ORIGINAL RESEARCH

Flight from COVID-19: Multiscale and Multilayer Analyses of the Epidemic-Induced Network Adaptations

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Abstract

Pandemic waves are worldwide disasters that can create long-term disruptions in critical industries. Airline transportation is a crucial industry for the US economy. We empirically study how vital industries such as airlines adapt in response to massive disasters like COVID-19. This paper investigates the changes in the network of the US domestic flights caused by the start of the COVID-19 epidemic. Using a novel dataset, we examine the epidemic-induced network adaptations in the US airline industry and quantify the strength of the flight network's response to the epidemic network activation. We find that the overall disruption in the flight network is large in size. When considering a natural multilayer structure of the flight network represented by airlines, we find that the COVID-19 epidemic changes the multilayer structure, and some layers are more resilient than others.

Keywords Flight network · Disasters · Multilayer networks · Epidemics on networks · COVID-19

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1 Introduction

Pandemics, including Antonine Plague, Black Death, New World Smallpox, and Spanish Flu, had a significant impact on the course of human history. Pandemic waves are worldwide disasters that can create long-term disruptions in critical industries. Air transportation is a crucial industry for the US economy. We empirically study how vital industries such as airlines adapt in response to massive disasters like COVID-19. The flights conducted by the airlines can be viewed as a network, which allows a deeper understanding of the COVID-19 adaptation in the airlines' operations through the changes in the network size and structure.

In interconnected networks, disruptions in a network can amplify and cause ripple effects, for example, a so-called bullwhip effect [1] in supply chain networks. Despite growing research attention to the network effects [2–7], few studies have looked at the real effects of epidemics on the physical networks, even though epidemic spread can have a clear negative impact on other networks. From its start, the COVID-19 epidemic had a large impact on the university network (with many colleges moving from face-to-face to online education to slow the spread of the virus in a coordinated fashion [8]), the networks of college and professional sports (with basketball tournaments being canceled or changed due to epidemic spread [9]), and the hospital networks (with many healthcare facilities changing their operations in response to national and local COVID-19 dynamics [10]). Arguably, the COVID-19 epidemic spread had a major impact on many socio-economic areas in the USA and worldwide, and air travel was one of the most disrupted [11]. The airline flights form a distinct physical and economic network that serves as a bloodline for professional travel, conference travel, and leisure travel to various destinations.

A significant barrier to developing better models of network adaptations is a lack of real-world data on multilayer networks [12]. We address this challenge by identifying a new application for the initial effects of an epidemic on the multilayer network of flights, for which real data can be obtained. In this paper, we investigate how the start of COVID-19 epidemic in the USA impacted an economic subnetwork of domestic airline flights. How did the response to the epidemic affect the network flows as measured by the flight frequency changes? Specifically, does the arrival of pandemic lead to forced flight drops, and what network layers (i.e., airlines) are the most affected? The airline network is interesting in relation to the epidemic network and spread of COVID-19 because of the potential for interdependence. On the one hand, any travel, including airline travel, could potentially facilitate epidemic spread by quickly seeding new areas. Some people (in particular those who are temporarily out of a job or school or those who are at an increased health risk or are flexible) may decide to temporarily migrate to areas less affected by the epidemic. On the other hand, people may reduce travel to the most affected areas as they become aware of the spread of the epidemic. This could lead to lower demand and the airlines responding to the change in demand by adjusting the frequency of flights offered to those areas. This *potential* interdependence between the epidemic network and the flight network is illustrated in Fig. 1. The figure is produced using available datasets of the US flights and COVID-19 cases.
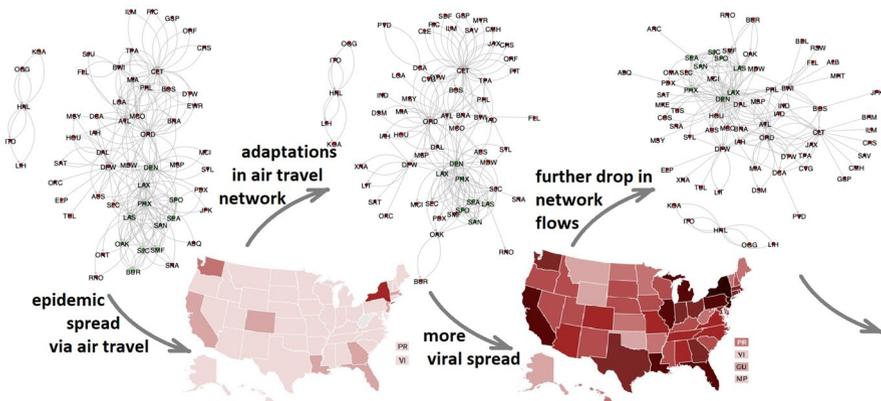
Fig. 1 The ripple effects of the viral activation and the airline network adaptations during the initial months of COVID-19 epidemic community transmission in the USA

Alternatively, one may argue that anti-pandemic interventions such as the strict lockdowns and quarantine restrictions rather than the number of COVID-19 cases drove the travel decisions. The pandemic response by both states and the federal government had an impact on the demand and supply of air travel. Heavily unionized, the airline industry has three different labor unions, namely pilots, flight attendants, and mechanics. Each union, concerned with employee rights, worked with airlines and the federal government to preserve the pay and benefits for the members.

Our paper deals with the ripple effects of the epidemic on the flight network. To better understand these effects, we study the temporal changes in the connectivity and flow of the airline network from immediately before the news reports about COVID-19 to the rise in infections in April 2020. We document the sudden and precipitous drop in the flight frequency from and to different domestic airports in response to acceleration in infection rates and the anti-epidemic interventions. Interestingly, despite the dramatic reduction of flows through the airline network, the network structure formed by unweighted links is disrupted to a much lesser extent. We interpret these findings as evidence of the effect of protective measures to preserve the airline industry.

In this paper, we analyze the response of the flight network to the epidemic, including overall disruption or failures, temporal interaction dynamics, and multilayer responses in the flight network. In particular, we empirically measure the impact of COVID-19 on total flow through the flight network and find the decrease due to the epidemic to be 3 to 5 times larger in magnitude than annual and seasonal increases in recent years. This implies that disruption in the air travel network is economically significant in its size. We also study the impact of the epidemic on the structural properties of the underlying directed graph of the flight network. We find the COVID-19 epidemic decreases the edge weights and the graph density and possibly increases the number of strongly connected components, implying that trimmed connections create stronger interconnected graphs.

Importantly, we zoom in on the early period in activation of the epidemic to understand the development of ripple effects based on what parts of the air travel network fail and what parts survive in those 4 weeks. Finally, we construct a multilayer network with layers given by a specific airline and examine the differences between the hub and non-hub nodes regarding the airlines' response to COVID-19. We find that the impact of COVID-19 appears more significant at the airline hubs for an airline, and some layers are more resilient than others. This suggests that the ripple effects of the pandemic changed the multilayer structure of the air travel network.

2 Literature and Hypotheses Development

This paper establishes a nexus of two important branches of literature, namely failures and adaptations in networks and a viral spread on networks, including the spread of COVID-19. Within the first branch of research, network failures have received more attention than network adaptations. In a seminal paper [2] on failures in interdependent networks, the fundamental property of an interdependent network is defined as the possibility of recursive failures among interdependent nodes on coupled subnetworks. In other words, interconnections among networks allow random or adversary-induced failures in one (sub-)network to cause failures in connected parts of the other network. This mutual connectedness creates fragility [13] that can result in failures propagating through the coupled networks [2, 3, 14, 15].

The literature on failures and adaptations in interdependent and multilayer networks ranges from a general understanding of vulnerabilities in interdependent infrastructure networks [5, 16] to modeling and analysis of failure cascades using random graph theory and statistical mechanics (e.g., see [2, 3]) to the identification of critical network components using stochastic optimization and integer programming problems [6, 7]. A review of the literature on failures in single and interdependent networks may be found in [12]. Our study of airlines' response to COVID adds to this literature by statistically analyzing adaptations of a real-world network at different time scales and multiple network levels. We also contribute to this literature by *empirically measuring* the disruption in the US flight network using novel data.

Impact of COVID-19 on airline network was discussed in [17]; authors have conducted study of airline network dynamics, and found that with raise of COVID-19 cases average degree of airline network decreased, and average node betweenness centrality increased.

The large literature on viral spread on networks includes seminal papers on the spread of computer viruses in scale-free networks [18], susceptible/infected/removed (SIR) models of epidemics [19], and influence maximization on social networks [20–23], along with research on network dismantling [24, 25]. The research on coevolution spreading in complex networks is reviewed in detail in [26]. We share with this literature the coevolving nature of single layer networks of the domestic airline travel in the USA. However, the coevolution examined in this paper is distinct from the prior studies because the evolution dynamics of the subnetworks

are neither purely competing nor purely cooperating. The airline network experiences a contraction as a response to the arrival of the COVID-19 epidemic. Still, local changes in airline travel differ among the flight network layers.

We propose to test the following hypotheses. First, we hypothesize that *the initial response to the epidemic causes overall disruption and edge failures in the flight network*. To put it simply, the lockdowns and quarantine requirements during the epidemic expansion of COVID-19 causes the overall contraction of airline travel. Additionally, the community spread of COVID-19 and the rapid rise in the number of infected should reduce the willingness to travel as travelers face the risk of catching a novel deadly disease. Another potential explanation is that private and public companies may cancel or reduce work-related travel to avoid liability exposure (e.g., many US universities issued policies to reduce international and domestic air travel). Regardless of the precise mechanism between the COVID-19 epidemic and flights, we expect a disruption in the flight network as a response to the epidemic.

Second, the ripple effect of COVID-19 affects different parts of the flight network so that some parts fail and others survive. Hence, we hypothesize that *the resilient parts of the flight network are spatially associated with higher subsequent activation of the epidemic network than the failed parts*. In other words, the infection rates tend to rise in the areas where the high flows of air travel persist at least partially because of an increased likelihood of seeding from the highly infected to the less infected locations which are far away. Alternatively, some parts may stay resilient due to either greater importance for operations of some airlines (and hence protection) or less strict lockdowns and travel restrictions.

Third, we hypothesize that *the multilayer structure of the airline network changes in response to the arrival of the epidemic*. Simply put, hubs and hub-like (i.e., base, focus) airports undergo redistribution of airline flows due to COVID-19. Airlines strategically choose hubs and base airports through which to route their traffic to optimize their operations. When travel demand is high, the airlines based at other hubs can successfully compete for travelers with other airlines by sending more traffic through the hubs of the other airlines. If COVID-19 depresses the demand for air travel and reduces the prices, then the airlines do not compete at hubs of the other airlines that are not their hubs. Hubs are the backbone of an airline, and so a hub would remain highly utilized by an airline based at that particular hub despite reduced demand. Alternatively, if the disruption in demand is large enough that the airlines have to reduce their service dramatically, then the hubs would be the most affected. In case of a large drop in flights, the cuts must come from where the bulk of operations originates.

3 Methodology

3.1 Data

We use a novel dataset to test several hypotheses empirically. This dataset comprises data on all domestic flights in the USA for the first four months in 2018, 2019, and 2020. Having data for the additional years allows us to better identify the impact of

COVID-19-related changes compared to the recent trends in changes in air travel from one consecutive year to another.

We have performed a collection of data from the Bureau of Transport Statistics (https://transtats.bts.gov/). We collected all flights within the USA from January 1, 2020, to April 30, 2020. In total, there were more than 2M flights. For comparison, we also collected US flights for the same period in 2019 and 2018.

3.2 Analyses of Overall Network Impact

First, we examine the changes in the overall network. We construct the overall network of US air travel as follows. We let the *nodes V_t* of the network be given by all the source and destination airports. While the *arcs E_t* of the network are given by all the flights between two different airports. The network nodes and arcs depend on time t, which can be discretized by week, day, or time of the day (e.g., early morning, morning, etc.). For this network, we calculate the *total daily flow* (TDF), the *total weekly flow* (TWF), and total flows for different periods within the day. The total flow measures the aggregate air travel for the entire USA. However, similar measures can be computed for finer geographic units within the USA such as regions (Northeast, Midwest, Southwest, etc.), states (Alabama, Alaska, Arizona, etc.), and counties.

To analyze the changes in the air travel network during the epidemic, we choose 2019 as a baseline year and compare the relative difference in total weekly (or daily) flows for the pandemic year 2020 and for the recent prior year 2018, where the relative difference is taken with respect to the baseline year 2019. We plot the two time series of the differences in the total flows (i) between 2020 and 2019, and (ii) between 2018 and 2019. The comparison shows that without the epidemic, the difference would remain at a steady level. However, as a result of the epidemic, there has been a sharp contraction in total flow through the flight network. We perform similar analyzes for total inflows and outflows by state (as well as by region and by county).

Furthermore, we study the impact on the structure of the network by calculating the symmetric differences in nodes and arcs (i) for the epidemic year (2020) and the baseline (2019), and (ii) for the non-epidemic year (2018) and the baseline (2019). These differences give us the changes in nodes and arcs with respect to the baseline network of 2019. Again, we plot the time series of the numbers of changed nodes and changed arcs, respectively, for 2020 and 2018. The subplots for the changes in nodes and for the changes in arcs once again show dramatic contraction with the rapid community spread of the pandemic in the USA.

Second, we consider a network of the COVID-19 epidemic in the USA. Using the coronavirus data at https://coronavirus.jhu.edu/, we construct the epidemic network as follows. The nodes of the epidemic network can depend on the geographic scale, ranging from the state level to the county level. For medium-coarse spatial resolution, the states S_t serve as the nodes of the epidemic network with pairs of bordering states (for example, NY and NJ) connected by the arcs (S_t^1, S_t^2). Analogously, the network is

constructed for finer spatial resolutions. For coarsest spatial resolution, the nodes are regions with arcs linking neighboring regions. For the finest resolution, the counties are the nodes, and the arcs are given by two counties with a shared border. Using the coronavirus dataset maintained by JHU, we calculate the intensities at the nodes as the infection rates (or alternatively, death rates) per thousand of the population.

We study how the arrival of the COVID-19 pandemic in the USA impacts the flow and the structure of the downstream network of domestic flights. The month of March 2020 marks the beginning of the rapid community spread of COVID-19 in the state of New York, where the first case is identified on March 1, 2020, and the state soon becomes the COVID-19 epicenter in the USA. Therefore, we split the data for *all years* into two subsamples, namely January–February and March–April (or alternatively, April–May). In an econometric interpretation, these subsamples can be viewed as the control and the treatment (*TREAT*) data, respectively. Furthermore, we differentiate between the time before March 2020, and the time on and after March 2020. In econometric terms, the observations up to and including February 2020 are referred to as preceding the event (i.e., *PRE*) and the observations on and after March 2020 are post-event data (i.e., *POST*). Hence, the impact of the initial activation event on the US epidemic network (i.e., the COVID-19 arrival) in March 2020 on the network of flights can be identified by the regressions of the following general form:

$$Y_{jt} = \beta_0 + \beta_1 POST_{jt} + \beta_2 TREAT_{jt} + \beta_3 TREAT_{jt} \times POST_{jt} + \alpha X_j + \varepsilon_{jt}, \quad (1)$$

where index t is time (e.g., date or week), and index j is a component (e.g., a node, an arc, a connected component, an entire graph) of the flight network; Y_{jt} is a dependent variable such as the total flow through network component j at time t or the numbers of nodes or arcs in network component j at time t; β_i, $i = 0, 1, 2, 3$ are real-valued parameters; $POST_{jt}$ is an indicator variable if the data point (j, t) has time $t \geq$ March 1, 2020; $TREAT_{jt}$ is an indicator variable if the data point (j, t) has month $m \in \{\text{March}, \text{April}\}$ (or alternatively $m \in \{\text{April}, \text{May}\}$); X_j is a vector of additional explanatory variables; and ε_{jt} is an error term. Constants α, β_k ($k = 0, 1, 2, 3$) denote regression coefficients. Importantly, the coefficient β_3 in this regression identifies the causal impact of the epidemic activation event on a feature of the network of flights given by the dependent variable Y_{jt}.

Alternatively, to measure the percentage change in the dependent variable Y_{jt} we re-estimate the regressions in the following form:

$$\ln Y_{jt} = \gamma_0 + \gamma_1 POST_{jt} + \gamma_2 TREAT_{jt} + \gamma_3 TREAT_{jt} \times POST_{jt} + \delta X_j + \varepsilon_{jt}, \quad (2)$$

where $TREAT_{jt}, POST_{ij}, X_j, \varepsilon_{jt}$ are defined as above. These variable definitions are used when working with daily data and with intra-day data (e.g., times of the day or hours). Constants δ, γ_k ($k = 0, 1, 2, 3$) denote regression coefficients. Analogously, the coefficient γ_3 in this regression identifies the causal impact of the epidemic arrival on the percentage change in Y_{jt}.

3.3 Multiscale Network Analyses

We examine dynamics in the connectivity of the airline network arising from raise in viral infections, hospitalizations, and deaths. We consider several dimensions of the phenomena by varying the time scale when constructing the networks. Specifically, we aggregate the airline traffic data by week, day (e.g., weekday, or Saturday), and hours (e.g., early morning: 12am–5am, morning: 5am–11am, noon: 11am–1pm, afternoon: 1pm–5pm, early evening: 6pm–9pm, evening: 9pm–12am). The coarser scale of week offers insights into most significant changes to the overall network. While the medium scale allows us to better understand whether differences between weekday and weekend network are erased by the epidemic-induced changes in work-at-home arrangements. Furthermore, the finer timescale of time of the day offers an alternative laboratory for understanding macro and microdynamics of the airline network's reaction to the pandemic.

At scales coarser than daily, such as when data are aggregated by weeks, the econometric approach described in Section 3.2 needs to be modified to allow the application of the difference-in-difference estimation method. Otherwise, the indicator variable *POST* and the interaction term *POST* × *TREAT* are identical. Therefore, in analyses of weekly data, we re-define *POST* differently. Specifically, $POST_{\text{week}}$ is an indicator variable if the observation has its year $y = 2020$ because, in the USA, the COVID-19 epidemic happened during 2020. In other words,

$$POST_{\text{week}} := \mathbf{1}_{\{y=2020\}} = \begin{cases} 1 & y = 2020 \\ 0 & y \neq 2020 \end{cases} \qquad (3)$$

3.4 Multilayer Network Analyses and Dynamics of the Connectivity at the Network Hubs

In addition to our analyses of the COVID-induced contraction of the network at multiple scales, we conduct an investigation of subnetworks by airline name. To do this, we break the airline network into subnetworks by the airline and then combine them together into a multilayer network by overlaying and interconnecting networks through the major airline hubs (e.g., New York City area airports in NY and NJ such as JFK, LGA, EWR; Los Angeles area airports in CA such as LAX; Miami area airports in FL such as MIA; Atlanta (ATL) in GA, etc). This representation of the airline network as a multilayer network allows us to compare and contrast the impact of the epidemic on the network contraction dynamics of individual layers at a given network node. For simplicity, we consider three major domestic airlines in the USA based on scheduled passenger enplanements in 2017–2018 and compare them to the remaining airline traffic. Specifically, we define an airline-aggregated in- and out-degree distributions for a given hub as the incoming or outgoing traffic in a number of flights, respectively, for each major airline servicing the hub area with respect to the total incoming or outgoing traffic of all the other airlines (besides the major three) at the hub.

4 Computational Results

We discuss some computational results. First, we present visual evidence of the network flow dynamics and the changes in degree distributions. Second, we investigate the dynamics of the ripple effects of the epidemic on the flight network. Third, we empirically measure the impact of epidemic spread on the overall network at alternative time scales and present the statistical analyses. Fourth, we study the multilayer network effect and present the visual evidence of the degree distribution dynamics for different layers at the hub and non-hub nodes.

4.1 The Dramatic Decrease in Network Flows and Changes in Degree Distributions of the Overall Network

In this section, we test our first hypothesis about overall disruption in the flight network due to activation and viral spread on the social network. For three 16-week samples of 2018, 2019, and 2020, we compute the daily and weekly flight counts by aggregating flights across all airlines and all airports. The results are displayed in Figs. 2 and 3.

The daily flights figure shows a dramatic decrease between late March and mid-April. The intra-week seasonality that indicates the weaker demand for travel on Saturdays is less pronounced during the onset of the epidemic, as seen in Fig. 2 in late April. The period in March and April shows a a ripple effect of COVID-19 on the overall airline network. When changing in time resolution from daily to weekly, the dynamics of overall network throughput are smoother and show a dramatic and almost linear decrease in network flow from week 13 to week 16 of 2020 as compared to similar weeks in two prior years. Importantly, Figs. 2 and 3 both vividly
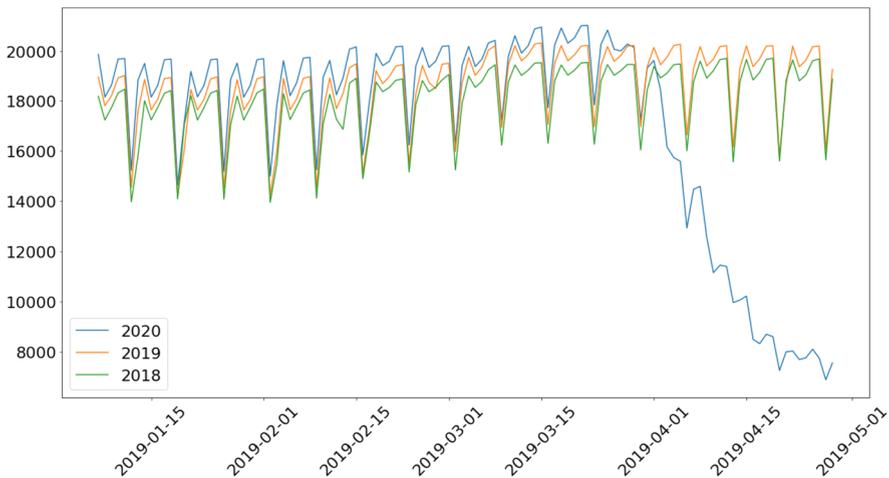
Fig. 2 The total daily flight counts immediately preceding and during the COVID-19 epidemic community transmission in the USA. The 2020 line drops
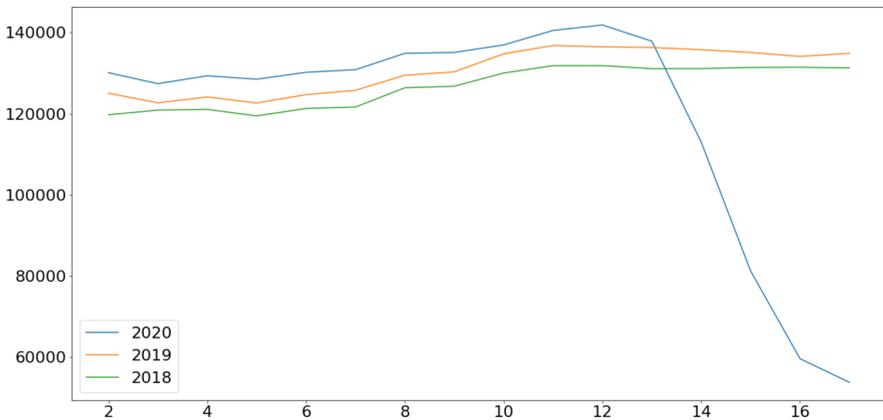
Fig. 3 The total weekly flight counts immediately preceding and during the COVID-19 epidemic community transmission in the USA. The line of the 2020 flight counts exhibits a decrease compared with continuing "parallel trends" for 2018 and 2019

show the parallel trends prior to the response to the community spread of COVID-19 in the USA. The parallel trend assumption is necessary to apply the econometric technique of differences-in-differences [27].

We compute the relative in-degree and out-degree changes as a difference in the number of flights in and out of, respectively, a given airport between week 2 (January 6–12) and week 16 (April 20–26), normalized by the respective total in- and out-degree numbers in week 2. We consider the relative changes to allow for comparison among airport nodes with varying amounts of traffic. Next, we construct histograms for the relative change in the in-degree and the change in the out-degree, shown in Fig. 4. These histograms estimate the distributions of the total inflow and outflow contraction in the airline network during the start of epidemic transmission in the USA. The values of the relative change in in-degree and out-degree on the horizontal

(a) the drop in the network inflows   **(b)** the drop in the network outflows
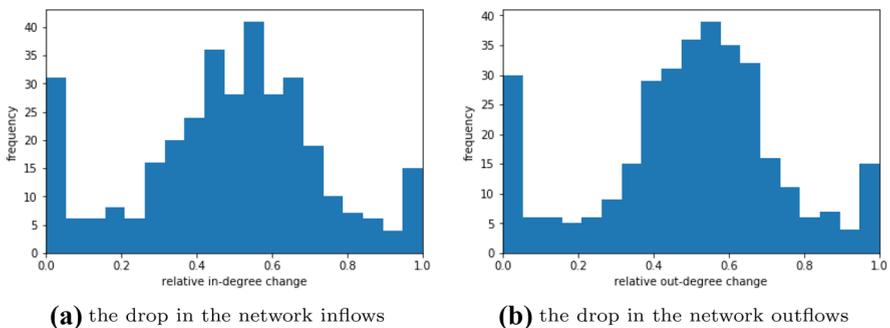
Fig. 4 The empirical distributions or histograms of a relative drop in network inflows (left) and a drop in network outflows (right) between the first full week in January 2020 and the last full week in April 2020

axis range from a zero drop (0.0), which represents no change in directed flow from no community spread to a complete drop (1.0), which denotes a node disconnected from the airline network.

The fact that drops in in-degree and out-degree coincide when the nodes are disconnected is a simple consequence of the fundamental network constraint on the equality between inflows and outflows of any given node. It is noteworthy that although both are trimodal, the distributions of the relative drops in the in- and out-degree are distinct, with the relative in-degree drop having greater variance and being skewed more to the left than the relative out-degree. We interpret this to indicate detectable changes (approximately 40%–65%) in traffic routing due to epidemic onset.

4.2 Dynamics of the COVID-19 Ripple Effects on the Airline Travel Network During the 4 Weeks

In this section, we test the second hypothesis about the spatial association of the resilient (failed) components of the flight network with subsequent higher (lower) activation and viral spread on the epidemic network. After establishing that the node activation and viral spread on the epidemic network result in the degradation of edges on the flight network, we analyze the dynamics of the edge degradation process. This allows us to better understand how the COVID-19 effects propagate through the network of flights. To examine the dynamics of the COVID-19 ripple effects on the flight network, we construct directed graphs of flights for the 4r weeks when a dramatic drop in total flows is observed.

We construct a sequence of flight digraphs as follows. We consider a period from March 30, 2020, to April 26, 2020, that consists of 4 (Monday–Sunday) weeks. These weeks are weeks 14–17 in the 2020 sample. For each week, we build a digraph with nodes given by airports and directed edges represented by direct scheduled flights between source and destination pairs of airports. The edge weights are calculated as the number of scheduled flights. For week 14, we estimate threshold θ of the 95th percentile of all the edge weights. For each week, we drop the edges with weights below this cutoff θ when constructing the respective digraph. Additionally, we find the core of each digraph. Together, the four digraphs represent changes in the most popular routes.

The constructed digraphs are displayed in Fig. 5. The four subfigures show that each digraph consists of two connected components, with the smallest 5-node components representing five major airports in the Hawaiian Islands. In this small component, Honolulu International Airport, Oahu (HNL) serves as the central node with the other four nodes completing the directed star graph. This component remains robust throughout the 4-week plummet of the flight network, which is consistent with the rate of COVID-19 epidemic remaining relatively low in Hawaii.

On the other hand, the large component, which includes mainland airports as its nodes, undergoes a sequence of changes that suggest the ripple effect of the epidemic on the flight network. In fact, the node representing LaGuardia airport (LGA) in Queens, New York is highly connected (e.g., to and from ATL, BOS, CLT, MIA,

(a) Week 14 (March 30 − April 5, 2020)

(b) Week 15 (April 6 − April 12, 2020)

(c) Week 16 (April 13 − April 19, 2020)

(d) Week 17 (April 20 − April 26, 2020)
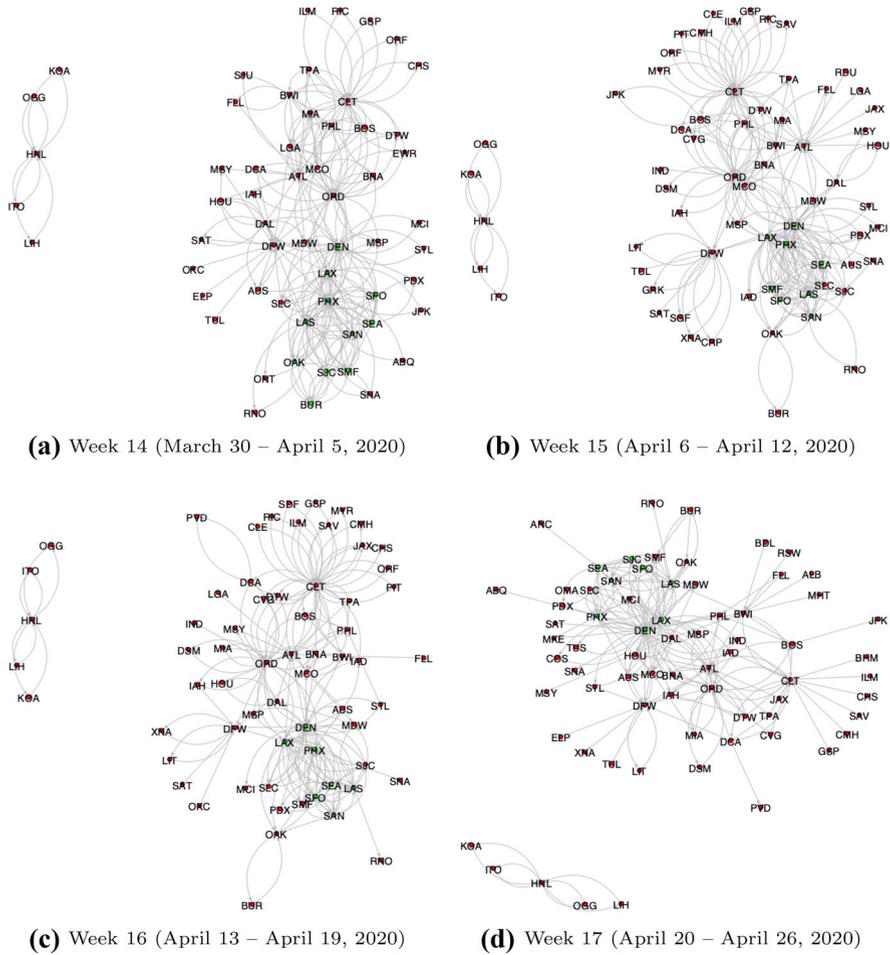
Fig. 5 Adaptations of the flight network due to the COVID-19 epidemic activation in the USA

ORD) in Fig. 5a and becomes loosely connected (to ATL) in Fig. 5b. This shows that the connectivity of the LGA node undergoes significant degradation from week 14 to week 15, as the epidemic rate in New York City (NYC) area has risen dramatically. At the same time, the epidemic rates spiked around the areas close to the airport nodes highly connected to the LGA node, despite their geographical distance from the NYC area, such as the state of Illinois (the ORD node) and Miami-Dade county (the MIA node).

Similarly, the core of the flight digraph both changes in response to COVID-19 and likely facilitates further node activation of the epidemic network. The core originally includes eleven nodes (DEN, LAX, PHX, LAS, SEA, SAN, SFO, SJC, SMF, BUR, and OAK in week 14 shown in green in Fig. 5a) and later shrinks to eight, seven, and eight nodes, respectively (DEN, LAX, PHX, LAS, SEA, SAN,

SFO, SMF in week 15 shown in green in Fig. 5b; DEN, LAX, PHX, LAS, SEA, SAN, SFO in week 16 shown in green in Fig. 5c; DEN, LAX, PHX, LAS, SEA, SAN, SFO, SJC in week 17 shown in green in Fig. 5d). The contraction of the core shows that the nodes in the San Francisco Bay Area, which is greatly affected by the epidemic, become significantly less connected. Furthermore, the part of the core that remains unchanged includes airports in CA, WA, and CO, the states which have developed high epidemic rates in late March and April of 2020. Hence, the persistent high flows in the resilient part of the core may have contributed to seeding new areas in and around Denver, CO from initial COVID-19 epicenters in Seattle, WA and the San Francisco Bay Area.

Next, we produce rank plots for edge weights of the flight network graphs. Each curve in the rank plots represents the weight of each edge for a given week, sorted by its rank. The rank-weight plots help us understand the shape of the edge weight distribution. Both subplots in Fig. 6 suggest that the edge weights exhibit a power-law distribution. As the weeks go by and the COVID-19 epidemic continues, the edge weight values continue to decrease. Still, the power-law nature of the rank-weight function $w = f(r)$ is preserved, and some edges with very large weights remain.

4.3 Overall Contraction of Airline Travel Network: Statistical Analyses of Epidemic Impact for Two Timescales

This section describes additional, formal tests of the first hypothesis about overall disruption and edge failures in the flight network because of activation and viral spread on the social network. Table 1 presents the summary statistics of total flight counts aggregated by day (Panel A) and by week (Panel B) as well as the summary statistics of graph characteristics of the weekly flights (Panel C). Daily data include 112 observations per year in 2018, 2019, and 2020 resulting in 336 observations. The 2020 sample has a much wider range than the two prior years. The 2020 minimum of 6870 flights per day in 2020 about half of the prior years' minimums of 13,950 and 14,201 flights per day in 2018 and 2019, respectively. Weekly data include 16 observations per year in 2018, 2019, and 2020, corresponding to the full

(a) edge weight distributions in odd weeks (Weeks 9, 11, 13, 15, 17 of 2020)

(b) edge weight distributions in all week (Weeks 15–19 of 2020)
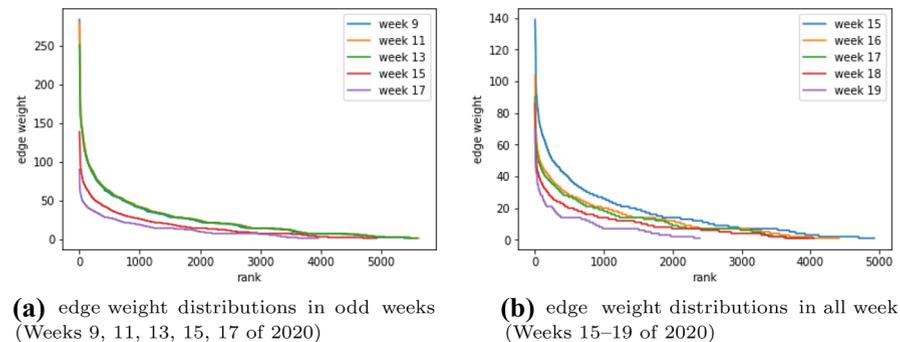
Fig. 6 Edge weight distributions by rank for odd weeks 9–17 and for every week 15–19 due to COVID-19 adaptations of the US flight network

Table 1 Descriptive Statistics

Panel A: Level Data of Total Daily Flight Counts

Sample Period	Obs	Mean	Std.Dev.	Min	Max
Jan 8, 2018–Apr 29, 2018	112	18,100.95	1477.968	13,950	19,709
Jan 7, 2019–Apr 28, 2019	112	18,652.49	1542.638	14,201	20,324
Jan 6, 2020–Apr 26, 2020	112	17,062.77	4170.392	6870	21,021
2018, 2019, 2020 Combined	336	17,938.74	2776.819	6870	21,021

Panel B: Graph-based Characteristics of Weekly Flights Network

Sample Period	Obs	Mean	Std.Dev.	Min	Max
Jan 8, 2018–Apr 29, 2018	16	126,706.6	5105.194	119,450	131,852
Jan 7, 2019–Apr 28, 2019	16	130,567.4	5537.829	122,644	136,829
Jan 6, 2020–Apr 26, 2020	16	119,439.4	28,409.040	53,686	141,886
2018, 2019, 2020 Combined	48	125,571.13	16,968.639	53,686	141,886

Panel C: Graph-based Characteristics of Weekly Flights Network

Sample Period: Jan 8–Apr 29, 2018

Variable	Obs	Mean	Std.Dev.	Min	Max
nodes	16	334.8125	1.641899	332	338
edges	16	5051.063	78.15324	4946	5188
density	16	.0451916	.0004315	.0442399	.0457592
connected components	16	1	0	1	1
strongly con. components	16	2.375	.5	2	3
diameter	16	5	0	5	5

Sample Period: Jan 7–Apr 28, 2019

Variable	Obs	Mean	Std.Dev.	Min	Max
nodes	16	346.5	1.154701	345	349
edges	16	5339.5	75.77862	5243	5450
density	16	.0446019	.000633	.0439223	.0455558
connected components	16	1	0	1	1
strongly con. components	16	1.4375	.5123475	1	2
diameter	16	6	0	6	6

Sample Period: Jan 6–Apr 26, 2020

Variable	Obs	Mean	Std.Dev.	Min	Max
nodes	16	348.6875	3.13515	340	352
edges	16	5286.313	466.1111	3965	5634
density	16	.0435494	.0031973	.0344005	.0461236
connected components	16	1	0	1	1
strongly con. components	16	1.0625	.25	1	2
diameter	16	5.8125	.4031129	5	6

7-day weeks (starting from the second week of a year). Hence, the combined sample consists of 48 observations. Because only the full weeks are used, the average weekly flight counts are seven times the average daily counts. As in the daily data, weekly flight counts have a much wider range in 2020. And the minimum in 2020 is half as small as the minimums in 2018 and 2019.

For each week in the combined sample, we constructed a network with airports as the nodes and direct flights between a pair of airports as the directed edges. The number of direct flights gives the weights of each edge during the week. For each weekly flights network, we compute the following six characteristics: (i) the number of nodes, (ii) the weight of edges, (iii) density, (iv) the number of connected components, (v) the number of strongly connected components, and (vi) diameter. Panel C of Table 1 presents the summary statistics of six graph-based characteristics of the weekly flight network. The number of nodes has a range and a standard deviation that are about twice as large in 2020 than in 2018 and 2019. Both the edge weights and the graph density have a considerably larger range and a much smaller minimum in 2020 than in the other two years. The number of connected components stays at one each year, including 2020. Because of the lack of variation, we exclude this characteristic from regressions. The average number of strongly connected components (SCC) is trending down from 2.38 in 2018 to 1.44 in 2019 to 1.06 in 2020. Interestingly, the standard deviation of SCC is virtually the same in prior years at 0.5 and 0.51 in 2018 and 2019, respectively, but only half of that at 0.25 in 2020. Lastly, the diameter is constant for each prior year (5 in 2018 and 6 in 2019) but varies between 5 and 6 in 2020.

Table 2 reports the results of estimating the impact of the epidemic on overall flows through the flight network using (1) and (2). Panel A of Table 2 shows the differences-in-differences regression (1) for daily and weekly total flight counts. Even though the samples are relatively small (especially the weekly data sample), all coefficients are statistically significant at $p < 0.05$ level or better. The Post coefficients are positive that indicates an increase in airline traffic in 2020 with respect to 2018 and 2019, which is consistent with an observation from Figs. 2 and 3. The daily (weekly) flight counts increased on average by 1631 direct flights per day (6933 flights per week) in 2020 compared to prior years. This increase is attributed to recent economic growth in the airline industry before the epidemic. The Treat coefficients in daily and weekly regressions are also positive because the two spring months tend to have more airline travel than the two winter months during the same year. The total flight numbers increase from winter to spring months by an estimated 1023 flights per day or 9530 flights per week on average. Most importantly, the interaction coefficient of Post×Treat measures the impact of the COVID-19 epidemic. As expected, for both daily and weekly regressions, this coefficient is negative and large. In particular, the total number of flights decreased due to COVID-19 by an estimated 5403 flights per day (3.3 and 5.4 times greater in magnitude than annual and seasonal changes, respectively). The weekly flights decrease due to COVID-19 by an average of 32,261 flights per week, which is about 4.7 and 3.4 times the magnitude of annual and seasonal changes, respectively.

Panel B of Table 2 displays the differences-in-differences regression (2) for daily and weekly total flight counts. The use of a natural logarithm of the total flights

Table 2 The Effects of COVID-19 Epidemic Activity on Flights Network

Panel A: Dep. Variable: Total Flight Counts

	Daily	Weekly
Variables	(1)	(1)
Post	1631***	6933***
	(247.8)	(1276)
Treat	1023***	9530***
	(169.9)	(1019)
Post×Treat	-5403***	-32,261**
	(765.2)	(13,121)
Constant	18,028***	123,872***
	(121.5)	(830.3)
Observations	336	48
R-squared	0.205	0.264

Panel B: Dep. Variable: ln(Total Flight Counts)

	Daily	Weekly
Variables	(2)	(2)
Post	0.0905***	0.0546***
	(0.0130)	(0.00993)
Treat	0.0570***	0.0743***
	(0.00971)	(0.00800)
Post×Treat	-0.379***	-0.330**
	(0.0556)	(0.141)
Constant	9.796***	11.73***
	(0.00713)	(0.00666)
Observations	336	48
R-squared	0.237	0.272

Robust standard errors in parentheses

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

allows us to estimate the percentage changes in total flights. The coefficients are again statistically significant at $p < 0.05$ level or better. The annual increases in flights are 9% daily and 5.5% weekly. The seasonal increases are 5.7% daily and 7.4% weekly. Importantly, the COVID-19-related decreases in daily and weekly total flights are 37.9% and 33%, respectively. This impact is 4.2 to 6.6 times the annual and seasonal changes.

Table 3 reports the results of estimating the impact of COVID-19 on the structural properties of the airline graph using (1) and (2). Panels A and B present the results of the linear and logarithmic model fit for five graph characteristics that have

Table 3 The Effects of the COVID-19 Epidemic on Graph Structure of Flights Network

Panel A: Dep. Variable: Properties of Weekly Flight Graphs

	Nodes	Edges	Density	Str.Conn.Comp.	Diameter
Variables	(1)	(1)	(1)	(1)	(1)
Post	9.778***	290.7***	-8.21e-05	-1.056***	0.500***
	(1.493)	(48.69)	(0.000219)	(0.174)	(0.123)
Treat	1.754	103.5*	0.000436**	-0.341	0
	(2.205)	(56.44)	(0.000210)	(0.239)	(0.186)
Post×Treat	-3.992	-456.3*	-0.00289*	0.484*	-0.429
	(2.770)	(253.6)	(0.00171)	(0.276)	(0.270)
Constant	339.9***	5150***	0.0447***	2.056***	5.500***
	(1.475)	(39.89)	(0.000137)	(0.174)	(0.123)
Observations	48	48	48	48	48
R-squared	0.368	0.158	0.242	0.370	0.154

Panel B: Dep. Variable: The Logarithm of Properties of Weekly Flight Graphs

	Nodes	Edges	Density	Str.Conn.Comp.	Diameter
Variables	(2)	(2)	(2)	(2)	(2)
Post	0.0285***	0.0553***	-0.00182	-0.652***	0.0912***
	(0.00439)	(0.00927)	(0.00490)	(0.0956)	(0.0224)
Treat	0.00515	0.0200*	0.00970**	-0.177	0
	(0.00647)	(0.0108)	(0.00468)	(0.140)	(0.0339)
Post×Treat	-0.0116	-0.0950*	-0.0717*	0.276	-0.0781
	(0.00808)	(0.0524)	(0.0422)	(0.170)	(0.0492)
Constant	5.828***	8.546***	-3.108***	0.652***	1.701***
	(0.00434)	(0.00774)	(0.00305)	(0.0956)	(0.0224)
Observations	48	48	48	48	48
R-squared	0.366	0.157	0.247	0.396	0.154

Robust standard errors in parentheses

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

variation. These characteristics are the number of nodes, the weights of edges, the graph density, the number of strongly connected components, and the diameter. The annual changes are positive and statistically significant at $p < 0.01$ for nodes and edges in both Panels, showing that the airline graph was growing in nodes and edges from year to year in 2018–2020. There is no statistical difference in nodes from two winter months to two spring months in 2018–2020, but the edges increase statistically significantly at $p < 0.1$. Importantly, the decrease due to COVID-19 is statistically significant at $p < 0.1$ level for edges but not for nodes, and is almost twice as large in magnitude as the annual changes. The COVID-19-related decrease in nodes is not statistically significant, implying that most of the initial COVID-19 impact happens due to reduced flights rather than inactive airports. The density increases

from winter to spring and decreases due to COVID-19 slightly less in magnitude than the seasonal change. Even though nodes and edges increase annually, the evidence suggests that the density stays the same (as we cannot reject the null hypothesis of no annual change in density). This suggests that the new flights are added in the sparse areas of the flight network, or to and from the newly added edges. The number of strongly connected components decreases annually and increases due to COVID-19, although the epidemic-related increase is not statistically significant in the logarithmic model. The diameter increased annually in 2018–2020, but the COVID-19 decrease in diameter is not statistically significant.

4.4 Multilayer Analyses: COVID-19 Impact on the Hub and Non-hub Nodes for Three Major Airlines and the Other Airlines

In this section, we test our third hypothesis about changes in the multilayer structure of the flight network in response to the arrival of the COVID-19 epidemic. Here we present visual evidence of the *multilayer network effect* of COVID-19. The flight network can be represented as a multilayer network where each layer is given by flights operated by a specific airline. For simplicity, we construct a network with four layers, namely three layers of three major airlines and a layer representing the flights by all remaining carriers. According to the Federal Aviation Association, three major domestic airlines by the number of enplaned passengers in 2017 and 2018 are Southwest, Delta, and American (with 163.606, 152.029, and 148.181 million passengers in 2018). Therefore, we construct and study the network layers of Southwest (WN), Delta (DL), and American (AA).

We hypothesize that airlines redistribute their flows differently based on whether the airport is a hub or non-hub in response to the community spread of COVID-19 in the USA. In particular, we investigate dynamic changes in the in-degree across layers (i.e., airlines) for a representative sample of eight nodes (i.e., airports) of the multilayer network. This sample is shown in Table 4. The eight airport nodes include airports, which are hubs for different subsets (and combinations) of three major airlines (i.e., all three airlines, two airlines, a single airline,

Table 4 The Representative Sample of Hub and Non-hub Airports for Three Major Domestic Airline Carriers

Airport	American (AA)	Delta (DL)	Southwest (WN)
Los Angeles International (LAX)	hub	hub	base
Miami International (MIA)	hub	–	–
Orlando International (MCO)	–	–	base
Atlanta International (ATL)	–	hub	base
Newark Liberty International (EWR)	–	–	–
John F. Kennedy International (JFK)	hub	hub	–
LaGuardia (LGA)	hub	hub	–
Portland International (PDX)	–	–	–

(a) Newark Liberty Intl. Airport (EWR)   **(b)** Portland Intl. Airport (PDX)
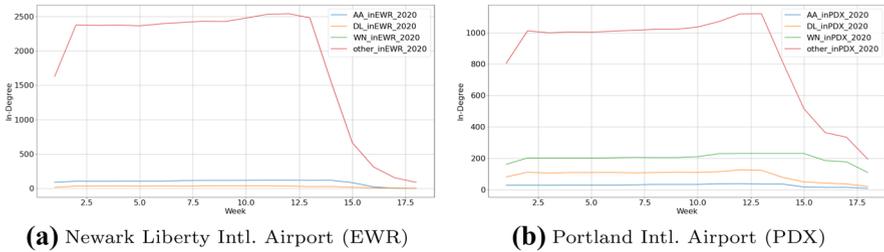
Fig. 7 The weekly flight in-degrees of the airports that are non-hub for three major airlines (AA, American; DL, Delta; WN, Southwest) during 2020

or none of three airlines). Although we do not exhaustively choose all $2^3 = 8$ possible combinations of carriers (AA, DL, WN), we choose two or three airports that are (i) a non-hub (EWR, PDX) of all three airlines, (ii) a hub (MIA, MCO) of a single airline carrier, and (iii) a hub (JFK, LGA, ATL) of two airlines. We also include an airport (LAX) that is a hub for all three airlines. The latter appears to be the only airport that is a hub for all three.

It is worth pointing out a key distinction among the three airline carriers regarding their use of hubs. Unlike its competitors Delta and American, Southwest does

(a) Miami Intl. Airport (MIA),   **(b)** Orlando Intl. Airport (MCO),
an AA hub   a WN "hub"
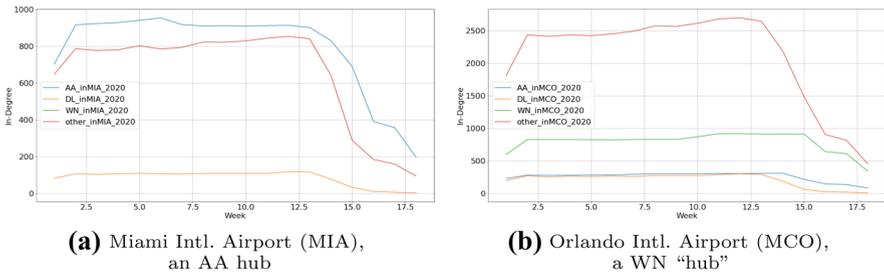
Fig. 8 The weekly flight in-degrees of the airports that are a hub for only one major airline and non-hub for the other two airlines among three major airlines (AA, American; DL, Delta; WN, Southwest) during 2020

(a) John F. Kennedy Intl. Airport   **(b)** LaGuardia Airport (LGA),
(JFK), an AA and DL hub   an AA and DL hub
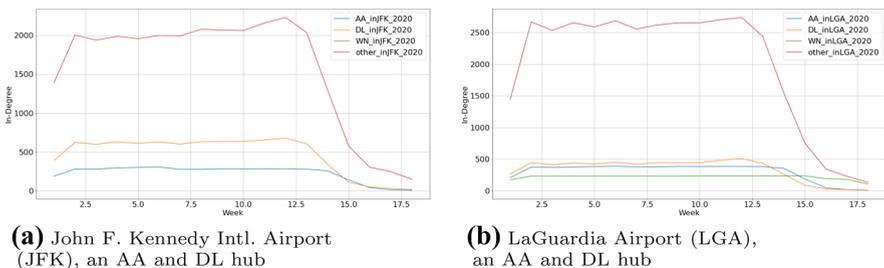
Fig. 9 The weekly flight in-degrees of the airports that are a hub for two major airlines and non-hub for the other airline among three major airlines (AA, American; DL, Delta; WN, Southwest) during 2020

(a) Atlanta Intl. Airport (ATL),
a DL and WN hub

(b) Los Angeles Intl. Airport (LAX),
an AA, DL, and WN hub
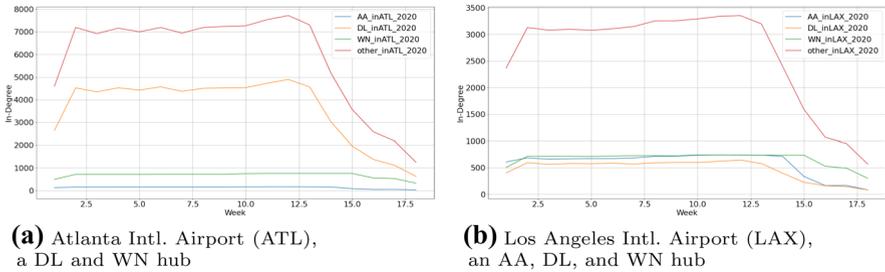
Fig. 10 The weekly flight in-degrees of the ATL airport that is a hub for two major airlines and non-hub for the other airline among three major airlines (AA, American; DL, Delta; WN, Southwest) and the LAX airport that is a hub for all three airlines during 2020

not operate as a hub-and-spoke system. Hence, we use Southwest *bases* as a substitute for a hub or an analog of a hub. Furthermore, Southwest utilizes as bases some alternative airports nearby large hubs like Chicago International (ORD) to reduce its operational costs.

In our analyses, we consider *four network layers* given by Southwest, Delta, American, and the remaining airlines, and *eight nodes with a large in-degree* given by different airports across the USA as described in Table 4. For each layer and each node in this sample, we compute the in-degree of weekly flights during the first 18 weeks of 2020. The results are presented in Figs. 7, 8, 9, and 10. The horizontal axis represents week numbering in 2020, and the vertical axis gives the respective in-degree of a given layer (i.e., the airport inflows of a given airline). The layers are displayed by the respective lines. Some plots have all four layers (i.e., airlines), and others have less than four if a carrier does not serve the analyzed airport. The in-degree in week 1 is lower than other pre-COVID-19 weeks because the first week of the year is not a full week (i.e., it has less than seven weekdays).

Several observations come from the plots in Figs. 7, 8, 9, and 10. First, the epidemic-related drop in the in-degrees of network layers tends to happen sooner for Delta (DL), followed by American (AA), and finally Southwest (WN). This suggests that COVID-19 impacts different network layers at varying times. Second, the magnitude of the epidemic-induced drop in the in-degrees tends to be greater in the layers for which the node is a hub of the respective airline. This suggests that the impact of COVID-19 on airline flows is greatest at the airline hubs. Third, Southwest, with its later and smaller drops in inflows, appears more robust to the initial impact of the COVID-19 epidemic. In the future, it is worth investigating whether the pattern holds in the months after April 2020 and what airline characteristics lead to more robust network layers.

5 Conclusions

In this study, we investigate the disruptions and adaptations in a crucial industry brought on by the start of a worldwide disaster. Specifically, we examine the overall impact and the ripple effects of the first wave of the COVID-19 pandemic on the network of US flights. We collect a novel dataset and combine airline travel and COVID-19 statistics. We identify the COVID-19-induced network contraction and reorganization of inflow and outflow routing. We perform multiscale and multilayer network analyses to better understand the ripple effects of a disaster and the resulting network reorganization. Our study is one of the first to deal with network transformation and contractions due to disaster response to the COVID-19 pandemic. Although we apply this to a particular network, specifically the airline traffic network, the results in our study can be further translated and generalized to other networks vulnerable to pandemics or other massive disasters. In particular, our methodology could be applied to study and compare the ripple effects of different waves of the COVID-19 epidemic on networks in higher education, employment, sports, and supply chains.

Importantly, we quantify the effect that the responses to the first epidemic wave have on overall disruption and edge failures in the coupled network of flights. Specifically, we empirically estimate the magnitude of the negative impact of COVID-19 in the USA on the flight network. We find the COVID-19-related decrease in the daily total flights is 5403 flights per day or 30% of the average of the total daily flights in our sample. The COVID-19-induced decrease in the total weekly flights is 32,261 flights per week or 25.7% of the weekly average flow through the flight network. An alternative estimation using the logarithmic model shows a COVID-19-related decrease in daily and weekly total flights of 37.9% and 33%, respectively. We find the epidemic changes the structure of the flight network, reducing the edge weights by 9.5% and the graph density by 7.2% and increasing the number of strongly connected components by 0.5 on average.

Furthermore, we demonstrate that the resilient parts of the flight network likely can facilitate further epidemic spread. To understand transformations in the multilayer structure of the flight network during the COVID-19 arrival, we examine the multilayer network, where layers are formed by airlines. The evidence suggests that the COVID-19 epidemic affects some layers later than others. For a node that is a hub of a given airline, the in-degree is affected less by COVID-19 in a layer representing the airline. In other words, the layer tends to be more resilient at its hub nodes.

Data Availability This publication is supported by multiple datasets, which are openly available at locations cited in the data section.

Declarations

Conflict of Interest The authors declare no competing interests.

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