EUROPEAN AIRLINE NETWORKS – WHICH STRATEGY FOR AIRLINES ?

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Abstract:
Airline networks may be interpreted as structures that express strategic choices made by airlines to serve or not to serve given airports. Research into network strategies of airlines in the past has focused on economies (of density) and market power. More recent research focuses on managerial decisions related to capacity choices, such as the frequency or scheduling of flights, which are related to the size and evolution of hub-and-spoke networks. Other streams of research within the natural sciences, have characterized many networks as not random chaotic structures but as efficient complex formations. This paper will interpret European hub-and-spoke networks as complex networks in the sense of statistical physics and classify their structural components into distinctive connectivity distributions. From the identified distributions, implications will be drawn for strategic management in general and for hub-and-spoke airlines in particular.

Keywords:
Network competition, small worlds, air traffic, connectivity distribution, capacity management

1. INTRODUCTION

Management research into network competition among airlines in general focuses on two general assertions: One assertion is that a hub-and-spoke network allows an airline to exploit economies of density. The basic idea is that by combining passengers with various destinations on the same aircraft, the airline can reduce per passenger costs (Brueckner, et al. 1992; Brueckner and Spiller, 1991). By funneling all passengers into a hub, such a system generates high traffic densities on its "spoke" routes. Bailey, Graham et al. argued that this increases the average number of passengers per flight, letting the carrier take advantage of such economies that arise from employing bigger aircraft. Given such a network form, the size of network (i.e. the number of city-origins and destinations) as well as the size of the connected cities would furthermore increase density within such a system and marginal costs of carrying an extra passenger on a non-stop route would fall as traffic rises.

Another major assertion about hub-and-spoke systems is the market power argument. HS networks can provide an airline with the opportunity to exercise unilateral market power and barriers to entry at dominated airports would further insulate the dominant airline from competitive pressure (Borenstein, 1989 and Levine, 1987). Such research regularly used prices to measure welfare effects (see Panzar (1979), Lederer (1993), Morrison and Winston (1995), and Brueckner and Zhang (2001)). Studies of airline mergers often targeted on ticket prices when determining consumer welfare, suggesting that such mergers would harm consumers (e.g. Borenstein 1990; Kim and Singal, 1993).

This research then is extended to take into account entry/ exit decisions within networks. Sinclair (2002), for example, provides empirical evidence on the effect of network characteristics on entry and exit. A bivariate model of entry and exit specifies threshold functions which depend on market structure and firm specific characteristics. It is an elaboration on previous work by Morrison and Winston (1990), which presents the results of a simple entry and exit model that captures the effects of hub airport characteristics on entry and exit decisions. Their findings add to the growing evidence that hub and spoke systems are crucial determinants of competitive success. The article suggests (alike Kahn, 1993) that, while such systems may allow airlines to reduce per passenger costs, route and airport dominance may tempt an airline to exploit its market power in the same time.

Another stream of empirical research focuses on Cournot-type capacity choices, i.e. flight frequency. For example, Morrison and Winston (1986, 1995) link the increase in flight frequency to the growth of the size of the network. Berechman and Shy (1998) establish a relationship between the growth of HS networks and scheduling in an incomplete model. Bruckner and Zhang (2001) show that flight frequency is higher in a hub and spoke network than in a fully connected network. They suggest that the downward pressure on fares due to economies of density may be partly or fully offset by the effect of higher flight frequency, so that the net fare impact of such HS networks becomes uncertain. Richard (2003) predicts changes in flight frequency in a merger, but also its relative consequences on consumer welfare.

In other scientific fields outside that of management science, the complex and evolving nature of networks has garnered an increasing amount of interest that focuses on the structural elements of the network: All networks share a common construct of nodes connected together by links. The very simple concept of one location connecting to another quickly becomes an extremely complex phenomenon as the number of nodes and connections increase. Figuring out how these simple concepts evolve into incredibly complex and dynamic networks has produced a flurry of work in physics, computer science, molecular biology, sociology, and many other fields. The one aspect of networks that tends to be overlooked by management science in this new field of inquiry is the specific structure of networks beyond a generic classification into HS or not HS.

In an attempt to fill the gap in analysis this paper examines the European airline infrastructure as a complex network. This analysis has two steps. First, the European airline infrastructure is analyzed under the framework of existing complex network models developed using statistical physics. Second, a model of complex networks is developed that distinguishes the different European countries in which the airports are located. Through the airports that are served, the connectivity structure of European airlines becomes apparent. Before proceeding to the analysis an overview of complex networks and their study is presented. Lastly the paper concludes with a discussion of what impacts the structural specifications (i.e. connectivity distributions) of the small world of European airlines may have with regards to competitive strategy.

2. A REVIEW OF SMALL WORLDS AND COMPLEX NETWORK RESEARCH

The mathematical study of networks commonly falls under graph theory. Graph theory has been used to model a wide array of networks for empirical analysis, including transportation, communications, and neural networks. Sometimes networks are less apparent, as with economics where companies are vertices and transactions between them are edges, or social networks where people are nodes and acquaintance is the edge (Arthur 1999, Wasserman and Faust 1994, Hayes 2000a, p.10). Early graph theory analysis was confined to relatively small networks with a computationally manageable number of edges and vertices. This work included many applications from geographical analysis, especially with transportation networks. Kansky (1963), Garrison (1968), Haggett and Chorley (1969) as well as many others used the graph theoretical implications of transportation networks to help explain aspects of regional and national economies. There was also attention specifically given to the small world problem outlined by Milgram (1977) - how many steps does it take to link any two people, selected at random? - specifically in the context of geography. Stoneham (1977) investigated the spatial aspects of the small world problem, examining, “the general distribution of steps with parameter changes; channelling effects; the sensitivity of the overall structure to disconnection; and ghettoisation of an area” (p.185).

During roughly the same period, Erdös and Renyi (1960) were doing theoretical work focused on large complex graphs. Erdös and Renyi (ER) endeavoured to use “probabilistic methods” to solve problems in graph theory, where a large number of nodes were involved (Albert and Barabasi 2002, p. 54). Under this assumption they modelled large graphs utilizing algorithms where n nodes were randomly connected according to probability P, and found that when vertices were connected in this fashion they followed a Poisson distribution (Albert and Barabasi 2002, p 49). A more thorough review of random graphs can be found in the survey work of Bollobás (1985).

The absence of detailed empirical data for complex networks left random network models as the most widely used method of network simulation (Barabasi 2001). As computing power increased and real world network data began to become available and several empirical findings emerged. Three network characteristics frequently resulted from analysis of complex networks:

1. Short average path length
2. High level of clustering
3. Power law and exponential degree distributions

(Albert and Barabasi 2002, p. 48-49)

Short average path length indicates that the distance between any two nodes on the network is short; they can be reached in a few number of hops along edges. Clustering occurs when nodes locate close to each other in cliques that are well connected to each other. Lastly, the frequency distributions of node density, called degrees, often follow power laws.

Watts and Strogatz (WS) (1998) formalized this concept of clustering for complex networks. Using several large data sets, they found that the real-world networks studied were not entirely random but instead displayed significant clustering at the local level. Further, that local clusters linked across the graph to each other forming "small worlds". To model this effect Watts and Strogatz (1998) took a regular lattice where all neighbours are connected to their two nearest neighbours and randomly rewired nodes in the lattice. These short cuts across the graph to different clusters of vertices introduced a level of efficiency[1] not predicted in the ER model. The distribution was not Poisson as with the ER model, but was bounded and decayed exponentially for large sets of vertices (Watts and Strogatz 1998). Watts (2003) has extended this work recently to cover topics ranging from, "epidemics of disease to outbreaks of market madness, from people searching for information to firms surviving crisis and change, from the structure of personal relationships to the technological and social choices of entire societies (p.1)." The work by WS was not the first, though, to investigate the effects of rewiring:

> …Fan R. K. Chung, in collaborations with Michael R. Garey of AT&T Laboratories and Béla Bolobás of the University of Memphis, studied various ways of adding edges to cyclic graphs. They found cases where the diameter is proportional to log *n* (Hayes 2000b, p.106).

Another significantly different finding from either the expected exponential or Poisson distribution was that of a power law. In a power law distribution there is an abundance of nodes with only a few links, and a small but significant minority that have very large number of links (Barabasi 2002). It should be noted that this is distinctly different from both the ER and WS model; the probability of finding a highly connected vertex in the ER and WS model decreases exponentially, thus, "vertices with high connectivity are practically absent"[2] (Barabasi and Albert 1999, p.510). The reason, according to Barabasi and Albert (1999), was that their model added another perspective to complex networks, incorporating network growth; the number of nodes does not stay constant as in the WS and ER model. The BA models added growth over time and the idea that new vertices attach preferentially to already well-connected vertices in the network.

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[1] Efficiency in this case refers to the network characteristic of a large number of nodes having a low diameter.

[2] Barabasi and Albert's definition of high connectivity is relative to the number of nodes in the network, and in this context simply means a large proportion on the total connections in the network. The odds of a node having a large proportion on connections in a network are small enough that they are likely to be "practically absent".

The difference between the random model of Erdös and Renyi and the model described by Barabasi and Albert becomes clearer when seen in a visual representation. *Figure 1* illustrates the structural difference between a random ER network model and a scale free network model.

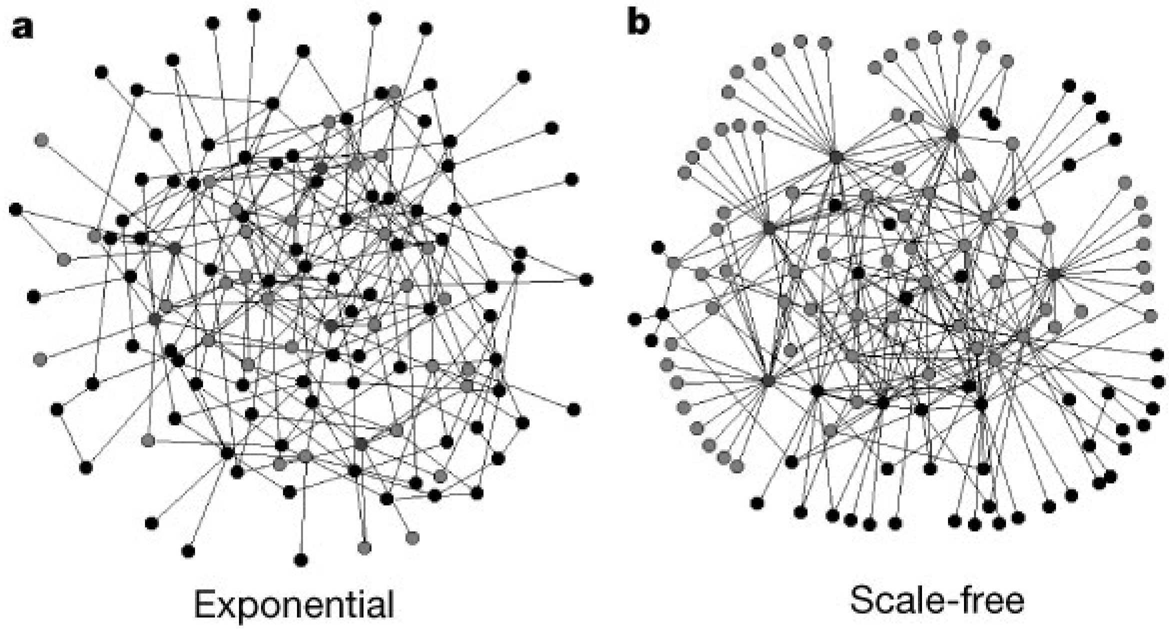


Figure 1: Exponential versus scale-free connectivity distributions

This leaves the rather fuzzy question of what is a small world and what is a scale free network. As stated earlier Albert and Barabasi (2002) see small worlds and scale free networks as explanations for two different phenomena occurring in complex networks. The WS small world model explains clustering and the scale free model explains power law degree distributions (Albert and Barabasi 2002, p.49). There have, though, been other opinions on how small world and scale free networks should be classified, Amaral et al (2000) posits that scale free networks are a sub class of small world networks. Further, that there are three classes of small world networks:

1. Scale-free networks, characterized by a vertex connectivity distribution that decays as a power law.
2. Broad-scale networks, characterized by a connectivity distribution that has a power law regime followed by a sharp cut-off.
3. Single-scale networks, characterized by a connectivity distribution with a fast decaying tail.

(Amaral et al 2000, p.11149)

An exact delineation of where small world and scale free networks diverge is still somewhat fuzzy in the literature, but the area of study is still evolving. It can be safely said that the two are inter-related and that generally speaking scale free networks exhibit the clustering and short average path length of small world networks, but not all small world networks exhibit the power law distribution of scale free networks (Gorman et al 2004, pp.4-6).

The implications of this new research into the structure of complex networks were very broad for a number of disciplines as varied as genetics, economics, molecular physics and sociology. As for airline networks, Amaral et al. (2000, p.11150) examined traffic at some 2000 airports in the world. They found these air traffic connections to form single-scale networks, characterized by a connectivity distribution with a fast decaying tail, such as exponential or Gaussian. After comparing the validity of this finding with traffic at European airports, the question of the significance of their connectivity distributions with regards to airline strategies remains to be addressed.

3. NETWORK CONNECTIVITIES IN EUROPEAN AIR SPACE

Networks can be planar or non-planar[3], a feature that can prove crucial in the context of airports. In planar networks, the number of edges that can be connected to a single node is limited by the physical space available to connect them. This constraint may make the large number of connections needed for a power law distribution quite difficult to obtain. In airport networks the number of connections is limited by the space available at the airport, “such constraints may be the controlling factor for the emergence of scale-free networks” (Amaral et al 2000, p.11149).

It should be noted that Amaral et al (2000) did find that the network of world airports was a small world because of its small average path length. The examined connectivity distribution shows that there was no power law regime and that air traffic among the worlds airports shows exponentially decaying tails, implying that there is a single scale for the connectivity. Amaral et al (2000, p.11149ff) infer that physical constraints would prevent the formation of scale free networks in traditional transport networks, i.e. that of air traffic.

Amaral’s assessment of the various connectivies of world airports was based on the number of passengers in transit at airports (as well as cargo loads for a second connectivity distribution) rather than data on the number of distinct connections provided through a given airport. In particular, Amaral et al. expect that the number of distinct connections from a major airport is proportional to the number of passengers in transit through that airport. To this end, Amaral makes two assumptions: First, there is a typical number of passengers per flight. As the number of seats in airplanes does not follow a power law distribution, the assumption seems to be reasonable. The second assumption is that there is a typical number of flights per day between two cities. In the cases examined, there are a maximum of about 20 flights per day and per airline between any two cities, thus the distribution of number of flights per day between two cities is bounded.

In analogy to Amaral’s approach, we shall assess the connectivity distribution of European air traffic. This analysis will endeavour to do two things: (1) determine whether European air traffic connections form a scale free network or not (2) develop a small world model that distinguishes geo-spatial aspects such as domestic, European or inter-continental connectivity to compare the network structures among European airline incumbents (next chapter).

Data was collected for the years 2000, 2001 to perform analysis (Part 1) and more detailed data for 2004 entered into further analysis (Part 2, see next chapter). Data for the years 2000 and 2001 was obtained through the Airport Council International (ACI) that ranked 330

[3] Planar network form vertices whenever two edges cross, where non-planar networks can have edges cross and not form vertices.

European airports and showed both the number of total passengers as well as total air traffic movements for the given years. This data included domestic, European and intercontinental flights. These first two data sets are very similar in composition to that used by Amaral. Our approach allows to further simplify the assumptions made by Amaral: observed movements at airports are supposed to be proportional to the number of city-pair links on that given airport, a condition that can safely be assumed. As the typical number of flights in the observed sample was below 10 per airline and city pair, the bounded distribution criteria (see Amaral) holds as well.

For these first two data sets the total number of air traffic movements connecting into a European airport was tabulated. Since binary connectivity data (i.e. detailed links between city-pairs) was not available for 2000 and 2001 total air traffic movements was utilized for comparison across the two years of data. This approach is commonly used when structural network data is not available or the number of nodes is too small for a log-log plot. Utilizing such a measure to assess connectivity also makes sense since it takes into account the large number of city-pairs connected to many airports and the common practice of reshuffling among certain destinations through airlines or code-sharing of such links.

In the first graph, the data for 2000-2001 was plotted as rank order distributions with linear log plots (*Figure 2*). For each graph the *y*-axis is the number of aircraft movements for a particular airport (on a log scale) and the *x*-axis is the airport ranked in descending order.

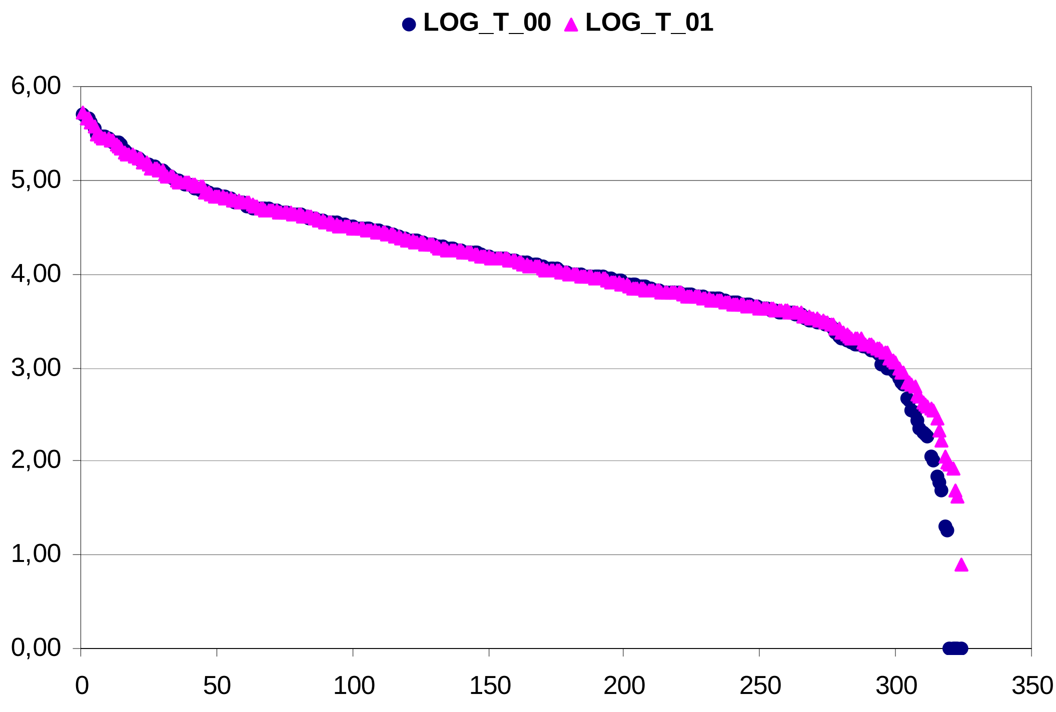


Figure 2: Connectivity distribution for traffic movements – linear log plot

The data shows consistency with an exponential decay for the distribution of the first some 275 largest European airports. Comparing the years 2000 and 2001, no difference becomes apparent in this respect with regards to these 275 bigger airports. Only for the smallest 10 to 15% of our airports sample, this distribution will decay significantly faster than exponentially. Also, the threshold for such faster decay appears to have moved slightly upwards to bigger airports between 2000 and 2001. We suggest that this may be due to the demand shocks that were incurred after September 11, 2001 and adaptations in capacity as a consequence that mostly penalized the smaller airports in our sample.

The same data then was plotted again as rank order distributions with log-log plots (*Figure 3*). This plot confirms that the tails of the distribution decay much faster than a power law would. One can observe a sudden cut-off of the connectivity distribution. Applying Amaral's classes of small world networks, the graph may be considered over a wide range as approximating a power law, with a sudden cut-off at the tail. In order to approximate such a power law for the relevant range of the sample, we restrict it to the first 275 airports.

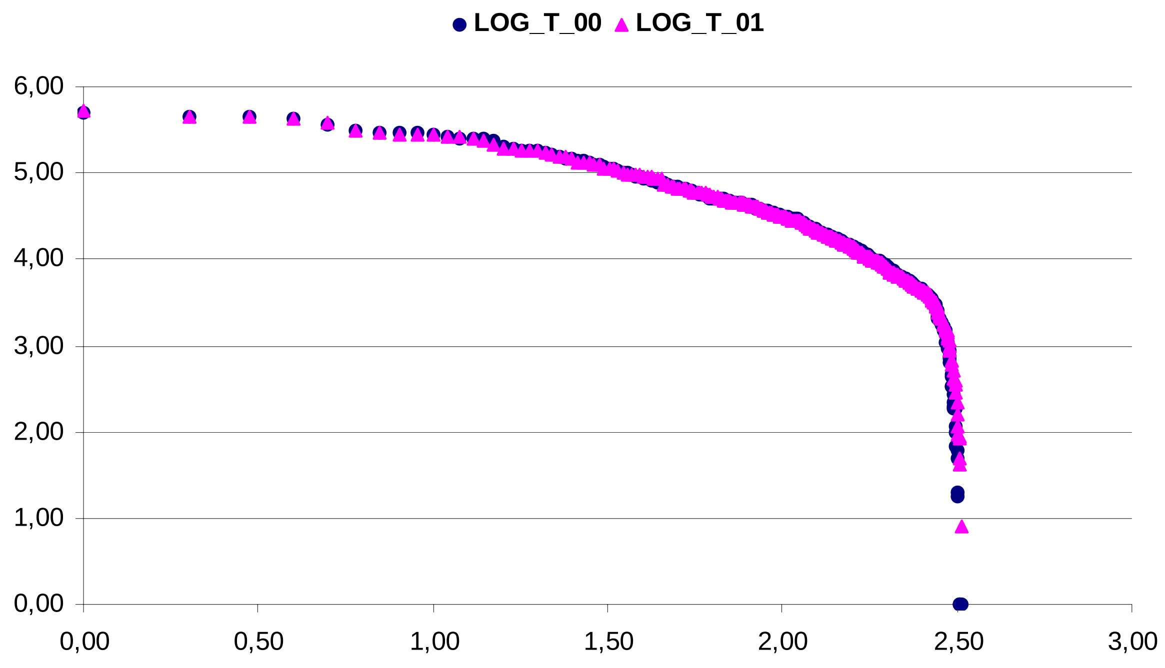


Figure 3: Connectivity distribution for traffic movements – log log plot

The power law results in table 1 are calculated from $P[X = x] \sim x^{(k+1)} = x^{-a}$ where the exponent of the power law distribution is $a = 1+\kappa$ (where κ is the Pareto distribution shape parameter) (Adamic 2000). The exponent provides a rate of increase indicator, an exponent of -2 would indicate an increasing sequence of 1,4,9,16,25 or an exponent of 3 would indicate an increasing sequence of 1,8,27,64,125. The European airport network has left practically unchanged its power law exponent for the years 2000 and 2001: The results ware found through regression analysis and show a R^2 score of 0.902 and 0.904 respectively for 2000 and 2001. By the year 2000 (2001) the network's power law exponent is -1.238 (-1.240), but as suggested by the graphs above and limiting the sample size for our regression equation, this distribution at best only applies to the first 275 airports of the sample.

Upon closer inspection, we find the slope of the connectivity distribution to be flatter for the 16 biggest airports (log_rank ≤ 1.2) than for the rest of our restricted sample of 275 airports. It appears as if above a critical threshold of some 200,000 flight movements per year, the incremental cost of adding new links (i.e. flights) to the network is significantly constraining the number of new links that can be added to these hubs. Amaral et al. (2000, p.11151) explicitly cite world airports as such an example and our results conclude the same for European airports.

This finding is relevant with the regards to the BA model's characteristic of preferential attachment. Preferential attachment stipulates that there is a higher probability for a new or existing node to connect or reconnect to a vertex that already has a large number of links than there is to (re)connect to a low degree vertex (Barabasi and Albert 1999). As the network grows incrementally it expands following preferential attachment. The probability (Π) that a new vertex will connect with another vertex (i) depends on the connectivity k_i of that vertex so that $\Pi(k_i) = k_i / \Sigma_j k_j$ (Barabasi and Albert 1999). Because of preferential attachment, a vertex that acquires more connections than another one will increase its connectivity at a higher rate; thus, an initial difference in the connectivity between two vertices will increase further as the network grows. However, our findings suggest that these most highly connected hubs are saturated; i.e. adding new links becomes very expensive. As a consequence, network growth risks to be compromised.

Historically, the national airline incumbents had well established airport bases in certain cities, among which some played the lead role. The location of these airports had not significantly changed over the last decades within the national borders. While the rank order of the top ten cities may have shifted across Europe since deregulation started in the early 1990's, the same airports have consistently benefited from preferential connectivity to maintain the majority of connections within their given networks. During the two years of observation, the top ten cities have on average accounted for 21.7% (in 2000) and 21.9% (in 2001) of total movements (see *Table 1*). Among these top-10 European airports, the fall of Sabena and the near bankruptcy of Swissair allowed Lufthansa's Munich hub to surpass both Brussels and Zürich airport. However, both airports remained within the top-ten listing.

Table 1: Airline movements at Europe's biggest airports

Rank 2000	**AIRPORT**	**2001**	**2000**
1	PARIS (CDG)	523400	517705
2	LONDON (LHR)	463568	466836
3	FRANKFURT/MAIN (FRA)	456452	458746
4	AMSTERDAM (AMS)	432101	432534
5	MADRID (MAD)	375558	358357
8	MUNICH (MUC)	337653	319143
7	ZURICH (ZRH)	309230	325505
6	BRUSSELS (BRU)	305535	326078
9	COPENHAGEN (CPH)	288739	303616
10	ROME (FCO)	283748	283465
11	STOCKHOLM (ARN)	276445	279520
13	BARCELONA (BCN)	273118	256931
12	LONDON (LGW)	252453	260799
14	MILAN (MXP)	237029	251356
15	PARIS (ORY)	219498	243616
17	VIENNA (VIE)	204608	206884
16	NICE (NCE)	204224	217260
18	OSLO (OSL)	197498	204238
19	MANCHESTER (MAN)	197230	198022
20	DUSSELDORF (DUS)	193513	194095

Source: ACI Europe, data compiled from ACI data base, available upon request

The 2000-2001 data sets appears to support the rule of preferential attachment as one of many factors in the growth of the network. In particular, many hubs maintained or even increased traffic movements in 2001, despite of the important drops passenger demand that had severly affected their intercontinental routes. However, the actual testing of the BA equation given the 2-year time series was not possible since matrix connectivity data for specific city pairs was not available for these years. Such matrix connectivity data was compiled for the year 2004 and we shall analyse its distribution in more detail in the following chapter.

4. A SPATIAL SMALL WORLD MODEL

In a first step we tried to approximate and analyse airport infrastructure as it exists today in Europe using methods devised by statistical physics. We were able to identify some salient features: (1) Exponential decay of connectivity for the biggest 275 European airports and even faster decay for the smaller ones. (2) The rule of preferential attachment still holds, but due to capacity saturation the potential for growth in the networks seems compromised.

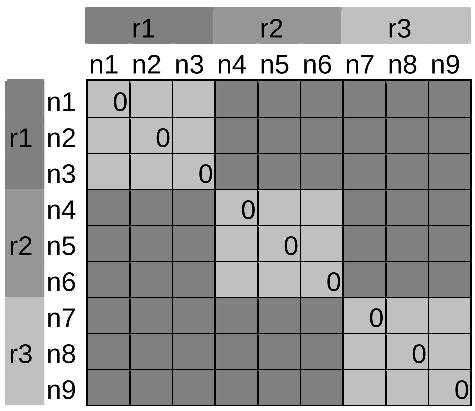
The problem with this previous model of analysis is that it only looks at actual traffic movements across all airports in terms of a rank order distribution. Looking at summary parameters alone (capacity or traffic at airports), we can not say *how* these airports are connected with each other across Europe or worldwide. It is the role of airlines to accomplish such cross-border connectivity among airports and that's where their strategies might matter: Which connectivity distributions follow particular airlines' networks for different international destinations ? The relevance of such connectivity matrices for competitive strategy shall be discussed in the last part of the paper after the following analysis.

We shall assess the connectivity of European airports with regards to domestic, intra-European and inter-continental city-pair links. To this end, data was collected for the 184 biggest airports in Western Europe. Utilizing data from our self assembled data-base (OAG and Euroavia, as well as the individual airports), we may analyse domestic as well as cross border connections at the airport level. When looking at European airline networks, we find that nodes are interdependently linked to each other. It is obvious that the European rank order distribution of network connectivity is not represented simply as a function of city size or wealth, for example. To develop a small world model that takes into account the different links in matrix form, national borders of countries become relevant to distinguish the geographies of airport links.

Applying the idea of small worlds to European based networks would mean that networks gain efficiency by having a large number of local (i.e. domestic) links and a few global (i.e. international) links connecting local clusters together. Watts (1999) explicitly examines spatial graphs and the role of Euclidean distance in his analysis of small world networks and found that, "It appears, in fact, that spatial graphs with more exotic distributions do display small world features, but the matter is formally unresolved" (Watts 1999, p.42). Indeed, local and global can be considered primarily a geographic concept, but the choice between both is determined by the airline's strategy. This analysis will not try to resolve the problems of Euclidean distance, but instead will examine the problem from the perspective of strategic choice utilizing the country origin rather than distance to distinguish network features. This approach through airport connectivity to analyse airline strategies is reasonable as it is the incumbent airlines within the national borders that still dominate the airports.

To do so a binary matrix of the city pair connections involving the biggest 184 airports in Western Europe was utilized as a test case. The European Union is divided into 15 nation states and each airport in the city pair in the matrix was assigned to its country of origin. Airlines that provided service between these airports were registered in the matrix, with airlines that served domestic city-pairs being distinguished from those that served cross-border city pairs. National borders are an appropriate choice for airline-specific units of analysis assessing network strategy because of the national dominance of flag carrier incumbents, a form of dominance that manifests itself regularly through the airline's presence and market power at hub airports. Utilizing domestic/ international city-pair links as our basic unit of analysis, the following procedure was established: for each airport the number of domestic links to other airports within the same countries were totalled along with the number of cross-border links connecting to airports in other countries. From this data the following approach was developed to identify airports that provide the "global" connections within a European or intercontinental network:

Consider a large network of *n* nodes (airports), spanning an area *A* (Western Europe) consisting of *m* regions (i.e. countries), with a variable number of nodes inside each region that have a variable number of connections from each region to other regions. For a region *r* with *p* number of nodes, a *p x p* contiguity matrix represents connections between these nodes. This needs to take into account the domestic and foreign airlines that establish the links between these airports, but we assume that it is the domestic airlines that determine the network structure which involves the domestic airport nodes and hubs. Then, one could construct a contiguity or adjacency matrix for the entire network of *m* regions, as a block diagonal matrix, where matrices along the main diagonal refer to the contiguity matrices for each of the regions, while cross-border connections are represented as the off-block-diagonal elements. Let *M* denote such a matrix (*Figure 4*).



r = region
n = airport node
light gray = intra-regional links
dark gray = inter-regional links

Figure 4: Matrix Construct of the Spatial Small World Model

If a node *i* in region *r* is connected to another node *j* in the same region, then that connection is considered as a local link and is denoted by $q_{i(r)j(r)}$, where the value is one if a link exists and zero if it does not. On the other hand if node *i* in region *r* is connected to node *l* in region *s* then that connection is considered as a global (cross-border) connection and is denoted by $g_{i(r)l(s)}$, where the value is one if a link exists and zero if it does not. Thus, in theory, one may associate with each node node *i*(*r*), a global connectivity index as a ratio between its global and local connections, weighted by the total number of global and local connections for the entire network.

The total number of global connections *G* is computed from the elements of the block upper triangular matrix of M, of *m* regions, each with variable number of nodes:

$$G = \sum_{i(1)} \sum_{s>1}^{m} \sum_{l(s)} g_{i(1)l(s)} + \sum_{i(2)} \sum_{s>2}^{m} \sum_{l(s)} g_{i(2)l(s)} + \mathrm{K} + \sum_{i(m-1)} \sum_{s>m-1}^{m} \sum_{l(s)} g_{i(m-1)l(s)} \qquad (1)$$

Note that, since *m* is the last region in the block diagonal matrix, its global connections have already been computed in the previous *m*-1 blocks.

The total number of local connections *L* is a sum over all the local connections over *m* regions and is given by:

$$L = \sum_{i(1)} \sum_{j(1)>i(1)} q_{i(1)j(1)} + \sum_{i(2)} \sum_{j(2)>i(2)} q_{i(2)j(2)} + \mathrm{K} + \sum_{i(m)} \sum_{j(m)>i(m)} q_{i(m)j(m)} \qquad (2)$$

Then the global connectivity index for a node *i* in region *r* is given by:

$$C_{i(r)} = \left(\frac{\sum_{s \neq r}^{m} \sum_{l(s)} g_{i(r)l(s)}}{1 + \sum_{j(r), j \neq i} q_{i(r)j(r)}} \right) \times (G + L) \qquad (3)$$

The numeral of 1 in the denominator indicates a self-loop of a node.

The ratio of global links to local links provides an indicator of how well the airport acts as a global connector in the network and the weighting of the scores by the total number of links balances the measure with the overall connectivity of the node. To test the model the equations were run with the 2004 airport data on some 184 biggest Western European airports. For each city equation 1 produced an indicator of the number of global connections, using separate indicators for European and intercontinental links. Equation 2 produced an indicator of the number of local (domestic) connections, and equation 3 provides a ratio of global to local connection weighted by the total connectivity of the city. In the case of European global connections, the weight **G+L** included European and domestic links only. In the case of intercontinental "global" links, all destinations served by the given airport enter into the weight factor.

The links in the diagonal of the regional matrix totalled 1,483 and the off diagonal global links totalled 4,426 for European and 2,328 for intercontinental links, illustrating the small world character of the network to be apparent only when intercontinental links were compared to the domestic plus European links – a large number of local connections with a smaller number of global links connecting clusters.

Figure 5 compares both European and intercontinental "global" connectivity indices (Equation 3) on a linear-log plot. The European weighted connectivity shows a line falling relatively straight, which suggests an exponential decay. In comparison, the intercontinental global connectivity distributions served by European airports show more important negative slopes of decay which do not fall on a straight line neither. It is important to note that from the 60th biggest airport on, intercontinental connectivity indices become insignificant and rapidly disappear.

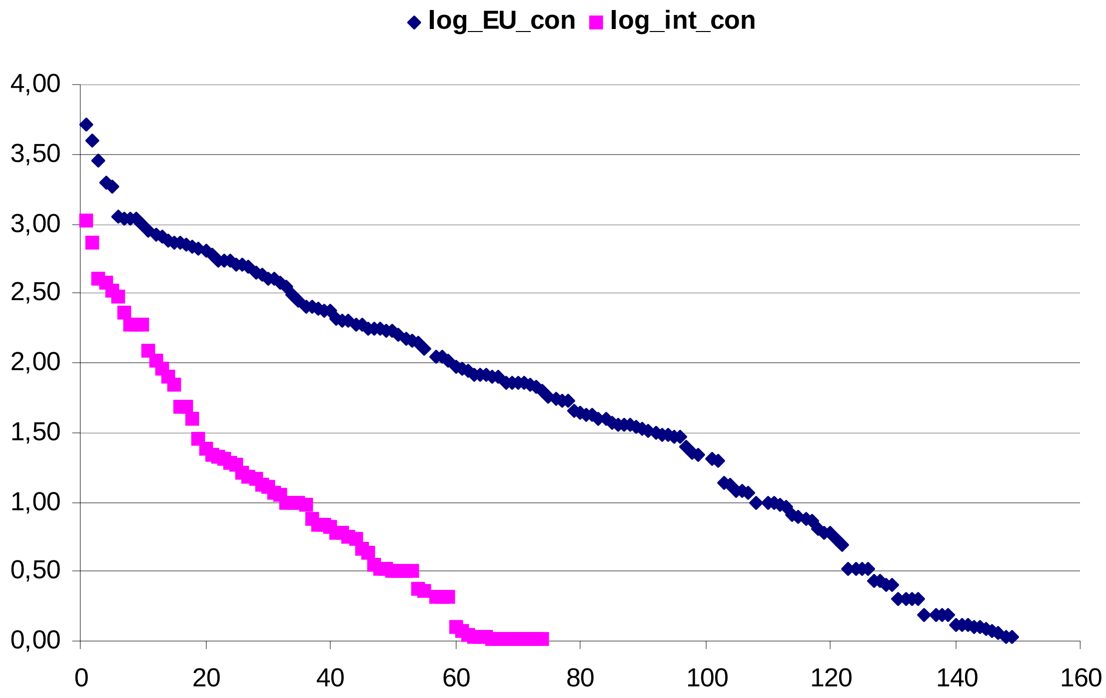


Figure 5: Global connectivity indices – linear log plot

For closer inspection, we shall look at the log-log plot (*Figure 6*) of both global connectivity distributions. The exponential decay of the European global connectivity seems confirmed: the tails of the distribution decay faster than a power law would. As for the intercontinental global connectivity, a straight line can be identified that becomes kinked at the log(rank) of about 1. From that point on, the line again becomes straight to fall with a steeper slope. In other words, from the value of log(rank) ≥ 1 on, the distribution suggests a power law. And before that threshold, the data is consistent with a power law decay as well, but the slope of that decay is flatter. Interestingly, in this range of 0 < log(rank) < 1, the slopes between both European and intercontinental global connectivity indices appear almost the same. By identifying the concerned airports, we find that those that were ranked the first five for each distribution are not the same (compare *Table 2*). No conclusions therefore can be drawn as with regards to the relationship between both distributions.

The kink that can be observed may be due to the saturation of capacity in these airports; the costs of adding new links to these airports may be prohibitively high. This appears to be consistent with our findings from the previous chapter as far as total movements at airports are concerned. Although the European airports do not form "small worlds" among themselves, important characteristics of their connectivity distribution resemble that of the intercontinental index: it shows the same symptoms of saturation for the 10 most highly ranked airports (*Figure 6*) as well as a single scale of exponential decay (*Figure 5*) for the airports thereafter. However, this single scale is less pronounced than that of the intercontinental index. Apparently, intra-European links dominate overall connectivity among European airports. Their nature is highly transversal and consists mostly of point-to-point connections with many cross-border links compared to few domestic feeder links.

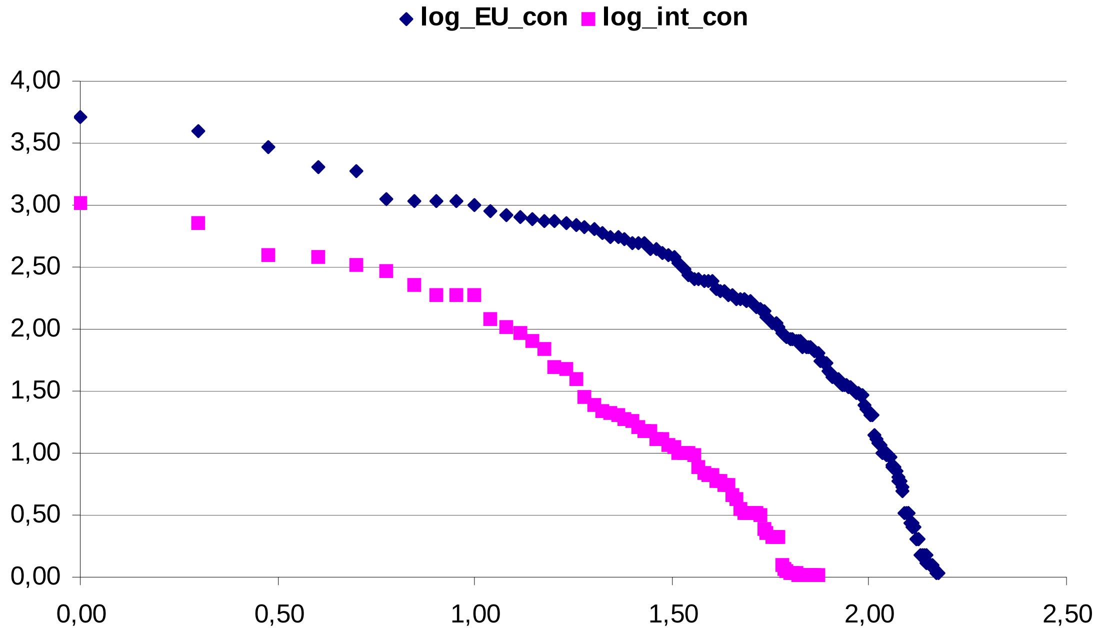


Figure 6 : Global connectivity indices – log log plot

Table 2 provides the results of equation 3 and then ranks the scores from highest to lowest for the top twenty-five airports. Connectivity stands for the number of destinations that were served in 2004 by the given airport (including domestic, European and intercontinental). G_connect represents the global connectivity ratio between global to local links provided by the airport during 2004 and is weighted by the number of destinations as explained through equation 3. The prefix EU or INT. indicates whether European or intercontinental links are considered to be "global".

Running the model produced an interesting distribution of airport rankings: The most marked differences between the level of connectivity of an airport and their global connectivity index for intercontinental routes show up with Amsterdam, London Heathrow and Rome. The latter two seem to put more emphasis on their intercontinental links compared to the overall number of destinations served. Amsterdam is ranked 4 notches lower on global (intercontinental) connectivity compared to overall connectivity: Amsterdam puts less weight on intercontinental links relative to all of its destinations served. This is consistent with the finding that Amsterdam ranks first for trans-European global connectivity.

Apart from Amsterdam and London Gatwick and perhaps Zürich, it is difficult to find much resemblance between rankings of simple connectivity and that of weighted connectivity indices for Europe. Again, this suggests that apart from the exceptions quoted in the above, the biggest European airports use their capacity for intercontinental connections rather than trans-European ones.

Table 2: Airport ranking along connectivity indices (2004)

Rank	Connectivity	EU G_connect.	INT G_connect.
1	PARIS (CDG)	AMSTERDAM (AMS)	PARIS (ORY)
2	PARIS (ORY)	ZURICH (ZRH)	COPENHAGEN (CPH)
3	AMSTERDAM (AMS)	BRUSSELS (BRU)	PARIS (CDG)
4	COPENHAGEN (CPH)	PRAGUE (PRG)	FRANKFURT/MAIN (FRA)
5	FRANKFURT/MAIN (FRA)	BASEL-MULHOUSE (BSL)	ZURICH (ZRH)
6	ZURICH (ZRH)	VIENNA (VIE)	AMSTERDAM (AMS)
7	MILAN (MXP)	LONDON (LGW)	LONDON (LHR)
8	LONDON (LGW)	DUBLIN (DUB)	DUSSELDORF (DUS)
9	DUSSELDORF (DUS)	LONDON (STN)	LONDON (LGW)
10	MUNICH (MUC)	OSLO (OSL)	MILAN (MXP)
11	MADRID (MAD)	COPENHAGEN (CPH)	MUNICH (MUC)
12	LONDON (LHR)	LISBON (LIS)	MADRID (MAD)
13	PALMA DE MALLORCA (PMI)	MUNICH (MUC)	ROME (FCO)
14	MANCHESTER (MAN)	SALZBURG (SZG)	MANCHESTER (MAN)
15	BARCELONA (BCN)	FRANKFURT/MAIN (FRA)	VIENNA (VIE)
16	LONDON (STN)	PALMA DE MALLORCA (PMI)	HELSINKI (HEL)
17	HELSINKI (HEL)	ROTTERDAM (RTM)	BARCELONA (BCN)
18	VIENNA (VIE)	MAASTRICHT (MST)	LISBON (LIS)
19	OSLO (OSL)	LONDON (LHR)	PRAGUE (PRG)
20	ROME (FCO)	MANCHESTER (MAN)	OSLO (OSL)
21	PRAGUE (PRG)	DUSSELDORF (DUS)	NICE (NCE)
22	DUBLIN (DUB)	HAHN (HHN)	MAASTRICHT (MST)
23	GRAN CANARIA (LPA)	GENEVA (GVA)	GENEVA (GVA)
24	NICE (NCE)	MILAN (MXP)	BRUSSELS (BRU)
25	HAMBURG (HAM)	CORK (ORK)	TOULOUSE (TLS)

Countries such as Germany or the UK present several airports (three to four) with high global connectivities on both European and intercontinental routes. Spain shows two airports (Madrid, Barcelona) that show high weighted connectivities on intercontinental traffic, but only one airport (Palma) that may be considered an important trans-European global connector. Countries such as Austria, the Netherlands, Norway, Denmark or Portugal each show one hub that shows high global connectivities on both European and intercontinental traffic. Switzerland can also be considered part of this group, as the Bâle-Mulhouse airport is not really dominated by Swiss. Probably the most striking connectivity distribution is that of French airports: none of them makes it into the 25 most highly (weighted) connected airports for European traffic. Paris CdG and Orly show the highest global connectivities for intercontinental destination, with Nice being ranked 21st. It must be concluded that French airports are very weak trans-European connectors. Italy has two airports that rank high on inter-continental, but fail to obtain high European ranks. The same applies to Finland, with Helsinki ranking 16th on intercontinental, but failing to show strong intra-European connectivity.

5. DISCUSSION

After the connectivity indices for European airports were assessed, their significance for airlines' strategies shall be discussed. The search of airlines to obtain *economies of density* can be seen as another form of the efficiency advantages provided by small world networks: many local routes funnel into few global links which allow to exploit such economies. Often more expensive investment in new technology (i.e. bigger aircraft) requires such global connectors that are linked to many feeder routes. In principle, the steeper the slope of the connectivity index, the higher the economies that can be realized within the network: a flatter slope would indicate more airports with a high ratio of global links compared to local ones. The capacity constraints at airports as well as the limited size of aircraft may explain why a power law distribution (a small, but *significant* proportion of highly connected nodes) prevails for intercontinental global links. Scheduling decisions and choices of flight frequency aim to optimise these economies.

A strategy of *market power* can be seen in the light of the preferential attachment condition of the BA model. The saturation of airport hubs imply often prohibitive costs of adding new links. It becomes evident that airlines that seek market power will target such hubs to exert their control over less highly connected airports linked to the hub. In contrast to smaller airports with spare capacity and possibilities to expand, entrants can easily be deterred. Airline incumbents are interested in occupying the biggest airports (or form alliances with those). In principle, a steeper slope of airport connectivities within airlines' networks allows for better control, whereas within a flatter distribution entry may be prevented (or controlled) less easily. If the airports involved are close to or fully saturated, market power may be exerted through a small, but significant minority of such airports: a power law connectivity distribution may prevail over exponential decay. Ceteris paribus, flight frequencies between given airports should be higher, if at least at one end-point the airline's hub is involved.

The situation changes completely when we look at those European airports that do not constitute hubs: as with regards to the intra-European connectivity index, an exponential, slow decay, not a power law is observed. Such connectivity distributions suggest that airlines will not be able to compete neither through economies of density nor through market power. Many cross-border links compared to domestic links (weighted by the overall number of destinations) do not suggest funnelling or the utilization of more specific and efficient technologies that may require higher volumes and could take advantage of such funnelling. Market power is difficult to obtain as new links, including that provided by new entrants can easily be added to the given airport at low cost. In order to follow a power law for European connectivity, these airports could constrain capacity at the given airports and restructure their portfolio of destinations served, for example. The first measure may limit the addition of new links and allow for airlines present to find their return on investment by exerting some degree of market power. Secondly, route restructuring would deploy expensive bigger aircraft to a few destinations only and ensure its efficient exploitation through frequent domestic destinations feeding into the airport. As many of these medium-sized airports today are being used as feeder routes into incumbent airlines' intercontinental links, such measures are likely to increase bargaining power for these airports as well. In this respect the analysis of connectivity indices may help to improve the competitive situation for medium sized airports.

REFERENCES:

Adamic, L. (2000) Zipf, Power-laws, and Pareto - a ranking tutorial, Internet Ecologies Area – Parc Xerox, http://ginger.hpl.hp.com/shl/papers/ranking/ranking.html

Albert R., Barabási, A. (2002) Statistical mechanics of complex networks, *Reviews of Modern Physics* 74, 47-97

Albert R., Jeong H., Barabasi A. (1999) The diameter of the World Wide Web, *Nature* 401, 130-131

Amaral L., Scala A., Barthelemy M., Stanley H. (2000) Classes of small-world networks, *Proceedings of the National Academy of Sciences* 97 (21), 11149-11152

Bailey, E., Graham, D. & Kaplan, D (1991) *Deregulating the airlines*, MIT Press: Cambridge, Mass.

Barabasi A. (2001) The physics of the Web, *Physics World* July 2001, http://www.physicsweb.org/article/world/14/7/09

Barabasi A., Albert A. (1999) Emergence of scaling in random networks, *Science* Oct, 509-512

Berechman, J., Shy, O. (1998) The structure of airline equilibrium networks, *Recent Advances in Spatial Equilibrium Modelling*, Springer, Berlin

Bollobás B. (1985) *Random Graphs,* Academic Press, New York

Borenstein, S. (1989) Hubs and high fares: Dominance and Market Power in the US airline industry, *Rand Journal of Economics* 20, 344-365

Brueckner J.K., Zhang Y. (2001) A model of scheduling in airline networks, *Journal of Transport Economics and Policy* 35 (May), Part 2, 195-222

Brueckner, J.K. & Spiller, P.T. (1994) Economies of traffic density in the deregulated airline industry, *Journal of Law and Economics* 37(October), 379-413

Brueckner, J.K., Dyer, N.J. & Spiller, P.T (1992) Fare determination in airline hub and spoke networks, *Rand Journal of Economics* 23(3), 309-333

Erdos P., Renyi A. (1960) On the evolution of random graphs, *Publication of the Mathematical Institute of the Hungarian Academy of Science* 5, 17-67

Garrison W. (1968) Connectivity of the interstate highway system, in Berry B, Marble D, *Spatial Analysis,* Englewood Cliffs, NJ: Prentice Hall, 239-249

Gorman, S.P., Kulkarni, R. (2004) Spatial small worlds: New geographic patterns for an information economy, *Environment and Planning B* 31, 273-296

Hayes B. (2000a) Graph theory in practice: Part I, *American Scientist* 88 (01), 9-13

Hayes B. (2000b) Graph theory in practice: Part II, *American Scientist* 88 (02), 104-109

Kahn, A. (1993) The competitive consequences of hub dominance: a case study, *Review of Industrial Organization* 8, 379-405

Kansky K. (1963) Structure of Transportation Networks: Relationships Between Network Geometry and Regional Characteristics, University of Chicago, Department of Geography, Research Papers

Kim, E.H., Singal, V. (1993) Mergers and Market power: evidence from the airline industry, *American Economic Review* 83 (3), 549-569

Milgram S. (1977) The small world problem, *The Individual in a Social World: Essays and Experiments*, Milgrim, S, Sabini, J, (Eds), Reading, MA: Addison-Wesley, 281-295.

Morrison, S.A., Winston, C. (1990) The dynamics of airline pricing and competition, *American Economic Review* 80(2), 389-393

Morrison, S.A. (1996) Airline mergers: a longer view, *Journal of Transport Economics and Policy* 30(September), 237-250

Morrison, S.A. and Winston, C. (1995) *The evolution of the airline industry*, Brookings Institution, Washington D.C.

Richard, O. (2003) Flight frequency an mergers in airline markets, *International Journal of Industrial Organization* 21(6), 907-922

Sinclair, R. (1995) An empirical model of entry and exit in airline markets, *Review of Industrial Organization* 10, 541-557

Sinclair, R.A. (1995) An empirical model of entry and exit in airline markets, *Review of Industrial Organization* 10, 541-557

Stoneham, A.K.M. (1977) The small-world problem in a spatial context, *Environment and Planning A* 9, 185-195

Wasserman, S. and Faust, K. (1994) *Social Network Analysis: Methods and Applications*, Cambridge Univ. Press, Cambridge

Watts D.J. (1999) *Small Worlds: The Dynamics of Networks between Order and Randomness*, Princeton University Press, Princeton, NJ

Watts D.J., Strogatz S.H. (1998) Collective dynamics of small-world networks, *Nature* 363, 202-204.

Watts, D.J. (2003) *Six Degrees: The Science of a Connected Age*, W.W. Norton, New York, NY

Zipf P.K. (1949) *Human Behavior and the Principle of Least Effort*, Addison-Wesley, Cambridge, MA