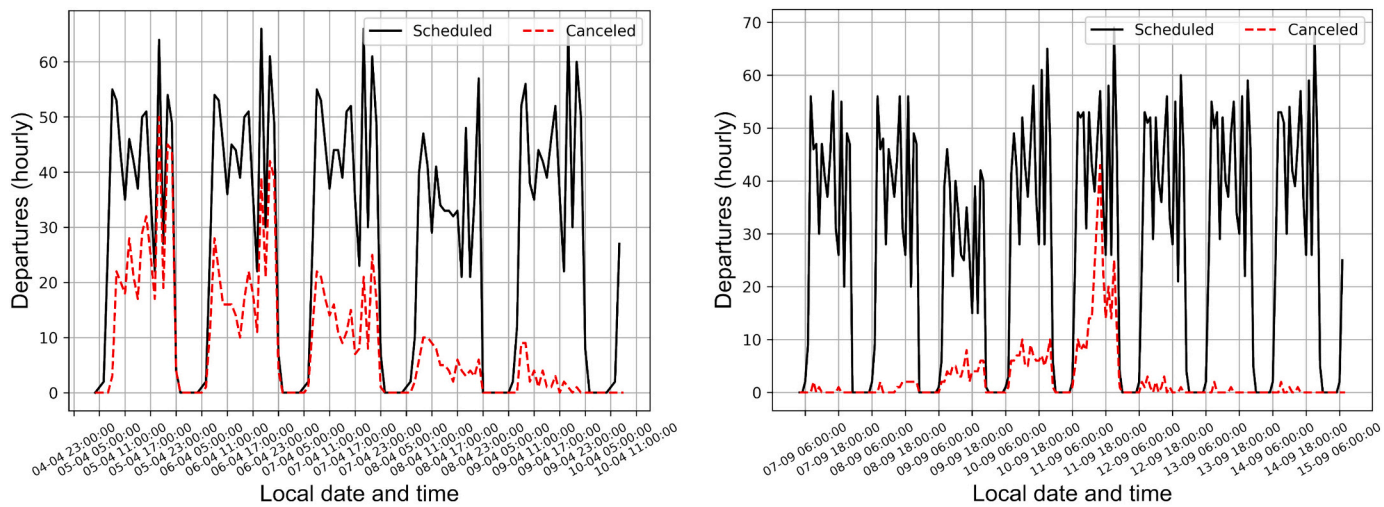


Fig. 6. CPNs for the different combinations of (TE, airline) analyzed. Node size is proportional to value of cancellations.



(a) TE4. (b) TE5.

Fig. 7. Scheduled vs. canceled DL departures (hourly) from ATL for TE4 and TE5.

in the online repository https://rpubs.com/jmsallan/dpn_cpn_jtg, together with supplementary material that complements this analysis. Originally created to visualize energy and material flows (Schmidt, 2008), Sankey diagrams display flows with curved lines of thickness proportional to flow transferred which, in our case, is the actual delay/cancellation being propagated along every OD pair of interest. While our graph-oriented visualizations highlight quite well the magnitude of delays and cancellations at the airport (node) level via the size of each node, they do not highlight differences in flows being transferred across different edges. Sankey diagrams explicitly map that instead. The second advantage of such representation is that it explicitly highlights feedback loops (i.e., a delay or cancellation that back-propagates to the starting location).

In Fig. 9 we present two examples of Sankey diagrams for the CPNs of (TE5, AA) and (TE5, WN). In the first case, we observe a behavior similar to DL (please refer to the online repository for the other Sankey diagrams). AA hubs CLT, MIA, and DFW act as main nodes of the CPN and as absorbers, although the incoming flows to those nodes is smaller than for the DL CPNs. Like in (TE5, DL), we observe loops between hubs and airports located in the geographical scope of TE5 (such as MIA and TPA). It must be noted that two of the three AA hubs are out of the geographical location of the extreme weather event. This can explain the smaller impact of propagation of cancellations for (TE5, AA) with respect to (TE5, DL). Finally, the CPN of (WN, TE5) is sparser than the other three. As in the network plot, we observe the relevance of ATL and FLL as absorbers. The sparsity of (WN, TE5) compared with the other events can be attributed to the business model of WN, which relies on point-to-point flights rather than on centralization of operations in hubs, hence having a more de-centralized concentration of resources. In a similar fashion to DPNs, we summarize results for the CPNs considered in terms of top generators, absorbers, and intermediate airports in Table 5.

5.4. Inter-dependencies between propagation of delays and cancellations

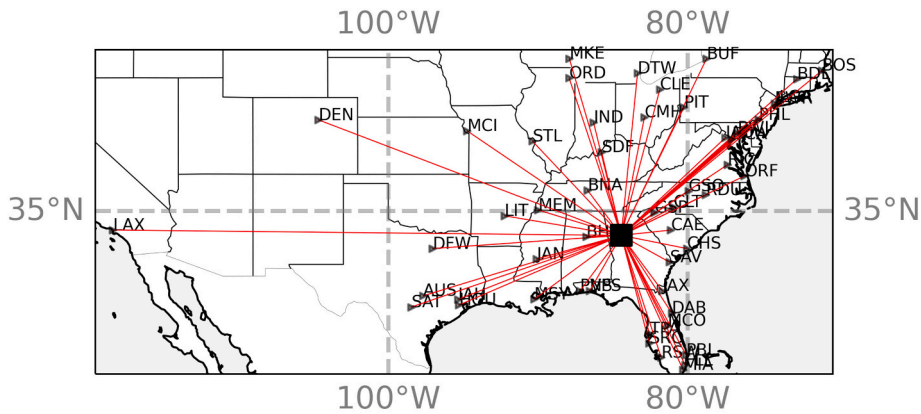
To assess the evolution of DPNs in the time events considered, in Fig. 10 we present for each event and airline the number of nodes $|\mathcal{N}^D|$ and edges $|\mathcal{E}^D|$, together with the proportion of canceled flights. First, UA seems to be unaffected by events TE4 and TE5 as the proportion of canceled flights is lower than the rest of airlines. Second, the size of the DPN of WN is larger than the ones of AA and DL. This remains true even after scaling by the number of nodes and edges of the WN airport network. Finally, we observe that in (TE5, AA) and (TE4, DL), i.e., the (TE, airline) pairs with the highest number of cancellations, the size of the DPN shrinks when compared to the other cases.

To complement the analysis, Fig. 11 presents the same metrics for CPNs. Here we observe that the size of the CPN increases quasi-monotonically with the percentage of cancellations. The largest CPN in absolute value is the one of (TE4, DL), the (TE, airline) pair with the highest percentage of cancellations.

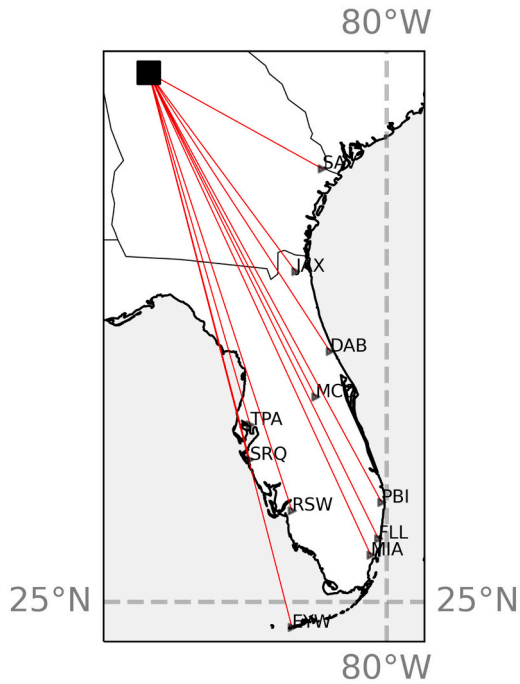
In Fig. 12, we compare the evolution of DPNs and CPNs for the two disrupted time events we considered (TE4 and TE5) and for the three airlines that were highly impacted (AA, DL, and WN). For each (TE, airline) pair, we compare the percentage of canceled flights with the size of the resulting DPN and CPN represented by the number of edges (y-axis) and nodes (size of the circle). For small percentages of cancellations ($\leq$7%), no significant CPN was identified. This is the case for (TE4, AA) and (TE4, WN), as the preliminary analysis of Section 5.1 suggested. As the percentage of cancellations increases, yet remains lower than a tipping point ($\simeq$10%), the size of both DPNs and CPNs grows. The disruption is causing a significant propagation of delays, but cancellations are now significant enough to define their own propagation network. It can be assessed, again, the different performance between the large size of the DPN of WN, with a number of edges almost quadruple than its counterparts. Finally, the DPN size decreases dramatically as cancellations increase. This behavior is evident for (TE5, AA), where a cancellation rate of 13% already halves the size of the DPN when compared to TE4. The effect is even stronger for (TE4, DL), where the DPN is completely dismantled and the associated CPN is larger than any other flag-carrier DPN or CPN presented in Figs. 10–11.

In summary, we have identified an emerging property mapping the inter-dependencies between DPNs and CPNs. For very low values of flight cancellations, only DPNs are defined, as cancellations do not affect in a significant manner the network. For low values of flight cancellations, both the DPNs and the CPNs increase in size as cancellations are now significant enough to define their own CPN. Simultaneously, they still act as indicators that the system is malfunctioning and generating larger delays. Once a tipping point is reached, cancellations become the dominant factor and cause a rapid decrease in size of any DPN (note, again, that this does not imply that delays are disappearing from the system, but that delay causality relationships are). Hence, the shape of a DPN expressed as (% canceled flight, $|\mathcal{E}^D|$) resembles an inverted-V, with the tipping point in the [7, 12]% range.

Admittedly, our final data set only included six (TE, airline) pairs



(a) TE4.



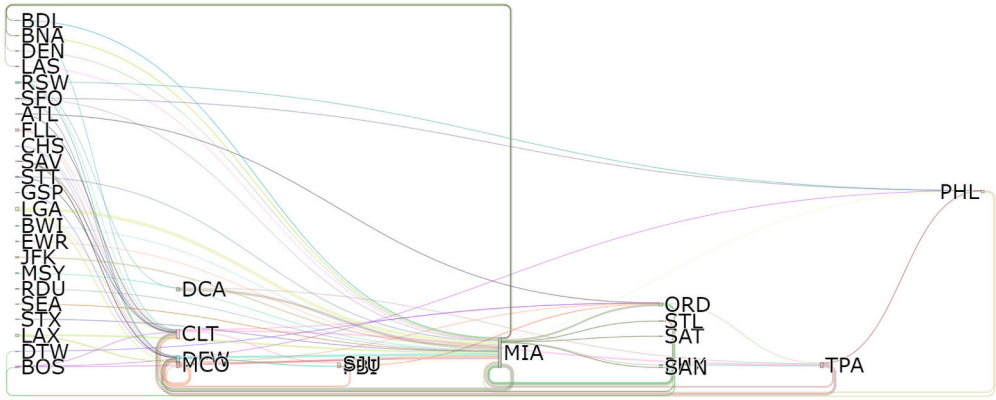
(b) TE5.

Fig. 8. Origin airports in the CPNs of TE4 and TE5 featuring a percentage of canceled flights vs. scheduled flights ≥20% and a number of canceled flights ≥10 towards ATL. ATL is represented with a black square.

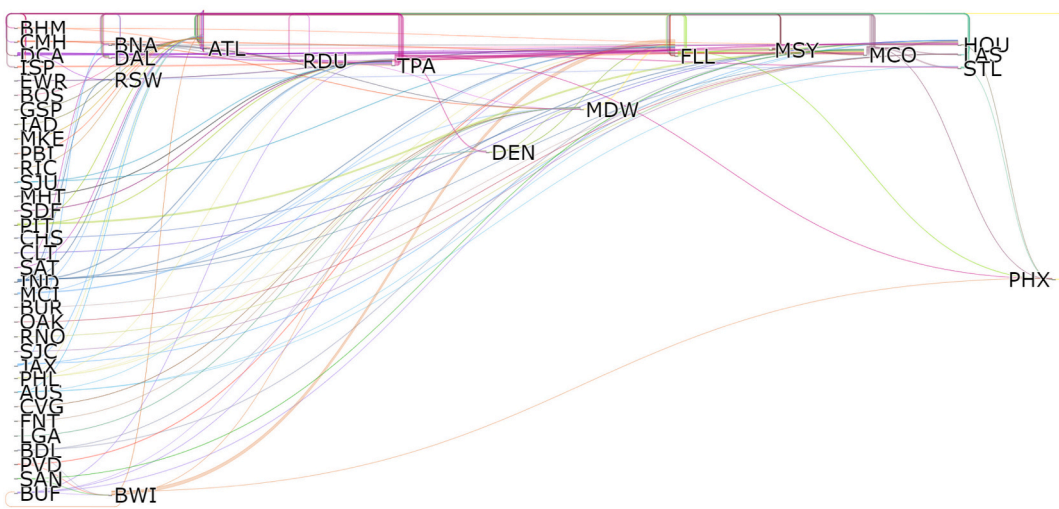
with a number of cancellations large enough to identify significant CPNs to be compared with their associate DPNs. The observations that allowed us to detect the decline of the size of DPNs for a fraction of cancellations above 10% (right-hand side of Fig. 12(a)) involved full-service carriers only. A dataset spanning extreme weather events of multiple years would allow assessing if the inverted V-shaped behavior defining the evolution of the size of a DPN, observed for full-service carriers, can also be observed for low-cost carriers.

6. Discussion and conclusions

The analysis of the baseline case (TE6) gave us insight into the structure of delay propagation networks in a period of (allegedly) normal operations. As the number of canceled flights was low, hardly any cancellation propagation could be observed. The DPN of (TE6, WN) has more nodes and edges than the rest of airlines, reflecting that low-cost carriers have airport networks larger than flag carriers (Lordan et al., 2016). Sankey diagrams revealed that DPNs of full-service carriers are more hierarchical than the DPN of WN. They also revealed bidirectional relationships in the DPNs. This means that a route operating the same aircraft with round-trip flights may accumulate delays that are causally relevant along the day. As a consequence, we can expect that airports triggering delays may have not only outgoing edges, but also incoming edges in the propagation networks. The analysis of main generators, absorbers, and intermediary nodes showed the presence not only of central nodes of the airport network (hubs or main bases), but also of peripheral airports. Delays can have many causes: airline operations, security, weather, or late-arriving aircraft, among others (BTS, 2022b). The complex patterns of delays that emerge can cause some peripheral airports to be central nodes in the DPN. Nevertheless, central airports of airlines have usually a central role in the DPNs as well. The main airports of an airline usually act as absorbers (propagate less delay than they receive) and/or intermediaries (they are in the middle of a path of delay propagations without severely affecting the magnitude of such flow), rather than as generators. This has also been observed in previous DPN analyses (Du et al., 2018). As airlines concentrate more



(a) (TE5, AA)



(b) (TE5, WN)

Fig. 9. Sankey diagrams of cancellation flows for (TE5, AA) and (TE5, WN).

Table 5
Top-5 cancellation generators (𝔾), absorbers (𝔸), and intermediary (𝕀) airports for significant CPNs. In italics, airports located in the zone of event. In bold, main hubs of the airline. In bold and italics, main hubs of the airline that are also located in zone of event.

(TE4, DL)			(TE5, AA)			(TE5, DL)			(TE5, WN)		
𝔾	𝔸	𝕀	𝔾	𝔸	𝕀	𝔾	𝔸	𝕀	𝔾	𝔸	𝕀
MIA	***ATL***	***ATL***	*MCO*	*MIA*	*MIA*	*MIA*	***ATL***	***ATL***	*TPA*	*ATL*	*TPA*
BOS	**DTW**	**DTW**	LGA	**CLT**	**ORD**	*PBI*	JFK	*FLL*	**BWI**	*FLL*	*ATL*
MCO	**MSP**	**SLC**	DCA	**DFW**	**CLT**	*MCO*	**DTW**	JFK	DCA	HOU	MSY
DCA	LGA	LAS	*SJU*	**ORD**	**DFW**	LGA	**MSP**	**DTW**	IND	**DAL**	*RDW*
FLL	**SLC**	MSP	*FLL*	DEN	*TPA*	*JAX*	BOS	*MCO*	*MCO*	**DEN**	*FLL*

resources (aircraft and crew) in their main airports, they can undertake more actions to mitigate delays there than in peripheral airports (AhmadBeygi et al., 2008), as long as these delays are limited.

The first result of the observation of the impact of extreme weather on delay propagation was that the effects are heterogeneous across airlines. The metric which best describes this impact is the proportion of canceled flights. We identified three relevant groups of (TE, airline) pairs:

1. $\leq$ 7% of cancellations: (TE4, AA) and (TE4, WN).
2. [7, 12]% of cancellations: (TE5, DL) and (TE5, WN).
3. $\geq$ 12% of cancellations: (TE5, AA) and (TE4, DL).

The analysis of these combinations shows a pattern of interdependency between DPNs and CPNs. While CPNs grow with the proportion of canceled flights, DPNs shrink for proportions of cancellations in the [7, 12]% interval. For relatively high values of canceled flights, the possibilities of connectivity of airlines decrease severely, thus reducing the number of edges and nodes of the DPN. Medium values of canceled flights allow for larger DPNs, that is, with more nodes and edges. For those networks, propagators tend to be located in the geographical region of the event, while hubs or main airports act as

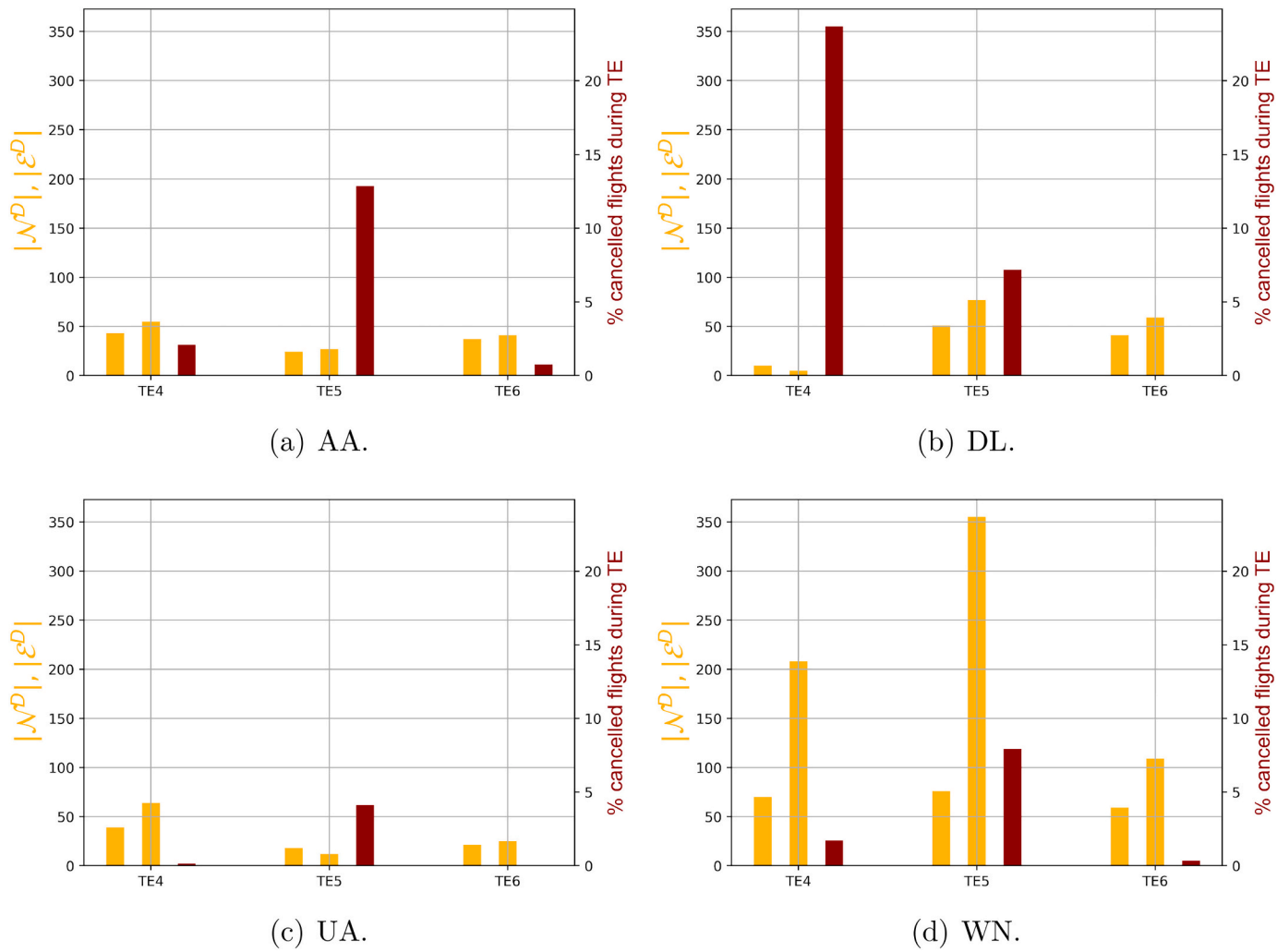


Fig. 10. Number of nodes $\mathscr{N}^{\mathcal{D}}$ and number of edges $\mathscr{E}^{\mathcal{D}}$ of the DPNs (in orange, left y-axis) and percentage of canceled flights (in red, right y-axis) for events TE4, TE5, and TE6. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

absorbers and intermediary nodes.

The events with medium and high percentages of canceled flights allowed us to examine CPNs. They are obtained in an analogous way to delay propagation networks, replacing average hourly delay by hourly number of cancellations. Those networks emerge in major disruptions of air transport, like extreme weather. Cancellations are more related to the disruptive event than delays, so the appearance of high number of cancellations in other regions is the result of propagation effects. Propagated cancellations come from the absence of key resources (aircraft and crew) coming from airports where traffic was disrupted. The four CPNs obtained here prove this, as they show how cancellations starting in the region of the event spread through all US territory. The origin of CPNs is more localized than DPNs: for the (TE4, DL) case a concentration of nodes through the South and East can be observed, and for the events related to TE5 airports located in Puerto Rico, Florida, Georgia, and Alabama are present in the CPN. Like in DPNs, the CPN of the low-cost carrier WN is more homogeneous and more distributed spatially than the ones of AA and DL. Sankey diagrams of CPNs reveal that the main flows pass through hubs, like ATL for DL or through large airports located in the zone of extreme weather, like MIA for AA and FLL for WN. Airports located in the zone of events act as central nodes in the CPN as generators, absorbers of intermediary, with hubs mostly playing the role of cancellation absorbers.

In addition to the contribution of description of propagation patterns in the context of extreme meteorological events, this research has also methodological implications regarding the analysis of propagation networks. Firstly, the heterogeneous behavior across airlines observed for each disruption shows that propagation networks are better modelled as multi-layered networks, as suggested in Zanin (2015). The role of common resources in delay and cancellation propagation (Li and Jing, 2021) calls for examining relationships only in OD pairs where each airline operates direct connections. Finally, the evaluation of causal paths of propagation requires performing a large number of statistical tests. Therefore, researchers need to control for *p*-value inflation limiting the false discovery rate (Benjamini and Yekutieli, 2001).

This research has implications for operational management of airlines. For airlines operating a hub-and-spoke route network, the hubs can act as absorbers of delays in normal conditions (Du et al., 2018). Airlines concentrate most of their resources in those airports, so they can reduce the impact of delays and avoid propagation of cancellations. But those hubs can act as a double-edged sword when extreme events occur. If many flights arrive late at the airport because of late departures, airlines can decide to delay connecting flights, so that the hub switches from being an absorber to being a generator. This is the case in (TE4, DL) and (TE5, DL), where the DL hub ATL is acting as generator of delays. In the case of (TE4, DL), the propagation is reduced because of the large number of cancellations. Additionally, in both (TE4, DL) and (TE5, DL) ATL generates delays, but acts as a cancellation absorber as it can still operate more outbound flights with respect of the many inbound cancellations. As such, the different behavior of ATL in the DPNs and CPNs

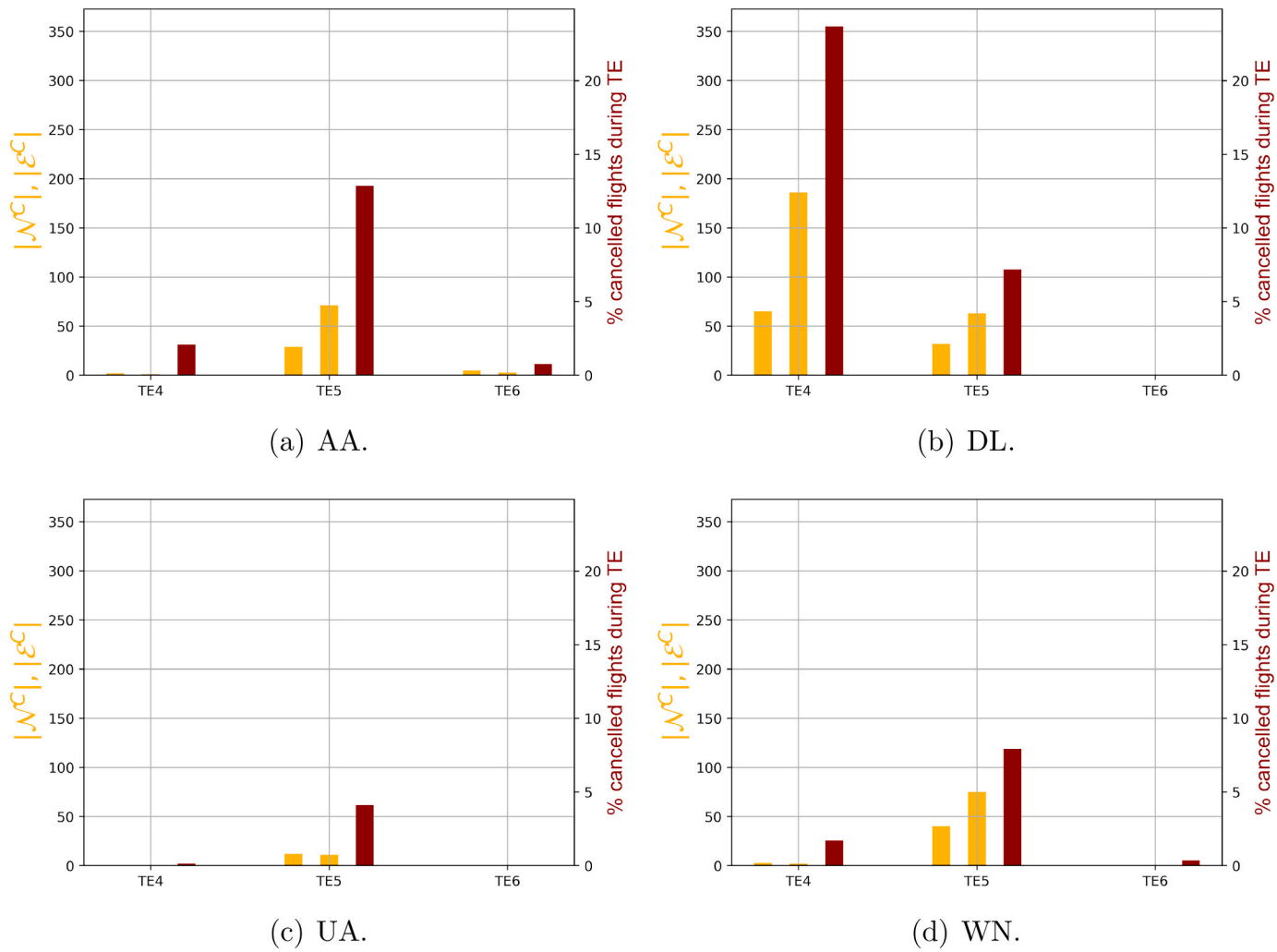


Fig. 11. Number of nodes $\mathscr{N}^{\mathcal{C}}$ and number of edges $\mathscr{E}^{\mathcal{C}}$ of the CPNs (in orange, left y-axis) and percentage of canceled flights (in red, right y-axis) for TE4, TE5, and TE6. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

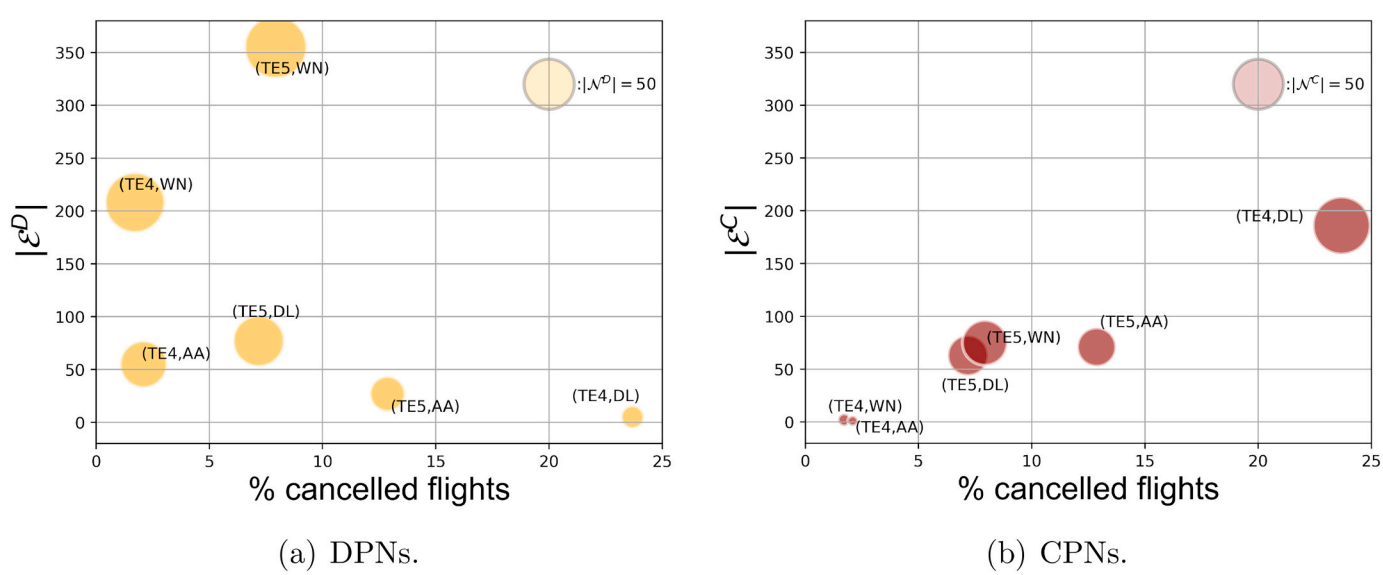


Fig. 12. Comparison between percentage of canceled flights and size of the resulting network for six (TE, airline) pairs of interest.

of (TE4, DL) and (TE5, DL), i.e., a delay generator but a cancellation absorber, is corroborated by its own mega-hub role. On the other hand, airlines operating a point-to-point route network have longer delay propagation patterns scattered all over the US. The damage of airlines adopting point-to-point route networks like WN is more severe in terms of airports and routes affected than hub-and-spoke adopters, even after scaling by nodes and edges of the airport network. These airlines suffer for a more dispersed propagation patterns, although smaller in total volume of delays. As airlines schedule aircraft and crew prioritizing high resource utilization for higher efficiency, they are less able to absorb disruptions (AhmadBeygi et al., 2008). The effect of these disruptions can be mitigated by adopting aircraft and crew scheduling patterns which not only minimize use of resources, but also maximize resilience to air traffic disruptions.

This research was limited by our data, which covered domestic flights in the US during 2017. As we eventually used six data points to highlight the emerging property that links DPNs and CPNs as a function of canceled flights, a larger dataset and data-processing campaign is needed to fully corroborate our findings. In addition, we explicitly focused on extreme weather events. This means that other sources of major disruptions, like air traffic controllers strikes, could not be examined in the current setting. More research is needed about delay and cancellation propagation for those events, which can be substantially different from extreme weather events. Propagation patterns can be different in more fragmented air transport markets like the European airspace or intercontinental flights, where airline alliance members collaborate in offering connecting flights. Additionally, differences in the management of delayed flights by Air Traffic Control between Europe and US (Campanelli et al., 2016) can lead to different delay and cancellation propagation patterns.

The trend towards a higher occurrence of extreme weather events driven by climate change is a call for researchers and practitioners of airline management to define policies to tackle such events, that will be more frequent in the near future. A future line of research can address mitigation techniques like air and ground buffer scheduling (Brueckner et al., 2021) or turnaround and aircraft recovery models (Evler et al., 2022), considering the generator, absorber, and intermediary roles of airports in the disruption propagation networks.

CRediT authorship contribution statement

Alessandro Bombelli: Methodology, Software, Formal analysis, Data curation, Writing – original draft, Visualization. **Jose Maria Sallan:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft.

Declaration of Competing Interest

None.

Data availability

We provide supplementary material in terms of additional analyses here: https://rpubs.com/jmsallan/dpn_cpn_jtg

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Appendix A. Overview of relevant publications addressing delay propagation

Table A.1
Overview of the main previous works addressing flight delay propagation, sorted by publication year.

Reference	Methodology	Geographical focus	Main findings
AhmadBeygi et al. (2008)	Propagation trees	Domestic US	The severity, depth, and magnitude of a single flight delay propagation decrease as the origin time of the root flight increases
Fleurquin et al. (2013)	Agent-based model	Domestic US	Passenger and crew connections most effective single mechanism to induce network congestion
Zanin (2015)	Complex network theory and Transfer Entropy (TE)	Europe	Properties of networks representing a single airline are often lost when a multi-layer representation is built
Campanelli et al. (2016)	Agent-based model	Domestic US and Europe	First Come First Serve (FCFS) performs worse than Air Traffic Flow Management (ATFM) approach in managing flight delays
Du et al. (2018)	Complex network theory and Granger Causality (GC)	Domestic China	Large airports are generally affected by upstream airports but impact fewer downstream airports
Pastorino and Zanin (2021)	Complex network theory, GC, and clustering	Europe	Delay propagation network dominated by triangular routes and large airports
Zanin (2021)	GC and clustering	Europe	Causality clustering approach to group airports based on similar roles in the network rather than based on community structure
Sismanidou et al. (2022)	Neural Network (NN)	Domestic US	The presence of a unique dominant carrier in an airport translates into a stronger correlation between arrival and carrier delays with respect to airports where the market share is more evenly distributed

Appendix B. Airports considered in the study

In Fig. B.1 we show all the airports that were part of the original dataset, excluding Antonio Won Pat airport (GUM) in Guam and Pago Pago International airport (PPG) in American Samoa.

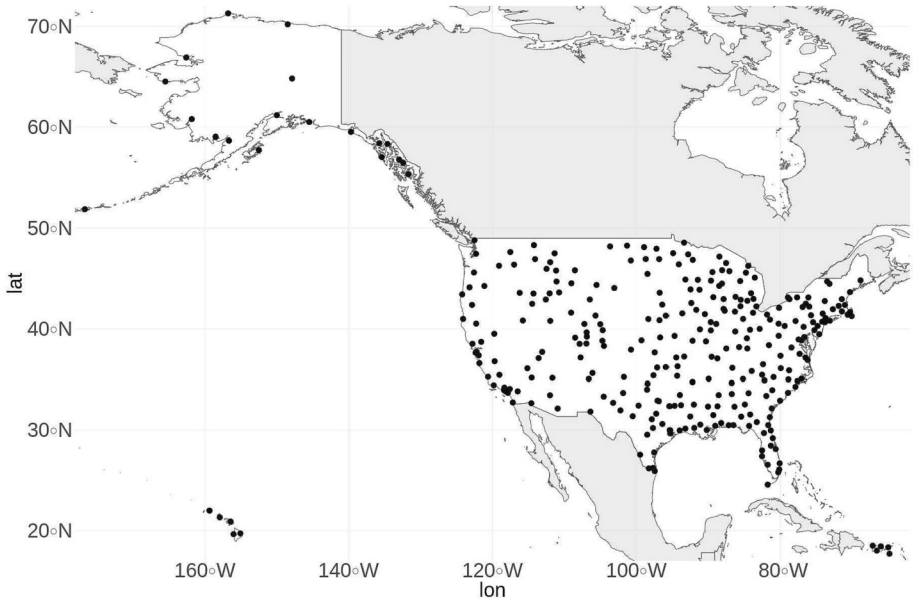


Fig. B.1. US airports included in the analysis (excluding GUM and PPG).

Appendix C. Delay propagation network in the baseline case

The baseline event TE6 represents a week without extreme meteorological events. The DPNs for the four airlines in TE6 are presented in Fig. C.1.

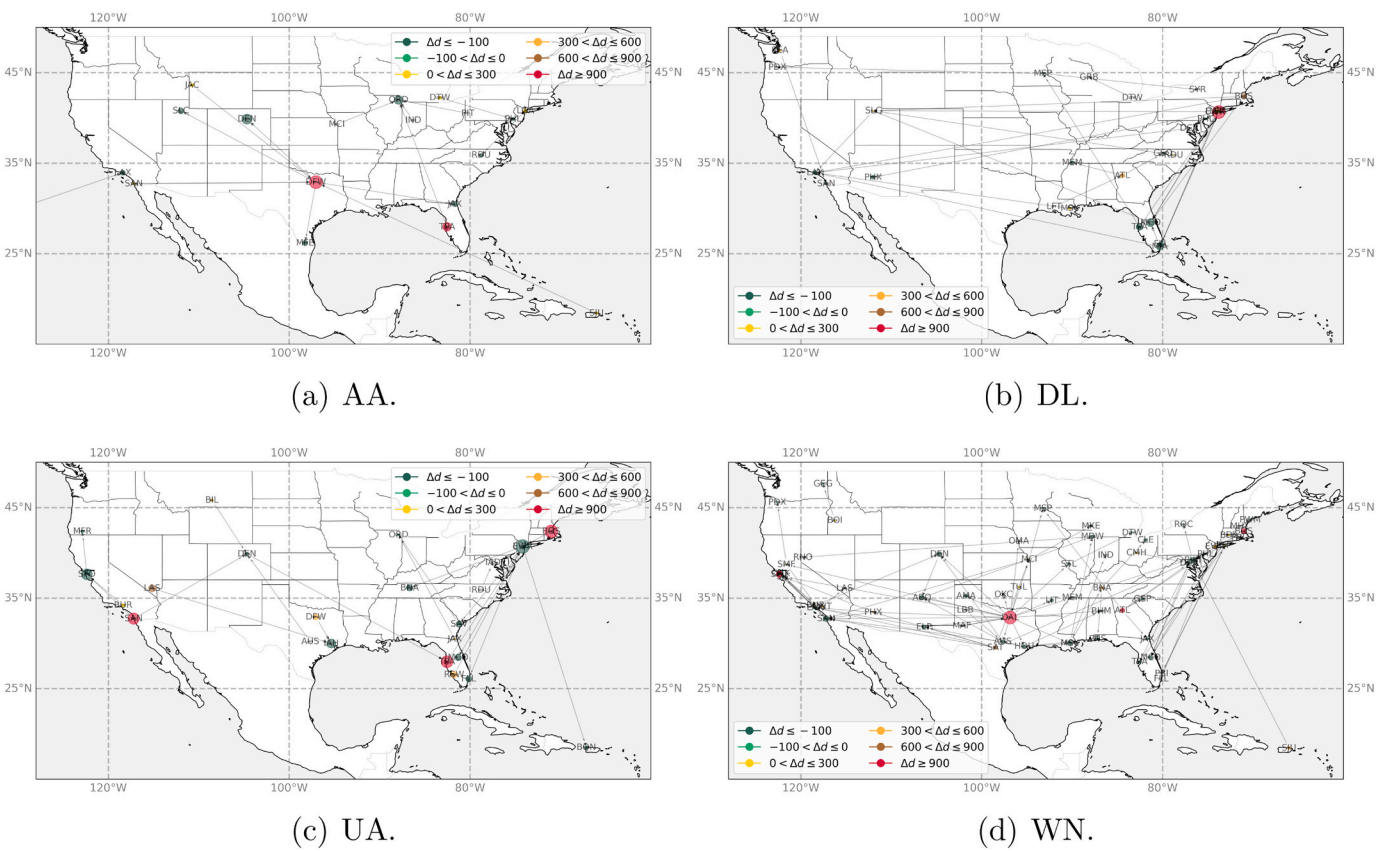
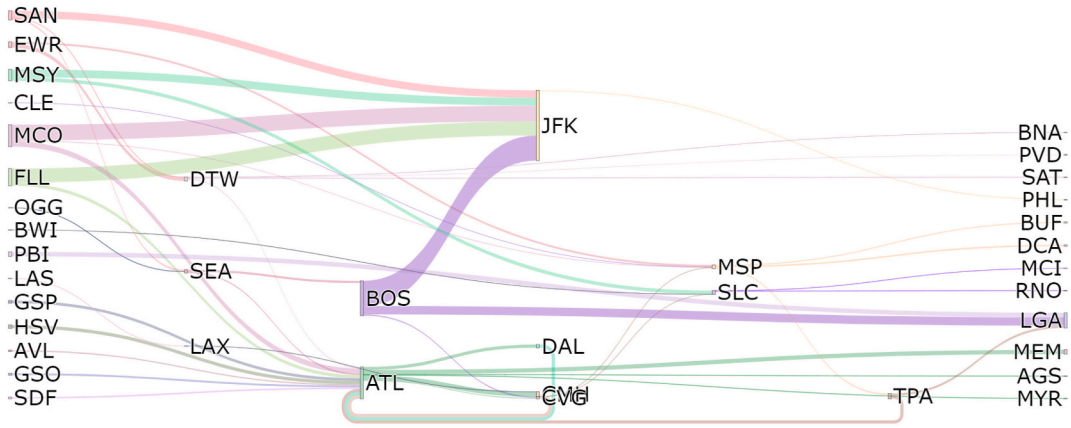


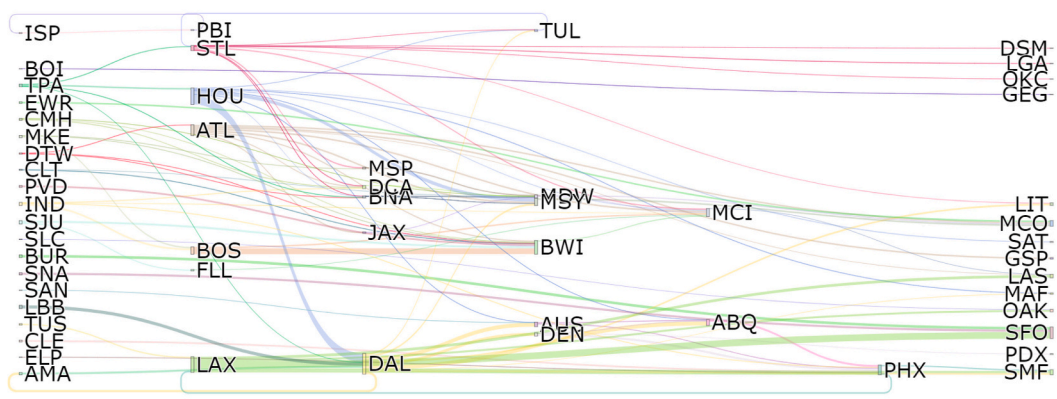
Fig. C.1. DPNs for TE6. Node size is proportional to absolute value of delay.

Although we may expect some relationship between number of flights and delay, large absorbers or generators are not necessarily hubs or bases of the airline. Examining the size (in terms of number of nodes and edges) of the DPNs of the four airlines, we observe that the network of the low-cost WN is larger and sparser than the other three, as there are more edges and nodes than in the other three networks. As WN operates a point-to-point basis, it shows more complex delay propagation patterns than companies operating hub-and-spoke route networks.

The Sankey diagrams of (TE6, DL) and (TE6, WN) point out the differences between the two DPNs. The one of DL is hierarchical, with most intermediary traffic going through JFK (mainly an absorber), BOS (mainly a generator), and ATL which absorbs and generates delays. Meanwhile, the DPN of WN is not only larger, but less hierarchical, as the flow of delays is propagated through more intermediary airports.



(a) DL.



(b) WN.

Fig. C.2. Sankey diagrams of delay flows for some DPNs related to TE6.

We finish the analysis of the baseline event TE6 presenting in Table C.1 the top-5 generators, absorbers, and intermediary nodes of the DPN of each airline.

Table C.1
Top-5 delay generators ($\mathbb{G}$), absorbers ($\mathbb{A}$), and intermediary ($\mathbb{I}$) airports for TE6. In bold, main airports of airline.

AA			DL			UA			WN		
$\mathbb{G}$	$\mathbb{A}$	$\mathbb{I}$	$\mathbb{G}$	$\mathbb{A}$	$\mathbb{I}$	$\mathbb{G}$	$\mathbb{A}$	$\mathbb{I}$	$\mathbb{G}$	$\mathbb{A}$	$\mathbb{I}$
MIA	**DFW**	**CLT**	BOS	JFK	**ATL**	BOS	**EWR**	**IAH**	HOU	**BWI**	**DAL**
BOS	**PHL**	**ORD**	MCO	**ATL**	**MSP**	TPA	**ORD**	EWR	LAX	SFO	PHX
ORD	DCA	RDU	FLL	LGA	CVG	FLL	BDL	BNA	ATL	MCI	STL
IAH	MCO	SJU	MSY	MEM	TPA	PBI	PHX	LAS	**DAL**	PHX	LAX
SNA	BWI	**PHX**	SAN	CMH	DTW	MCO	LAS	**ORD**	BOS	MSY	TUL

With the exceptions of ORD in AA and DAL in WN, hubs or bases tend to be either absorbers or intermediary airports in the DPN. Main airports can act as absorbers of delay propagation because airlines tend to concentrate more resources in those airports, so they have more operational flexibility to smooth delays than secondary airports. If airlines cannot mitigate delay propagation at main airports, those can also act as intermediary nodes in the DPN. This intermediary role is reinforced by the reciprocal flows observed in the Sankey diagrams. Finally, we observe that most of the generators, low rank absorbers, and intermediary nodes do not belong to the top-5 list of airports of each airline. This shows that generation of delays can also be triggered at peripheral nodes of the airport network.

Appendix D. Airport specifications

In Table D.1 we report the specifications of the main airports cited in the paper. Airports are sorted by descending order of enplanements in 2017. The term enplanements refers to the total number of revenue passengers boarding an aircraft in a specific airport, and includes both origin and transfer passengers.

Table D.1
Specifications of the main airports cited in the paper. Adapted from https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/passenger/previous_years.

Airport name	IATA Code	Major cities served	State	Enplanements
Hartsfield-Jackson International Airport	ATL	Atlanta	GA	50,251,964
Los Angeles International Airport	LAX	Los Angeles	CA	41,232,432
O'Hare International Airport	ORD	Chicago	IL	38,593,028
Dallas/Fort Worth International Airport	DFW	Dallas, Ft. Worth	TX	31,816,933
Denver International Airport	DEN	Denver	CO	29,809,097
John F. Kennedy International Airport	JFK	New York City	NY	29,533,154
San Francisco International Airport	SFO	San Francisco	CA	26,900,048
Harry Reid International Airport	LAS	Las Vegas	NV	23,364,393
Seattle-Tacoma International Airport	SEA	Seattle	WA	22,639,124
Charlotte Douglas International Airport	CLT	Charlotte	NC	22,011,251
Newark Liberty International Airport	EWR	Newark, New York City	NJ	21,571,198
Orlando International Airport	MCO	Orlando	FL	21,565,448
Phoenix Sky Harbor International Airport	PHX	Phoenix	AZ	21,185,458
Miami International Airport	MIA	Miami	FL	20,709,225
George Bush Intercontinental Airport	IAH	Houston	TX	19,603,731
Logan International Airport	BOS	Boston	MA	18,759,742
Minneapolis-Saint Paul International Airport	MSP	Minneapolis & Saint Paul	MN	18,409,704
Detroit Metropolitan Airport	DTW	Detroit	MI	17,036,092
Fort Lauderdale-Hollywood International Airport	FLL	Fort Lauderdale	FL	15,817,043
LaGuardia Airport	LGA	New York City	NY	14,614,802
Philadelphia International Airport	PHL	Philadelphia	PA	14,271,243
Baltimore/Washington International Airport	BWI	Baltimore	MD	12,976,554
Salt Lake City International Airport	SLC	Salt Lake City	UT	11,615,954
Washington Dulles International Airport	IAD	Washington, D.C.	VA	11,506,310
San Diego International Airport	SAN	San Diego	CA	11,139,933
Midway International Airport	MDW	Chicago	IL	10,912,074
Tampa International Airport	TPA	Tampa	FL	9,548,580
Dallas Love Field	DAL	Dallas	TX	7,593,361
St Louis Lambert International	STL	St. Louis	MO	7,194,745
Nashville International	BNA	Nashville	TN	6,902,771
William P Hobby	HOU	Houston	TX	6,538,976
Metropolitan Oakland International	OAK	Oakland	CA	6,413,842
Norman Y Mineta San Jose International	SJC	San Jose	CA	6,130,878
Louis Armstrong New Orleans International	MSY	New Orleans	LA	6,022,318
Raleigh-Durham International	RDU	Raleigh, Durham	NC	5,692,659
John Wayne Airport-Orange County	SNA	Anaheim, Irvine	CA	5,082,716
Cleveland-Hopkins International	CLE	Cleveland	OH	4,446,555
San Antonio International	SAT	San Antonio	TX	4,382,127
Southwest Florida International	RSW	Fort Myers	FL	4,364,224
Luis Munoz Marin International	SJU	San Juan	PR	4,203,766
John Glenn Columbus International	CMH	Columbus	OH	3,689,570
Cincinnati/Northern Kentucky	CVG	Greater Cincinnati	OH	3,269,979
Bradley International	BDL	Windsor Locks	CT	3,164,647
Palm Beach International	PBI	West Palm Beach	Fl	3,110,450
Memphis International	MEM	Memphis	TN	2,102,739
Tulsa International	TUL	Tulsa	OK	1,374,424
Dane County Regional-Truax Field	MSN	Madison	WI	943,363
Asheville Regional	AVL	Asheville	NC	478,061

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