Analysis of airline carrier network design strategy

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1 Introduction

The $800 billion (USD) [1] global airline market is serviced by a collection of strategically developed individual carrier networks. The design efficiency of this network in terms of both minimizing cost to customers and robustness of the network to disturbance has significant ramifications on a carrier's viability in the market. Furthermore, the effective growth of a carrier's network is at the epicenter of its ability to capture market share and service new customers.

This work analyzes the networks of major airline carriers in the United States with the goal of understanding the fundamental graph structure that manifested as a consequence of the gradual development of their networks as well as the specific strategies that drove this development. We will investigate the building blocks that comprise these networks by studying motif composition relative to baseline graph structures. Additionally, each individual carrier network will be evaluated for its resilience to disturbances such as airport closures or flight cancellation in the present day and in the context of strategic airline acquisitions and mergers. We will also evaluate subgraph significance and robustness over time to derive insights about the evolution of the strategies pursued by airline carriers.

2 Related work

2.1 Motif analysis

Motifs are small, connected subgraphs found within networks in frequencies much higher than a randomly generated graph. As such, they can be considered the building blocks of larger networks. Motifs were first described by Milo et. al [2] and shown to be present in a diverse set of domains ranging from biochemistry to engineering.

The air transportation network is also composed of these elementary building blocks. Motif analysis of the route network for a single air carrier, Southwest Airlines, was conducted by Agasse-Duval and Lawford [3]. Southwest Airlines is especially interesting as the airline eschewed the hub-and-spoke model of its contemporaries and instead pioneered the point-to-point model. As a result of its motif composition, the study concluded Southwest Airlines' network expressed "small-world" characteristics and was robust to disruption as compared to random networks. This work focused solely on Southwest Airlines and small motifs.

2.2 Robustness

Robustness (also referred to as resilience) of transportation networks is a concern for both economic and public safety reasons. The discipline involved with such analysis is known as resilience engineering, which studies the ability of complex networks to react and adapt to perturbations in their structure [4]. There is a large body of existing work on the resilience of transportation networks [5] [6], but much of it focuses on road and rail networks.

Resilience of the air transportation network was previously studied by Wuellner et. al [7]. Their work concluded airlines like Southwest Airlines were more resilient to a large proportion of airports (nodes) being removed due to their point-to-point routes. However, they do not consider the effect of airline alliances. While other works have evaluated the resilience of alliances upon a member exit [8],

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our work seeks to answer whether alliances are structured to increase the whole network resilience in the case of disturbances.

2.3 Structural evolution

Critical to explaining network structure is an understanding of the evolutionary dynamics and the mechanism by which these structures grow and change over time. This understanding empowers us to explain historical trends in a network and forecast future evolution. This is particularly interesting when the evolution is the consequence of deliberate strategy, as is the case when airlines add routes.

Santoro et. al [9] propose a general approach to study evolution for both atemporal and temporal indicators based on the time varying graph formalism previously introduced in [10]. Of particular interest to our work is the framework for studying atemporal indicators based on sequences of static graphs that cover successive time windows.

3 Data

The Bureau of Transportation Statistics [11], part of the United States Department of Transportation, collects and makes available information on the nation's transportation systems, including the aviation system. We utilize the "Air Carriers: T-100" data set which contains domestic flight data of air carriers operating in the United States. This data set provides information on 37 attributes of the flight records including carrier, origin, destination, number of passengers, quantities of freight, etc.

We focus our static network analysis on 2018, the last full year of data, a collection of 250,355 individual flight records. We pre-processed this data set to remove all flight records having the same origin and destination (sightseeing flights, aerial observation flights, etc.), leaving 249,367 flight records. Including flights with the same origin and destination in the network constructs self-loops in the graph, which has significant implications for the motif analysis we pursue in this work. These remaining records represent 15,660 unique directed flight routes over 1,302 airports for 148 different airline carriers in our network. Table 6 in the Appendix contains a summary of basic statistics for all carriers in our data set.

To perform temporal analysis of the airline transportation network, we acquire the "Air Carriers: T-100" data set for different years and repeat the pre-processing steps outlined above. Specifically, we collect the data for 1992 and for every 3 years thereafter until 2019, allowing us to perform network evolution analysis over nearly three decades. At the time of our analysis, data for 2019 is published through May. We include this year in our temporal analysis out of interest in analyzing the latest available data for trends.

The "Air Carriers: T-100" data set lacks geographic coordinates. To produce geographical visualizations we leverage OpenFlights [12] as a mapping from the International Air Transport Association (IATA) codes in the government data set to latitude and longitude for each airport. We are then able to use the open source geospatial data visualization library Kepler [13] to present our data in Figure 5.

4 Methods

4.1 Graph definition

Borrowing from the structure used in [3], we construct an undirected graph G_U for each individual carrier network and for the aggregate records. G_U has vertices $v_i \in V$ where each vertex represents an airport and edges $e_{ij} \in E_U$ for every unique flight route connecting two airports i and j. This enables us to analyze the basic structure of carrier networks in the United States under similar assumptions as in the work surveyed in our related work section, but we are also interested in extending this analysis to directed edges. To do so, we construct a second graph, G_D, with the same vertices V but with edges $e_{ij} \in E_D$ which are constructed directionally from origin to destination airports.

We also construct a time varying graph as a sequence of static graphs as proposed in [10]. That is, we construct G_U and G_D not only for each individual airline carrier (and the aggregate airline network), but we repeat this for snapshots of the air transportation network representing different time periods. Namely, we use the data from 1992 and every third year thereafter until 2019 to construct separate graphs. This time varying graph formalism allows us to leverage methods used for analyzing static graphs to create a temporal analysis.

4.2 Motif analysis

We aim to build upon the related work and extend it to both larger networks (e.g. the aggregate airline network for all airlines in the United States) and larger subgraph sizes (up to eight nodes). Therefore we require more sophisticated algorithms than the brute force approach applied in [3].

4.2.1 Static motif analysis

We apply the algorithm for subgraph identification discussed in the course lectures: Exact Subgraph Enumeration (ESU). Then, we utilize the Nauty algorithm [14] to test for subgraph isomorphism, enabling us to produce a count of occurrences for each unique subgraph type. This approach enables us to enumerate subgraph counts for small templates comprised of up to 3-nodes for out dataset. However, for larger subgraph templates this algorithm is too slow. In order to analyze larger subgraphs, we apply the publicly available Fast Approximate Subgraph Counting and Enumeration (FASCIA) [15] implementation. After tuning the number of iterations parameter to achieve approximation error $\epsilon = 0.1$ with confidence $\delta = 0.9$ we are able to feasibly compute the frequencies of subgraphs with up to 8-nodes for our carrier networks and the aggregate network via this algorithm.

Intuitively, the directionality of edges appears to be a critical element of the structure of airline carrier networks. Surprisingly, we found meaningful justification for conducting motif analysis on only undirected, non-induced graphs. Namely, as identified in [3], the vast majority of directed edges in airline networks are complemented by a reciprocal edge (i.e., most flights are complemented by a return flight). With this in mind, we elected to perform directed and undirected motif analysis for small templates (2-3 node subgraphs) with the ESU algorithm, whereas we perform only undirected motif analysis on larger templates (4-8 node subgraphs) with the FASCIA algorithm. Our motivation for leveraging this justification is derived from two important facts: (1) the ESU algorithm is not computationally feasible for the larger subgraph sizes considered in our work and (2) the publicly available FASCIA implementation supports only undirected, tree-like, non-induced subgraphs (note that while the color coding algorithm theoretically allows for directed templates and networks [16], the implementation of FASCIA made available by the authors currently only supports undirected subgraphs [15]). Finally, we argue that the enumeration of non-induced subgraphs is meaningful because real-world networks like ours often include spurious edges (e.g. flights not part of regularly scheduled offerings, emergency landings) which may considerably alter induced subgraph analysis. Non-induced subgraph counts are more robust to these data inconsistencies [15].

To determine whether a subgraph qualifies as a motif we require baseline expected values for the counts. To generate these baselines we construct networks from a random graph model with the same number of nodes, edges, and degree distribution as the network of the carrier under examination. We accomplish this using the configuration model. We construct many instances of random graphs and compute significance values (Z) relative to these baselines for the carrier's network, informing us whether a particular subgraph i is over- or under-represented in the network, using $Z_i = \frac{N_i^{\text{real}} - \bar{N}_i^{\text{rand}}}{\text{std}\left(N_i^{\text{rand}}\right)}$.

4.2.2 Temporal motif analysis

Our work also evaluates changes in the structure of the aviation network over time. Legacy carriers cemented the hub-and-spoke model, which is represented as a small number of central nodes ("hubs"), each connected to a large number of peripheral nodes ("spokes"). Recently, legacy carriers and the hub-and-spoke model have seen their popularity wane in favor of the low-cost carriers and their point-to-point model [17], which instead promotes direct pairwise links between major cities ("points"). We aim to understand the results of this transformation.

To perform temporal motif analysis we run experiments over a sequence of static graphs. We focus our attention on the application of the FASCIA algorithm and compute the approximate subgraph significance values for all 3- to 8-node templates. This allows us to capture the significance of each subgraph in each carrier network over time under the increased compute constraints. Given that airlines have evolved through deliberate strategy, this investigation reveals which particular subgraphs an airline has concerted an effort to construct and whether subgraph composition has evolved over the last three decades of growth alongside the hub-and-spoke to point-to-point transition.

4.3 Robustness

Our goal is to evaluate the health of the network in the face of disruptions. We employ a metric, which we term "relative travel time" (RTT), to compare characteristics of a network after a disruption relative to its non-disrupted state. RTT was previously introduced as resilience by Wuellner [7].

First, we must approximate travel time for every path between any two nodes i and j: $d_{ij}/v + m\theta$, where d_{ij} is the summed geographic distances, $v = 500.0$ is a characteristic airplane velocity, m is the number of hops, and $\theta = 1.0$ is the layover cost in hours. Where two nodes (airports) are connected directly by an edge (direct flight), travel time is proportional to great circle distance between the airports. For indirect flights, this measure adds θ layover time for each hop in the path.

After calculating travel time for each path, we run Dijkstra's algorithm [18] to find the optimal path between any two nodes i and j, $t_{ij} = min\,\{d_{ij}/v + m\theta|\text{path between i,j}|\}$. By first defining travel time and then computing the optimal path, we find the shortest travel time between two nodes rather than just the shortest geographic distance. We then determine the total travel time for a graph G across a set of nodes M, $T_G(M) = \frac{1}{2}\sum_i \sum_j t_{ij}$.

To model disruptions, we remove some node and its adjacent edges from the network using a strategy S to create an altered graph $G^A(N^A, E^A)$. Strategies evaluated include targeted removal of high-degree nodes (simulating geopolitical events) and random removal of nodes (simulating environmental events). After removal, travel time across the entire network may be infinite due to newly disconnected nodes. Therefore, we consider only the travel time between nodes in the largest connected component C of the altered network. Finally, we define $RTT(G, G^A, C) = \frac{T_{G^A}(C)}{T_G(C)}$. Intuitively, RTT is the ratio of the total travel time across the disrupted network and the total travel time across the fully functioning network.

4.3.1 Historical Analysis

Historical analysis of airline network robustness was also conducted to discover the existence of any trends. We calculated robustness under both targeted and random disruption starting in 1992 and every three years thereafter until 2019.

4.3.2 Merger Analysis

While prior work has investigated the robustness of individual airline networks, there has been little investigation into the robustness of airline alliances. Unfortunately, this sort of analysis is impractical for the United States domestic market as no two major airlines share an alliance.

Therefore, in order to model the impact to robustness of allied networks we instead investigated the effect of airline mergers in the United States. Mergers are similar to alliances in that stakeholders of two companies, each with their own network, must evaluate the benefits of combining networks. Regulators and customers, in particular, are concerned about the robustness of the combined network. The period from 2008-2016 saw mergers and acquisitions by almost all of the top US airlines [19] and therefore provides a recent reference over which we can evaluate robustness. The mergers investigated are outlined in Table 1.

Acquiring Airline	Acquired Airline	Year Announced	Year Closed
Delta Air Lines Inc.	Northwest Airlines Inc.	2008	2010
United Air Lines Inc.	Continental Air Lines Inc.	2010	2012
American Airlines Inc.	US Airways Inc.	2013	2016

Table 1: Significant mergers in the US domestic aviation industry between 2008-2016

For each merger, we compute RTT of the component airlines in the year of the announcement of the merger and then again in the first year where airlines began reporting jointly. By choosing the year of announcement, rather than any of the years between announcement and completion of the merger, we gain insight into the shape of the networks at the time of the decision to merge. As networks are strategically formed, this models the information available to stakeholders deciding on the merger.

5 Results

5.1 General network structure

As a preliminary survey of our data and analysis of the prevalent graph structure we focus on two particularly interesting carrier networks as well as the aggregate network. The two carriers of interest are Southwest Airlines and Federal Express Corporation (FedEx). We begin our analysis with these particular carriers because of their remarkable structure, the former being the largest network in terms of number of distinct routes and the latter being the largest non-charter network in terms of airport coverage, as identified in Table 6 in the Appendix.

5.1.1 Static network analysis

Immediately apparent from our analysis of these two carrier networks is a significant difference in structure. As identified in [3], Southwest Airlines resembles a point-to-point network. This can be seen in the visualization of the graph in Figure 6. This figure conveys that the nodes are extremely well embedded in the network, having high degree and linking to many other nodes. On the other hand, we can see in Figure 7 that the FedEx network strongly resembles a hub-and-spoke model with few extremely well connected nodes that hold the graph together and connect other destinations. This seems intuitive when we consider the business models of these two carriers: Southwest Airlines is optimizing an objective function focused around getting passengers where they need to go quickly, and FedEx is focused on supply chain optimization for the collection and redistribution of packages.

5.1.2 Temporal network analysis

In order to frame our temporal analysis of individual airlines, we also performed temporal analysis on the aggregate air traffic network. Specifically, we calculated the number of nodes, the number of edges, the modularity, and the clustering coefficient on the aggregate network from the years 2008-2018. The results are documented in Table 2.

Year	# Nodes	# Edges	Density	Clustering	Modularity
2008	1199	16944	0.011796	0.499391	0.317652
2009	1207	16272	0.011179	0.502489	0.328693
2010	1228	16746	0.011114	0.507665	0.334236
2011	1245	15905	0.010269	0.500933	0.334759
2012	1208	15155	0.010394	0.528052	0.343679
2013	1170	14356	0.010496	0.513814	0.339830
2014	1186	14843	0.010561	0.526332	0.339516
2015	1228	14989	0.009948	0.505985	0.341596
2016	1236	14991	0.009821	0.506445	0.327037
2017	1268	15527	0.009665	0.514674	0.326025
2018	1302	15660	0.009245	0.515963	0.335715

Table 2: Temporal statistics on the US domestic aviation network

We can see that while the number of airports has increased marginally, the number of routes has actually decreased. While the density of this graph is understandably low (most airports are not directly connected to most other airports), we see an observable drop in density in the network over time. Meanwhile, both clustering and modularity have trended up over time (with peaks in 2012). We observe that the peaks in clustering and modularity immediately follow the mergers outlined in Table 1, as mergers result in new hubs absorbed from the acquired airline and increased concentration in existing hubs due to routes from the acquired airline.

5.2 Motif analysis

5.2.1 Static motif analysis

For our motif composition analysis we present the results for Southwest Airlines, FedEx, and the aggregate airline carrier network (AGGREGATE). We highlight the key results below, but a full summary of subgraph counts and significance values for these select carriers as produced by the ESU algorithm for small templates is shown in Table 4 for undirected subgraphs and Table 5 for directed subgraphs. For significance values produced by the FASCIA algorithm for the same carriers using larger 3- to 8- node templates see Figure 1.

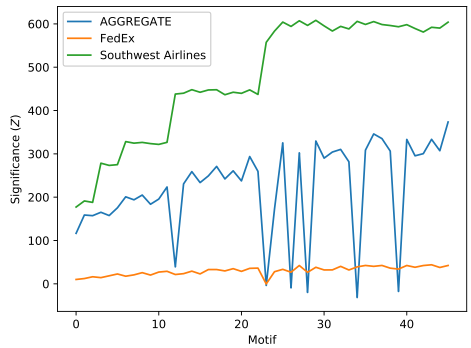
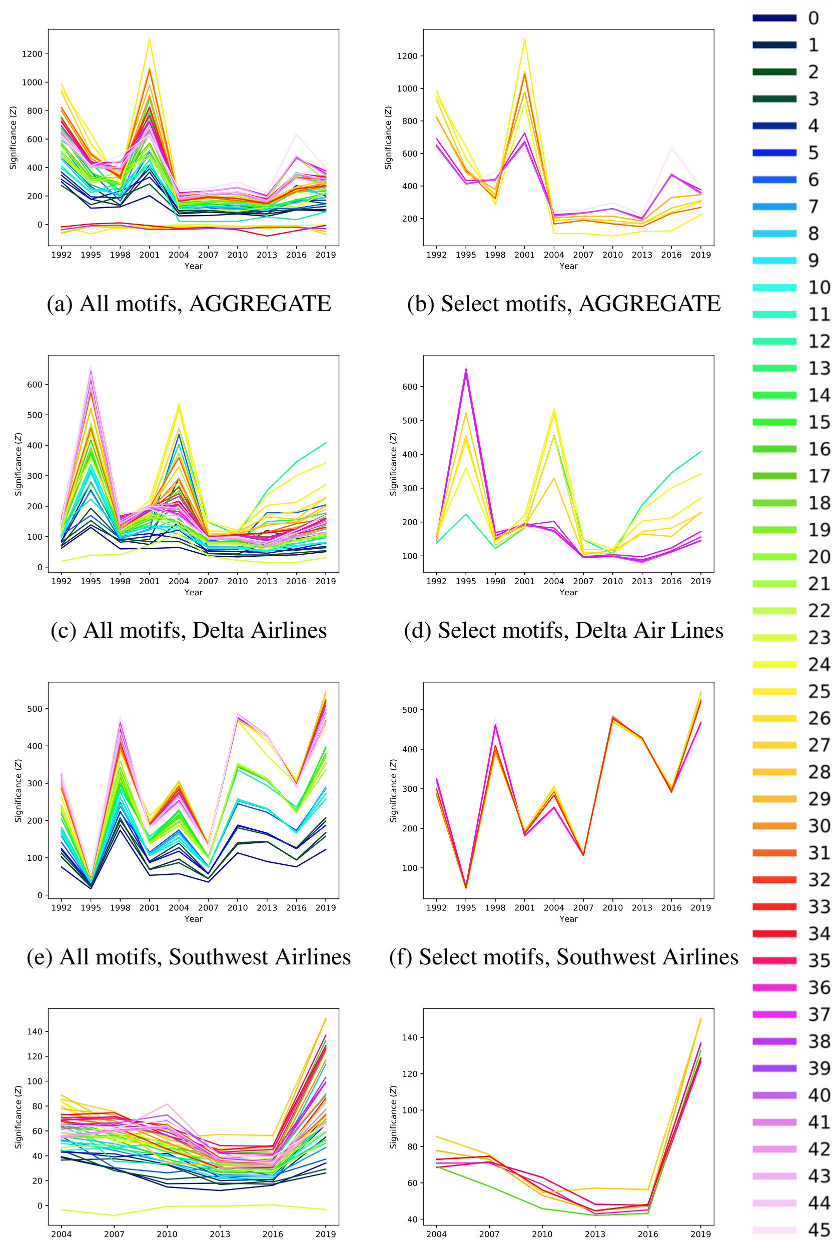


Figure 1: Subgraph significance values for all tree-like, non-induced subgraphs of size 3-8 nodes. For the mapping from motif ID to graph structure see Table 3 in the Appendix.

Unsurprisingly, we can see from Tables 4 and 5 that the highest significance subgraphs in the Southwest Airlines network for 2- and 3- nodes are the most tightly connected subgraphs minimizing the number of edges between any two nodes (e.g. complete connected triangles). This is in agreement with related work that suggests the Southwest Airlines network represents a point-to-point model, as the connected structure observed corresponds to direct point-to-point flights between many cities. The FedEx network, however, tells a different story. In this case, the most frequent subgraph is by far the bi-directional chain structure, with extremely high significance. Interestingly, however, it is not the most significant subgraph. In this case, the fully connected subgraph of three nodes in which all directed edges exist is again the most significant subgraph. This is because in the random graph models generated for this network this subgraph never occurred. This is explainable by the large increase in nodes and even larger decrease in edge count compared to the Southwest Airlines network. On inspection of the network (see Figure 7), the chain and star structure appears to be a key design element of the network and in agreement with a hub-and-spoke model. From this analysis we begin to see the topological implications of the FedEx network hub-and-spoke strategy as compared to a point-to-point strategy like Southwest Airlines.

From Figure 1 we can see that Southwest Airlines has interesting motif composition for larger templates. There is a large collection of motifs with high significance, some of which portray chains (e.g. 45, 36) whereas others suggest central nodes (e.g. 24, 27). However, we find the high significance of motifs 26, 28, 34, and 39 to be the most interesting takeaway. This is remarkable because: (1) these do not obviously reflect the point-to-point model which Southwest ostensibly pioneered and (2) from the same plot we note that these four subgraphs are by far the most under-represented in the aggregate airline transportation network. Thus, we observe that these unique subgraphs are critical to Southwest Airlines network but are extremely scarce in all other airline carrier networks. From inspection, we notice that they have interesting structure that combines elements of both hub-and-spoke (nodes that are central) and point-to-point (chains of nodes). Consequently, we coin the term “weak hubs" for these peculiar subgraphs. The explanation of their significance in only Southwest Airlines is simple but unclear until a temporal analysis of the network is performed, and so we defer expounding this finding until section 5.2.2.

It is less straightforward to draw concise conclusions about motif composition for FedEx from this plot. The significance curve is markedly less striking than that of Southwest as the significance values are more stable and less extreme than in Southwest's network. The most significant motifs, albeit only marginally, are those with ids 43, 37, and 35. Interestingly, all of these motifs can be characterized as having a single well embedded node (hub) with spokes longer than a single node (tendrils). This finding is highly intuitive. However, we were very surprised to find that motif 23 is by far the most under-represented, as intuitively we would expect this star-shape to be highly indicative of the hub-and-spoke model. From this, we conclude that tendrils are actually a critical component of the hub-and-spoke model. Not only are there key hubs that fundamentally connect the network, but nodes that directly connect to the hub are leveraged to a great extent to span to distant airports.



(a) All motifs, AGGREGATE (b) Select motifs, AGGREGATE

(c) All motifs, Delta Airlines (d) Select motifs, Delta Air Lines

(e) All motifs, Southwest Airlines (f) Select motifs, Southwest Airlines

(g) All motifs, FedEx (h) Select motifs, FedEx

Figure 2: Motif significance values over time as produced by FASCIA. Figures on the left are visualizations of significance values for all 3- to 8-node motifs. Figures on the right are visualizations of significance values for the set of 5 most significant motifs from each of the earliest and latest available dates considered. For the mapping from motif ID to graph see Table 3 in the Appendix.

5.2.2 Temporal motif analysis

In our temporal analysis we visualize four networks: Delta Airlines, Southwest Airlines, FedEx, and the aggregate airline carrier network (AGGREGATE) as a representative set of the patterns we uncover in the data. Visualizations of the motif significance values as produced by running the FASCIA algorithm over our time varying graph are shown in Figure 2.

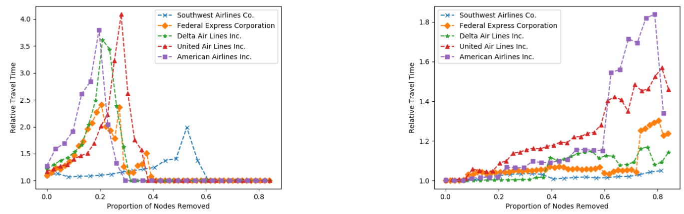
From Figure 2 we can draw several interesting conclusions. The first and most striking observation can be easily spotted in subplots (a) and (b): the overall airline carrier network composition has evolved dramatically over time. This is so much the case that of the five most significant motifs in the aggregate airline carrier network from 1992, only a single one of these motifs (the fourth most significant) appears in the five most significant motifs of the 2019 aggregate airline carrier network (the fifth most significant). This demonstrates that the shape of the US airline carrier network has evolved beyond just scaling to meet demand: it has flexed to adjust to market conditions by fundamentally changing network characteristics. Specifically, the most significant motifs to the aggregate airline carrier network (motifs 24 and 25) very strongly resemble star shape (hub-and-spoke) subgraphs as identified in Table 3. By the year 2019 the most significant motifs (45 and 36) look very different: chain-like structures. This directly demonstrates that the aggregate airline carrier network has transitioned away from the hub-and-spoke model over time. Recalling that the publicly available FASCIA implementation is designed for undirected, non-induced, tree-like subgraphs, we point out that of all the subgraphs enumerated, these chain-like subgraphs most frequent in recent years are in fact most similar to a point-to-point network.

In addition to observing that the aggregate airline carrier network has evolved, we can clearly detect the transformation of individual carrier networks. Visualizations of Delta Airlines' motif composition over time in Figure 2 (c) - (d) is a clear example of this, but it is also captured in the networks for Alaskan Airlines, Hawaiian Airlines, United Parcel Service, and several others. Throughout the 27 year period, three different motifs assume the position of most significant motif in Delta Airlines' network. In 1995 the most significant motif is a chain structure corresponding to motif 45, whereas during 2001-2010 this motif takes a backseat to the more significant star-like structure of motif 24. Then, in more recent years, motif 12 takes the top spot – a motif that is very similar to 24 but eschews the single tendril. This suggests that Delta Airlines has actually doubled-down on the strategy of the hub-and-spoke model. We find external validation of this observation: for example, a 2014 announcement from Delta Airlines that it would invest in the development of a Seattle hub [20]. Thus, our motif analysis has correctly captured the overall trends of specific airline carrier networks.

Finally, while we find convincing evidence that some airlines have evolved their networks, this was not the case for all carriers. Some airlines retained a structure consistent with their original strategy. In this visualization we elected Southwest Airlines and FedEx to represent this behavior for consistency with analyses presented elsewhere in this report, but it was also observed in other airlines such as Air Transportation International and Envoy Air. In these cases, we can clearly observe that the motif significance values fluctuate only in harmony. This is so much the case in FedEx's network that of the 5 most significant motifs in 2004 (the earliest date available for FedEx data), 4 remain in the top 5 by the year 2019. Additionally, we can see the consistency of strategy in Southwest Airlines' network through the distinct striations of significance values that remain tightly coupled throughout the entire time-span. Clearly, these significance values change over time as the network grows, but the fundamental motif composition merely scales. This resonates very well with the notion that Southwest Airlines pioneered a point-to-point model to which it abides even to this day. Additionally, we make the interesting observation that Southwest Airlines' network is strongly point-to-point in the earlier years considered as it favors chains like motifs 45 and 43. However, we observe the formation of what we previously outlined as "weak-hubs" in the later part of this data set. Motifs like 28 and 26 have elements of both hub structure and point-to-point nature and are the most significant by the end of this time-span. We attribute the appearance of these motifs in Southwest Airlines' network not to a deliberate transition of strategy, but merely a consequence of scale – as Southwest grows to service more routes there is a greater likelihood of routes intersecting at cities. It is easily observed from Figure 2 (e) that holistically the relative significance ordering of motifs over time remains stable, so it is an interesting discovery that weak-hubs manifest only in the most recent data for 2019.

5.2.3 Analysis of uncertainty in FASCIA results

Our FASCIA results deliberately neglected to discuss the implications of uncertainty for simplicity, and we justify this with a few key arguments. First, recall our hyper-parameter tuning was conservative to ensure at most 10% error with at least 90% confidence. Second, in all cases where uncertainty was at play, our analysis focused on the few most significant motifs. This was by design to ensure that we acknowledge the possibility that uncertainty could have minor ordering implications for significance. Finally, per the original paper on the FASCIA algorithm [15], in practice the algorithm performs with much greater accuracy than the theoretical error bounds suggest.



(a) Strategy of removing node with largest degree

(b) Strategy of removing a random node

Figure 3: The RTT of several US airlines, by proportion of nodes removed by strategy S.

5.3 Robustness

We applied the Relative Travel Time (RTT) algorithm described above to the networks of several airlines and observed clear differences. In Figure 3a, we visualize the results of a strategy that removed nodes with the largest degree, similar to geopolitical events. We see legacy US carriers such as American Airlines, Delta Air Lines, and United Air Lines all exhibit similar spikes in RTT albeit at different proportions of nodes removed. Removing 20% of nodes results in an over three-fold increase in RTT on American Airlines and Delta, whereas it takes around 25% to reach the same increase on United respectively. Our experiments also confirm results of previous work, showing Southwest Airlines as having a remarkably resilient network. Increases are barely noticeable until nearly 40% of nodes are removed, and it takes almost 50% of nodes being removed before the RTT meaningfully spikes. Note that RTT falls back to 1.0 after a large proportion of nodes are removed as isolated nodes become the largest connected components.

In Figure 3b, we instead use a strategy of random node removal as this better simulates environmental events such as weather. Although Delta Air Lines and United Air Lines are still the most susceptible to disruption, we observe that RTTs are much smaller in this case as the hubs are less likely to be affected. In the case of FedEx, we see travel times spike after random removal of a hub airport but the network can still stand more disruption than under targeted removal. For randomized removal, Southwest shows the highest resilience. Our observation is that point-to-point models have many nodes all with similar, low degree, and therefore removing nodes randomly is similar to removing nodes with large degree.

5.3.1 Historical Analysis

We computed the RTT of the largest US airlines over a period of 20 years, from 1992 to 2018, using both a targeted and random disruption strategy. Our findings found no systemic changes to RTT over this period of time, barring those caused by mergers as outlined in 5.3.2. Given that our work suggests airlines are deliberate about investing in particular network structure (motifs), we find it to be an interesting conclusion that this isn't related to an obvious correlation with resilience over time.

5.3.2 Merger Analysis

This work analyzes the impact to robustness from three major mergers, with results visualized in Figure 4. To further our analysis, we also visualized the route maps of all six airlines prior to the merger in Figure 5. Intuitively, redundant connections between airports (overlap in the route map) increases resilience to random and targeted disruption. By contrast, distinct hubs between merging airlines adds new points vulnerable to targeted disruption.

In the case of American-US Airways, we can see US Airways had a significantly better robustness profile than American Airlines and was more resilient to both targeted and random deletion. From Figure 5, we can see there is significant overlap between the route networks of both airlines. Consequently, American Airlines post-merger has largely adopted the characteristics of US Airways, improving its robustness to both targeted and random disruptions. In the case of random disruptions especially, American has seen outsized benefit that has made the combined network nearly resilient to significant disruption. For random disruptions, there was a clear benefit to American Airlines from expanding their network with the relatively equal sized US Airways.

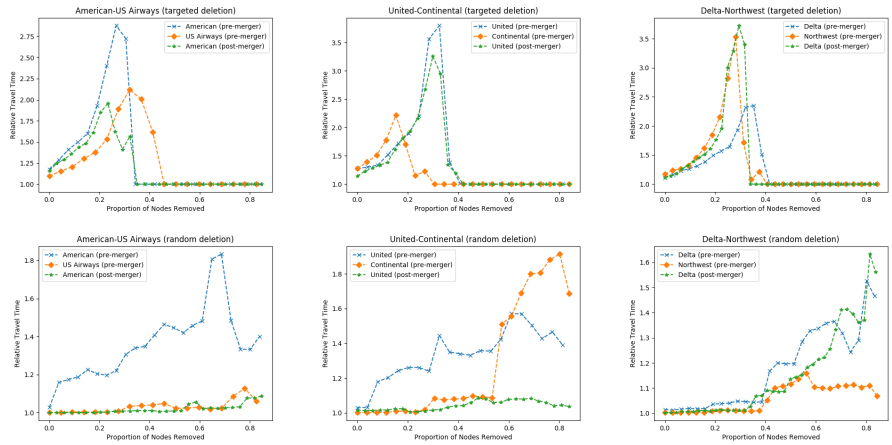
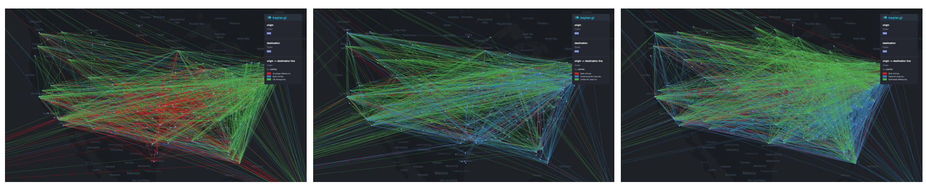


Figure 4: Pre- and Post- merger resilience characteristics of airlines, under both a targeted and random deletion strategy



American-US Airways United-Continental Delta-Northwest

Figure 5: Airline carrier route maps prior to mergers.

In United-Continental, we see a similar story. For targeted disruptions, United had arguably a better robustness profile as it could withstand a higher proportion of deleted nodes before a large spike in travel times. The merged airline follows that profile. Figure 5 shows Continental has a few routes and airports on the Eastern seaboard that are not covered by United, but otherwise there is significant overlap. This is reflected in the small improvement in targeted disruption. For random deletion, however, we see the redundancy results in more resilience than the component networks. For this merger, we can see a clear positive outcome from the merger for both airlines.

Delta-Northwest provides a contrasting narrative. Delta, the larger airline, was more robust before the acquisition. Figure 5 shows Northwest introduces many routes and airports in the northern US that are not covered by Delta and also that Northwest's activity is concentrated to a few hubs. With random disruptions, there isn't much change in robustness due to the smaller size of Northwest. However, Northwest, as a domestically concentrated airline which instead focused on international routes [21], added major points-of-failure that made the combined domestic network less resilient to targeted disruptions.

5.3.3 Conclusion

Through motif analysis we demonstrate that the fundamental topology of the aggregate airline transportation network has dramatically evolved over three decades. We show that subgraph composition is a key design component of the networks and that some carriers have deliberately evolved such strategy (e.g. Delta Airlines) while others have not (e.g. FedEx, Southwest Airlines). We also identify the emergence of a new structure: "weak-hubs".

Through robustness analysis we show that point-to-point networks are more resilient to targeted or random disruption. We show that mergers and alliances can be leveraged to increase resiliency, but only if the component networks have sufficient overlap. We also observe that historically there has been little variation in robustness, other than through mergers.

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6 Appendix

6.1 Fascia subgraph identifiers

ID	subgraph	ID	subgraph	ID	subgraph	ID	subgraph
0		12		24		35	
1		13		25		36	
2		14		26		37	
3		15		27		38	
4		16		28		39	
5		17		29		40	
6		18		30		41	
7		19		31		42	
8		20		32		43	
9		21		33		44	
10		22		34		45	
11		23		35			

Table 3: Ordered mapping of ID to subgraph used in the FASCIA algorithm.

6.2 ESU subgraph significance

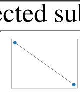
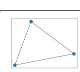
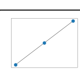
	Southwest Airlines		FedEx		AGGREGATE	
undirected subgraph	count	Z	count	Z	count	Z
	3117	55.45	1269	14.18	15660	106.85
	129034	98.83	5290	61.37	431110	208.78
	31030	-36.26	23019	9.66	923523	38.79

Table 4: Counts of all 2- and 3- node undirected subgraphs as well as their significance values.

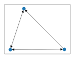
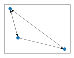
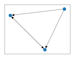
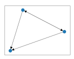
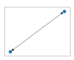
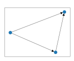
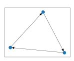
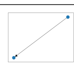
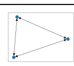
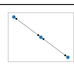
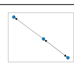
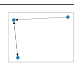
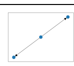
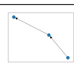
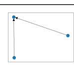
	Southwest Airlines		FedEx		AGGREGATE	
directed subgraph	count	Z	count	Z	count	Z
	33792	121.14	2404	105.83	137956	34.06
	3130	22.70	495	7.88	22531	2.92
	1888	24.81	280	8.85	13482	3.03
	1656	21.14	250	7.11	16392	3.83
	2622	84.49	556	57.66	9755	88.05
	464	4.15	443	0.57	5586	-0.51
	174	4.08	72	-0.34	1942	-0.57
	495	6.61	713	0.49	5905	0.39
	87434	738.89	1156	∞	227880	576.31
	19154	228.22	9689	110.16	375037	310.80
	4971	36.30	4518	9.84	228695	7.28
	5149	35.73	3523	7.79	194383	6.46
	458	7.32	1605	-7.14	36209	-5.49
	879	5.40	2191	-0.27	60326	-0.42
	419	9.54	1493	-7.58	28873	-5.62

Table 5: Counts of all 2- and 3- node directed subgraphs as well as their significance values.

6.3 Summary and visualization of carrier networks

Carrier name	Airports	Routes
AGGREGATE	1302	25415
Southwest Airlines Co.	128	5739
United Air Lines Inc.	201	2688
Delta Air Lines Inc.	195	2438
SkyWest Airlines Inc.	270	2213
Jet Aviation Flight Services, Inc.	336	1934
Swift Air, LLC d/b/a Eastern Air Lines d/b/a Eastern	238	1876
Federal Express Corporation	297	1825
Allegiant Air	266	1680
CFM Inc d/b/a Contour Airlines d/b/a One Jet Shuttle	351	1408
American Airlines Inc.	157	1403
Hageland Aviation Service	121	1304
Sun Country Airlines d/b/a MN Airlines	247	1242

Republic Airline	115	1171
Miami Air International	208	1127
Tradewind Aviation	300	1096
Frontier Airlines Inc.	97	984
United Parcel Service	110	924
ExpressJet Airlines LLC	156	917
Endeavor Air Inc.	143	829
JetBlue Airways	93	806
Atlas Air Inc.	133	738
Envoy Air	176	729
Ameristar Air Cargo	175	689
Mesa Airlines Inc.	138	665
Avjet Corporation	172	606
Alaska Airlines Inc.	95	551
Trans States Airlines	135	540
Spirit Air Lines	45	538
PSA Airlines Inc.	106	527
Corvus Airlines, Inc d/b/a Era Aviation d/b/a Ravn Alaska	117	500
GoJet Airlines LLC d/b/a United Express	106	477
Commutair Aka Champlain Enterprises, Inc.	53	469
Bering Air Inc.	71	436
Air Wisconsin Airlines Corp	98	418
USA Jet Airlines Inc.	162	389
Grant Aviation	80	385
Caribbean Sun Airlines, Inc. d/b/a World Atlantic Airlines	90	370
Kalitta Charters II	128	359
Ryan Air f/k/a Arctic Transportation	117	348
XTRA Airways	131	337
Paklook Air, Inc d/b/a/ Airlift Alaska d/b/a/ Yute Commuter Service	53	319
Tatonduk Outfitters Limited d/b/a Everts Air Alaska and Everts Air Cargo	135	296
ADVANCED AIR, LLC	129	294
Horizon Air	51	248
Aerodynamics Inc. d/b/a SkyValue d/b/a SkyValue Airways	93	240
Piedmont Airlines	74	224
Western Global	67	215
Wright Air Service	61	194
Iliamna Air Taxi	59	187
Gulf And Caribbean Cargo	108	173
Empire Airlines Inc.	73	171
Compass Airlines	45	169
ABX Air Inc	56	164
Kalitta Air LLC	49	164
Alaska Central Express	56	149
Air Transport International	46	149
Lynden Air Cargo Airlines	60	148
Omni Air International LLC	57	133
Air Canada	42	133
Northern Air Cargo Inc.	52	132
Via Airlines d/b/a Charter Air Transport	63	117
Island Air Service	44	113
Kenmore Air Harbor	36	105
Virgin America	28	99
Mokulele Flight Services, Inc.	16	98
Maritime Helicopters, Inc.	47	96
Warbelow	32	96
Hawaiian Airlines Inc.	28	95
Kalinin Aviation LLC d/b/a Alaska Seaplanes	21	94
Cape Air	40	91
Amerijet International	42	91
Bidzy Ta Hot Aana, Inc. d/b/a Tanana Air Service	31	85
KaiserAir, Inc.	50	84

Venture Travel LLC d/b/a Taquan Air Service	22	84
Grand Canyon Airlines, Inc. d/b/a Grand Canyon Airlines d/b/a Scenic Airlines	21	77
Sky Lease Cargo	26	68
Eastern Airlines f/k/a Dynamic Airways, LLC	32	66
Boutique Air	36	66
National Air Cargo Group Inc d/ba National Airlines	47	65
Silver Airways	29	57
Pacific Airways, Inc.	20	55
Sun Air Express LLC dba Sun Air International	24	54
Tropic Ocean Airways LLC	25	52
Peninsula Airways Inc.	18	50
Southern Air Inc.	19	47
Harris Air Services	15	43
Elite Airways LLC	18	40
London Air Services Limited	39	39
Polar Air Cargo Airways	24	38
Hillwood Airways, LLC f/k/a ATX Air Services, LLC	18	31
Multi-Aero, Inc. d/b/a Air Choice One	11	30
Delux Public Charter LLC	10	28
Air Charter, Inc d/b/a Air Flamenco	7	27
Scott Air LLC dba Island Air Express	11	26
Great Lakes Airlines	9	23
Smokey Bay Air Inc.	9	23
Frontier Flying Service	18	20
Rhoades Aviation dba Transair	5	20
Trans Northern Airways d/b/a Air Unlimited Charter Services	14	19
Asia Pacific	9	19
Aloha Air Cargo	5	18
Spernak Airways Inc.	6	17
J&M Alaska Air Tours, Inc. d/b/a Alaska Air Transit	6	16
Polaris Aviation Solutions, LLC	10	14
Vieques Air Link Inc.	5	12
Star Marianas Air Inc.	4	12
Menagerie Enterprises Inc d/b/a Monarch Air	5	12
40-Mile Air	6	12
Antonov Company	11	11
Katmai Air	4	11
Ultimate JetCharters LLC dba Ultimate Air Shuttle	6	10
Rectrix Aviation, Inc.	4	9
Volga-Dnepr Airlines	11	8
Seaborne Virgin Islands, Inc.	5	8
Air Excursions LLC	4	7
Air Sunshine Inc.	4	6
Bemidji Airlines	3	6
Public Charters, Inc. d/b/a North Country Sky d/b/a Regional Sky d/b/a Texas Sky	4	6
Key Lime Air Corporation	3	6
Ellis Air Taxi Inc.	3	4
Makani Kai Air Charters	3	4
Ward Air	3	4
Polynesian Airlines Ltd.	3	4
Norwegian Air UK Limited	6	3
British Airways Plc	4	3
Norwegian Air Shuttle ASA	6	3
City Wings Inc dba Seaflight	2	2
Reeve Air Alaska, LLC	2	2
Gem Air LLC	2	2
New England Airlines Inc.	2	2
Friday Harbor Seaplanes	2	2
VistaJet Limited	4	2
Privatair	2	2
PM Air, LLC	2	2

Asiana Airlines Inc.	2	2
Klm Royal Dutch Airlines	2	1
Cargologicair Limited	2	1
Westjet	2	1
Sunwing Airlines Inc.	2	1
Virgin Atlantic Airways	2	1
Grand Canyon Helicopters	2	1
Cayman Airways Limited	2	1
Primera Air Scandinavia	2	1
Oceanair Linhas Aereas S A	2	1
Finnair Oy	2	1
SkyLink Express Inc.	2	1
Blue Jet SP Z o o	2	1

Table 6: A summary of basic carrier statistics for each carrier in our data set as well as the aggregate airline network for the year 2018. The Airports column represents the total number of airports covered by the network and the Routes column represents the number of unique directed flight routes in the network.

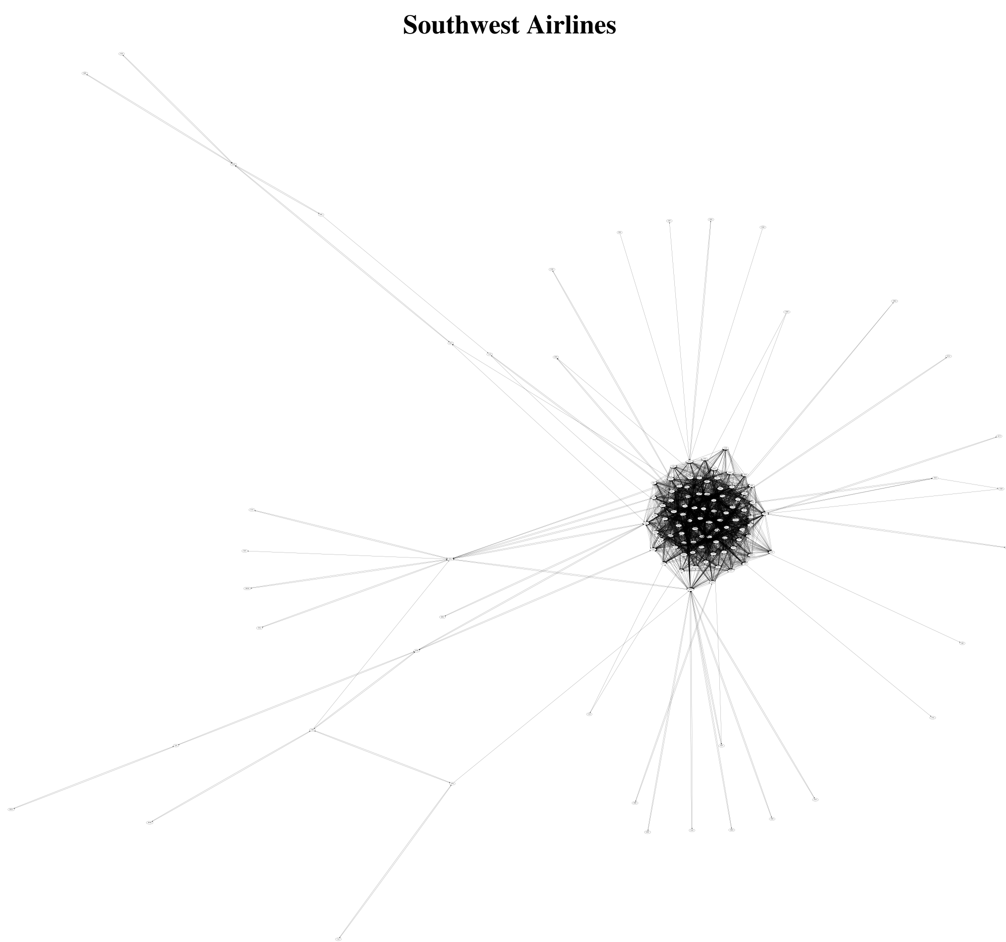


Figure 6: At 128 airports and 5739 directed flight routes, Southwest Airlines is the largest airline carrier in our data set with respect to number of unique flight routes.

FedEx

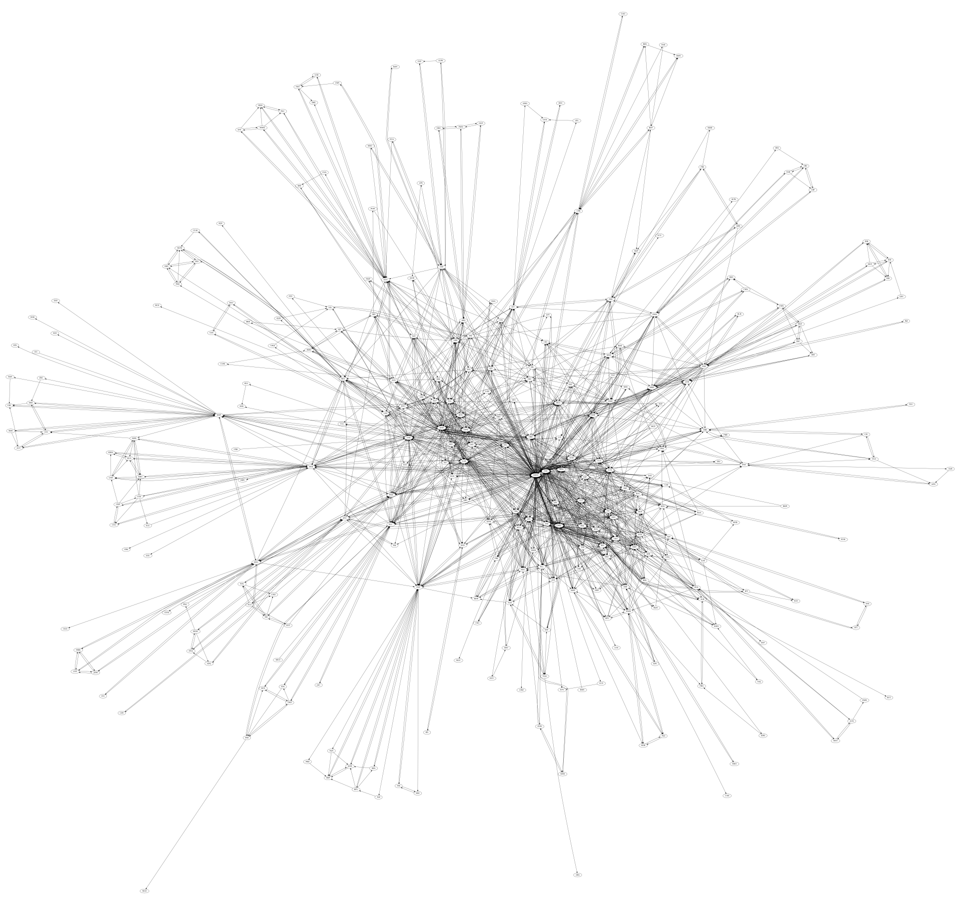


Figure 7: At 297 airports and 1825 directed flight routes, FedEx is the largest non-charter airline carrier in our data set with respect to number of airports with either an origin or destination flight.