



SERC DISCUSSION PAPER173

Exploring the Geography of China's Airport Networks: A Hybrid Complex-Network Approach

Wenjie Wu (Heriot-Watt University, Edinburgh and SERC)
Zhengbin Dong (China Development Bank, Beijing)

March 2015

This work is part of the research programme of the independent UK Spatial Economics Research Centre funded by a grant from the Economic and Social Research Council (ESRC), Department for Business, Innovation & Skills (BIS) and the Welsh Government. The support of the funders is acknowledged. The views expressed are those of the authors and do not represent the views of the funders.

© W. Wu and Z. Dong, submitted 2015

Exploring the Geography of China's Airport Networks: A Hybrid Complex-Network Approach

Wenjie Wu* and Zhengbin Dong**

March 2015

* Heriot-Watt University, Edinburgh and Spatial Economics Research Centre

** China Development Bank, Beijing

The authors would like to thank Jiaoe Wang, Fengjun Jin, Wenzhong Zhang, Civil Aviation Administration of China. We would also like to thank participants in the workshop of Advanced Data Mining and Applications in Beijing in 2009 where earlier versions of this paper were presented.

Abstract

Air networks are normal examples of transportation systems among ubiquitous big data networks in the dynamic nature. This is particularly the case in developing countries with rapid airport network expansions. This paper explores the structure and evolution of the trunk airport network of China (ANC) in major years during 1980s-2000s. We generalise the complex network approach developed in existing studies and further test for statistical properties of weighted network characteristics by using pair-wise traffic flows. The spatiotemporal decomposition of network metric plots and the visualization maps leads to a rich harvest of stylized ANC structures: (i) national hub-and-spoke patterns surrounding mega-cities; (ii) regional broker patterns surrounding Kunming and Urumqi, and (iii) local heterogeneous disparity patterns in isolated geographical cities, such as Lhasa, Lijiang, Huangshan, etc. These findings have important implications towards understanding the geopolitical and economic forces at stake in shaping China's urban systems.

Keywords: Airport system, complex network, regional development, China

JEL Classifications: C55; O18; R12; P25

1 Introduction

Air transportation systems are increasingly represented by complex topology networks as an analogy for studying their structures and geographical implications on urban and regional development (O’Kelly, 1998). The recent decades have seen the emergence of airport hubs such as the London Heathrow Airport in the UK, as principal means by which periphery regions are connected to the network for public transportation services. Hence, airport network expansion is often seen as a policy lever that can stimulate city connectivity, in the same way that highway and railway investments improved hub-and-spoke transport systems¹. This is a particularly important question today in the context of China, given that China has become as the world’s second largest air transportation market country since 2000s (Civil Aviation Administration of China, 2006). There is considerable debate over the institutional and network characteristics of the evolution of airport systems in China since the late 1980s (e.g., Zhang, 1998; Zhang and Chen, 2003; Wang and Jin, 2007; Zhang and Round, 2008; Shaw et al., 2009; Lei and O’Connell, 2011; Wang et al., 2011; Lin, 2012). Evaluations of the evolution of airport networks face several empirical challenges, including accurately identifying spatiotemporal patterns of network structures, precisely measuring network dynamic features and studying potential

¹ These policies frequently combine transport network dynamics with economic objectives under the conventional wisdom that better accessibility promotes the growth of hub city and spreads of economic benefits to peripheral cities. In this context, many explanations of transport networks rely on the economic foundation of spillover effects that lead to theories of trade and market competition, productivity, and economic integration (Brueckner, 2003; Redding et al., 2011). In this paper however, we step back from theoretical concerns and focus on the stylized facts to be explained.

economic geography channels at work.

This paper explores the evolution of China's intercity airport network expansions during 1980s-2000s, using location-based data sources and a weighted complex network approach that permit us to meet many of empirical challenges. The first data source is detailed Geographically Information System (GIS) maps we constructed of the precise locations of airports as they evolved over time. With maps of both existing airports and newly-built airports, we identify the evolution of airport network expansions in multiple ways, allowing us to provide more insights on seeing regional disparities through geo-tagged air traffic flow data. The second is the civil aviation big database, which includes airflight routes and location information between airport-pairs with regular flight timetables in the period 1980s-2000s—a period that China has experienced the most dramatic air transportation expansion. By constructing precisely pair-wise air traffic flow information and combining this information with GIS maps, we can use the complex network approach to measure topological characteristics of airport networks based on in each given year, in each airport and at different geographic scales.

To conduct our analysis, we generalize the unweighted complex network approach developed in Dong et al (2009) and other recent studies (Wang et al., 2011 and Wang et al., 2014). The fundamental value of the geo-computations in those papers is to compare the statistical distribution of unweighted network metrics. This provides a test for purely statistic-based interpretations about China's aviation networks at the national scale. In this paper, we develop this approach further to test

for the combination of unweighted and weighted complex network metrics of intercity airflight interactions at different geographical scales over time (see Section 2 for detailed comparisons). In addition to the importance of national hub-and-spoke patterns, we consider network disparity features and find strong evidence of abnormal regional community patterns around Kunming and Urumqi, and local heterogeneous disparity patterns in isolated geographical cities, such as Lhasa, Lijiang, Huangshan, etc. This is also novel.

The remainder of this paper is organized as follows: Section 2 reviews the existing literature that are relevant to our study. Section 3 describe the methodology framework, and Section 4 presents the data and study area. Section 5 presents the results. Section 6 discusses the implications of this study and potential channels at work. Section 7 concludes.

2 Related work

Most existing research on assessing the evolution of airport networks has focused on the US and European countries. Despite the central role of airport network topology models, these studies have mostly emphasized the network structure consequences of airline industry deregulations, the presence of low-cost carriers, liberalization and other policy reforms (Chou, 1993; Bowen, 2002; Dobruszkes, 2006; Goetz and Vowles, 2009; Ison et al., 2011). There have been fewer studies about the evolution and efficiency of airline systems in developing countries (Bowen and Leinbach, 1995; O'Connor, 1995; Bowen, 2000), largely due to a lack of systemic

geo-tagged data about air transportation infrastructure, a lack of clear understanding regarding airport and airline policy arrangements, and the difficulty of tracking airflight routes across cities. This section summarizes and highlights existing research that are relevant to our study.

Our work contributes to a substantial empirical literature that investigates various aspects of China's airport development. Much of it is concerned with variations in China's airport development policy reforms, an issue that is not directly related to our work. Typically, these studies review the market-oriented policy reform process of the China's airline industry (Zhang, 1998; Zhang and Chen, 2003; Zhang and Round, 2008; Yang et al., 2008). More recent work has moved away from the macro-policy research towards an explicit comparison of market competition outcomes of state-owned airline companies versus privately-owned airline companies before and after the airline consolidation policy reform led by the Civil Aviation Administration of China (CAAC) in the early 2000s. It also shifted its focus away from hard-to-measure policy consolidation variables to the implications on contemporary airport network patterns (Shaw et al., 2009). The results vary across studies. Many studies succeed to find that the three-giant Chinese airline companies (AirChina, Eastern China Airline, Southern China Airline), created by state-led consolidation reforms, tend to use Beijing, Shanghai and Guangzhou as their distinct national hubs and small airport cities as periphery areas to balance airline market competition structures (Ma and Timberlake, 2008; Lei and O'Connell, 2011). These findings, however, could fail to fully capture the spatial characteristics of airport

networks. Indeed, it is very likely that airline market competition structures may not be overlapped with the precise spatial structure of airport networks for which outcomes of interest---such as topological characteristics of intercity flight linkages---can be measured.

Our work is also related to a growing body of complex network literature dealing with the statistical, topological and geometric structures of transport systems, including the railways (Sen et al., 2003) and the airways (Bagler, 2008; Xu and Harriss, 2008). By showing that the worldwide airport network (WAN) has a scale-free property and small-world structure, Guimerà et al.(2005) provide the most convincing evidence about the hub-and-spoke airport network structure across the globe. The Airport Network of China (ANC), a network much smaller than the WAN, has recently been analyzed for its topology and traffic dynamics (Li and Cai, 2004; Zheng et al., 2009; Wang et al., 2011; Lin, 2012). Its topology was found to have small-world network features and a two-regime power-law degree distribution. These studies have almost exclusively examined the static state of a network in one year. In what are probably the most closely related papers to our own, Dong et al (2009) and Wang et al (2014) examines the dynamics of China's airport network patterns over the past decades based on approximately 10-year time intervals. On the surface, our research design resembles the investigation in Dong et al (2009) and Wang et al (2014). We make a similar complex network mining approach, but note that more careful consideration reveals three important differences between our research and that in Dong et al (2009) and Wang et al (2014). First, it is certainly true that a longer

time span can offer more information about the evolution of airport network structure. As indicated by Wang et al (2014), ANC did not experience significant expansions during 1930 to 1980 due to the World War II and civil wars (1930-1949) and strict central-planned socialist economy system (1949-1980). In our study, instead, we restrict our focus on the evolution of ANC in the period 1980-2006---a period that China has experienced dramatic economic growth and significant changes in civil aviation policy reforms. Thus, our identification is even easier to defend in selecting appropriate years and reflect the heterogeneous effects of airport network expansions. Second, previous studies have often used basic network metrics such as degree, clustering coefficient, short path for assessing the unweighted topological network centrality evolution process of the ANC. In truth, an unweighted network is a special case of weighted networks when all edge weights are the same. The spatiotemporal distributions of our network metrics allow us to shed more lights on the geo-political implications of the evolution of China's airport network patterns. This is novel. Third, previous studies are concerned with the global hub-and-spoke network centralization process at the national level, while we look at the distributions of hub-and-spoke network structure at different geographical scales--an important complementary inquiry.

3 A complex network modeling framework

A complex network modeling framework is coded in Matlab after a substantial modification and secondary programming based on Freeman (1979)'s seminal work.

The specific modeling framework setup is detailed below.

3.1 Defining a connected network graph

For any airport network, it comprises nodes (cities) and edges (airline routes) connecting them. Two nodes are defined to be neighbors if there is a link between them. In this paper, the ANC is abstracted as a connected network graph be $G = \{(V, E) \mid V \text{ is a set of nodes, } E \text{ is a set of edges. } E \subseteq V \times V, \text{ an edge } e = (i, j) \text{ connects two nodes } i \text{ and } j; i, j \in V, e \in E\}$. This setting is necessary for the calculation of network metrics such as degree, shortest path, diameter, clustering coefficient as detailed below.

3.2 Basic network connectivity measures

The starting point for evaluating network connectivity is to introduce three basic and important network metrics: degree, shortest path, and diameter as below (Haggett and Chorley, 1969; Taaffe et al., 1996; Black, 2003):

The degree of a node v in a network, represented as $d(v)$, is the number of connections or edges the node shares with others (Barabasi and Albert, 1999). Let $N(v) = \{u \mid (v, u) \in E \text{ and } v, u \in V\}$, which is a set of the neighbor nodes of v in the graph G . so $d(v)$ is the size of set $N(v)$.

A path in a network is defined as a sequence of nodes (n_1, \dots, n_k) such that from each of its nodes there is an edge to the successor node. The path length is the number of edges in its node sequence. A shortest path between two nodes, i and j , is a minimal length path between them. A shortest path between two nodes is referred to as a

geodesic. The distance between i and j , noted as $d(i, j)$, is the length of its shortest path. The diameter of the network is the length of the longest shortest path that quantifies how far apart the farthest two nodes in the graph are.

3.3 Clustering coefficient

Knowing basic network metrics are not enough for quantifying how the node and its neighbors are clustered to being a complete graph. Thus we calculate the network clustering coefficient. This index was first introduced by Watts and Strogatz (1998) to determine the network structure.

The clustering coefficient of node v , noted as C_v , measures the extent of the inter-connectivity between the neighbors of node v and is the ratio of the number of edges between the nodes in the direct neighborhood to the number of edges that could possibly exist among them, C_v can be defined as:

$$C_v = \frac{2 \left| \bigcup_{i,j \in N(v)} e(i, j) \right|}{d(v)(d(v)-1)} : e(i, j) \in E \quad (1)$$

where $d(v)$ is the degree of node v and $N(v)$ is the set of the neighbor nodes of v . Based on the clustering coefficient of a node, we can define the clustering coefficient of a network, which is the average of the clustering coefficients of all nodes in the graph:

$$\bar{C} = \frac{1}{n} \sum_{i=1}^n C_i \quad (2)$$

3.4 Betweenness centrality

Centrality is a core concept for the analysis of social networks, and betweenness is one of the most prominent measures of centrality. It was introduced independently by Freeman (1979), and measures the degree to which a node is in the position of geographical centrality (brokerage) by summing up the fractions of shortest paths between other pairs of vertices that pass through it (Borgatti and Everett, 2006). We define the betweenness centrality in a network as follows: Let $\sigma(s,t)$ as the number of shortest paths (sometimes referred as *geodesics*) from s to t and let $\sigma(s,t|v)$ be the number of shortest number from s to t passing through some vertex v other than s, t . If $s = t$, let $\sigma(s,t)=1$, and if $v \in \{s,t\}$, let $\sigma(s,t|v)=0$. The betweenness $c_B(v)$ of a vertex v can be defined to be:

$$c_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \quad (3)$$

This measure is interpreted as the extent to which a city has control over pair-wise connections between other cities. In the airport network analysis, a city with high betweenness means that it is on the position of geographical centrality (brokerage) between other pairs of city connections. Given massive new airport development in China, it is important to identify which cities are acting as geographic brokers in the ANC and their dynamics over time and space.

In addition to betweenness centrality, are there any other centrality measures missing? Of course, yes. Alternative centrality measures such as closeness, straightness could also capture characteristics of transport networks (Ma and

Timberlake, 2008). In this study, we only consider the degree centrality and betweenness centrality for the following reasons. First, degree and betweenness are the most meaningful centrality metrics to quantify different dimensions of network connectivity by geographers. Second, in our results that are not reported due to space limits, we find that the ANC patterns are robust to the inclusion of alternative centrality measures such as the closeness index.

3.5 Weight, intensity and disparity coefficient

For transport networks, weighted quantities such as traffic flows and travel distance have recently been applied to investigate the heterogeneity in the intensity of connectivity patterns--measured by edge weights--between node pairs. In our study, we define the node intensity S_i as follows:

$$S_v = \sum_{j \in N(v)} w_{vj} \quad (4)$$

where s_v is the weighted degree of airport city v . w_{vj} is the weight of edges based on the annual traffic flows between two airport cities, $N(v)$ is a set of neighbor airport cities with respect to airport city v . In addition to the node intensity, we measure the disparity coefficient for each node:

$$Y(v) = \sum_{j \in N(v)} \left(\frac{w_{vj}}{S_v} \right)^2 \quad (5)$$

where $Y(v)$ is the disparity coefficient for airport city v . It reflects the degree of the heterogeneity with respect to the intensity of airport connections.

3.6 Distribution of network metrics

Characterizing the distribution function of network metric correlations is crucial to reveal multiple structural dimensions of airport network features. This section introduces the node-degree distribution, degree-clustering coefficient distribution, and degree-betweenness distribution.

The node-degree distribution $p(k)$ of a network is defined to be the fraction of nodes in the network with degree k . Thus if there are n nodes in total in a network and n_k of them have degree k , we have $p(k) = n_k/n$. In essence, the node-degree distribution reflects a node's network connectivity status. It can be measured by the correlation between the node degree and the average degree for all of its connected nodes: $K_i(k) = \frac{1}{k_i} \sum_{j \in V(i)} k_j$ where k_i is the degree of node i . $V(i)$ includes all neighboring nodes of i .

Considering the node-degree distribution patterns between cities (nodes) will allow us to assess if most nodes are not neighbors of one another and if most of them can be reached by a small number of edges in the network (Newman, 2003). Technically, we can break down the scenario into two sub-categories: a disassortative mixing scenario occurs if high-degree nodes tend to connect with low-degree nodes, whereas the assortative mixing scenario indicates that high-degree nodes tend to link with other high-degree nodes.

The degree-clustering coefficient distribution reflects the hierarchical organization of complex networks (Rabasz and Barabasi, 2003). The

degree-clustering coefficient distribution $p(C)$ of a network, is defined to be the fraction of nodes in the network with clustering coefficient C . Thus if there are n nodes in total in a network and n_k of them have clustering coefficient C , we have $p(C) = n_k/n$. The average clustering coefficient of degree k , noted as $C(k)$, is defined as the average value of clustering coefficient of nodes with degree k . The larger the value of C is, the more likely nodes are to reach one another within a short distance (i.e., airline connections). Following the same principle, we can use $\overline{c_B}(k)$ to represent the average value of betweenness of the vertices with the same degree k , and define the betweenness-degree distribution.

4 Implementation

In this section, we discuss the implementation of the complex network model introduced in the previous sections based on a public data stream of real-time flight timetables. Figure 1 shows the system architecture of flight frequency rates between airport pairs. The selection of airports (as shown in Figure 1) is mainly dictated by data availability.

China is known in the post-cold war era for its rapid airport network expansions. Our first step is to retrieve data from the Timetable of Air Carriers in China (1983, 1993, 2006), obtained from the Civil Aviation Administration of China (CAAC). We select these approximately 10-year intervals in order to meet with national development plans, and milestone events occurred in China's civil aviation development policy reforms (Zhang, 1998; Zhang and Yuen, 2008; Zhang and Round,

2009). For example, 1983 was the year that Boeing 747 and 737 aircrafts were first operated in China, indicating the opening of China's airport markets to Western aircraft companies. 1993 was the year that the CAAC was re-structured as a direct government organization under the State Council, and published the market-oriented airline management policy reform². 2006, was the year when China has become as the second largest airport market in the world and launched a series of new air transportation policy reforms. We did not select the air traffic information after 2006 because that the post-2006 high-speed rail development may have market competitions with airflights and influence the evolution of transport networks (Yang and Zhang, 2012). Provided by the CAAC, our data set is an extremely rich database which contained details information about trunk airports with regular airline routes in the mainland China (excluding Hong Kong, Macao and Taiwan). Because our database do not have a comprehensive source for civil-military mixed-use airport information, we exclude cities whose airports information are missing.

In the second step, we use the GIS techniques to match the precise locations of airports with flight route information between airport pairs, and use the annual flight frequency³ as the edge weight to construct the weighted complex network graph. For a more rigorous assessment, direct and transfer-over airline routes are considered and combined in the data set. The transfer-over airline routes are divided into two parts: from the departure city to the transfer-over city, and then from the transfer-over city to

² See original government policy details in <http://www.caac.gov.cn/b1/B6/200612/P020061219658214793463.pdf>

³ It is certainly the case that international airflight information would offer more complete characteristics of airport networks. However, collection of international airflight flow data with precise origin-destination location information would be very costly due to the lack of stable and systemic timetables for different airline companies. Following the convention, this study focuses on the domestic airport network throughout the analysis.

the final destination city. Duplicated airline routes are displayed as one route but are weighted by annual air flight frequency.

Figure 1 maps the location information of airport network nodes and edges. Each dot represents a city node, and each line represents the airline connections between cities, weighted by the annual air flight frequency. As can be seen from the maps, China's domestic airport network is characterized by regional inequality but move towards a more balanced spatial pattern. In 1983, almost all airport city connections occurred in the east side of the famous “Aihui-Tengchong Line”, a hypothesized “geographic-demographic disparity line” in China (Hu, 1935). Based on the 1980 population census, 93.5% of Chinese residents lived in the east side of this line, however, this figure fall to 90.8% in the recent 2000 census. When we turn to looking at airport network expansions from 1983 to 2006, dynamic roles of cities are more difficult to discern from a purely visual inspection of the data. Thus, we use the complex network mining approach to make more precise diagnostics about the dynamics of the network structure and inter-city airport connection trends. We let the Airport Network of China (ANC) comprise domestic airports of China and airlines connecting them. Let an undirected binary graph be $G = \{(V, E) \mid V \text{ is a set of nodes, } E \text{ is a set of edges. } E \subseteq V \times V, \text{ an edge } e = (i, j) \text{ connects two nodes } i \text{ and } j \text{ and } i, j \in V, e \in E\}$. In the ANC, the nodes of the network represent the airports and the edges between the pairs of nodes represent the airlines between the cities. Figure 2 uses the visual mining methods (Batagelj and Mavar, 1998) to show the evolution of ANC structure in major years during 1980s-2000s, respectively.

5 Results

5.1 Statistical properties of the global network structure

We begin the network analysis by looking at statistical properties of the global network structure and how it evolves over the past twenty years. Performing this analysis requires a clear interpretation of network metrics, such as degree, average path length/diameter and the clustering coefficient. Table 1 compares the basic network metrics of the ANC to other countries as reported in the existing literature. We find that the average degree, clustering coefficient and path length indicators of the ANC are similar to those of airport networks in India and Italy, though much smaller than those of the US. This is not a surprising finding because the US airport network is much larger than the ANC, with about more than two times the number of airports and more than six times the number of edges. In addition, airport networks in developed countries like US, Italy are very stable and remain as maturity markets (Xu and Harriss, 2008).

As a second step towards understanding the ANC structure and evolution, we need to know the tendency between the number of airport cities and the number of airline routes over time and the tendency of diameter change. The conventional wisdom of these two questions is that: 1) constant average degree, i.e., the number of airline routes grows linearly with the number of airport cities; 2) slowly growing diameter, i.e., as the network grows, distances between cities grow. Perhaps surprisingly, ANC does not follow these two presumptions. As shown by the degree

distribution plotted in Figure 3(a), we find that the ANC's node-degree distribution fits the heavy-tail distribution law (Clauset et al, 2009) but not follow the power-law distribution law. This suggests that the ANC is a small-world network but not a typical scale-free network like other airport networks (Guimera et al, 2005). A credible explanation is that a few large Chinese cities (i.e. Beijing, Shanghai and Guangzhou) connect with almost all other airport nodes in the entire network.

To go more in depth, we find that a densification trend of inter-city airport connections in China. For example, the average network degree has increased by 123.5% from 1983 to 2006 and the average network clustering coefficient has increased by 42.6%, from 0.38 in 1983 to 0.54 in 2006. This is consistent with the decreasing trend of the ANC diameter and the highly-skewed clustering coefficient distribution relative to city node distribution (Figure 3b). These results suggest that inter-city airport connections in China are very dense and people can arrive at their flight destinations with fewer flight connections.

When plotting, in Figure 4(a), the degree-clustering coefficient distribution, we find that airport cities with higher degree centrality values tend to have lower clustering coefficients. A typical example is Beijing, which connects almost all other cities in the network, and therefore, Beijing's degree centrality is very high and its clustering coefficient is very low. This diversified degree-clustering coefficient distribution pattern is not the entire story. To illustrate the variations in individual airport city centrality outcomes, we use $\overline{c_b}(k)$ to represent the average betweenness value of airport cities with the same degree k and plot the distribution in Figure 4 (b).

As is immediately clear, degree-betweenness distributions of ANC after scaling follow the exponential distributions and the plotted curves can be fitted by using the exponential function as below: $y = y_0 + Ae^{R_0x}$. This exponential distribution of degree-betweenness correlation function suggests that cities with high degree levels tend to be cities have high betweenness levels. In light of this tradeoff, our results suggest that the most connected cities are the most central cities in China. This is different from the existing findings in developed countries, where the most connected cities may not necessarily be the most central cities. The underlying reason for this unique pattern is that the worldwide airport network has multi-community structure while the ANC is very dense and does not have obvious community structure. The airport cities connecting different communities should have higher betweenness. However, all airport cities in China are connected closely and circled around a few hubs, e.g. Beijing, Shanghai and Guangzhou. This provides supportive evidence to the abnormal left-skewed distribution of clustering coefficient given above. In addition, we find that there is an obvious outlier airport city (marked by a blue circling buffer) in the degree-betweenness distribution in 2006, which represents a very unique abnormal pattern in the ANC and we will discuss it in detail in the following sections.

5.2 Spatiotemporal decomposition of regional heterogeneity patterns

In this section, we turn to the examination of differences in the evolution of network patterns at the regional scale. Proceeding as before, we use the degree centrality index to symbolize the connectivity level for each node because it measures

the number of airline routes that a city connects with others. We also construct a betweenness centrality to measure the extent to which cities have control over pair-wise connections between other cities in the network.

We begin by assessing the dynamics of airport network patterns across China's three regions (Western region, Central region, and Eastern region)⁴ in major years during 1980s-2000s. For each region, we computed the standardized change ratio of its average clustering coefficient, betweenness centrality, and degree centrality relative to the national average level (Figure 5). We find high values of clustering coefficients across regions, suggesting that Chinese regions have experienced a similar densification networking trend over the past twenty years. In terms of degree variations, we find that the flight connectivity of the Western region has a much faster growth rate than that of Central and Eastern regions. When looking at the betweenness centrality, we find that the Western region has experienced the strongest improvement and the Eastern region remains at a high and stable level, however, the Central region has experienced the significant decreasing trend. This heterogeneous pattern may partly reflect the correlations with uneven population and economy distributions in China, where western and central regions are less developed than the eastern region.

⁴ Following the convention, researchers and policymakers used to divide mainland China into three regions. Western China include 12 provinces: Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, Inner Mongoli. Central China include 7 provinces: Shanxi, Anhui, Jiangxi, Henan, Hebei, Hunan, Hubei. Eastern China include 12 provinces: Beijing, Tianjin, Shanghai, Heilongjiang, Jilin, Liaoning, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong and Hainan.

5.3 Spatiotemporal decomposition of network dynamics of airport cities

Further evidence on the evolution of China's airport network patterns can be shown from Figures 2(a-c). The red nodes represent the provincial capital cities and the blue nodes represent the non-capital cities. The size of the node is weighted by using its traffic flows, which is scaled by the maximum value of each year so that the patterns are comparable across figures. It is apparent that ANC is globally connected as a hub-and-spoke circling pattern, and there is no obvious community structure in the ANC. The centers of the circle are hub cities, for example, Beijing, Shanghai, Guangzhou (*the largest three mega cities in China*). These hub airport cities dominate the global network and the majority of nodes connect with hubs across space. We also find that airports in the provincial capital cities are closing to the center of the circling pattern center, with denser connection routes than periphery airport cities.

To reflect geographical implications underlying the above figures, Table 2 lists the 35 most dynamic airport cities in terms of changes in degree connectivity and betweenness centrality relative to national average levels. Four categories are emerged in the matrix table: The first category includes airport cities that have experienced better degree connectivity and betweenness centrality relative to national average levels. A potential interpretation for this category is that these airport cities that have connected with a large and increasing number of other cities, and have rising centrality roles to play in linking other city-pair connections. When looking at specific airport cities that underlie the first category, we find that a spatially heterogeneous group of cities for which their network connectivity and centrality roles are strong:

Beijing, Shanghai, Guangzhou, Shenzhen, Xi'an and Chengdu. This is arguably the first-tier city group in China's urban system that involves either similar demographic characteristics (e.g., population size, employment size, fractions of education attainment levels) or similar productivity levels in terms of GDP, tax revenue and foreign direct investment scale.

The second category includes airport cities that have experienced lower improvements in both of degree connectivity and betweenness centrality relative to the overall network, such as Hefei, Tianjin, Zhengzhou, Guiyang. It is likely that these airport cities have been dispersed their network centrality roles when new airport entrants have been added into the network system over time. We replicated the exercise, this time for airport cities that have experienced higher improvements in degree connectivity but lower improvements in betweenness centrality relative to national average levels. We find that the most dynamic airport cities in this category are: Shenyang, Nanjing, Chongqing, Changsha, Wuhan, Xiamen, Qingdao, and Hangzhou. Airport cities in this category may well be connected with many other cities, however, their centrality roles have been decreasing with the increasing number of new airports and airline routes in China.

Turning to the last category, we focus on airport cities that have experienced better centrality but lower connectivity relative to national average levels. Surprisingly, Kunming and Urumqi are the only two cities that meet this criteria in our sample. These two cities are relatively less centralized but have strong tendencies to act as important brokers for airports within their provinces. This result is consistent with the

anomalous outlier airport city (Kunming) found in Figure 4b. In 2006, the degree of Kunming in 2006 is 33, which is not very high compared to the maximum value of 54 of Beijing. However, Kunming's betweenness value is very high in 2006, and has experienced rapid growth rate relative to the national average level during 1980s-2000s. This is also consistent with the visualized evidence as shown by Figure 2, where Kunming connected many nodes with just one degree, such as Zhaotong, Lincang, Simao, Baoshan and etc. These one-degree nodes connect to other nodes in the ANC through Kunming, leading to its high betweenness centrality value. We call this pattern as the 'Broker' pattern. Urumqi (the capital city of the Xinjiang province) is another typical example for illustrating the 'Broker' pattern, where airport cities in the province of Xinjiang can only be transferred through the Urumqi airport if they want to connect to other places in China. One credible interpretation is due to the sparsely populated, isolated location, and complex landscape constraints in Xinjiang and Yunnan provinces. This picture is in line with the US evidence about the role of Anchorage to play as the most central city in Alaska whereas it is not the hub if one considers all US cities (Guimera et al, 2005). In truth, the geography characteristics of cities like Anchorage, Kunming and Urumqi and the spatial scale at which this broker pattern takes place are certainly supportive of this interpretation.

5.4 Abnormal disparity patterns in a weighted network

In this section, we use the weighted disparity coefficient to measure the spatial disparity patterns of inter-city airport connections---an issue that has not been

received considerable attention in China. We ask if air flight destinations for a given city are heavily pronounced for one particular city than evenly distributed among others.

To perform our analysis, we retained the airport cities with at least 2 degree connections in the network, and used the disparity coefficient to measure whether more than 50% of a given airport city's flights are connected with one particular destination city. Panel A of Table 3 shows that only five airport cities in 1983 exhibit strong disparity over space: Dalian (88.4% flights from Dalian are connected with Beijing), Qingdao (72.4% flights from Qingdao are connected with Beijing), Nanning (61.5% flights from Nanning are connected with Guangzhou), Lanzhou (52.1% flights from Lanzhou are connected with Beijing), Xiamen (51.7% flights from Xiamen are connected with Shanghai). Panel B of Table 3 suggests that there is no clear disparity evidence in 1993 aside from a mild disparity for air flights from Huangshan and Hohhot to be mainly connected with Beijing. In Panel C of Table 3, we find that four airport cities in 2006 have experienced significant disparity connections: Jiuzhaigou (75.3% flights from Jiuzhaigou are connected with Chengdu), Jinghong (72.3% flights from Jinghong are connected with Kunming), Lhasa (61.5% flights from Lhasa are connected with Chengdu), and Lijiang (53.9% flights from Lijiang are connected with Kunming).

The headline finding from here is that most airport city flights appear to have a balanced connectivity pattern. In a small proportion of cases, airport cities tend to be heavily connected with hub cities (e.g. Beijing, Shanghai and Guangzhou). These

facts make sense geographically. It is also noteworthy that airport cities with high disparity coefficient values in 1983 and 1993 are not on the high-disparity-coefficient airport city list in 2006. This implies that airport cities with high disparity coefficients before have rebalanced their airflight connection linkages over time. These results may also suggest that the tendency for China airport cities to have unbalanced flight-destination priorities (or not) is unaffected by the evolution of the global network structure in relation to existing hub cities that have flight connections with them. Further support is given by the insignificant Spearman-rank correlation across airport cities of top-quartile disparity coefficients versus airport cities of bottom-quartile disparity coefficients. Although more work is certainly needed, this finding is suggestive that spatial disparities of airport connections may act as a force to shaping urban systems in China for decades to come.

6 Implications of this study

The air traffic flow data provide large amounts of network metric information of significant value for studying transport systems. Nowadays, human geography and regional sciences benefit considerably from time-stamped and location-based traffic flow data at different geographical scales. The emerging big data harvested from traffic flows and from data-intensive GIS computing (Hey et al., 2009) are transforming ways for doing fieldwork-based human geographical analysis into computational-based virtual modeling approaches (Lazer et al., 2009). In this section, we discuss profound implications of this study for human geography and regional

sciences in general.

At least since Johann Georg Kohl's (1842) seminal work related to transportation and urban geographic theory, the importance of transport networks for shaping economic geography has fascinated geographers and urban researchers alike. The notion of airport cities implies a sort of bottom-up thinking in terms of urban systems and geographical data units. Conventional geographic data collected and maintained from the top down by authorities are usually sampled and aggregated by administrative boundaries. New geographic data harvested from timetables of air carriers are massive and dynamic, so they are loosely called 'big data.' Pair-wise air traffic flow data, supported by complex network technologies and data mining methods, constitute a potentially useful data source for geographic research (Sui and Goodchild, 2011). Conventional core-periphery urban systems are often imposed from the top down by governments, while hub-and-spoke airport cities are defined and delineated objectively from the natural air traffic manner, based on the head/tail network metrics distribution rule. This natural manner guarantees that we can see a visualized picture of airport systems and dynamics (e.g. Figure 2). This picture is fractal but may partly reflect the generalization of the Zipf's law (Zipf, 1949) about city-size rank distribution as documented in the existing literature: On the one hand, there are far more small edged airports than large ones, and on the other hand, each airport has an irregular connectivity pattern.

With the advancement of big data and GIS technologies, there is a growing literature that applies fractal geometry, chaos theories, and complexity into the

geographical analysis (Batty and Longley, 1994; Chen, 2009). The complex network approach adopted in this study, such as long-tail distribution, densification mathematical rule, and power-law-based statistics, can provide new insights into the evolution of airport cities in a large developing country context. To better predict the dynamics of transport systems and human geography processes, future works are needed through simulations rather than simple visualization and correlation analysis.

The complex network data mining approach is intellectually promising because it offers a powerful way for geographical data explorations. The mysterious aspect of the complex network data mining pattern is whether it is an effective way to derive a more complete understanding of urban systems over time. This open question is beyond the scope of this paper. However, quantitative geographers tend to believe that the diverse and heterogeneous patterns as shown by computers are likely to be important complementary evidence for helping economic experts, policymakers and planners to understand how cities connect and evolve. The massive amount of network edges from airport location points constructed the ‘vertex’, and collectively shaped the connectivity patterns of airport networks. Every single edge and node had ‘its role to play’ in the whole network evolution process. From the effectively derived intercity airport network patterns, we can see a brilliant future of complex network data applications.

It is important to note that the hub-and-spoke patterns of airport networks are biased by not just geopolitical considerations, but also driven by disparities in economic growth. Shenzhen is a good example to illustrate this point. Geographically

speaking, Shenzhen is just 200 kilometers away from Guangzhou (one of the largest three mega-cities in China) in terms of physical distance. In 1983 Shenzhen was a small village even without access to highways and railways. However, after the Political Leader Xiaoping Deng's famous southern tour visit in 1992, Shenzhen has been transformed as the Special Economic Zone in China (see Wang, 2013 for institutional details), and has experienced dramatic economic growth over the past twenty years. Nowadays, Shenzhen is known as one of four first-tier cities in China, and its airport that has played dominate connectivity and centrality roles in the entire national airport network. Spearman-rank correlation between Shenzhen's GDP growth and air traffic flow growth is very high and significant. This meets with potential economic geography channels at work. The first underlying channel derives from the neoclassical economic theory about increasing returns to scale (Krugman, 1980). Transportation infrastructure investments, like U.S. President Dwight D. Eisenhower's push to pass the U.S. Federal Highway Act of 1956, which established the interstate highway system that significantly improved ground transportation reliability and service, has been a boon for local and regional development. Similarly, intense airport interactions may increase the productivity of cities, whereas sparse air traffic flows could reflect frictions in the reallocation of production factors such as labor and capital resources within the core-peripheral urban systems. The second underlying channel is related to the Chinese urban transformation trends as found in the economic literature (Baum Snow et al., 2013). A key discovery from this literature is that access to transport infrastructure can have significant impacts in shaping the

decentralization process of urbanization and industrialization. These findings are relevant in the interpretation of our presented mapping evidence about the densification law as reflected from the evolution of airport networks in China. It is very likely that changes in airport accessibility could be related to a localized economic development process as reflected from the improved network centrality status. Are there any other socioeconomic factors that can affect a city's airport network roles? Of course yes. Test these mechanisms can provide more profound implications about interactions of airports and local economic outcomes. Future works are encouraged to consolidate the economic and geography implications of our study when better data information are available.

We face an unprecedented golden era for geography and regional sciences in general, with the development of big data applications. In this study, we documented the evolution of China's airport network at fine spatial and temporal scales. But one concern for our snap-shots analysis is that it could not reflect subtle changes that take place when each new airport is created in a particular place. To mitigate this source of bias, we checked our results against data from five-year intervals and found no significant differences. We could, in principle, have sliced the air traffic flows monthly, weekly, and even daily, and the observed nonlinearity would be even more striking over time. In fact, physicists and computer science researchers have already been working on exploring the rapidly changing network data information (Brockmann et al., 2006; Zheng and Zhou, 2011). We geographers, increasingly, should do our best efforts in this line of research.

7 Conclusion

This paper examines the evolution of China's airport network in major years during 1980s-2000s. Our novelty lies here is in the application of weighted complex network metrics to quantify the characteristics of airport connection patterns at different geographical scales.

We contribute to the existing literature in three-folds: First, it adds to the work on the big data application of the weighted complex network approach by using flight flows between airport pairs. We find that ANC is a typical small world network with high clustering coefficient and small diameter, however, ANC does not follow the power-law degree distribution like the US and other developed countries. The underlying mechanism could be attributed to the unique geo-political constraints in China. National airport hubs, such as Beijing, Shanghai and Guangzhou, have played the central roles in the network evolution process, whereas the connectivity and centrality of most provincial airport hubs still need to be strengthened. Second, our network metrics correlation analysis shows that the evolution of ANC meets the densification law and shrinking diameter law, though such laws are highly skewed across time and space. This provides supportive evidence about the disassortative mixing and the hierarchical organization of China's airport network structure over time (Lin, 2012). There is, however, a strong evidence of two abnormal community patterns around Kunming and Urumqi that can be interpreted by their sparse land-based transport systems and physical landscape constraints. Third, we use the visual data mining methods to find the existence and emergence of various spatial

structures within the ANC, such as national hub pattern, province capital pattern (Kunming and Urumqi) and disparity pattern (Lijiang, Huangshan, Lhasa etc). However, expansions of air flight routes and the competition from land-based transport systems may influence the persistence of a clear law for such disparity patterns.

These results have direct and important practical implications. Abnormally high improvements for a given airport city's network metrics like degree and betweenness centrality can be interpreted as the rising role of that airport city in the whole air transportation system. One thing to note is that, a city's airport network status is likely to be associated with its local economic performance and government endowments, for example, a cluster of new airline routes and new airports might be more likely to build in some places than others. Our analysis does not directly deal with this, since as a first step we want to be able to make statements about dynamics of airport networks and not about the underlying driving economic forces. However, the evolution of airport network is compatible with any explanation that relies on some form of causal effect but also with any explanation based on government endowments. Like Ellison and Glaeser (1997) and Duranton and Overman (2008), we think that it is helpful to be able to explore the dynamics of cities' airport network roles without knowing the right mix of causality and government endowments that led to this pattern. But the fact that airport networks seem to be formed by socioeconomic forces points to a natural question of how local economic performance interacts with airport network expansions. To go further on these conjectures, descriptive evidence might no longer

be sufficient. Instead, theoretical models and ‘casual-sense’ estimation strategy will need to be articulated. This, of course, warrants further studies.

References

- Bagler, G., 2008. Analysis of the airport network of India as a complex weighted network. *Physica A* 387, 2972–2980.
- Barabási, A.L., Albert, R., 1999. Emergence of scaling in random networks. *Science* 28, 509–512.
- Batagelj, V., Mavraj, A. 1998. Pajek-A program for large network analysis. *Connections*, 21(2): 47-57.
- Batty M. and Longley P. 1994. *Fractal Cities: A geometry of form and function*, Academic Press: London.
- Baum-Snow N., Brandt, L., Henderson, J.V., Turner, M. A. and Zhang, Q. 2013. Roads, railroads and decentralization of Chinese cities. Brown University Working Paper.
- Black, W.R., 2003. *Transportation: A Geographical Analysis*. Guilford, New York.
- Borgatti, S.P. and Everett, M.G., 2006. A graph-theoretic perspective on centrality. *Social Networks*, 28, 466–484.
- Bowen, J., 2000. Airline hubs in Southeast Asia: national economic development and nodal accessibility. *Journal of Transport Geography* 8 (1), 25–41.
- Bowen, J., 2002. Network change, deregulation and access in the global airline industry. *Economic Geography* 78 (4), 425–439.
- Bowen, J., Leinbach, T., 1995. The state and liberalization: the airline industry in East Asian NICs. *Annals of the Association of American Geographers* 85 (3), 468–493.
- Brockmann D., Hufnagel L., and Geisel T. 2006. The scaling laws of human travel. *Nature* 439, 462 – 465.
- Brueckner, J.K. 2003. Airline Traffic and Urban Economic Development. *Urban Studies* 40(8), 1455–1469.
- Chen Y. 2009. Spatial interaction creates period-doubling bifurcation and chaos of urbanization, *Chaos, Solitons & Fractals* 42(3), 1316-1325.
- Chou, Y.H., 1993. Airline deregulation and nodal accessibility. *Journal of Transport Geography* 1 (1), 36–46.
- Civil Aviation Authority of China. 2006. *The eleventh five-years plan of the Chinese civil aviation industry*, Beijing: China Civil Aviation Press.
- Clauset, A., Shalizi, C.R. and Newman, M.E.J. 2009. Power-law distributions in empirical data. *SIAM Review*, 51(4), 661–703.
- Dobruszkes, F., 2006. An analysis of European low-cost airlines and their networks. *Journal of Transport Geography* 14 (4), 249–264.
- Dong, Z., Wu, W.J., Ma, X.J., et al. 2009. “Mining the structure and evolution of the airport network of China over the past twenty years,” in *Proc. 5th International Conference on Advanced Data Mining and Applications (ADMA '09)*. Berlin, Heidelberg: Springer-Verlag.
- Duranton, G., and Overman, H. G., 2008. Exploring the detailed location patterns of UK manufacturing industries using microgeographic data. *Journal of Regional Science* 48, 213–243.

- Ellison, G. and Glaeser, E.L., 1997. Geographic concentration in US manufacturing industries: A dartboard approach. *Journal of Political Economy* 105, 889–927.
- Freeman, L.C., 1979. Centrality in social networks: conceptual clarification. *Social Networks* 1, 215–239.
- Goetz, A.R., Vowles, T.M., 2009. The good, the bad, and the ugly: 30 years of US airline deregulation. *Journal of Transport Geography* 17 (4), 251–263.
- Guimera, R., Mossa, S., Turtschi, A., 2005. The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles. *Proceedings of the National Academy of Sciences of the United States of America*, 102, 7794–7799.
- Haggett, P., Chorley, R.J., 1969. *Network Analysis in Geography*. Edward Arnold Ltd., London.
- Hey T., Tansley S., and Tolle K. 2009. *The Fourth Paradigm: Data intensive scientific discovery*, Microsoft Research: Redmond, Washington
- Hu, H.Y., 1935. The distribution of population in China. *Journal of Geographical Society (di li xue bao, in Chinese)*, 2, 33–74.
- Ison, S., Francis, G., Humphreys, I., Page, R., 2011. UK regional airport commercialization and privatization: 25 years on. *Journal of Transport Geography* 19 (6), 1341–1349.
- Kohl, J.G., 1842. Transportation and settlement of people and their dependence on surface terrain (*Der Verkehr und die Ansiedlungen der Menschen in ihrer Abhängigkeit von der Gestalt der Erdoberfläche in German*). London: Chapman and Hall.
- Krugman, P. 1980. Scale economies, product differentiation, and the pattern of trade. *The American Economic Review* 70(5), 950–959.
- Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A.-L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D., and Van Alstyne, M. 2009. Computation social science, *Science* 323, 721-724.
- Lei, Z., O'Connell, J.F., 2011. The evolving landscape of Chinese aviation policies and impact of a deregulating environment on Chinese carriers. *Journal of Transport Geography* 19 (4), 829–839.
- Li, W., Cai, X. 2004. Statistical analysis of airport network of China. *Physical Review E* 69, 046106.
- Ma, X., Timberlake, M., 2008. Identifying China's leading world city: a network approach. *GeoJournal* 71 (1), 19–35.
- Newman, M.E., 2003. Mixing patterns in networks. *Physical Review E* 67, 026126.
- O'Connor, K., 1995. Airport development in Southeast Asia. *Journal of Transport Geography* 3 (4), 269–279.
- O'Kelly, M., 1998. A geographer's analysis of hub-and-spoke networks. *Journal of Transport Geography* 6 (3), 171–185.
- Rabasz, E., Barabasi, A.L., 2003. Hierarchical organization in complex networks. *Physical Review E* 67, 026112.
- Redding, S. J., Sturm, D. M., Wolf, N. 2011. History and industry location: Evidence from German airports. *The Review of Economics and Statistics* 93(3), 814–831.

- Sen, P., Dasgupta, S., Chatterjee, A., 2003. Small-world properties of the Indian railway network. *Physical Review E* 67, 036106.
- Shaw, S-L., Lu, F., Chen, J., Zhou, CH., 2009. China's airline consolidation and its effects on domestic airline networks and competition. *Journal of Transport Geography* 17 (4), 293–305.
- Sui D. and Goodchild M. 2011. The convergence of GIS and social media: challenges for GIScience, *International Journal of Geographical Information Science* 25(11), 1737–1748.
- Taafe, E., Gauthier, H., O'Kelly, M., 1996. *Geography of Transportation*. Prentice- Hall, Upper Saddle River, New Jersey.
- Wang, J., Jin, F.J., 2007. China's air passenger transport: an analysis of recent trends. *Eurasian Geography and Economics* 48 (4), 469–480.
- Wang, J., Mo, H., & Wang, F. (2014). Evolution of air transport network of China 1930-2012. *Journal of Transport Geography* 40, 145–158.
- Wang, J., Mo, H.H., Wang, F.H., Jin, J.F., 2011. Exploring the network structure and nodal centrality of China's air transport network: a complex network approach. *Journal of Transport Geography* 19 (4), 712–721.
- Wang, J. 2013. The economic impact of Special Economic Zones: Evidence from Chinese municipalities. *Journal of Development Economics*, 101, 133–147.
- Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of “small-world” network. *Nature* 393, 440–442.
- Xu, Z., Harriss, R., 2008. Exploring the structure of the US intercity passenger air transportation network: a weighted complex network approach. *GeoJournal* 73, 87–102.
- Yang, H., & Zhang, A. 2012. Effects of high-speed rail and air transport competition on prices, profits and welfare. *Transportation Research Part B: Methodological*, 46(10), 1322–1333.
- Yang, X., Tok, S.K., Su, F., 2008. The privatization and commercialization of China's airports. *Journal of Air Transport Management* 14, 243–251.
- Zhang, A., 1998. Industrial reform and air transport development in China. *Journal of Air Transport Management* 4 (3), 155–164.
- Zhang, A., Chen, H., 2003. Evolution of China's air transport development and policy towards international liberalization. *Transportation Journal* 42 (3), 31–49.
- Zhang, A., Round, D., 2008. China's airline deregulation since 1997 and the driving forces behind the 2002 airline consolidations. *Journal of Air Transport Management* 14 (3), 130–142.
- Zheng, Y. and Zhou, X. 2011. *Computing with Spatial Trajectories*. Springer: Berlin
- Zipf, G. K. 1949. *Human Behavior and the Principles of Least Effort*. Addison Wesley: Cambridge, MA.

Table list

Table 1. Basic network characteristics of airport networks in China and other countries and worldwide

Author	Country	Year	Degree ((k))	Path length (L)	Clustering coefficient (C)	Network topology
This paper	China	1983	4.47	2.5	0.382	Small world
This paper	China	1993	9.95	2.22	0.485	Small world
This paper	China	2006	10.11	2.15	0.543	Small world
Bagler(2008)	India	2004	11.52	2.26	0.66	Small world
Guida and Maria(2007)	Italy	1991	12.40	1.98-2.14	0.07-0.1	Small world
Xu and Harriss(2008)	US	2005	48.28*	1.84-1.93	0.73-0.78	Small world
Guimera et al(2005)	World	2001	13.93	4.4	0.62	Small world

Note.---This table shows the average values of degree, shortest path length, and clustering coefficient of domestic airport networks of China and other countries as documented in the recent literature. Estimates of China' domestic airport networks 1983, 1993, 2006 are calculated in this paper. * denotes that this is calculated by the authors based on results shown in Xu and Harriss (2008). With respect to these basic network measures, one common network scenario emerged for airport networks: a small-world network, which is a network that has a small average path length, a high clustering coefficient, and a heavy tail degree distribution such as power-law or exponential-law.

Table 2. The 35 most dynamic airport cities

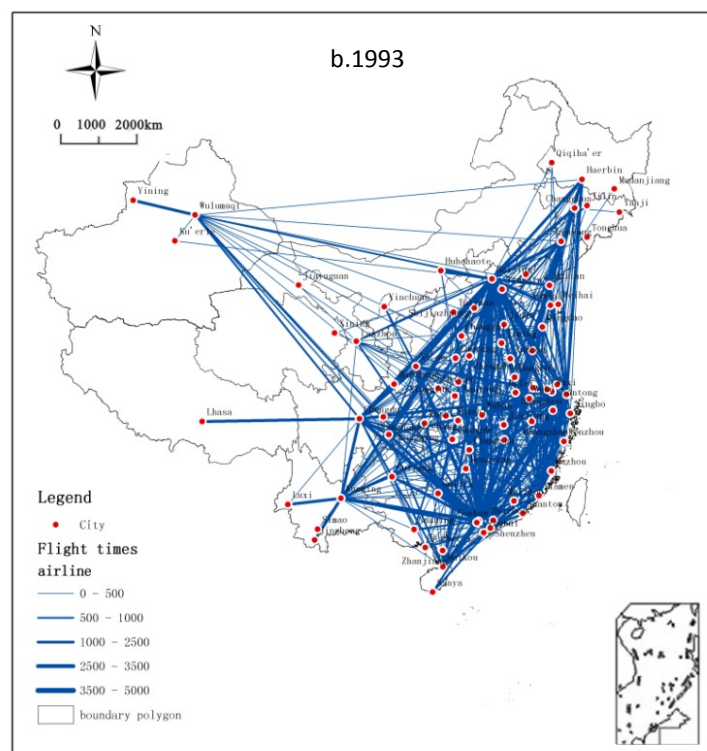
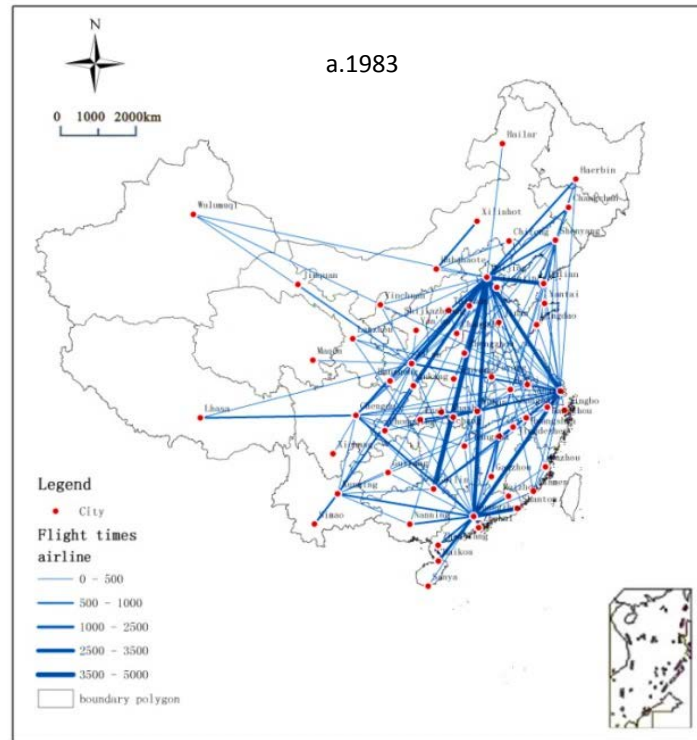
		Centrality	
		Better than the average	Lower than the average
Connectivity	Better than the average	Beijing; Shanghai; Guangzhou; Chengdu; Xi'an; Shenzhen	Shenyang; Chongqing; Changsha; Wuhan; Xiamen; Qingdao; Hangzhou; Nanjing
	Lower than the average	Kunming; Urumqi	Hefei; Hohhot; Wuxi; Sanya; Tianjin; Guiyang; Fuzhou; Harbin; Guilin; Zhenjiang; Dalian; Ningbo; Haikou; Jinan; Taiyuan; Changchun; Nanchang; Lanzhou; Wenzhou

Table 3. Airport cities with significant disparity coefficients

Panel A: 1983 (Year)			Panel B: 1993 (Year)			Panel C: 2006 (Year)		
Cities	Disparity coefficient	Target destination	Cities	Disparity coefficient	Target destination	Cities	Disparity coefficient	Target destination
Dalian	0.884	Beijing	Hohhot	0.539	Beijing	Jiuzhaigou	0.753	Chengdu
Qingdao	0.724	Beijing	Huang mountain	0.503	Beijing	Jinghong	0.723	Kunming
Nanning	0.615	Guangzhou				Lhasa	0.614	Chengdu
Lanzhou	0.521	Beijing				Lijiang	0.539	Kunming
Xiamen	0.517	Shanghai						

Note.---This table reports the disparity coefficients for cities if more than 50% of a given city's flights are connected with one particular targeted destination city in the network.

Figure list



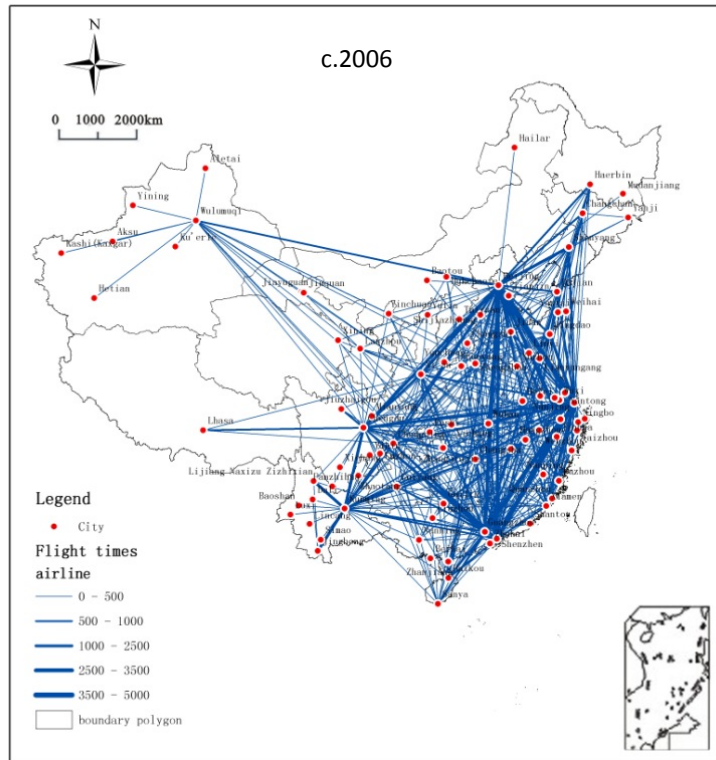
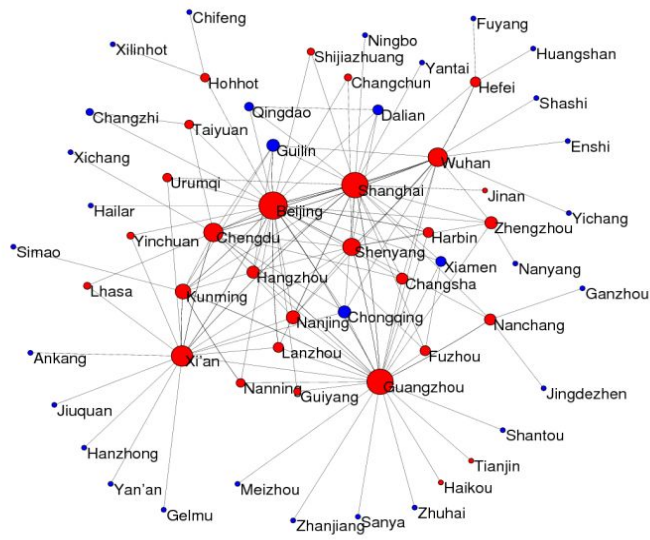
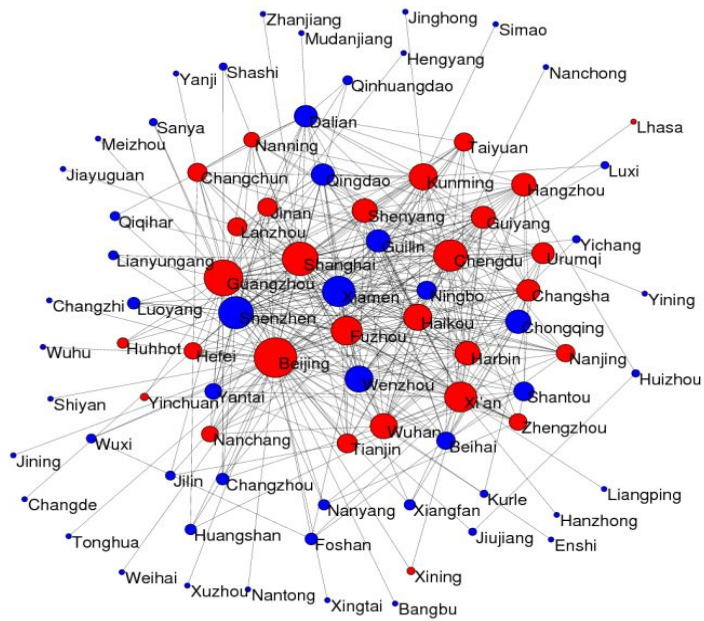


Figure 1. Airline frequency flows between airport pairs in China

a.1983



b.1993



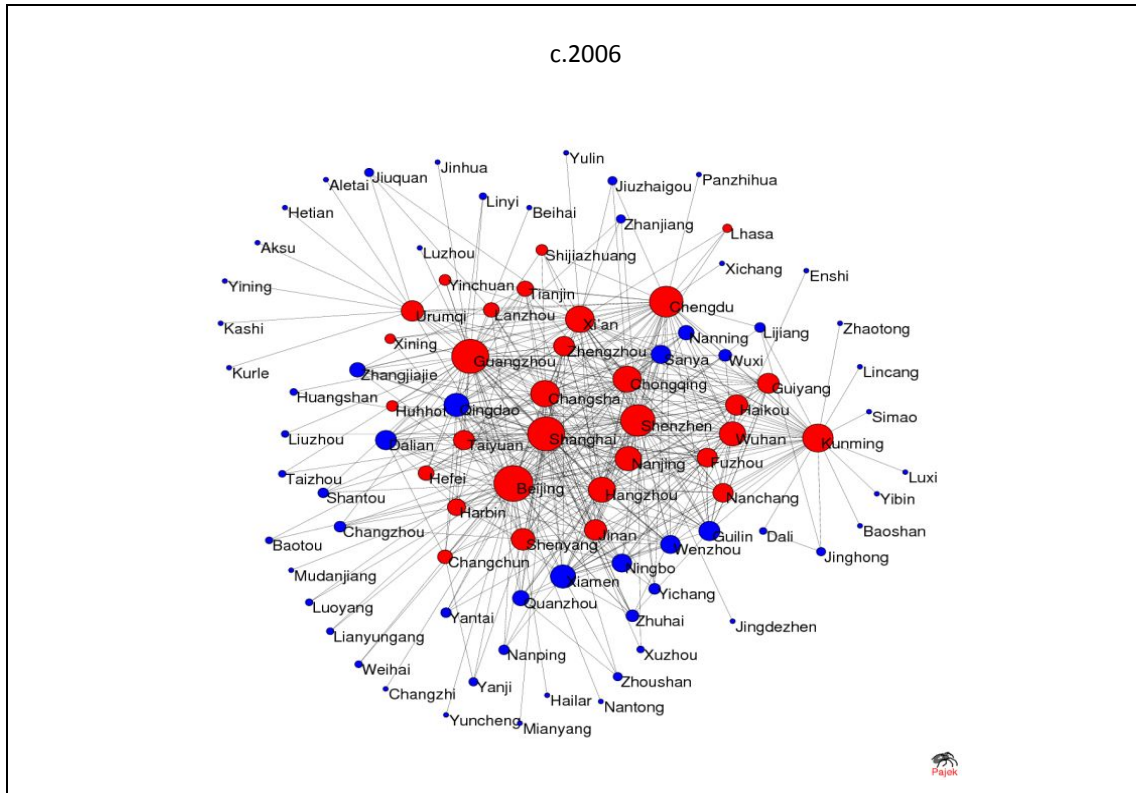
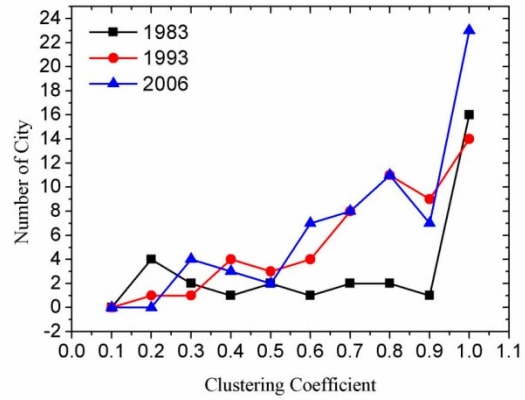
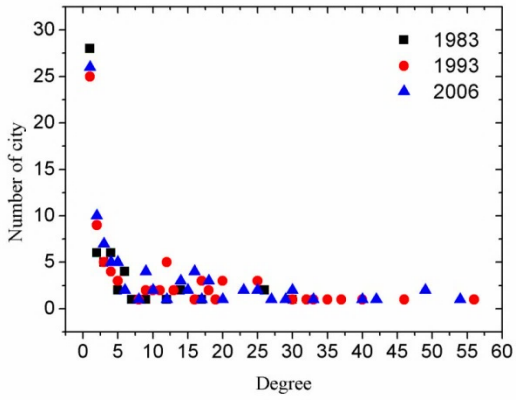


Figure 2. The topology structure of China's airport network

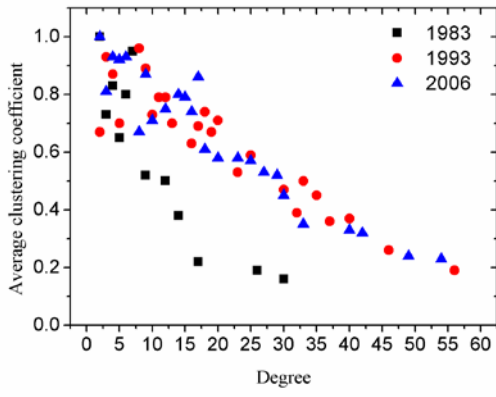
Note: The red points represent the provincial cities or capital cities in China, and the blue points in represent local cities. The size of the points has a proportional relationship to their traffic flows. The network was visualized by Pajek software.



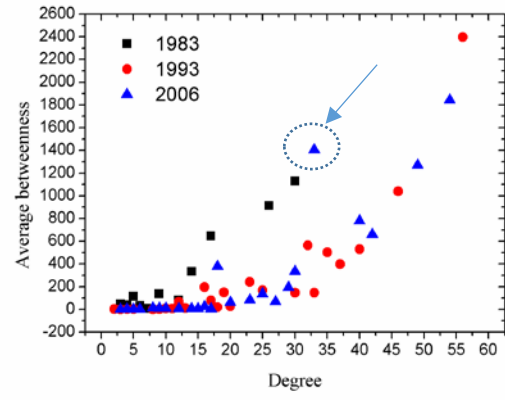
(a) The distribution of number of nodes and degree centrality

(b) The distribution of number of nodes and clustering coefficient

Figure 3. The distribution of number of nodes, degree and clustering coefficient



(a) Distribution of the degree and clustering coefficients



(b) Distribution of degree and betweenness centrality

Figure 4. The distribution of degree, clustering coefficient and betweenness

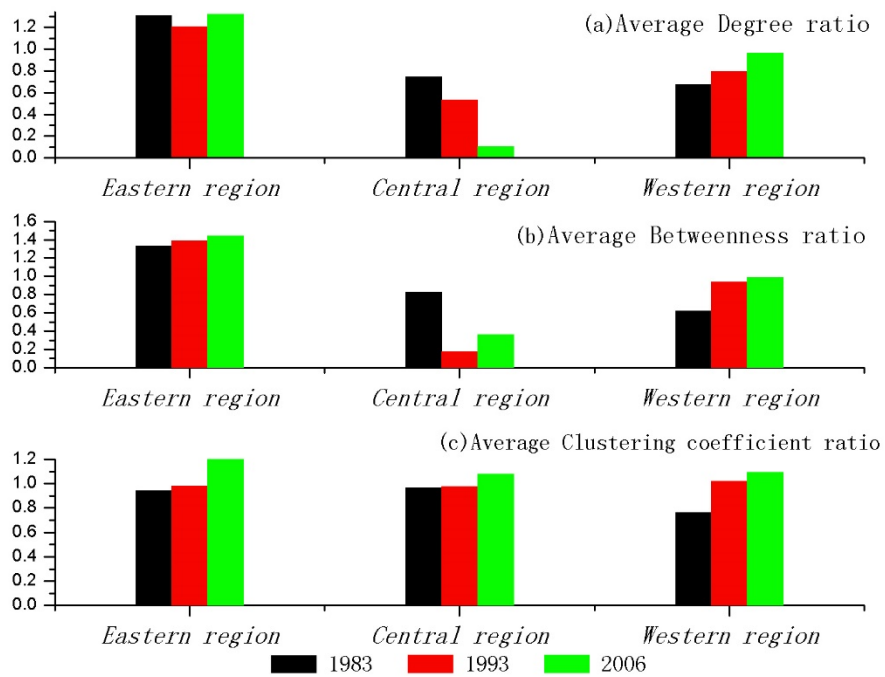


Figure 5. Regional airport network characteristics of China

Note. For each region, we computed the standardized change ratio of its average clustering coefficient, betweenness centrality, and degree γ relative to the national average levels.

Spatial Economics Research Centre (SERC)

London School of Economics
Houghton Street
London WC2A 2AE

Tel: 020 7852 3565

Fax: 020 7955 6848

Web: www.spatial-economics.ac.uk

SERC is an independent research centre funded by the Economic and Social Research Council (ESRC), Department for Business Innovation and Skills (BIS) and the Welsh Government.