INTER-CITY PASSENGER TRANSPORT CONNECTIVITY: MEASUREMENT AND APPLICATIONS

by

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Abstract

This study proposed a model to calculate connectivity of multiple transport modes involving quantity and multiple dimensions of quality. Ranking results have been produced for the air-rail connectivity of 2016 and the air connectivity of 2005-2016, with a focus on Chinese cities. The connectivity model incorporates multiple quality-adjustment (discount) factors, including capacity and velocity penalties to correct/adjust for the quality of a connection. The three major economic zones in China, namely, Beijing-Tianjin-Hebei, Yangtze-River Delta, and Pearl-River Delta, are found to have leading connectivity. We also identify the underlying drivers of the variation in airport connectivity over the period of 2005-2016. It is observed that Chinese airports experienced great increase in air connectivity over the study period. Beijing Capital, Shanghai Pudong, and Guangzhou Baiyun are far ahead of other airports in terms of overall connectivity, which is especially so in terms of international connectivity. However, the growth of some tourism cities and small cities has been stagnant and they suffered losses of connectivity at times. Airport competition measured by HHI, average fare, investment in local city’s fixed assets and airport facilities, macroeconomic conditions, and population are found to be closely associated with an airport’s connectivity. We also find the presence of low-cost carriers (LCCs) are conducive for air connectivity while HSR has the effect of decreasing airport connectivity.

Lay Abstract

This study is focused on grading cities with the performance of city-to-city transportation, which I call connectivity. A new model is proposed, with three major contributions.

First, services of multiple transport methods are evaluated and summarized into one comprehensive grade. When considering air and rail transport, both performance of air/rail service and the cooperation between air and rail are evaluated and merged into one score. Second, the model considers multiple dimensions of standards, such as availability of seats, transfer service, travel speed, etc. Third, the model is flexible and sensitive, because it evaluates with up-to-date trip-level schedule data. When one new flight is added or when a train is operated with higher speed, the score will be higher. It can be used to monitor the real-time performance and trace history performance.

Also, analysis has been conducted to find the economic factors that may have an effect on connectivity.

Preface

This dissertation is ultimately an original, unpublished, independent work by the author, Zhenran Zhu.

A version of Chapter 4 and part of Chapter 1 and 5 is under review with Journal of Transportation Research Part A. I was responsible for model construction, computing, and data analysis. Anming Zhang, Yahua Zhang, and Kun Wang were involved in concept formation, regression analysis, and manuscript composition.

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To my dearest parents. I love you.

1 Introduction

The transport network plays a critical role in the development of economies at both the inter-city and intra-city levels. Multiple transport modes, such as air, road, rail, water, and pipeline transport, work together on moving passengers and cargo from city to city. On the one hand, it is the rapidly growing transport network that has enabled the idea of globalization to come into reality in the past four decades. On the other hand, transport network is also a dash board showing the evolution of bilateral and multilateral relationship between countries and even cities. A large volume of literature has reported the causality relationship between transportation infrastructure and local economy (e.g., Li and Qi, 2016, and studies cited therein). Beside economy, transport network is also a major concern for security reasons (Iida and Bell, 2003; Taylor and D'Este, 2007). When natural disasters like earthquakes and floods happen, or when wars break out, well-connected transport network provides resilient service during extreme time and brings hope for trapped people and interrupted business. Therefore, it is important for government, business owners, as well as civilians to monitor the comprehensive status of transport network, and make strategic plans accordingly.

A lot of research has been conducted on the topic of transport network, especially in the field of air transport. Terminals like airports are usually compared and benchmarked in terms of the volume of passenger and traffic as well as operation efficiency (e.g., Oum et al., 2003). Although these indicators are valuable, they do not directly give clear information about the level of accessibility and competitive position of the terminal in the whole transport network (Burghouwt and Veldhuis, 2006; Burghouwt and Redondi, 2013). An appropriate measure is needed to assist policy makers and airport management to benchmark and monitor the network performance against that of other airports (Burghouwt and Redondi, 2013). This is the same for the other transport modes. Different transport modes can be simultaneously competitors and cooperators with each other. A measure that provides information of not only one transport mode but the whole transport network with multiple transport modes will be especially useful.

In computing, connectivity is defined as capacity for the interconnection of platform, systems and applications. In complex networks, connectivity is a measurement for the extent of nodes being connected with other nodes. In transportation, the concept of connectivity was first introduced to evaluate the importance of an airport in terms of its connection to other airports. In the field of transport economics, much literature defines connectivity based on infrastructure availability and capacity, inspired by the theory of complex networks. Terminals like airports and train stations are defined as nodes, and the routes connecting those terminals are defined as edges (Hossain and Alam, 2017). Connectivity has different definitions and metrics in different articles (Calatayud et al., 2016). A good summary of the commonly used connectivity models can be found in Burghouwt and Redondi (2013). They include the shortest path length accessibility model (Shaw, 1993; Shaw and Ivy, 1994; Malighetti et al., 2008), the quickest path length accessibility model (Paleari et al., 2010), the weighted number of connections model (Burghouwt and de Wit, 2005), and the NetScan connectivity unit (NCU) model (Veldhuis, 1997; Burghouwt and Veldhuis, 2006; Veldhuis and Kroes, 2002; De Wit et al., 2009). An air freight connectivity model (NetCargo) based on the NetScan model was developed in Boonekamp and Burghouwt (2017). However, they either consider only one aspect of the connection quality (Burghouwt and Veldhuis, 2006), mostly time, or they take limited number of connections into account (Shaw, 1993; Shaw and Ivy, 1994; Malighetti et al., 2008; Paleari et al., 2010; Mandel et al., 2017).

This research contributes to the literature that investigates connectivity by proposing a connectivity model (Connectivity Utility Model, CUM) involving multiple quality factors for passenger transportation taking into consideration every connection (every flight, train, etc.), following the Dynamic Weighted Model (Zhu et al., 2017) and NetScan model (Veldhuis, 1997; Burghouwt and Veldhuis, 2006; Veldhuis and Kroes, 2002; De Wit et al., 2009). By involving multiple quality factors, CUM produces connectivity result that is more comprehensive and more consistent with service quality, and therefore provides more valuable information for its audience. By including multiple modes, CUM provides a universal and transferrable connectivity result, and better reveals the quality and quantity of overall inter-city transport service. Also, as CUM is based on trip-level data, which means that it will catch all changes of transport service supply, including adding one flight or increasing the speed of one train, it can be used to predict future connectivity, track the real-time connectivity and history connectivity.

There are a number of studies discussing the relationship between different modes, especially between high-speed rail (HSR) and air transport. With wide application in Japan, Europe, China, and more to come, HSR has long been regarded as a competitor against air transport. Wang et al. (2016) discussed the effect of HSR network on the development of low cost carrier in China. There are also articles arguing that there is large potential for air and HSR transport to cooperate and integrate, especially in regions where the hub-and-spoke network strategy is well adapted by airlines (Givoni and Banister, 2006; Givoni, 2016). Air-rail alliances have been launched in some European airports, with railway service used as additional spokes for airlines. Travel agencies in China also started to sell air-rail ticket bundle with low price, guiding passengers to land at smaller airports with more available slots and then take HSR to get to first-tier cities. Xia and Zhang (2016a) have discussed the result of competition and cooperation between HSR and air transport, and concluded that cooperation would be a non-zero-sum game when the airport is short of capacity and the cost of linking train station with airport is not too high. The benefit of air-rail intermodal integration has been widely discussed (Xia and Zhang, 2016b; Cokasova, 2013; Román and Martin, 2014; Vespermann and Wald, 2011). However, studies measuring connectivity considering multiple transport modes and transfers across modes remain sporadic. In this paper, as air transport, rail transport, and cross-mode transfer are all counted, a different angle is provided to see how well the air and rail mode works together with the current infrastructure and time slots.

Connectivity could be an attribute not only for a terminal but also for a city. When we look at the connectivity of a city instead of a single terminal, all terminals contribute to the city's connectivity aggregately. For passenger transportation, the level of connectivity for a city is actually the utility passengers feel when using services at all terminals to get to their destination. As passengers need to get to the terminal from home or from work before the service, the location[1] of the terminal also has impact on the passenger's utility, and therefore on the city's connectivity. This research also takes into consideration the effect of terminal locations on the connectivity that a terminal contributes to the city.

In the past few decades, transport network in China has gone through major changes. And the change will continue in the foreseeable future. The geographic distribution of China's transport network is very uneven, concentrating in large cities like Shanghai, Beijing and Guangzhou, and in east part of China. In 2016, there were 28 airports that handled more than 10 million

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[1] Not only location but also transport service between residential area to the terminal would affect the passenger's utility. For example, although Pudong International Airport is 35 km away from city center, the maglev train takes only 7 minutes to go 30 km.

passengers and the passenger throughput of these 28 airports accounted for 79.1% of the nation's total passenger traffic. Beijing Capital International Airport handled about 90 million passengers while Shanghai's two airports processed more than 100 million. Large cities become more and more crowded and small cities are losing energy for the lack of young civilians. To help balancing the network and accelerate development in other parts of China, plans of transport infrastructure construction come out continuously. According to the updated "Medium-to-Long-Term Railway Network Plan" covering the period 2016-2025 with an outlook to 2030, China's HSR network will by 2025 reach a total of 38,000 km, including eight north-south and eight east-west trunk lines (Fu et al., 2015). By 2030, China's HSR network will reach a total of 45,000 km, and most cities with population of 0.5 million or more will be connected by HSR[2]. Before the Two Sessions[3], a concept of building metropolitan area with HSR was reported in early 2017. In March 2017, the Civil Aviation Administration of China (CAAC) declared that 74 new airports would be built in the next few years, which will bring the number of civil airports to 260 by 2020, to 370 by 2025.

Beside proposing the Connectivity Utility Model (CUM), this paper also provides numeric results with a focus on 40 major domestic cities of China and involving both air and rail transport. The next section gives a description about CUM and presents data sources. The numeric results are reported and analyzed in Section 3. A regression analysis based on 10 years of air connectivity to investigate the drivers behind airport connectivity is reported in Section 4. Section 5 contains some concluding remarks and policy implications.

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[2] Retrieved March 20, 2017, from http://www.chinanews.com/gn/2016/07-20/7946139.shtml

[3] National People's Congress and Chinese People's Political Consultative Conference

2 Methodology and Data

2.1 Connectivity Utility Model

The connectivity model used in this research is proposed based on the NetScan model first developed by Veldhuis (1997), and the Dynamic Weighted Model by Zhu et al. (2017). Traditional approaches measuring connectivity include using the number of destinations or the number of direct flights offered from a terminal. The NetScan model considers flight-level data, with both direct and indirect connections and the travel time involved. And the Dynamic Weighted Model considers connectivity contributed by direct connections of air and rail.

The basic idea of the NetScan model is to assign a quality index (ranging between 0 and 1) which measures the quality of relative travel time to every flight connection (De Wit et al., 2009). A quality index of 1 is given to a non-stop flight while connections with multiple stops will be discounted with an index smaller than 1 as multi-stop flight takes a longer time than non-stop flight. Additional time penalty for each stop the flight makes applies due to the inconvenience caused by the transfer, such as the risk of missing connections, loss of baggage, physical movement, etc.

However, time is not the only factor to affect connectivity. An airport is well-connected when a passenger can get to his/her destination with high utility, which means that a seat can be easily booked, with multiple choices for schedule, with low cost, etc. Here I propose the Connectivity Utility Model (CUM) and define connectivity of a connection k (flight, train, etc., both direct and indirect) from $\mathrm{terminal}_i$ to $\mathrm{terminal}_j$ as the aggregated utility for passengers taking the connection. The function can be expressed as:

$$\text{connectivity}_{ijk} = f(x_1, x_2, x_3, x_4, \dots) \tag{1}$$

Where x_1, x_2, x_3, x_4 refer to the preferences of passengers. Preferences could include the availability of seats, the freedom of choice in schedule, cost, etc. Preferences are generic across different transport modes, therefore, formula (1) can produce generic connectivity results for different modes when the utility function is the same. The utility function is open to all purposes of research or applications. For example, cost may be the most important factor to calculate connectivity for business passengers, while the freedom of schedule would be of more value for leisure passengers.

There are 2 kinds of connections, direct and indirect, as showed in Figure 1. Both direct and indirect connections produce connectivity for the start and end terminals, *i* and *j*. While the indirect connection also generates a different kind of connectivity at the middle terminal, terminal_x, because terminal_x works as the hub terminal and enabled connection k_1 and connection k_2 to cooperate. We define this kind of connectivity at hub as centrality. Centrality of terminal_x is the aggregated connectivity of indirect connections that transferred at terminal_x, which can be expressed as:

$$\text{centrality}_x = \sum_{\forall i,j,k\ transit\ at\ x} \text{connectivity}_{ijk} \tag{2}$$

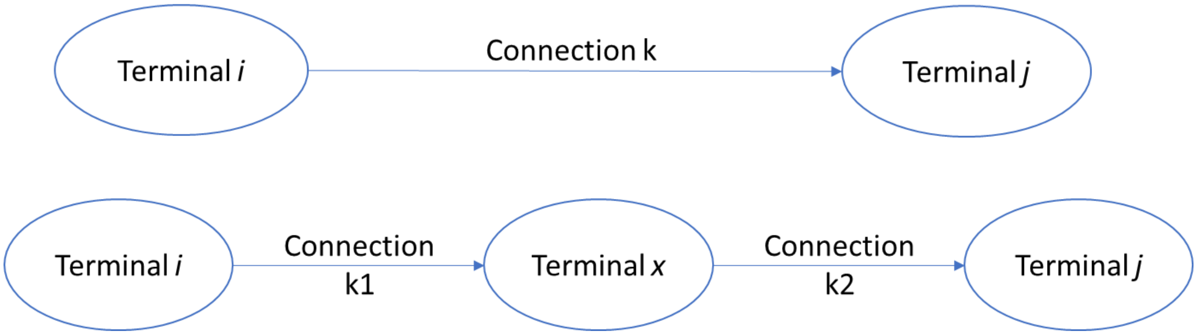

Figure 1 Two types of connections: direct and indirect

The directional connectivity for all connections from $\mathrm{terminal}_i$ to $\mathrm{terminal}_j$ is the connectivity of route i→j, which is the aggregated connectivity for all connections on the route. Connectivity of route i→j can be expressed as:

$$\mathrm{connectivity}_{ij} = \sum_k \mathrm{connectivity}_{ijk} \tag{3}$$

The connectivity of $\mathrm{terminal}_i$, including all connections from and to the terminal, is the aggregation of connectivity for all routes starting or ending at $\mathrm{terminal}_i$, which can be expressed as:

$$\mathrm{connectivity}_i = \sum_j \mathrm{connectivity}_{ij} + \sum_j \mathrm{connectivity}_{ji} \tag{4}$$

The connectivity of $city_a$ is the aggregated connectivity of all terminals that contributes to the city's transport service. There are different ways to aggregate terminal connectivity. One common method can be adding connectivity of all terminals within the administrative area of $city_a$. However, terminals also contribute to connectivity of adjacent cities in reality. For example, Shanghai Hongqiao International Airport also contributes to Suzhou's air connectivity because Suzhou is only 70 minutes away by highway and 20 minutes away by HSR from Hongqiao Airport. Even though there's no airport within the administrative area of Suzhou, it's easy for civilians in Suzhou to get to Hongqiao Airport and enjoy air service there, even easier than for some residents in Shanghai who live far away from Hongqiao Airport. Therefore, connectivity contribution from $\mathrm{terminal}_i$ to $city_a$ is assumed to be a function of $\mathrm{terminal}_i$'s connectivity and the relative location of $\mathrm{terminal}_i$ against $city_a$. Connectivity of $city_a$ can be expressed as:

$$\text{connectivity}_a = \sum_i f(\text{terminal}_i,\ location_{ia}) \tag{5}$$

Same as formula (1), the function in formula (5) is also open for all purposes.

As connectivity of routes and terminals in the CUM is calculated by aggregating connectivity of all basic connections in operation (a flight, a train, etc.), it carries full information of the transport network and represents the true real-time status of it. Connectivity_{ij}, which is the connectivity for route i→j and also the weight for edge_{ij} in the network, represents the service level from terminal_i to terminal_j. Connectivity_i, which is the connectivity of terminal_i, is the service level as well as importance of terminal_i in the network. Centrality_x, the amount of connectivity transiting at terminal_x, shows the service level of the terminal as a hub. And finally, connectivity_a is the level of transport service at city_a.

2.2 Data

Although the CUM can calculate connectivity for all transport modes, we only consider rail and air transport in the show case of this article because of data availability. Data of all flight schedules between Oct 4 to 26, 2016 is from IATA AirportIS database. Flight data includes flight number[4], number of seats, origin airport, destination airport, take-off time, landing time, and number of stop-overs. Time zone is then matched to every airport and block time is calculated in minutes. Data of train services is accessed from 12306.cn[5], for the same time period. Train data includes train number, vehicle code, start station, end station[6], from-station,

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[4] For code-sharing flights, only the operating flights are retained.

[5] The official website for China Railway, the only state-owned rail service supplier in China.

[6] Start station is the station where the train starts the service and end station is the last stop for the train.

to-station, available seats between from-station and to-station[7], time to depart at from-station, and time to arrive at to-station.

Although the analysis will be focused on 40 major Chinese domestic cities, the connection dataset is a full set of all existing air and rail services, from and to terminals both among and out of the 40 cities including international flights[8]. So, the overall connectivity, centrality, domestic connectivity and international connectivity[9] will all be produced. The list of 40 cities include all provincial capital cities, and sub-provincial cities. There are 41 airports and 95 train stations involved. The full list of the cities and terminals are attached in appendix 1 and 2, respectively.

Indirect connections are generated with direct connection data, following the enumeration method realized with codes written in R language. The produced indirect connection dataset is then filtered with loose constraints in travel distance and transfer time, which can be expressed as:

$$distance_{ih} + distance_{hj} \leq 2 \times distance_{ij} \tag{6}$$

$$30 \leq t_{{transit}_{ijk}} \leq 1440 \;\; for\ air - air \tag{7}$$

$$5 \leq t_{{transit}_{ijk}} \leq 1440 \;\; for\ rail - rail \tag{8}$$

$$60 + \mathrm{d}_t \times 1.5 \leq t_{{transit}_{ijk}} \leq 1440 \;\; for\ air - rail\ or\ rail - air \tag{9}$$

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[7] From-station and to-station are 2 stations between the first station and the last station of a train service. From-station is the original station of a train ticket, which is where the passenger gets on the train, and to-station is the destination station of a train ticket, where the passenger gets off the train. Although train tickets are sold with flexible origin and destination, there’s a planned supply for different sections according to history data on 12306.cn. As all train data is acquired 10 days before departure, we assume the seat inventory for every section is the supply of seats for that section.

[8] International flights including flights from and to all airports around the world except for airports in the region of South America, due to data availability.

[9] Flights from mainland China to Hong Kong and Macau are considered as international flights, as passengers need to go through customs. When comparing domestic connectivity of airports, flights from Hong Kong and Macau to mainland China are considered as domestic flights for Hong Kong and Macau.

$$\mathrm{d}_t \leq 100 \;\; for\ air - rail\ or\ rail - air \tag{10}$$

Where $distance_{ih}$ denotes the great circle distance[10] between origin terminal i and transit terminal h; $distance_{hj}$ denotes the great circle distance between transit terminal h and destination terminal j; $distance_{ij}$ denotes the great circle distance between origin terminal i and destination terminal j; $t_{transit_{ijk}}$ denotes the transfer time at transit terminal for indirect connection k from $\mathrm{terminal}_i$ to $\mathrm{terminal}_j$; and d_t denotes the great circle distance from the 2 transit terminals when the connection is air-rail or rail-air transfer. Formula (6) and (10) are the spatial constraints for transfer. When taking indirect connections, the total distance of the connection is constrained to be smaller than 2 times of the direct distance. And when taking air-rail and rail-air connections, the distance between the transit airport and the transport railway station is constrained to be smaller than 100 km. Formula (7) – (9) are the time constraints for transfer. 30 minutes and 5 minutes are assumed to be the minimum transfer time at airport and train station respectively. For air-rail and rail-air transfer, the minimum transfer time is assumed to be 60 minutes plus the time to move between 2 transit terminals. The speed to move between terminals is assumed to be 40 km/h. As mentioned above, (6) - (10) are loose constraints to help reduce the size of dataset and prepare for further processing.

2.3 Applied Connectivity Utility Model

In the show case of this paper, we consider only air and rail transport connections with maximum one stop. There are six categories of connections involved, direct air connection, indirect air

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[10] All great circle distances in this research are calculated with Python package “Geographiclib”, using GPS coordinates of OD.

connection with one stop, direct rail connection, indirect rail connection with one stop, air connection connected with rail connection, and rail connection connected with air connection. The six categories of connections are showed in Figure 2.

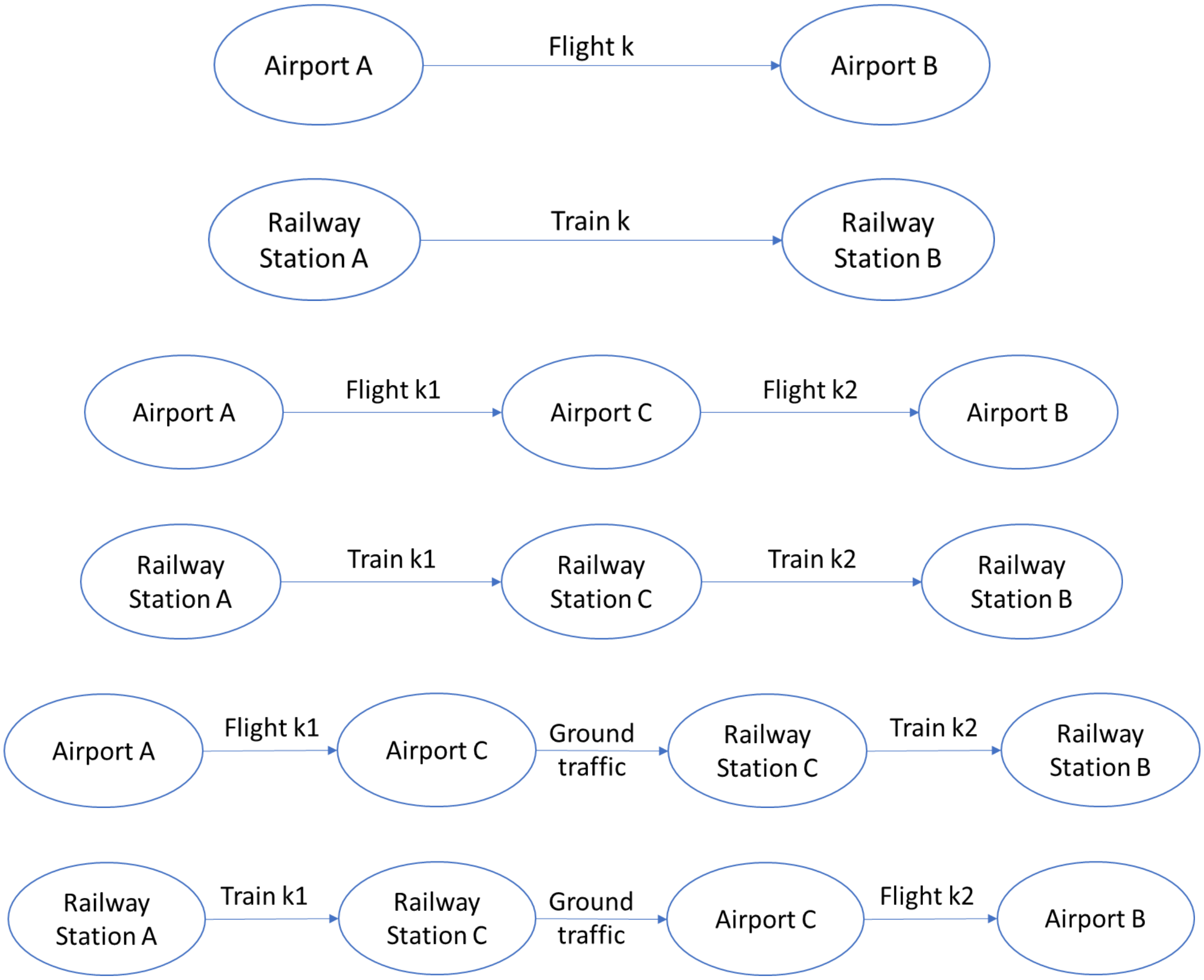

Figure 2 Six categories of connections

Specific functions for formula (1) and (4) are chosen in the show case. The preferences considered in this research are availability of seats (capacity), trip duration (velocity), and quality of transfer (for indirect connections). Other preferences like cost can be easily attached when the data is available. As there are multiple preferences, and the preferences, capacity, velocity and transfer quality, are independent from each other, the utility function should be either additive or multiplicative[11]. Furthermore, dissatisfaction of any of the three preferences would lead to 0 utility[12]. Therefore, multiplicative utility function is adopted. Here we assume equal weight for all preferences and scale utility score of all preferences to be between 0 and 1. All numeric results are produced following this assumption. When different weights or different formula is adopted, the numeric results will change accordingly. People using the model can emphasize on their focus and objective by adjusting the weights and the equation system.

The utility score of capacity, velocity and transfer quality are named as capacity discount, velocity discount and transfer discount respectively, for simplification. And here we have:

$$\text{Connectivity}_{ijk} = D_{Cap_{ijk}} \times D_{Vel_{ijk}} \times D_{Trans_{ijk}} \tag{11}$$

Where $D_{Cap_{ijk}}$ denotes the capacity discount for connection *k* between terminals *i* and *j*.[13] $D_{Vel_{ijk}}$ represents the velocity discount, and $D_{Trans_{ijk}}$ is the transfer discount[14].

Capacity is a key indicator measuring connection quality. Larger aircraft tend to carry more passengers, to provide more available seats, and thus increase connectivity, ceteris paribus. Two airports are better connected when airlines change the aircraft to larger ones when the frequency remains the same. Capacity discount is a function of available seats for a specific connection. We adopt a concave function (squared root) instead of a linear form for capacity discount. This is because we believe that the marginal benefit of adding more seats diminishes to a certain point,

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[11] Theorem 1 in (Keeney, 1974).

[12] Corollary in (Keeney, 1974). Also, intuitively, if the connection is super-fast and with not mid-stops, there would still be no connectivity when there's no available seat.

[13] Every connection on a route between terminal *i* and terminal *j* is treated as a different connection, even for the connection with the same connection number (flight number/train number) on a different date, as the connection might use a different type of vehicle. Therefore, the frequency for every connection in this model is 1.

[14] Transfer discount factor is always 1 for direct flights.

and the extra benefit of adding a 100-seat flight is larger than that of increasing the seat capacity from 100 to 200 for one flight, because of the benefit of schedule freedom the extra connection brings. The aircraft with the most available seats currently in use is Airbus 380, with 538 seats. The rail section with the most available seats in China has 2684 seats. We choose the capacity of Airbus 380 as a benchmark to calculate the capacity discount[15], which can be expressed as:

$$D_{Cap_{ijk}} = \sqrt{\frac{Seat_{ijk}}{\mathrm{Seat}_0}} \tag{12}$$

Where $Seat_{ijk}$ represents the number of seats on connection k. For indirect connections, the seat number is bounded by the section with fewer seats. Seat_0 is the number of seats of the benchmark vehicle, which in this study is 538.

Velocity is another important indicator for connection quality. The slower the velocity is, the longer time, i.e. more value of time, the passenger needs to sacrifice. The velocity is the average distance the passenger moves in a time unit. To move from $\mathrm{terminal}_i$ to $\mathrm{terminal}_j$, the time the passenger needed is not only the time in vehicle. The passenger also needs to arrive at terminal in advance to check in, check bags, go through security check, etc. He/she also needs to stay at the destination terminal for baggage pick up and security check. In addition, if the passenger takes an indirect connection, the time he/she spends at the transit stop would be more uncomfortable than in-vehicle time, because the next connection may be missed, the baggage may be lost, there may be a long distance of physical movements in between, etc. Additional time penalty for each stop the connection makes applies. Both the extra time at terminals and the penalty for transfer

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[15] Some connections with trains will have capacity discount larger than 1. This is ok because when we use a different benchmark capacity, capacity discount of all connections will rescale in the same way.

time should be represented in the velocity discount. Following the same structure of capacity discount, the velocity discount is calculated based on the following system of equations:

$$Duration_{Adjusted_{ijk}} = T_{arrive_{ijk}} - T_{depart_{ijk}} + \mathrm{p}_T \times t_{transit_{ijk}} + t_{terminal_{ijk}} \tag{13}$$

$$\text{Velocity}_{ijk} = \frac{Distance_{ij}}{Duration_{Adjusted_{ijk}}} \tag{14}$$

$$\mathrm{D}_{Vel_{ijk}} = \sqrt{\frac{\text{Velocity}_{ijk}}{\text{Velocity}_0}} \tag{15}$$

Where $Duration_{Adjusted_{ijk}}$ is the adjusted time length (duration) of connection_k from terminal_i to terminal_j. The scheduled in-vehicle time between two terminals is the difference between the scheduled arrival time and scheduled departure time,[16] represented by $T_{arrive_{ijk}} - T_{depart_{ijk}}$. Extra time at terminals is represented by $t_{terminal_{ijk}}$. When the connection has intermediate stop, the additional time spent at the transit terminal ($t_{transit_{ijk}}$) is penalized by p_T, the extra penalty assumed for the additional time spent at intermediate point. The velocity (Velocity_{ijk}) is calculated by dividing the great circle distance between terminal_i and terminal_j with adjusted time duration. Velocity discount is calculated by comparing the velocity of a connection against the benchmark velocity, Velocity_0. Again, we use a concave function instead of a linear functional form.[17]

Extra time at airports and extra time at train stations are different, as the procedures to go through are different. We assume the extra time needed at airport to be 100 minutes for domestic flights and 180 minutes for international flights, and the extra time needed at train station to be 45 minutes in this research. For air-rail and rail-air transfers, the assumed extra time at terminals

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[16] Transit time is included if the connection has an intermediate stop.

[17] It should be noted that in both our model and the NetScan model, short-haul routes would suffer more discount in terms of velocity, as the same benchmark of velocity is applied for all ranges of distance. In fact, the average velocity of short-haul connections should be slower than that of long-haul connections, especially when the extra time needed at terminals is taken into consideration. However, this is consistent with the fact that transport modes with shorter extra time needed, such as HSR and highway, are preferred for short-haul travels.

is listed in Table 1. Also, we assume the extra penalty for transit time to be 50%. The benchmark velocity, $\mathrm{Velocity}_0$, is assumed to be 800 km/h[18].

Table 1 Extra time at terminals for air-rail and rail-air transfers

First Section	Second Section	Extra Time at Origin Terminal	Extra Time at Destination Terminal
Domestic Flight	Train	90	15
International Flight	Train	120	15
Train	Domestic Flight	30	30
Train	International Flight	30	60

For indirect connections, connectivity is largely dependent on the quality of transfer. There are a lot of aspects to consider to reveal the level of transfer quality, such as transit time, procedures and distance to go through, services during transfer, etc. Also, for cross-mode transfer, like air-rail or rail-air transfer, the passenger needs to move from one terminal to another terminal. Sometimes the distance could be as far as 50 kilometers. Here we model transfer quality in two dimensions, time and service.

Time quality for transfer measures the quality of transfer time. For airports, minimum connection time (MCT) is the allowed minimum time between two connecting flights at the transit airport when a joint ticket is sold. Basically, when the transfer time is larger than MCT, the passenger should be able to catch the connecting flight, though with a risk to run at some time or depart without luggage. Although different airlines have different MCT at every airport, we assume the same MCT[19] for all airports and all airlines because of data availability. Here we define MCT for rail-rail, air-rail, and rail-air transfer, following the same intuition. MCT standards are listed in Table 2.

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[18] In the future with more advanced technology, the maximum velocity of a vehicle would be larger than 800 km/h, which would bring velocity discount larger than 1. This won’t affect the result because when we use a different benchmark velocity, velocity discount of all connections will rescale in the same way.

[19] The MCT standard here is from China Eastern Airline’s MCT at Shanghai Pudong International Airport and Shanghai Hongqiao International Airport.

Table 2 MCT for all possible transfers

First Section	**Second Section**	**Whether at the same terminal**[20]	**MCT (minutes)**
Domestic Flight	Domestic Flight	Yes	**60**
Domestic Flight	Domestic Flight	No	**100**
Domestic Flight	International Flight	Yes	**120**
Domestic Flight	International Flight	No	**160**
International Flight	Domestic Flight	Yes	**120**
International Flight	Domestic Flight	No	**160**
International Flight	International Flight	Yes	**90**
International Flight	International Flight	No	**130**
Train	Train	Yes	**30**
Domestic Flight	Train	No	$\mathbf{60 + 2 \times d_t}$[21]
International Flight	Train	No	$\mathbf{100 + 2 \times d_t}$
Train	Domestic Flight	No	$\mathbf{80 + 2 \times d_t}$
Train	International Flight	No	$\mathbf{120 + 2 \times d_t}$

Time quality is a function of the difference between the actual transfer time and MCT. When the transfer time is too short, the transfer will be impossible to make, and therefore the time quality is 0. When the transfer time is too long, though the transfer will be fully possible, the transfer will be less comfortable as the passenger needs to stay at the transit terminal for too long. The time quality is set to be 0.2 when transfer time is the same as MCT, 1 when transfer time is 30 minutes longer than MCT, and 0.7 when transfer time is 3 hours longer than MCT or even longer. Here we construct the time quality function as:

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[20] Transfers at the same airport but at different terminals are allowed, while transfers at different airports are not allowed in this research.

[21] d_t is the great circle distance between the destination terminal of the first section and the original terminal of the second section.

$$q_{ijk}^{T} = \begin{cases} 0, & \Delta t_{ijk} < -10 \\ (\Delta t_{ijk} + 10)\times 0.02, & -10 \le \Delta t_{ijk} < 0 \\ \dfrac{\Delta t_{ijk}}{30}\times 0.8 + 0.2, & 0 \le \Delta t_{ijk} < 30 \\ 1 - \dfrac{\Delta t_{ijk} - 30}{500}, & 30 \le \Delta t_{ijk} \le 180 \\ 0.7, & \Delta t_{ijk} > 180 \end{cases} \tag{16}$$

Where q_{ijk}^{T} represents the time quality for the transfer of indirect connection k from terminal_i to terminal_j; Δt_{ijk} represents the difference of time between the transfer time of connection k from terminal_i to terminal_j and MCT at the transit terminal of this connection. Δt_{ijk} is negative when the transfer time is shorter than MCT.

Service quality for transfer measures the quality of transfer service, such as easiness of moving, waiting room service, and flexibility when the second connection is missed because of delay, etc. Service quality is different for different transfer occasions. For air-air transfer, service quality is mainly decided by alliances. When both flights are served by the same alliance or same airline, the service quality is good. When one flight is served by low cost carrier, the service quality will be relatively worse. Service quality for air transfer is assumed to be 1 when both flights are served by the same airline that is not low cost carrier; 0.9 when served by the same alliance but different companies (alliance of low cost carriers is not counted); 0.3 when served by full-service airlines from different alliances[22] or the same low cost carrier; and 0.1 for other situations. For rail-rail transfer, the service quality is assumed to be always 1 as it’s easy to move from one train to another and all train services are provided by the same company, China Railway. For air-rail transfer and rail-air transfer, as there’s no alliance between railway and airlines in China yet, the service quality is mainly dependent on the transport service between the airport and train station. Though the transport service between airport and train station varies with different cities, it’s highly correlated with the distance between terminals. When the distance is short, like the Hongqiao Railway Station and Hongqiao International Airport, the service quality is high because the passenger doesn’t need to take a taxi and suffer the risk of congestion, the inconvenience of moving with luggage, and the cost of moving. When the distance is long, the

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[22] Some airlines from different alliances would cooperate in a small range of routes and provide great connecting services. However, this detail is ignored in this show case because of data availability.

service quality will be low. Even for Shanghai Pudong International Airport (PVG), which is connected by Maglev trains, the transport service would still be low for a large number of passengers who prefer to use taxi, or subway to get to the airport. We set service quality to 1 when the distance is shorter than 2 km, 0.5 when the distance is 5 km, 0.1 when the distance is 30 km, and 0 when the distance is longer than 100 km. Service quality for air-rail and rail-air transfer can be expressed as:

$$q_{ijk}^{S}=\begin{cases} 0, & \mathrm{d}_t>100 \\ 0.1-0.1\times\dfrac{\mathrm{d}_t-30}{70}, & 30\le \mathrm{d}_t<100 \\ 0.5-0.4\times\dfrac{\mathrm{d}_t-5}{25}, & 5\le \mathrm{d}_t<30 \\ 1-0.5\times\dfrac{\mathrm{d}_t-2}{3}, & 2\le \mathrm{d}_t<5 \\ 1, & \mathrm{d}_t<2 \end{cases} \tag{17}$$

Where q_{ijk}^{S} is the service quality of transfer for indirect connection k from terminal_i to terminal_j; d_t is the distance in kilometers between the transit airport and transit railway station for this connection. And then the transfer discount can be expressed as:

$$D_{Trans_{ijk}}=q_{ijk}^{T}\times q_{ijk}^{S} \tag{18}$$

With equation (11) - (18), connectivity of any connection can be produced. However, for indirect connections from terminal_i to terminal_j transferring at terminal_h, some direct connections from terminal_i to terminal_h and from terminal_h to terminal_j will be calculated for more than once. For example, in the case showed in Figure 3, connection k2, k3, and k4 take off from terminal_h 40, 60, and 90 min after the landing of connection k1, respectively. K1-k2, k1-k3, and k1-k4 are all indirect connections between terminal_i and terminal_j. Therefore, when calculating indirect connectivity from terminal_i to terminal_j through terminal_h, connection k1 is counted for 3 indirect connections. Under certain circumstances, the indirect connectivity from terminal_i to terminal_j through terminal_h will be higher than the direct connectivity from terminal_i to terminal_h, which is not reasonable.

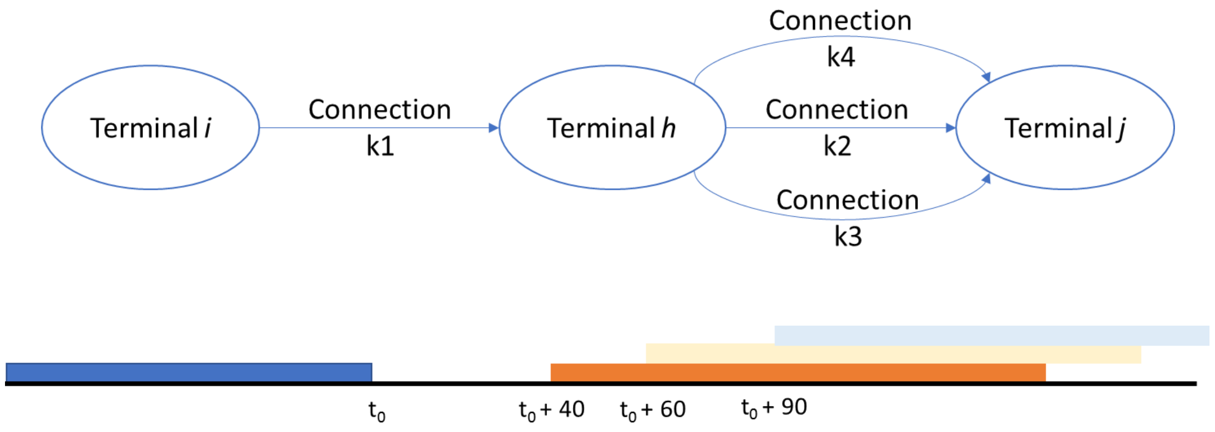

Figure 3 Example for repeated calculation

When multiple indirect connections share 1 direct connection, the best-case for indirect connectivity is that all capacity of the shared connection is used for those connecting flights. Therefore, the capacity of these indirect connections is constrained by the capacity of the shared connection, while velocity and transfer quality are not. Example showed in Figure 3 is the most simplified situation. Both the first section and the second section might be shared. Here we add an upper limit for indirect connectivity, which is:

$$\sum_{\forall k\ with\ s_{k\prime}^{1}} D_{Cap_{i(h)jk}} \leq D_{Cap_{ih(j)s_{k\prime}^{1}}} \tag{19}$$

$$\sum_{\forall k\ with\ s_{k\prime}^{2}} D_{Cap_{i(h)jk}} \leq D_{Cap_{ih(j)s_{k\prime}^{2}}} \tag{20}$$

Where $s_{k\prime}^{1}$ denotes a direct connection from terminal$_i$ to terminal$_h$, which works as the first section of multiple different indirect connections; $s_{k\prime}^{2}$ denotes a direct connection from terminal$_h$ to terminal$_j$, which works as the second section of multiple different indirect connections; $D_{Cap_{i(h)jk}}$ denotes capacity discount of indirect connection k from terminal$_i$ to terminal$_j$ transferring at terminal$_h$; $D_{Cap_{ih(j)s_{k\prime}^{1}}}$ denotes capacity discount of $s_{k\prime}^{1}$; $D_{Cap_{(i)hjs_{k\prime}^{2}}}$ denotes capacity discount of $s_{k\prime}^{2}$. The left-hand side of equation (19) sums up the capacity discount of all indirect connections taking the route i→h→j and uses $s_{k'}^1$ as the first section from terminal_i to terminal_h. The right-hand side of equation (19) gives the capacity discount of $s_{k'}^1$. Equation (20) sums up the capacity discount of all indirect connections taking the route i→h→j and uses $s_{k'}^2$ as the second section from terminal_h to terminal_j. The right-hand side of equation (20) gives the capacity discount of $s_{k'}^2$. With equation (19) and (20), capacity discounts of all indirect connections sharing one mutual section are constrained by the capacity discount of the shared section. The intuition behind equation (19) and (20) is that capacity of indirect connections is constrained by capacity of both direct connections involved in the indirect connection. When equation (19) or (20) is not satisfied, the capacity of the shared section is assigned to the connection with the best velocity discount and transfer discount, as it is assumed that when capacity discount is the same, connection with better quality in other dimensions attracts the most passenger volume.[23]

To aggregate connectivity of terminals to cities, a series of functions are adopted in this research. These functions are constructed in order to simulate the attenuation of terminals' contribution of connectivity for cities, when the distance between the terminal and the city becomes larger. As it's similar to the spread of radiation, I call the discount "radiation discount" and the function "radiation function". Here is an example:

$$D_{Rad_{ia}} = \begin{cases} e^{-\frac{d_{ia}}{70}}, & d_{ia} > 50 \\ \dfrac{\cos(\frac{d_{ia}}{31.84}) + 1}{2}, & 0 \le d_{ia} \le 50 \end{cases} \qquad (21)$$

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[23] With the upper limit for shared connections, every direct connection is still allowed to be counted for 1 time in each directional route. However, when the connection connects with connections with different destinations at the transfer station, the connection will still be calculated repeatedly, because it is difficult to assign capacity of the shared section to indirect connections of different routes. It allows direct connections with slots that cooperate better with other connections to contribute more connectivity.

Where ${D_{Rad}}_{ia}$ denotes the radiation discount of terminal_i's connectivity on city_a; d_{ia} denotes the great circle distance between centre of city_a and terminal_i. It is assumed that the distance between city centre and the terminal represents the average travel distance for passengers living in the city to get to the terminal. Segmented function is adopted here. When the distance is very short, for example 500 metres, passengers will simply walk there. When the distance is medium, 2 to 10 km, passengers can take bus or subway or drive a short distance to get to the terminal. When the distance is longer, the passenger will have to drive. The level of inconvenience to get to the terminal is very sensitive to distance when the distance is short. The cosine function is applied because it provides a right shape. While when the distance is very long, like 100 km, the passenger always needs to drive or take an inter-city bus service, the inconvenience level is less sensitive to distance, therefore an exponential function with negative power is adopted. In the example of radiation function shown in equation (21), connectivity contribution diminishes to 50% when the distance is 50 km, 25% at 100 km, and 5% at 200 km. The relationship between radiation discount and distance in equation (21) is shown in Figure 4.

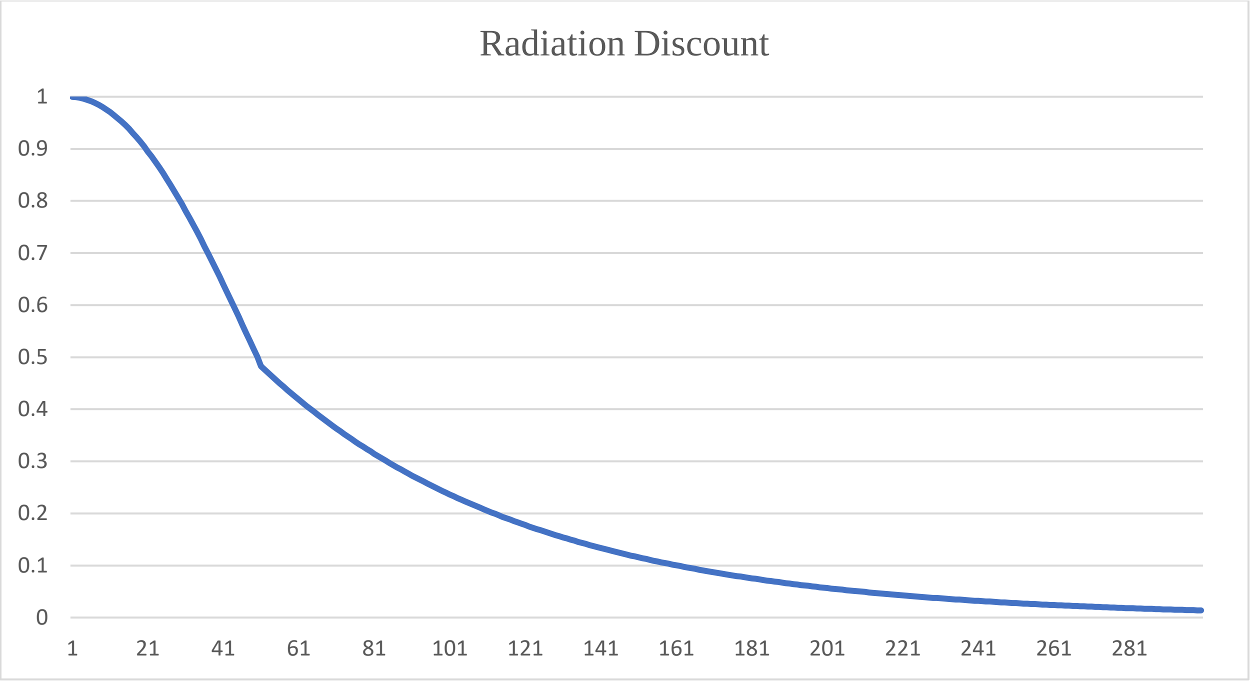

Figure 4 An example of radiation discount-distance

Radiation discount simulates a general process of inter-modal transportation, which is taking public transport or driving to get to air and rail terminals. Apart from representing the effect of location on a terminal's transport service level, radiation discount also allows terminals to generate connectivity for both passengers in the city and passengers in neighbourhood cities, which is true. Cities surrounded by large cities, like Suzhou and Shenzhen, are benefited by allowing connectivity radiation. In the meantime, connectivity varies with radiation discount function. Radiation discount function should be decided according to the purpose of connectivity measuring. Different radiation discount functions will be tested and discussed in the next section.

In this research, we use sum of connection's connectivity (which is a form of utility) as the connectivity of a route or a terminal. Mandel et al. (2017) made strong arguments that the service indicator of path i→j should be log sum of the Logit path choice model[24] instead of weighted

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[24] $\ln \sum_p \exp(V_p)$

sum of connection utility[25], which gives each connection a weight (probability to be used) according to their connectivity compared with other connections in the same route and then takes the weighted sum of all connections in the route as its connectivity. Though Logit model is not used in this research, it's interesting and useful to make sure that the same problem with models discussed in their paper do not happen with our model.

The major problem Mandel et al. argued against is that using weighted sum utility would lose information equal to the Shannon's measure (Shannon, 1948), $-\sum_p p_p \ln(p_p)$[26], compared with the log sum measure. The weighted sum of connectivity is more like taking the average connectivity of all connections. The amount of connections in a route is not appreciated. In some cases, the connectivity of a route calculated with weighted sum utility will decrease with extra connections added. For example, when a connection with poor quality, connectivity of 1, is added to a route with 1 good connection, connectivity of 5, the new connectivity of the route will be 4.928, which is smaller than the original connectivity. In our case, we use quality discount instead of p, which would always bring positive effect when there're more connections available, as connectivity scores of connections in one route are independent from each other in CUM. As a matter of fact, all connections in one route are taken into consider in CUM model, while Mandel et al. (2017) only allowed 7 alternative paths for each domestic route, 10 for European OD routes, and 16 for intercontinental routes when applying the log sum measure.

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[25] $\sum_p p_p \cdot V_p$, it is proved by Shannon (1948) that $\ln \sum_p \exp(V_p) = \sum_p p_p \cdot V_p - \sum_p p_p \ln(p_p)$.

[26] $p_p = \frac{\exp(V_p)}{\sum_{p=1}^{p=P} \exp(V_p)}$, where V_p is the utility (connectivity) derived by connection p, and p_p denotes the possibility of choosing connection p.

3 Numeric Results and Analysis

Numeric results and analysis with the applied CUM model are presented in 3 parts: terminal connectivity, city and region connectivity, and network connectivity.

3.1 Terminal Connectivity

Terminal connectivity is made up of air connectivity, rail connectivity, and mixed (air-rail and rail-air) connectivity. Both airports and railway stations have mixed connectivity apart from air/rail connectivity. Therefore, it is an advantage to cooperate with terminals of the other type in neighbourhood. Figure 5 shows the geographic distribution of terminals with their connectivity represented by colour and pie size. Three major metropolitan city groups with high connectivity are observed in Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta economic zones. This result is similar to the finding of Zhang et al. (2004) and Hui et al. (2004) in terms of connectivity in China's air cargo flows up to the early 2000s.

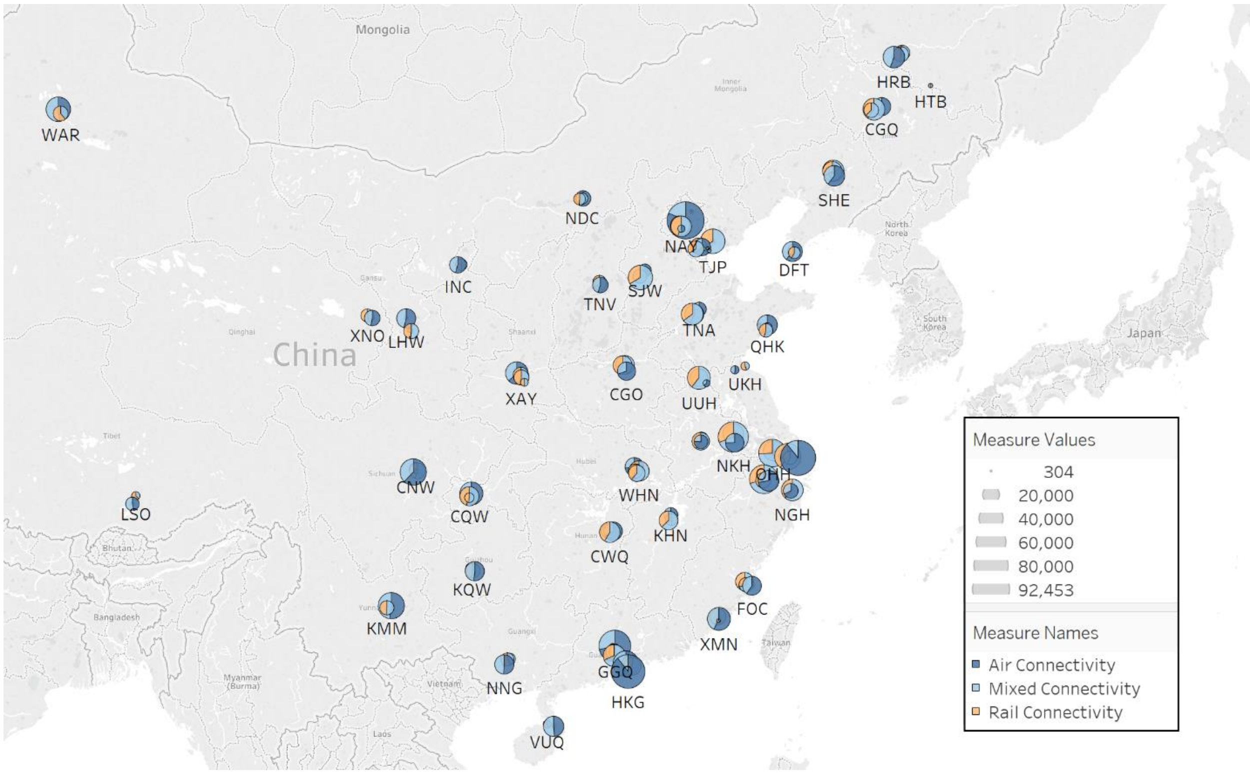

Figure 5 Geographical distribution of terminals

The top 20 terminals of overall connectivity are listed in Figure 6, and a full list of terminal connectivity is reported in Appendix 3. Though all top 4 terminals are airports, winner of the battle between airports and railway stations is hard to decide. Six out of the top 10 terminals are airports, and 11 out of the top 20 are airports. Beijing Capital International Airport (PEK) is the best-connected terminal, followed closely by Shanghai Pudong International Airport (PVG), Hong Kong International Airport (HKG), Guangzhou Baiyun International Airport (CAN), and Nanjing South Railway Station (NKH). NKH is the only railway station among the top 5 terminals. According to China Central Television, NKH is also the second largest railway station in the world and the largest in Asia in terms of gross floor area, with passenger throughput 2.23 million over 10 days from September 28 to October 7 in 2016[27]. Hangzhou East Railway Station

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[27] Retrieved March 20, 2017, from http://www.nanjing.gov.cn/xxgk/bm/jtj/201610/t20161008_4203956.html

(HGH_{Rail}), Suzhou Railway Station (SZH), Chengdu Shuangliu International Airport (CTU), Shanghai Hongqiao Railway Station (AOH), and Kunming Changshui International Airport (KMG), take 6th to 10th place respectively.

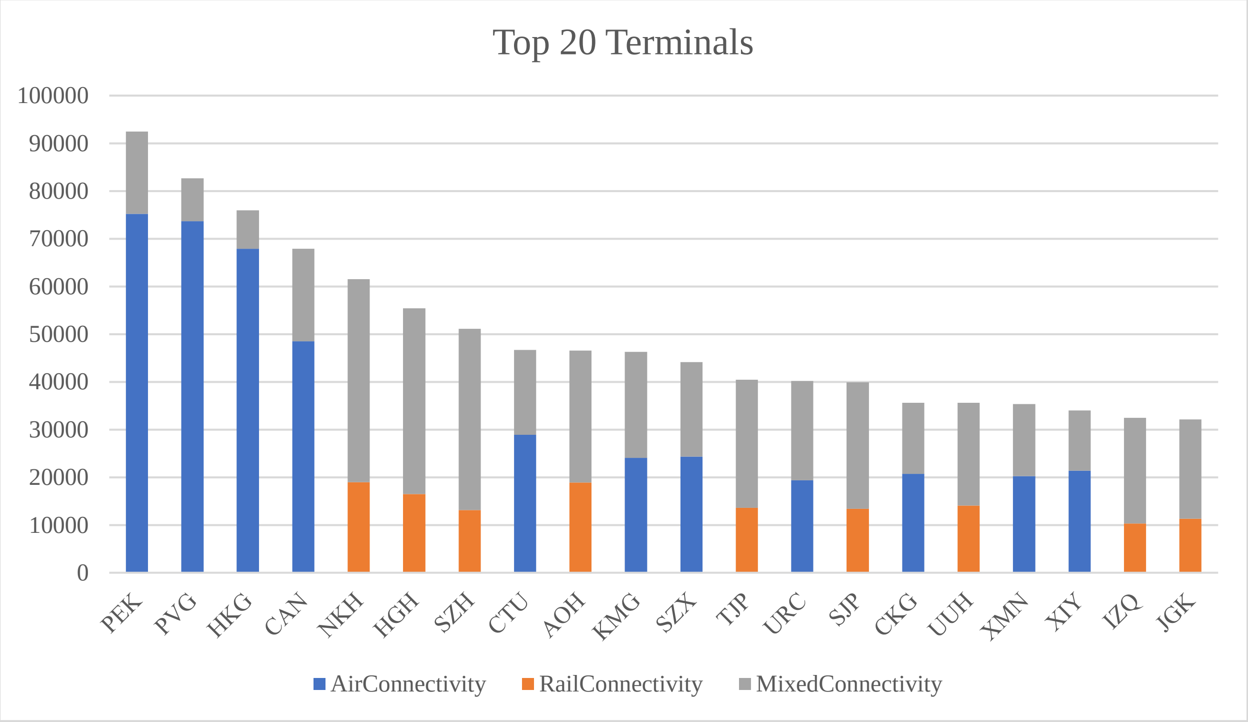

Figure 6 Top 20 terminals of overall connectivity

Though terminals in megacities (Beijing, Shanghai, Guangzhou, Hong Kong, etc.) are leading with big advantage, we see a large amount of “middle-class” terminals. There are 6 terminals with connectivity above 55,000, 13 above 40,000, 24 above 30,000, 57 above 20,000, 99 above 10,000, and 109 above 5,000. There are 8 terminals with connectivity below 1,000. HSR contributes largely to railway station’s connectivity. All train stations in the top 40 terminals have HSR service.

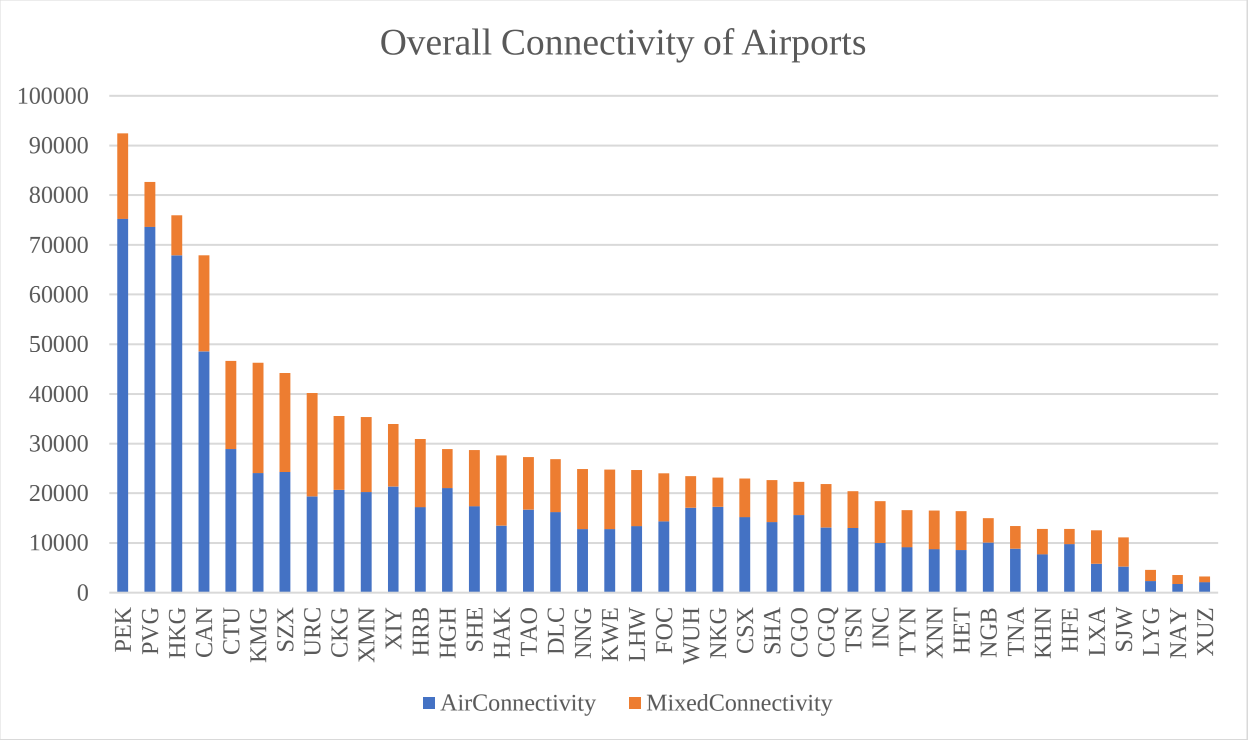

Figure 7 Overall connectivity of airports

Connectivity of airports is showed in Figure 7. PEK, PVG, HKG and CAN lead with large advantage in terms of overall connectivity. Figure 8 presents the proportion of direct air, indirect air, and mixed connectivity of airports. Figure 9 shows the proportion of domestic air, international air, and mixed connectivity of airports. It is found that ratio of mixed connectivity against the overall connectivity ($r_{mixed/all}$) is lower with better connected airports. Pearson's correlation between $r_{mixed/all}$ and overall connectivity is -0.571, with p-value at 0.000. Also, ratio of international connectivity against air connectivity (direct and indirect), $r_{int/air}$, is higher with better connected airports. Pearson correlation between $r_{int/air}$ and overall connectivity is 0.715, with p-value at 0.000. There is no clear correlation between domestic ratio (domestic air connectivity/air connectivity) and overall connectivity. This indicates that international flights are concentrated in mega airports. As a matter of fact, the top 4 airports, PEK, PVG, HKG, and CAN, contributed 46.55% of overall international connectivity and 69.41% of direct international connectivity, while their contribution in domestic connectivity is only 15.63% of overall and 19.17% of direct domestic connectivity. The concentration of international flights, especially on transcontinental routes, in top ranking mega airports will continue in the foreseeable future. However, with the development of the national HSR network, we can expect increase of international connectivity in inland areas.

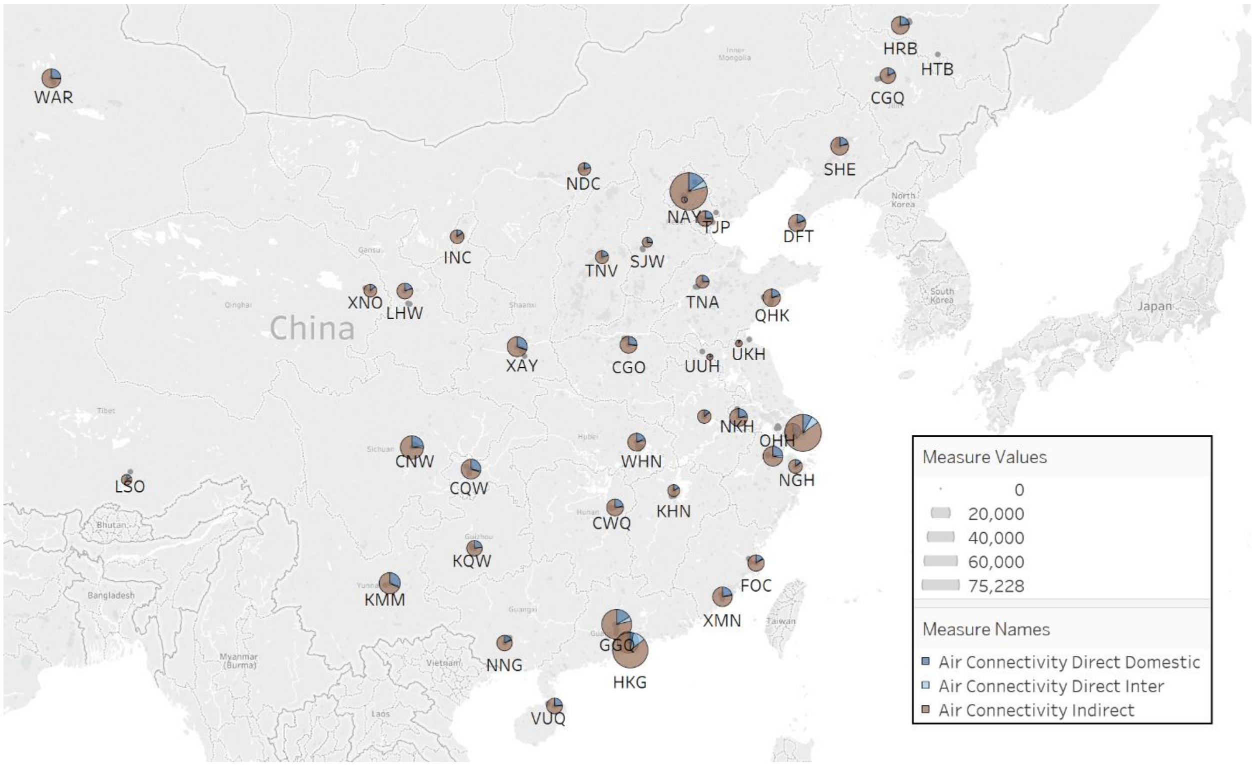

Figure 8 Airport connectivity components: direct, indirect and mixed

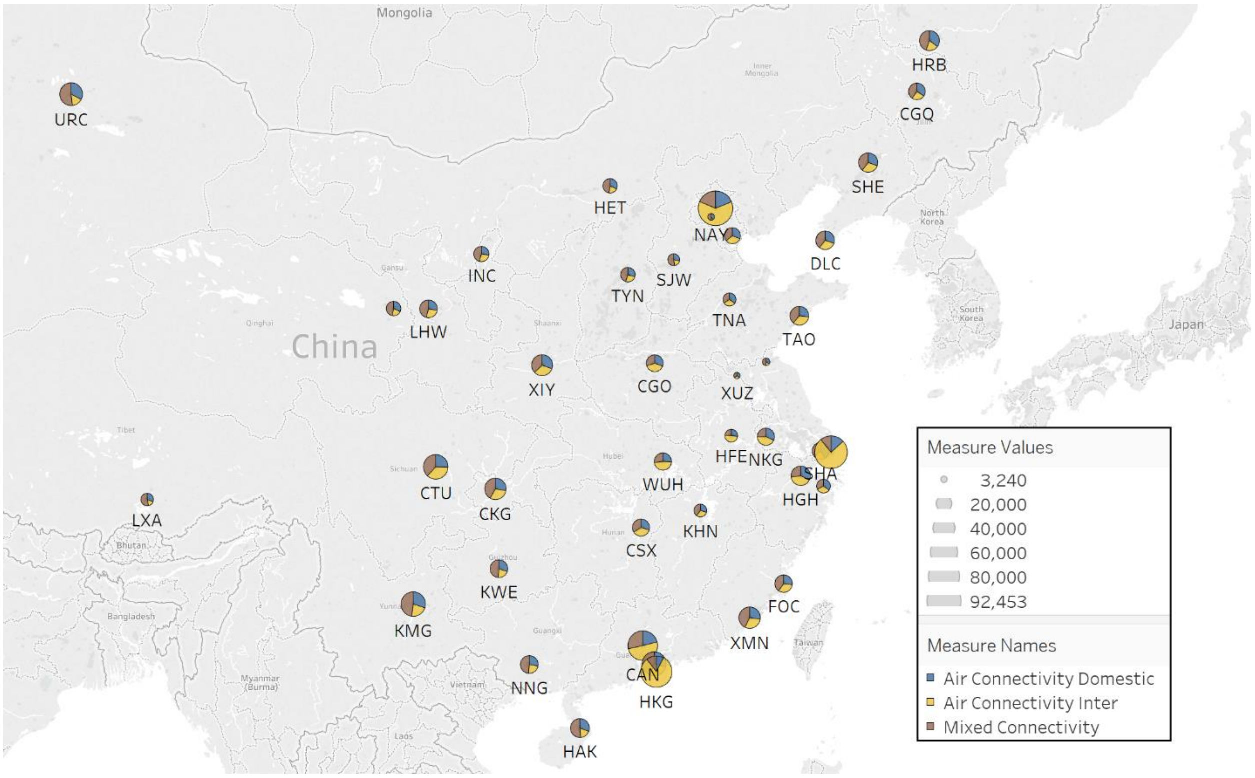

Figure 9 Airport connectivity components: domestic, international, and mixed

Connectivity of the top 40 railway stations are presented in Figure 10. Nanjing South Railway Station (NKH), Hangzhou East Railway Station (HGH_{rail}), Suzhou Railway Station (SZH), Shanghai Hongqiao Railway Station (AOH), Tianjin Railway Station (TJP), Shijiazhuang Railway Station (SJP), and Xuzhou East Railway Station (UUH), are the only 7 train terminals with connectivity over 35,000. NKH, AOH, HGH_{Rail}, UUH, and TJP are the top 5 considering only rail connectivity. SZH drops to the 8th position with rail connectivity only.

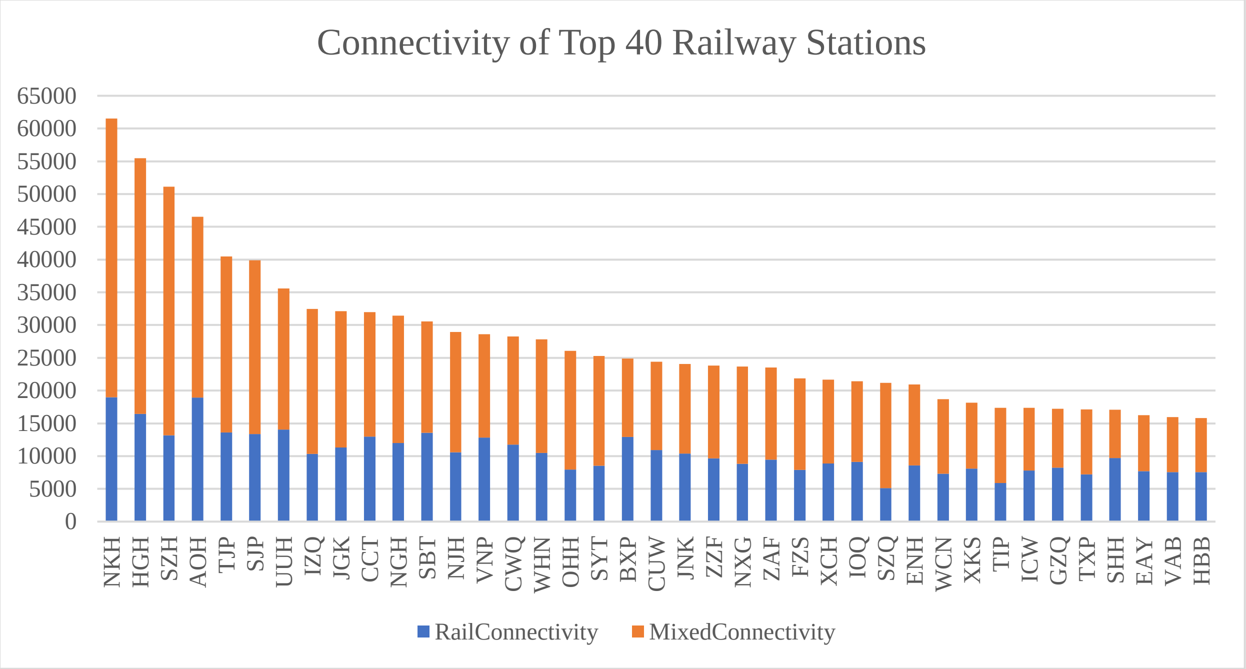

Figure 10 Top 20 railway stations of overall connectivity

Figure 11 gives the distribution and components of railway connectivity. Mixed connectivity (air-rail, rail-air) is critical for railway stations. The correlation between $r_{mixed/all}$ and overall connectivity for rail stations is 0.449, with p-value of 0.000. Mixed connectivity of a railway station represents the easiness of taking a train from the station to get close to an airport and then take a flight from the airport. For special cases like AOH, the railway station locates together with a well-connected airport, Shanghai Hongqiao International Airport (SHA), the mixed connectivity of AOH is not super high because passengers can just walk from AOH to SHA. However, this kind of colocation and cooperation between railway stations and airports is counted in the centrality of both terminals.

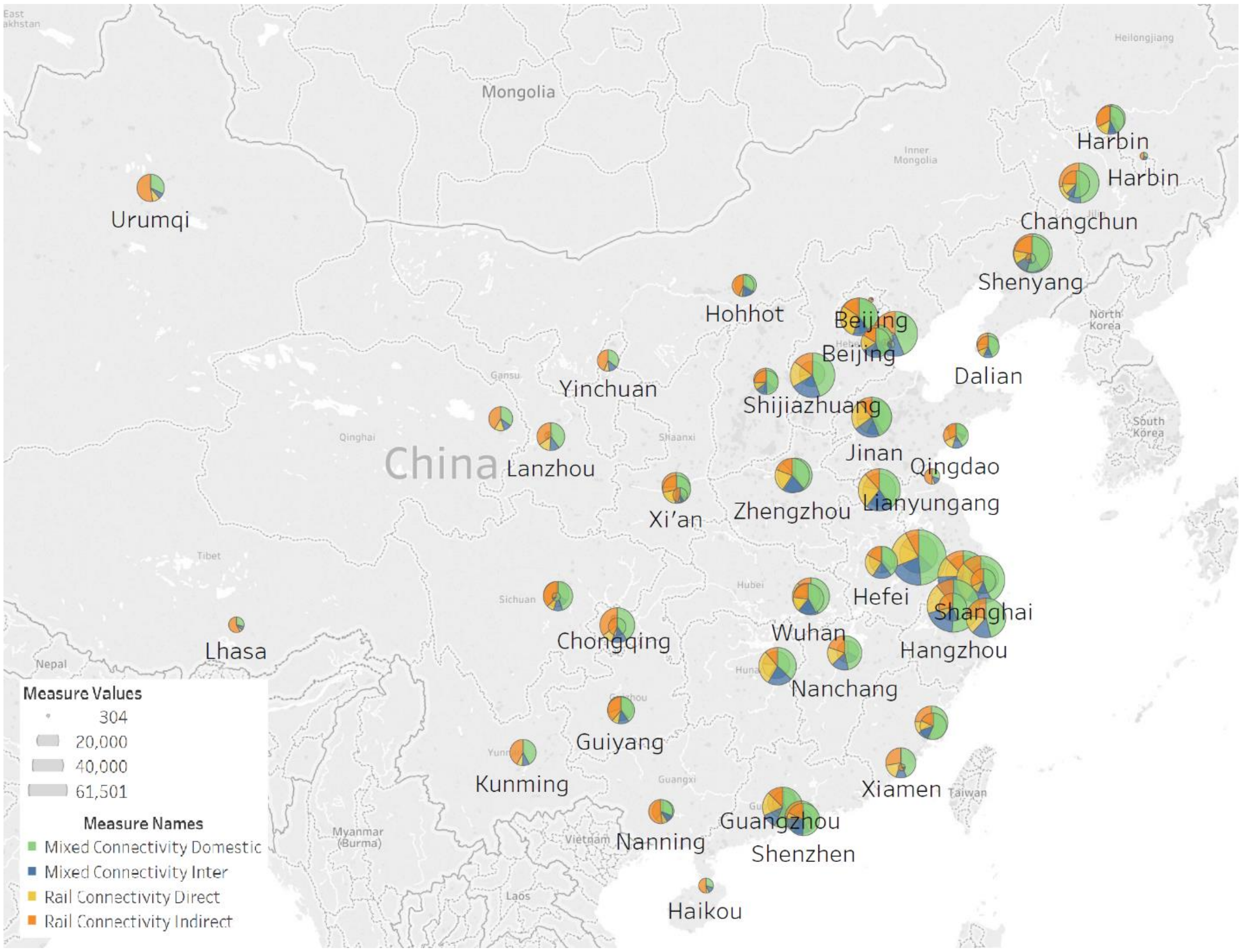

Figure 11 Components of railway station connectivity

Connectivity of international terminals, which are all airports in this research, is also calculated. International terminals' connectivity with China's domestic terminals is presented in Figure 12, and their connectivity aggregated by country is showed in Figure 13. Detailed results for foreign airports and countries are presented in Appendix 4 and 5. Top-ranking international airports in connecting China are mainly distributed in South-east Asia, East Asia, Europe, and west-cost North America. Bangkok International Airport (BKK) is the airport best-connected with China, with connectivity of 15,999.63. Singapore Changi International Airport (SIN) follows closely with connectivity of 15,955.22. Seoul Incheon International Airport (ICN, 12,323.00), Kuala Lumpur International Airport (KUL, 12,208.43), Frankfurt Airport (FRA, 11,861.63), San

Francisco International Airport (SFO, 11,705.79), Don Mueang International Airport (DMK, 11,613.43), Los Angeles International Airport (LAX, 11,443.80), Tokyo Narita International Airport (NRT, 13,790[28]), and Paris Charles de Gaulle Airport (CDG, 10,494.39), take 3rd to 10th place.

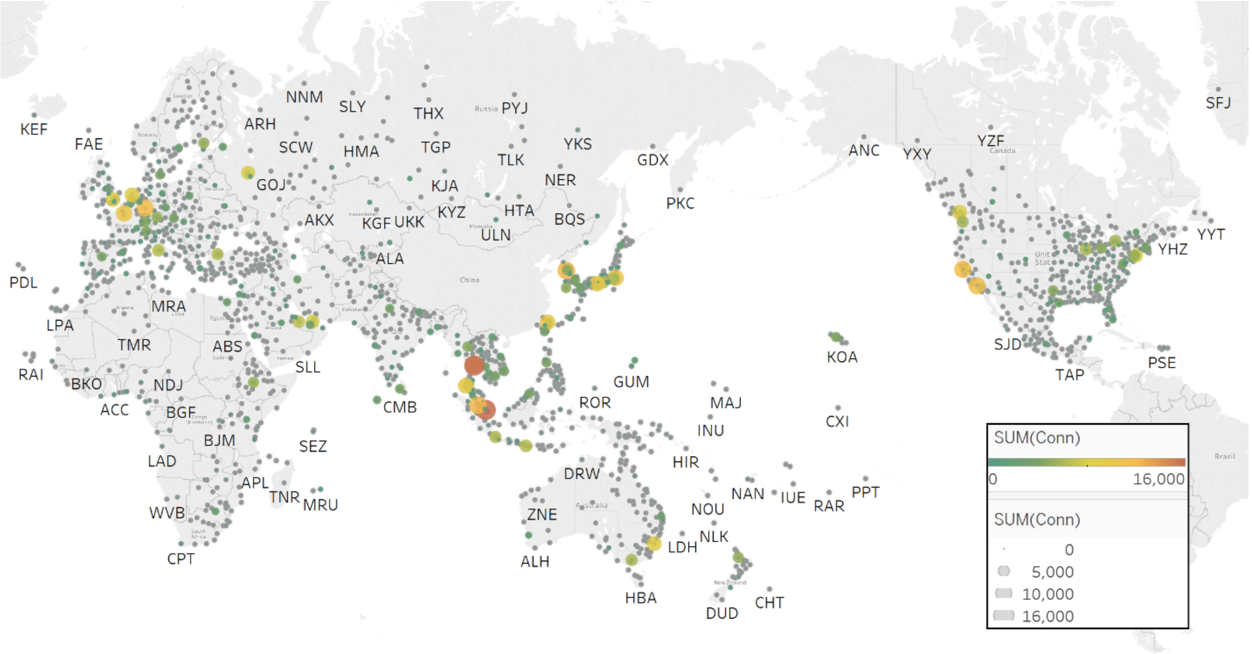

Figure 12 Connectivity of international terminals

When aggregated by country and region, United States (130,907) leads with big advantage to be the best-connected country with China. Thailand (52,890), Japan (50,978), Korea (28,980), Germany (25,484), Australia (23,275), Malaysia (21,973), and Canada (20,092) are the other 7 top-ranking countries and regions with connectivity higher than 20,000. For international airports and countries, high connectivity level with China represents the tight ties of economy, culture, politics, etc. between each other.

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[28] Though ICN's connectivity is higher than NRT, Tokyo is slightly better connected to China than Seoul when considering NRT and HND (Tokyo Haneda International Airport) for Tokyo and ICN and GMP (Seoul Gimpo International Airport) for Seoul.

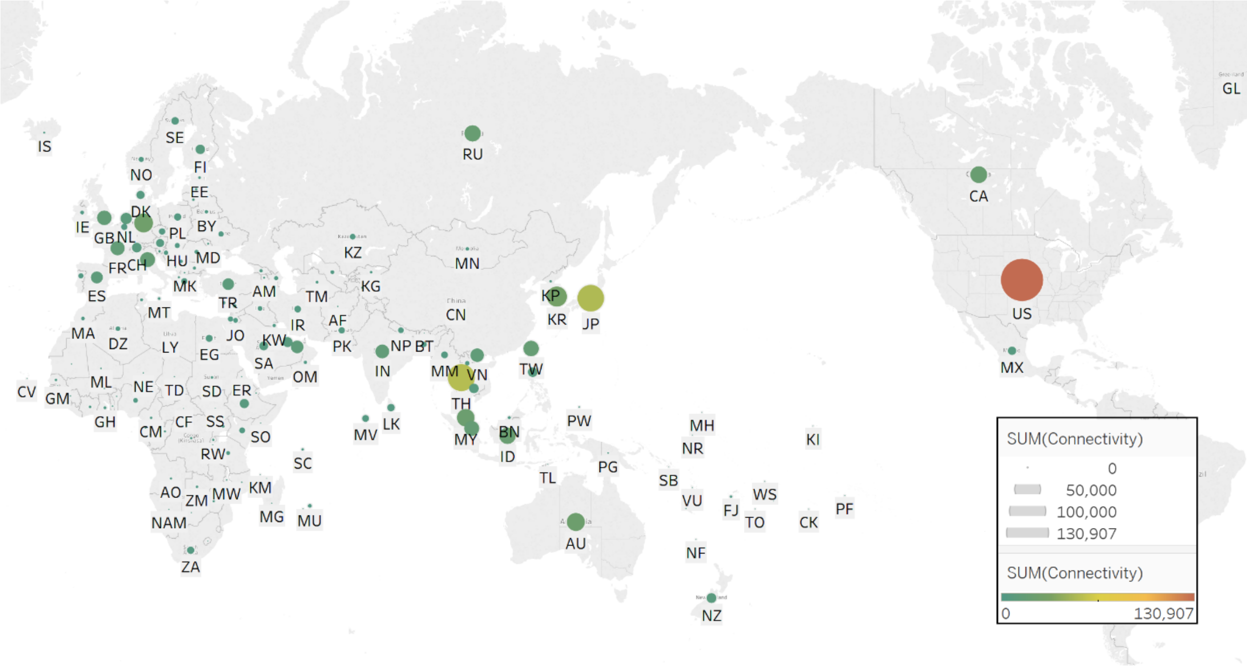

Figure 13 Connectivity of international countries

Compared with connectivity, centrality is more monopolistic. Figure 14 gives the centrality of top 40 terminals in centrality. PEK is the biggest hub, with centrality of 146985, while there are only 7 terminals beside PEK with centrality above 30000, which are PVG, CAN, SHA, HKG, AOH, HGH_{air} and CTU. While looking at the composition of connectivity, PEK, PVG, CAN, and HKG are mostly air hub only. While SHA and AOH stands out as cross-mode hub, with cross-mode centrality accounting for 83.6% and 77.6% of their overall centrality respectively. As a matter of fact, SHA and AOH are currently the only mega airport and mega train station co-located in China. Constrained by land resource, it will be hard and expensive to connect HSR station with airports that are already built. But cities to build new airports are favoring the idea. Chengdu and Shenzhen have both reported plans of HSR-airport co-location in 2016 and 2017 respectively. Shanghai has also reported plan in 2016 to build Shanghai East Railway Station by the side of PVG. Air-rail transfer will be more common and convenient in the future.

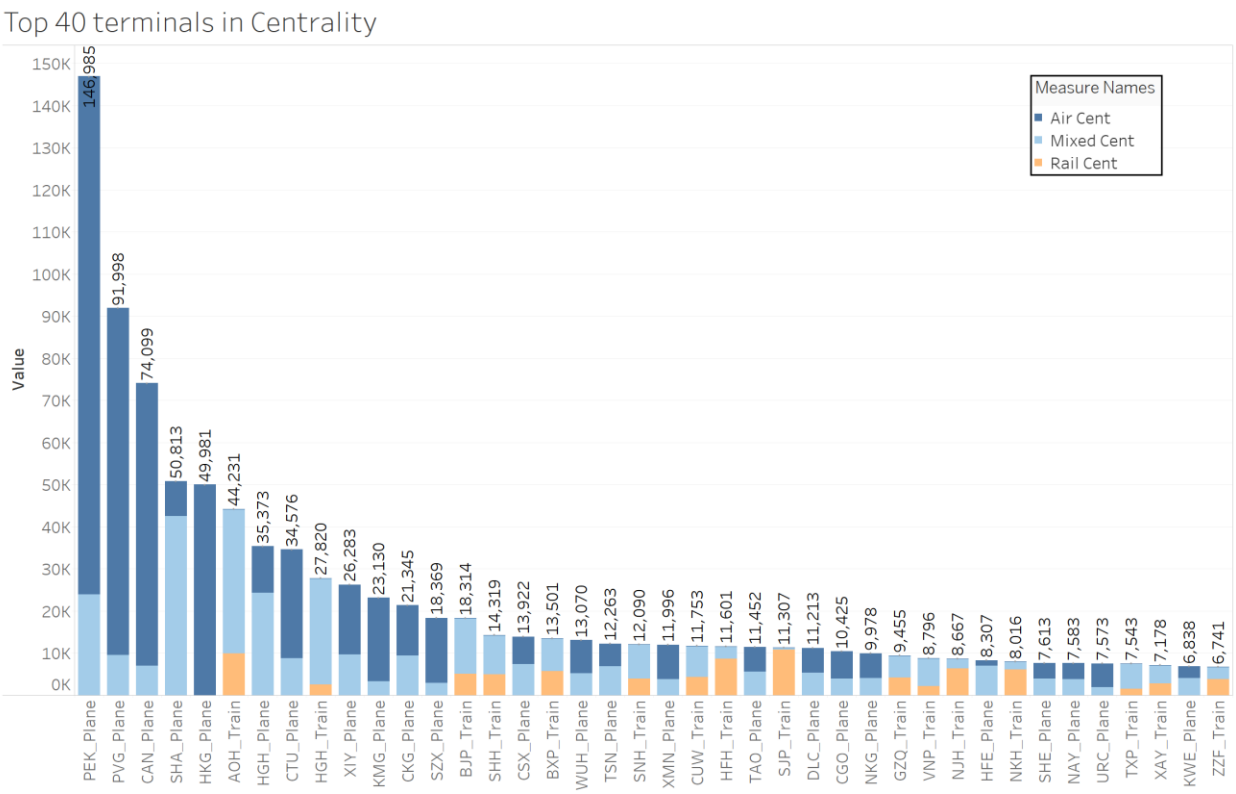

Figure 14 Centrality of terminals

Directional routes with connectivity higher than 100 are shown in Figure 15. A more detailed pattern of China's domestic routes (connectivity higher than 200) is presented in Figure 16. We can see that well-connected routes are still concentrated in east part of China. Furthermore, international routes are mostly limited on PEK, PVG, CAN, and HKG.

At route level, rail route AOH→NKH is the best-connected terminal-terminal route globally, with connectivity level 1079. All top 5 terminal-terminal routes are rail routes. The top 3 cross-mode routes between terminals are NKH→URC (Urumqi Diwopu International Airport), NKH→KMG, and NKH→SYX (Sanya Phoenix International Airport). The top air route between terminals is HKG-LHR (London Heathrow Airport). HKG-LHR, HKG-LAX, and PVG-LAX are the top 3 international routes (nondirectional). The top international routes connecting mainland China are PVG-LAX, PEK-LAX, and PVG-CDG (Paris Charles de Gaulle Airport).

Surprisingly, none of routes connecting the top 4 foreign airports (BKK, SIN, ICN, and KUL), is on the very top. One reason could be that long routes benefit in the CUM for the high average speed. This is also a signal that these airports are less dependent on limited number of hub airports and have developed good connections with more airports in China.

Figure 15 Global routes (larger than 100)

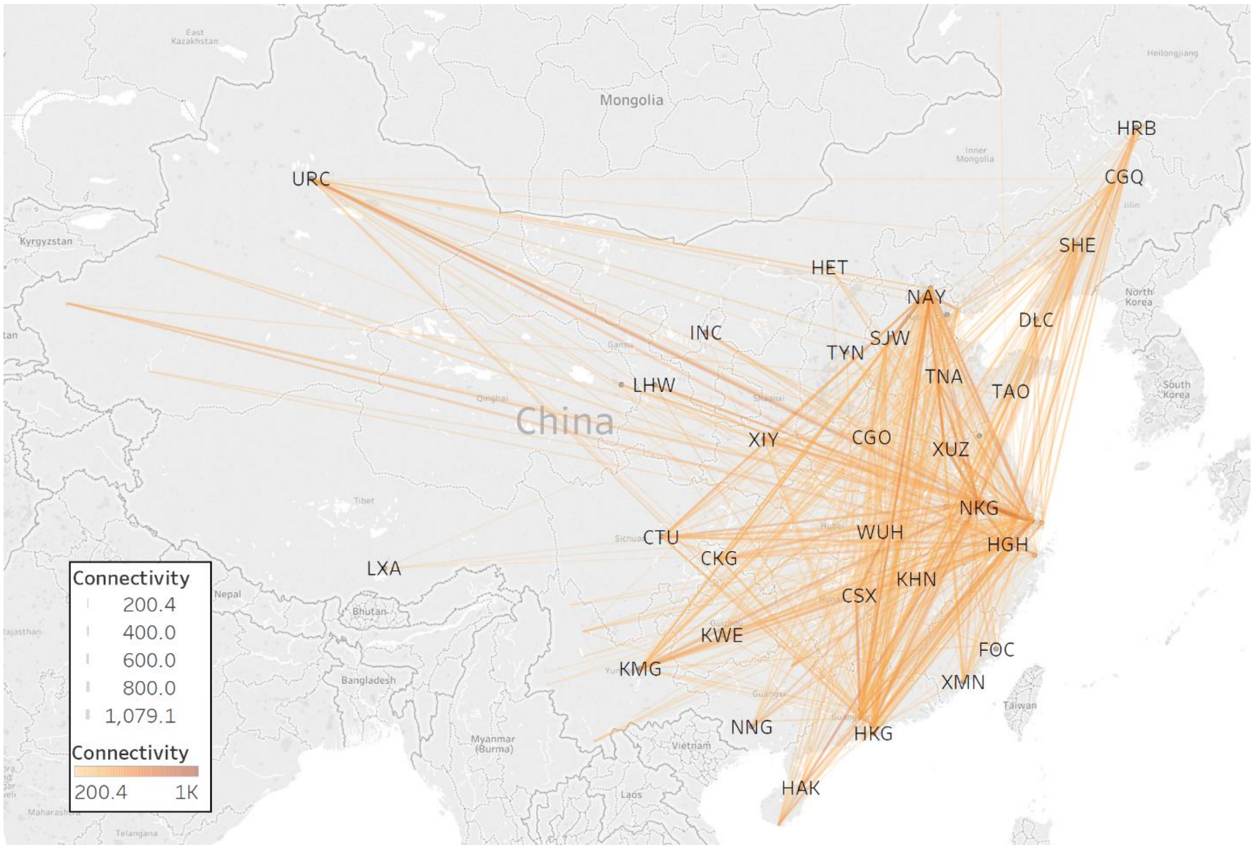

Figure 16 Domestic Routes (larger than 200)

3.2 City and Region Connectivity

It’s common for a city to have both railway station and airport, sometimes more than 1. Therefore, it is critical to look at connectivity aggregated at the level of city to see the overall inter-city transport service at the city. As the aggregation method has great effect on the result, city connectivity has been aggregated with 8 different radiation discount functions. The functions are listed in Table 3. The relationship between radiation discount and distance is presented in Figure 17. Results for cities under the 8 cases are presented in Appendix 6.

Table 3 Radiation discount experiments

Case No	**Discount Benchmark (50 km, 100 km, 200 km)**	**Function**
1	NA	Aggregate terminal connectivity by administration area.
2	(0.5, 0.25, 0.05)	$\begin{cases} e^{-\frac{d_{ia}}{70}}, & d_{ia} > 50 \\ \frac{\cos(\frac{d_{ia}}{31.84}) + 1}{2}, & 0 \leq d_{ia} \leq 50 \end{cases}$
3	(0.7, 0.35, 0.1)	$\begin{cases} 1.35 \times e^{-\frac{d_{ia}}{75}}, & d_{ia} > 50 \\ \frac{\cos(\frac{d_{ia}}{42.4}) + 1}{2}, & 0 \leq d_{ia} \leq 50 \end{cases}$
4	(0.9, 0.45, 0.15)	$\begin{cases} 1.68 \times e^{-\frac{d_{ia}}{79}}, & d_{ia} > 50 \\ \frac{\cos(\frac{d_{ia}}{76}) + 1}{2}, & 0 \leq d_{ia} \leq 50 \end{cases}$
5	(0.3, 0.15, 0.03)	$\begin{cases} 0.62 \times e^{-\frac{d_{ia}}{70}}, & d_{ia} > 50 \\ \frac{\cos(\frac{d_{ia}}{25.25}) + 1}{2}, & 0 \leq d_{ia} \leq 50 \end{cases}$
6	(0.1, 0.05, 0.01)	$\begin{cases} 0.2 \times e^{-\frac{d_{ia}}{71}}, & d_{ia} > 50 \\ \frac{\cos(\frac{d_{ia}}{20}) + 1}{2}, & 0 \leq d_{ia} \leq 50 \end{cases}$
7	(0.5, 0.35, 0.15)	$\begin{cases} 0.73 \times e^{-\frac{d_{ia}}{130}}, & d_{ia} > 50 \\ \frac{\cos(\frac{d_{ia}}{31.84}) + 1}{2}, & 0 \leq d_{ia} \leq 50 \end{cases}$
8	(0.5, 0.15, 0.01)	$\begin{cases} 1.75 \times e^{-\frac{d_{ia}}{40}}, & d_{ia} > 50 \\ \frac{\cos(\frac{d_{ia}}{31.84}) + 1}{2}, & 0 \leq d_{ia} \leq 50 \end{cases}$

Case 1 has no radiation discount and aggregates terminal connectivity by administrative area. Case 6, Case 5, Case 2, Case 3, Case 4 changes the overall speed of decay, from fastest (10% at 50 km) to slowest (90% at 50 km). Case 7 and Case 8 changes the speed of decay for long-distance range (above 50 km), from slow (35% at 100 km, 15% at 200 km) to fast (15% at 100 km, 1% at 200 km). Case 2 is the same as the radiation function discussed in Section 2.3. It's also considered as base case here.

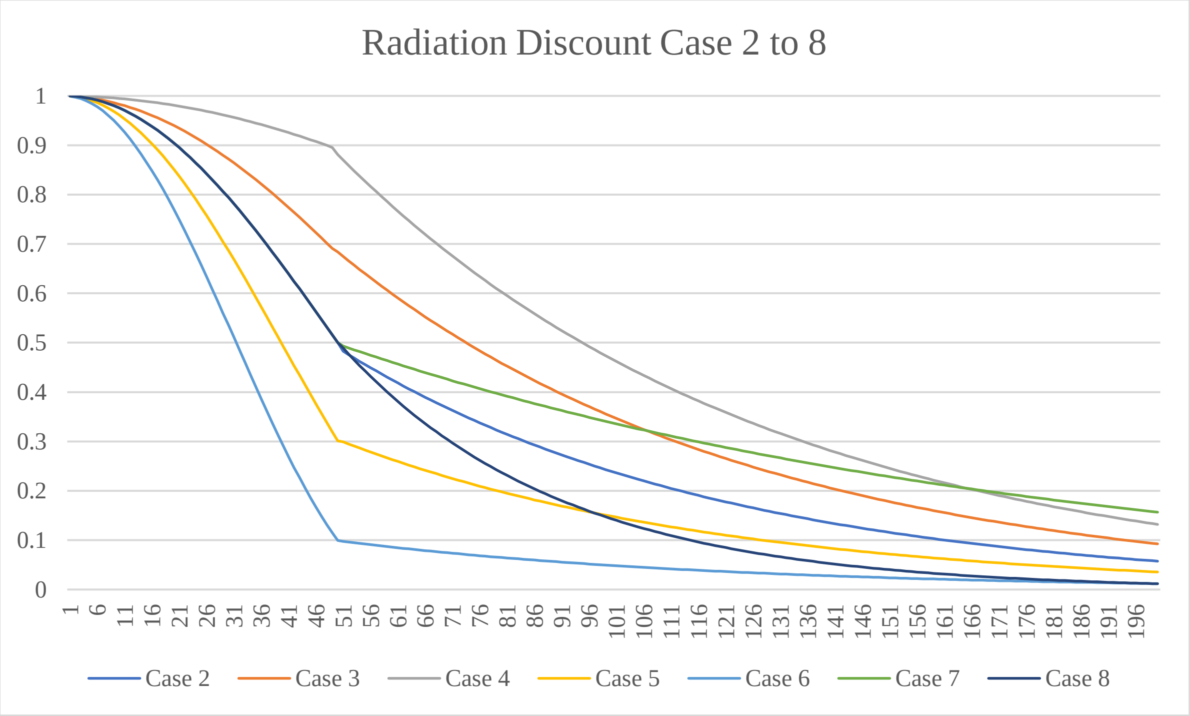

Figure 17 Radiation Discount VS distance for all cases

Connectivity of cities under all 8 cases are showed in Figure 18. Comparing city connectivity against Case 2, we see that Case 3, 4 and 7, where radiation discount decays slower, favours city connectivity, while in Case 5, 6, and 8, where radiation discount is more sensitive of distance, city connectivity is lower than Case 2. Some cities' connectivity is even lower than Case 1 in Case 5, 6, and 8, because even terminals within their administrative area are "far" away from city centre in these cases. In cases except for 5, 6, and 8, connectivity for most cities is always higher than when there’s no radiation discount, because when connectivity decays slower with distance, terminals benefit a larger area of residents and terminals with different service are able to cooperate with each other. Mega airports will be able to provide good service for passengers not only in mega cities but also in their adjacent cities. Airports in smaller cities with unique routes or lower fare will also benefit large cities nearby. Crowded terminals can direct low-value connections to smaller terminals in the neighbourhood and focus on high-value routes. Therefore, by improving the short-distance transportation service to terminals from residency area both in the city and in adjacent cities, connectivity of all cities in the metropolitan area will be improved.

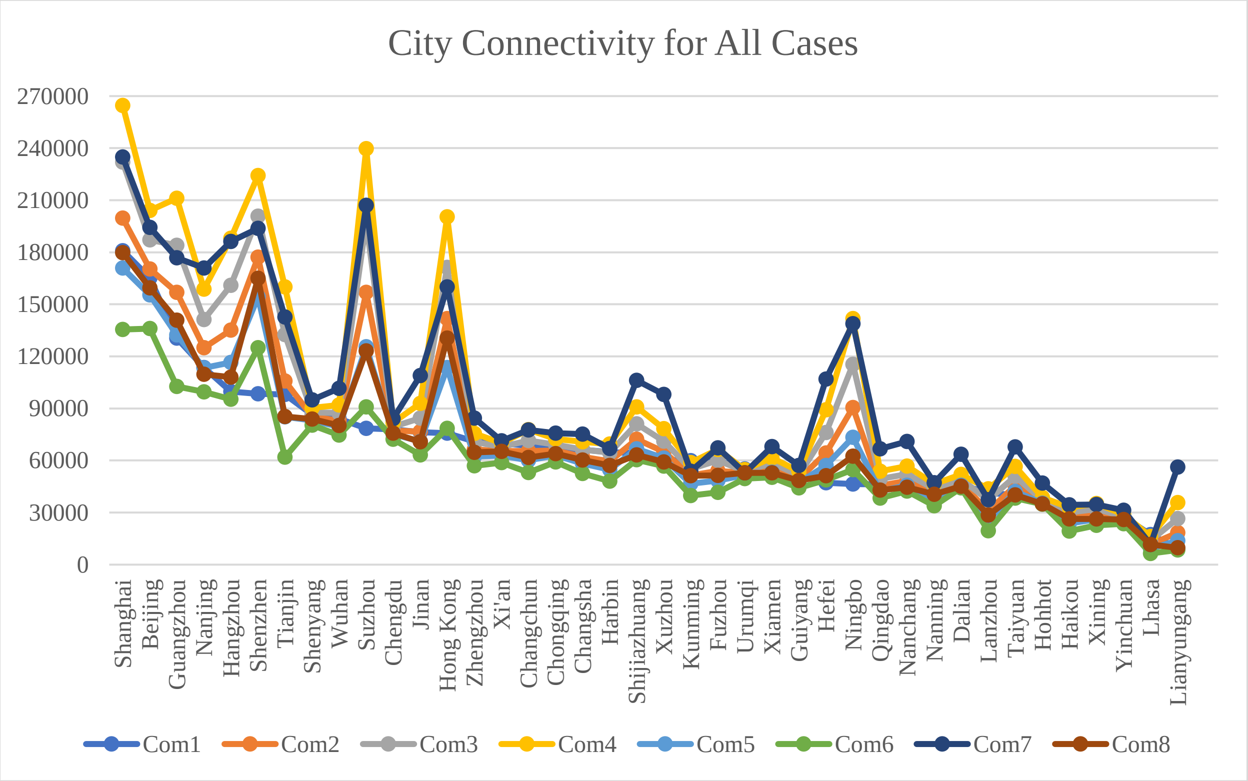

Figure 18 City Connectivity for All Cases

When comparing cities under all cases, it is observed that Hong Kong, Lianyungang, Suzhou, Hangzhou, Ningbo, Guangzhou, Shanghai, and Shenzhen are the cities benefited the most in all cases. While cities like Lanzhou, Kunming, and Lhasa always suffer with radiation discount. It seems that cities with other big cities in close neighbourhood benefit by accessing inter-city transport service of other cities. Distance is included in the radiation function to assess how easy it is to access terminals. Therefore, even though distances between cities would never change, when commute services are improved, e.g. when cities are connected with Maglev trains, or with faster highway, excellent inter-city transport service in mega cities will benefit a larger area of civilians.

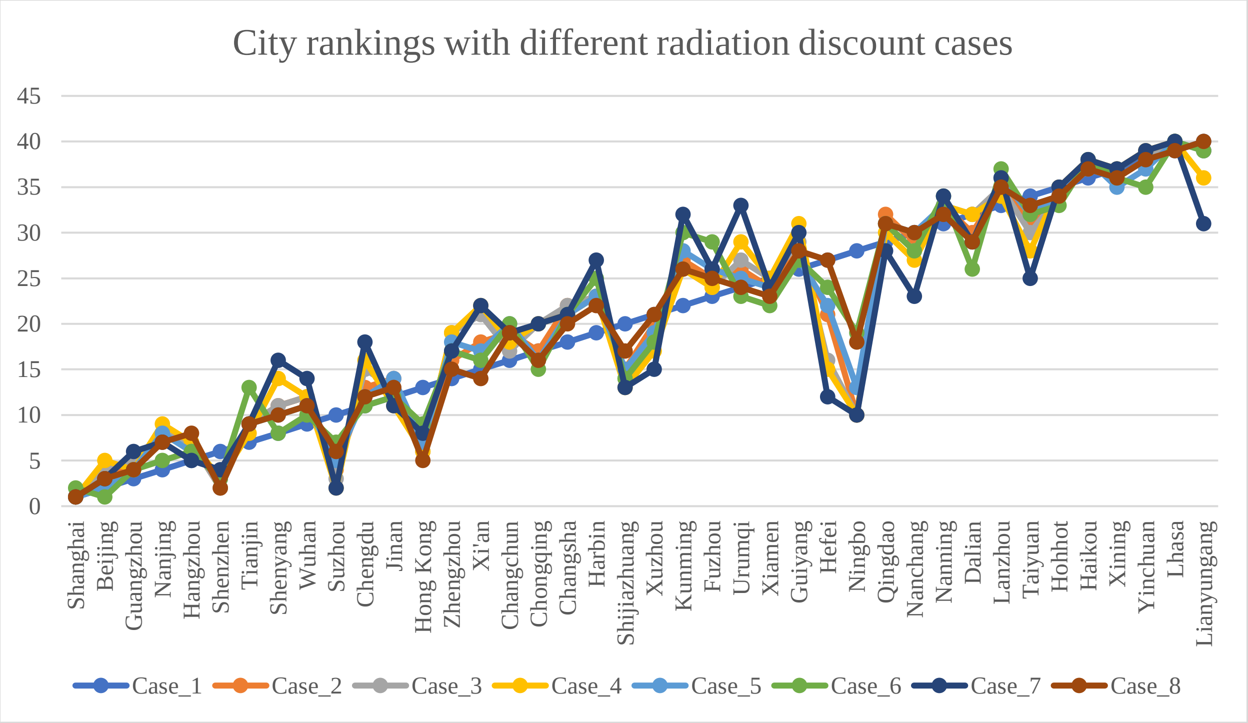

Figure 19 City rankings with different cases

The rankings of cities under different cases are presented in Figure 19. We can see that although some of the 8 cases are sensitive with distance while others are not, the ranking of cities are mostly consistent across all cases. For example, Ningbo’s ranking is always higher when radiation discount is enabled, so is Shijiazhuang, Suzhou, Shenzhen, etc. While cities like Urumqi, Changchun, Shenyang, etc., always rank lower with radiation discount. Shanghai ranks

1st in all cases except for Case 6. Distribution of cities with connectivity is presented in Figure 19, calculated with Case 2. It is observed that Yangtze-River Delta and Pearl-River Delta are better connected than Beijing-Tianjin-Hebei Economic Zone, a finding that is again consistent with the one in Zhang et al. (2004) and Hui et al. (2004) with respect to China's air cargo connectivity.

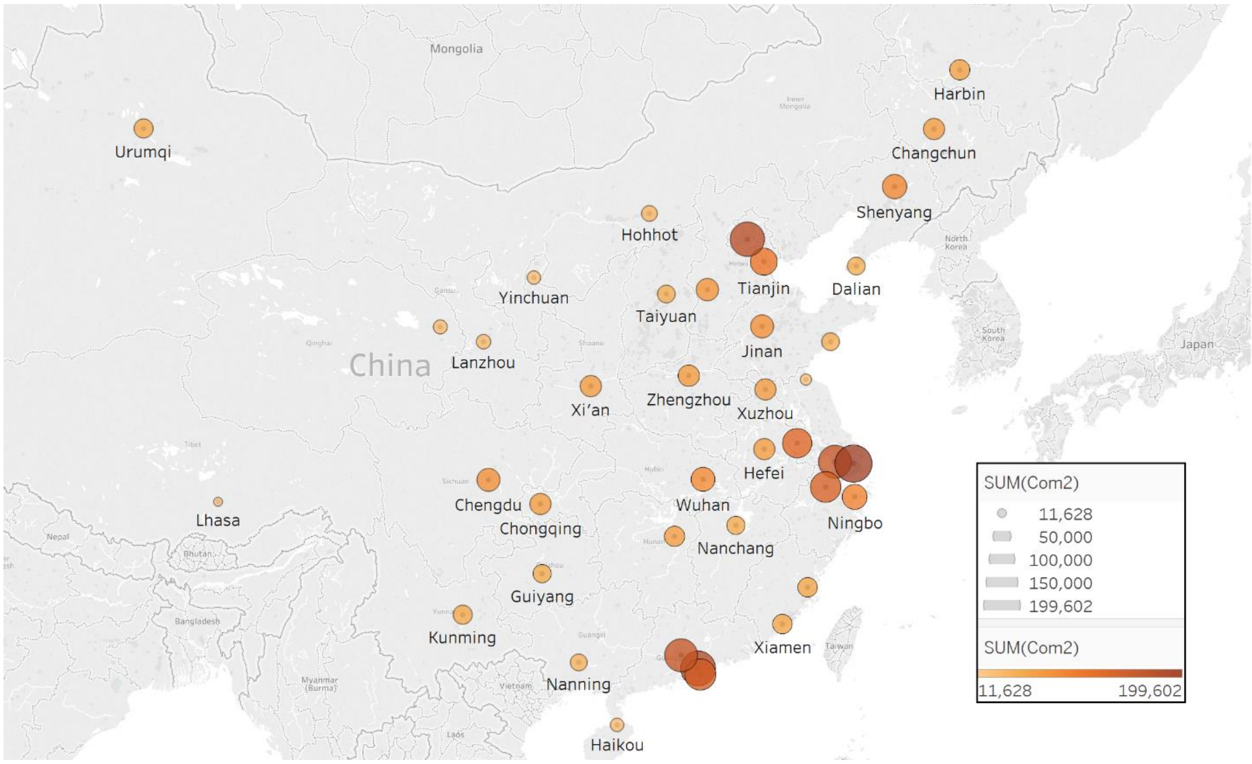

Figure 20 City connectivity with Case 2

At the level of inter-city route, Beijing-Guangzhou (5,400) is the winner, followed closely by Beijing-Shanghai (4,882), and Beijing-Shenzhen (4,826). All the top 3 city pairs are benefited by high level of indirect connectivity. When 2 cities are far away from each other, and have a lot of big cities in between, it is easier for passengers to find indirect connections, because there are a lot of feasible transit cities. While in terms of direct connectivity, short-haul routes have better performance. Shanghai-Nanjing (3,942), Nanjing-Suzhou (3,138), Shanghai-Suzhou (2,601), Beijing-Tianjin (2,435), and Shanghai-Hangzhou (2,306) are the top 5 routes. Rail connectivity, mostly HSR, contributes for more than 95% of direct connectivity for all top 10 routes in direct connectivity. Figure 20 presents connectivity of the top 20 non-directional inter-city routes.

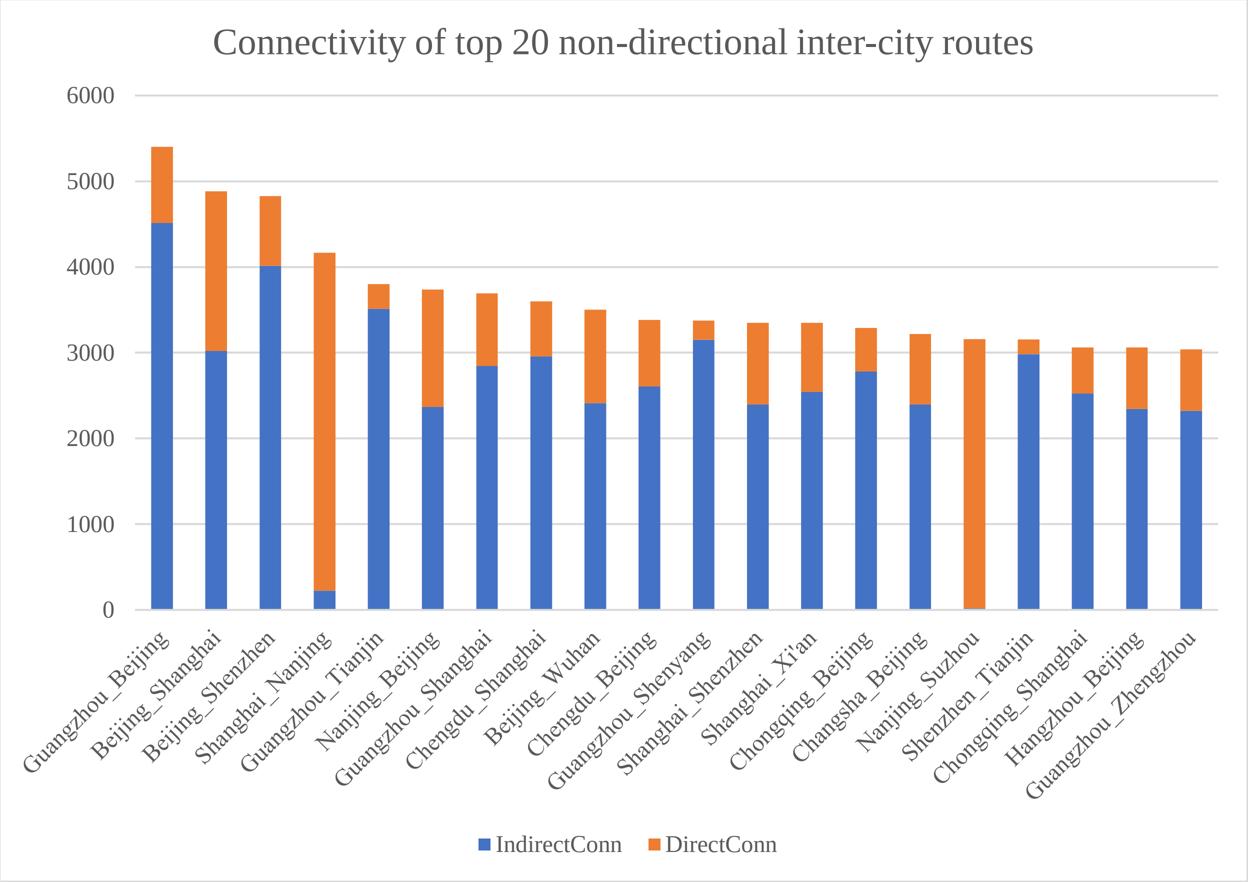

Figure 21 Connectivity of city routes

Figure 21 represents connectivity of inter-city routes between the 40 listed cities only. A diamond shape is observed with higher connectivity level within it, as marked with blue lines in Figure 22. Beijing-Tianjin-Hebei Economic Zone, Yangtze-River Economic Zone, Pearl-River Economic Zone, and Chengdu-Chongqing Economic Zone are the 4 vertices of the diamond. The strongest connections within this area are those connecting the 4 vertices.

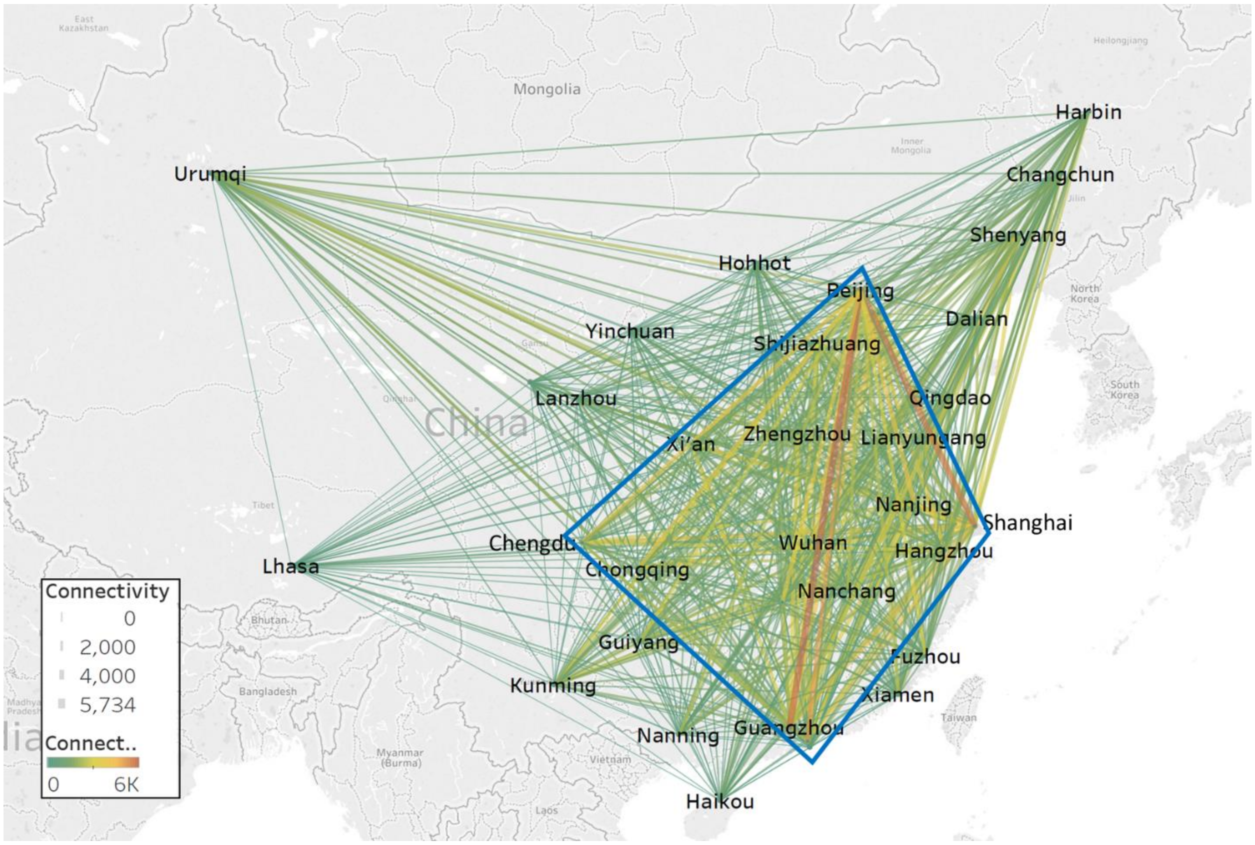

Figure 22 Routes between listed cities

The proportion of rail connectivity of routes[29] is negatively correlated with route distance, with Pearson's correlation of -0.610 (p-value 0.000). Rail connectivity accounts for larger share in short distance routes. The relationship between share of rail connectivity and route distance is showed in Figure 23. The line marked in blue shows the fitted values of rail's share in terms of distance. Although the HSR has been well recognized as the dominant transport mode only for short- and medium-haul route with distance below 700 km (Adler et al., 2010; Fu et al., 2014; Wan et al., 2016; Yamaguchi et al., 2008; Xia and Zhang, 2016a), the HSR has become a better and popular option for both medium- and long-haul routes up to 1500 km, with people building in confidence in its safety and punctuality. For example, rail accounts for 64.94% for Urumqi-

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[29] Proportion of rail connectivity is only calculated for routes with rail connections.

Xining, the great circle distance of which is 1443 km. Low cost may also be a critical advantage for rail transport. Rail has been a good complement for air transport on long-haul routes with insufficient air service.

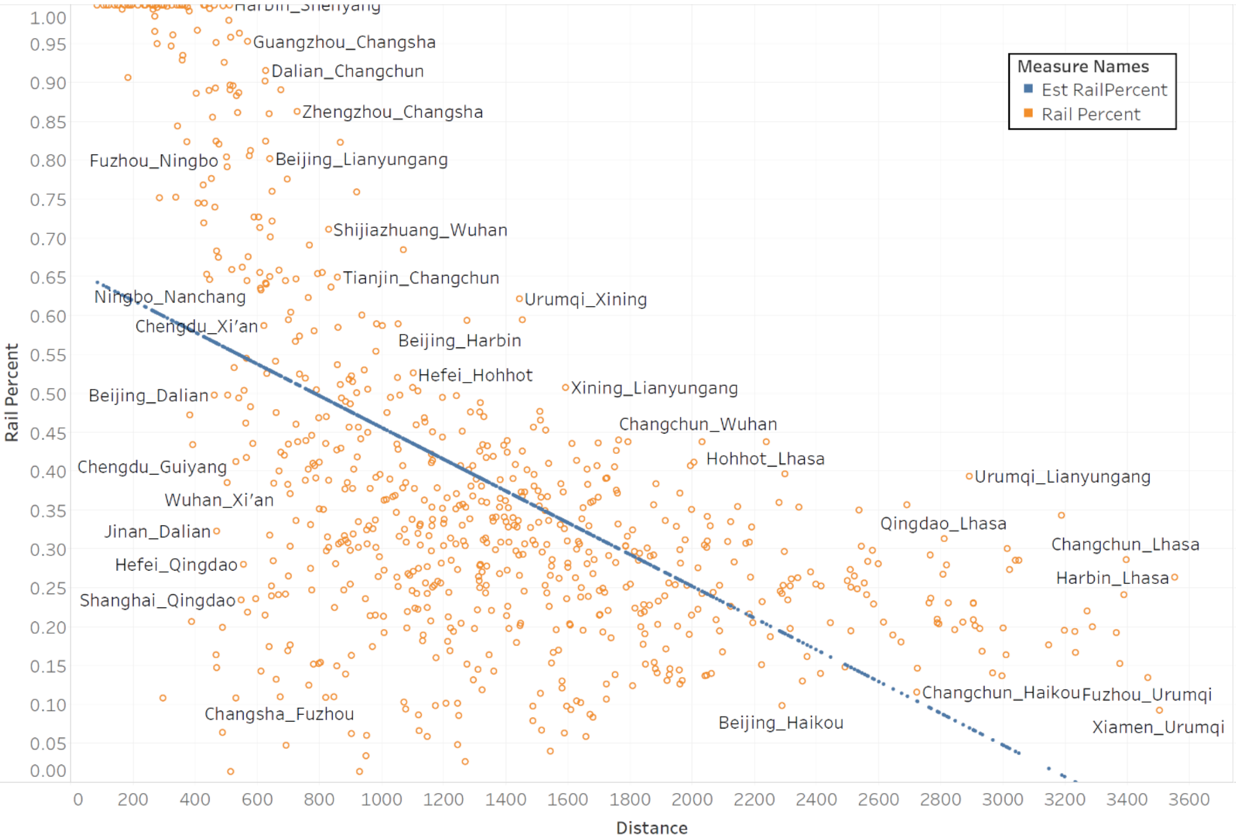

Figure 23 Share of rail connectivity against route distance

3.3 Vulnerability Analysis

Any kind of incident occurring on a city's transport network will affect the connectivity of the city. Train breakdowns, electrical failures, road construction, aviation control, etc., would all result in connectivity decrease. In extreme situations, such as war and natural disaster, it is possible to lose one entire route, one terminal, or even a city. Vulnerability, which is defined by Berdica (2002) as the degree of susceptibility of a network to certain incidents that may lead to reduced service or accessibility levels, is critical under these circumstances. When a city has a resistant transport network, which means that it will remain functional under extreme situations, it brings flexibility and easiness for government, companies, and individuals to rescue, rebuild, and balance back. Therefore, it is important to analyse vulnerability of city's transport service for enterprises before locating, and for government because of security reasons.

A lot of research concerning how to define, evaluate, and handle vulnerability of cities' transport system has been well-conducted (Berdica, 2002; Taylor et al., 2006; Taylor, 2008; Rodríguez and García, 2014). In this research, characteristics of incidents are not concerned. The focus is on the consequence in terms of connectivity, when the incident has already happened and destroyed a terminal or route.

In this research, two kinds of vulnerability will be discussed. First, city impact, which is the loss of overall network connectivity when a city is lost. When a city is lost, not only the city's connectivity but also connectivity of other cities connecting with it will be lost. City impact represents the importance of the city in the network. Figure 24 presents city impact of top 25 cities, in terms of overall connectivity and direct connectivity. Shanghai, Beijing, Guangzhou, and Nanjing are the top 4 cities in overall city impact. When Shanghai is lost, 9.6% of overall connectivity and 15.1% of direct connectivity in the whole city network will be lost. Nanjing surpasses Guangzhou to be the 3rd most important city in direct connectivity. Hangzhou, Wuhan, Zhengzhou, Changsha, Tianjin, and Xuzhou also rank higher in terms of direct city impact than overall city impact. These cities are extremely important because direct connections are more efficient and effective than indirect connections in extreme situations.

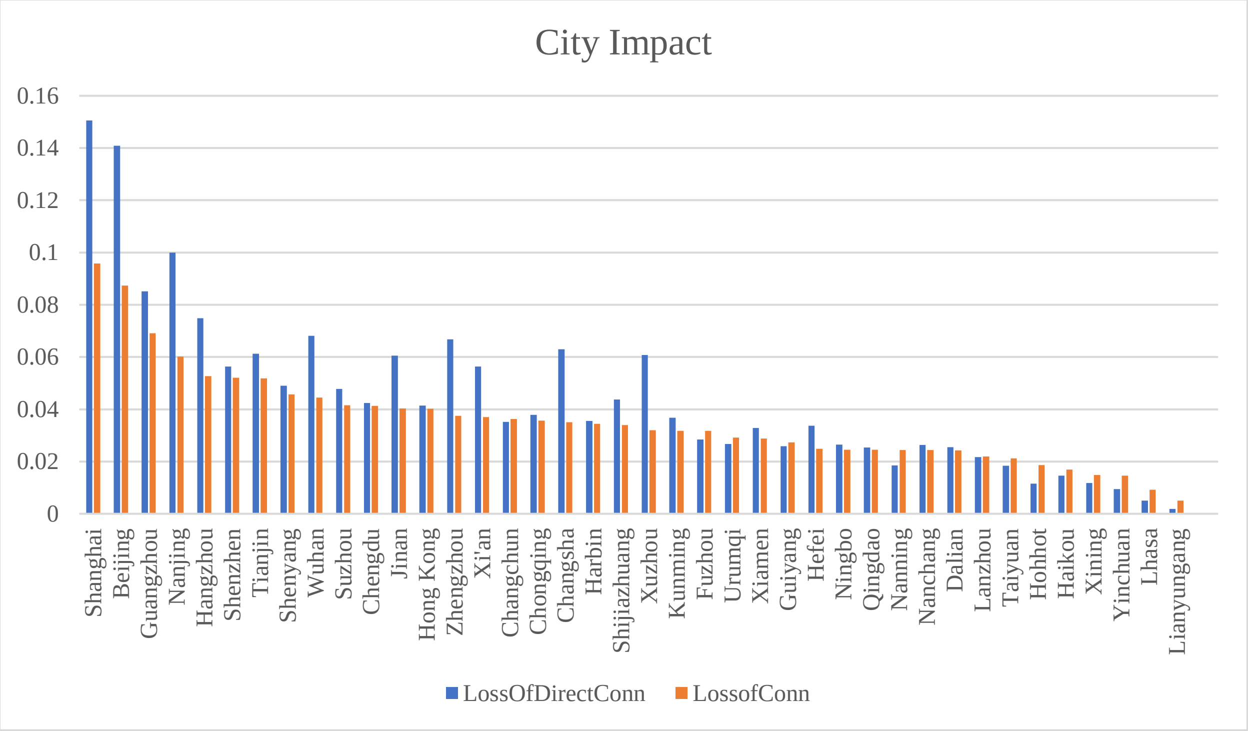

Figure 24 City impact

Second, city resistance, which is the loss of the city's remaining connectivity when a certain number of top ranking routes connecting it are lost, compared with original connectivity. If a city is only well connected with one city, it will be disconnected from the world when the only route is destroyed. However, if a city is well connected with multiple cities, the city will still be well-connected when one route is lost. Figure 25 presents city's remaining connectivity when top 1, top 2, up to top 20 routes connecting the city are lost. Only cities ranking in the top 5 and the bottom 5 are presented. It is observed that Hong Kong, Shanghai, Beijing, Hangzhou, and Ningbo are more resistant of route loss. Hong Kong is the winner of resistance, keeping 88.94% of its original connectivity without the top 20 routes. While Lhasa would keep only 59.05% of its connectivity when top 20 routes are cut.

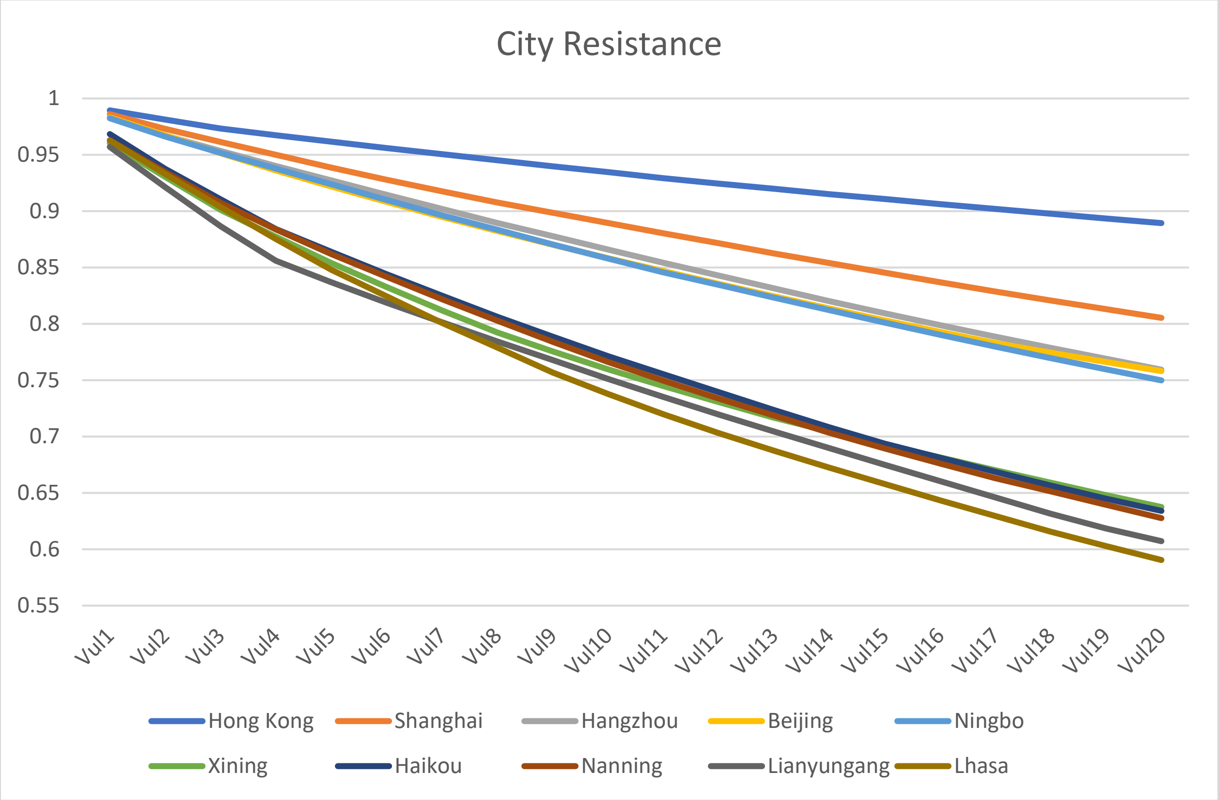

Figure 25 City Resistance

3.4 Robustness Analysis

All numeric results in previous parts of Chapter 3 are produced with the applied CUM, with equal weight for all quality factors. When the weight of quality factors changes, the result will be different. In this part, the robustness test will be performed for direct flights to see how the weight of quality factors will change the connectivity of applied CUM. As capacity and velocity are the only 2 quality factors that will affect direct flights, only weight of them will be changed.

$$D_{Cap_{ijk}} = (\frac{Seat_{ijk}}{\mathrm{Seat}_0})^{v1} \tag{22}$$

$$\mathrm{D}_{Vel_{ijk}} = (\frac{\mathrm{Velocity}_{ijk}}{\mathrm{Velocity}_0})^{v2} \tag{23}$$

For a multiplicative model like CUM, to change the weight of a factor is to change the sensitivity of its discounting equation. Equation (22) and (23) present the generic capacity and velocity discount. In the applied CUM, $v1$ and $v2$ are both set to be 0.5. When $v1$ and $v2$ increase, the sensitivity of capacity discount and velocity discount will increase. When $v1$ and $v2$ decrease, the sensitivity will decrease. Especially, when $v2$ increases, the discrimination against short-haul flights increases. Here, as showed in Table 4, 4 different sensitivity levels are tested for capacity and velocity, which produces 16 sets of scenarios.

Table 4 Robustness tests

(V1, V2)	**Low**	**Mid-low**	**Mid-high**	**High**
Low	(0.25, 0.25)	(0.25, 0.5)	(0.25, 1)	(0.25, 2)
Mid-low	(0.5, 0.25)	**(0.5, 0.5)**	(0.5, 1)	(0.5, 2)
Mid-high	(1, 0.25)	(1, 0.5)	(1, 1)	(1, 2)
High	(2, 0.25)	(2, 0.5)	(2, 1)	(2, 2)

All 16 scenarios are tested for direct flights. Air connectivity of the 41 listed Chinese major airports for all scenarios are presented in Figure 26. Air connectivity is normalized with the highest connectivity under each scenario. We can see the normalized connectivity for most airports is consistent across scenarios. Generally, the more sensitive the scenario is, the more differentiated the connectivity will be. PEK, PVG, CAN, and HKG are still the 4 dominant airports. PEK is always the best-connected airport. Connectivity of PVG is also very stable under all scenarios. HKG always benefit from higher sensitivity, because flights connecting HKG have larger capacity and longer distance compared with other airports. URC also benefits from increased sensitivity on velocity discount because URC is far away from other airports in China and flights serving URC are usually longer than other flights in distance. HET is similar as URC. Figure 27 presents the ranking of domestic airports under different scenarios. We can see that ranking is relatively robust across scenarios.

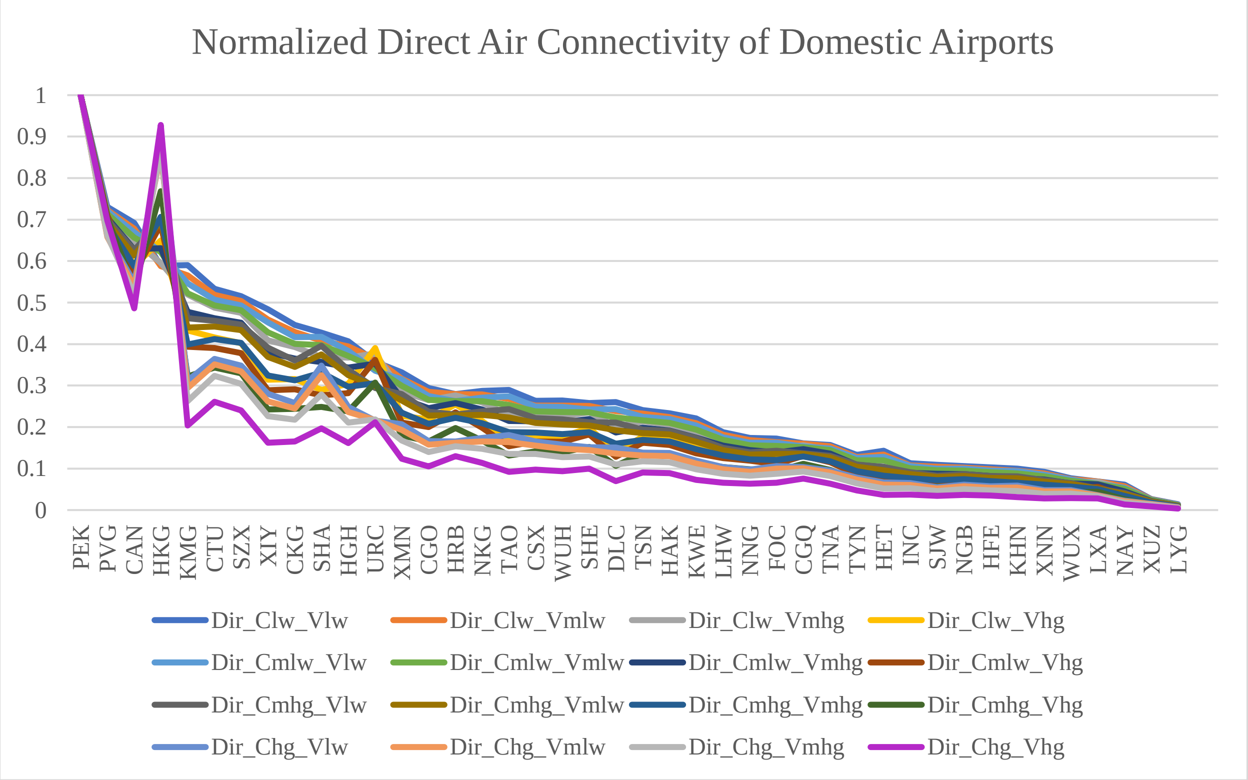

Figure 26 Robust test on domestic airports-normalized connectivity

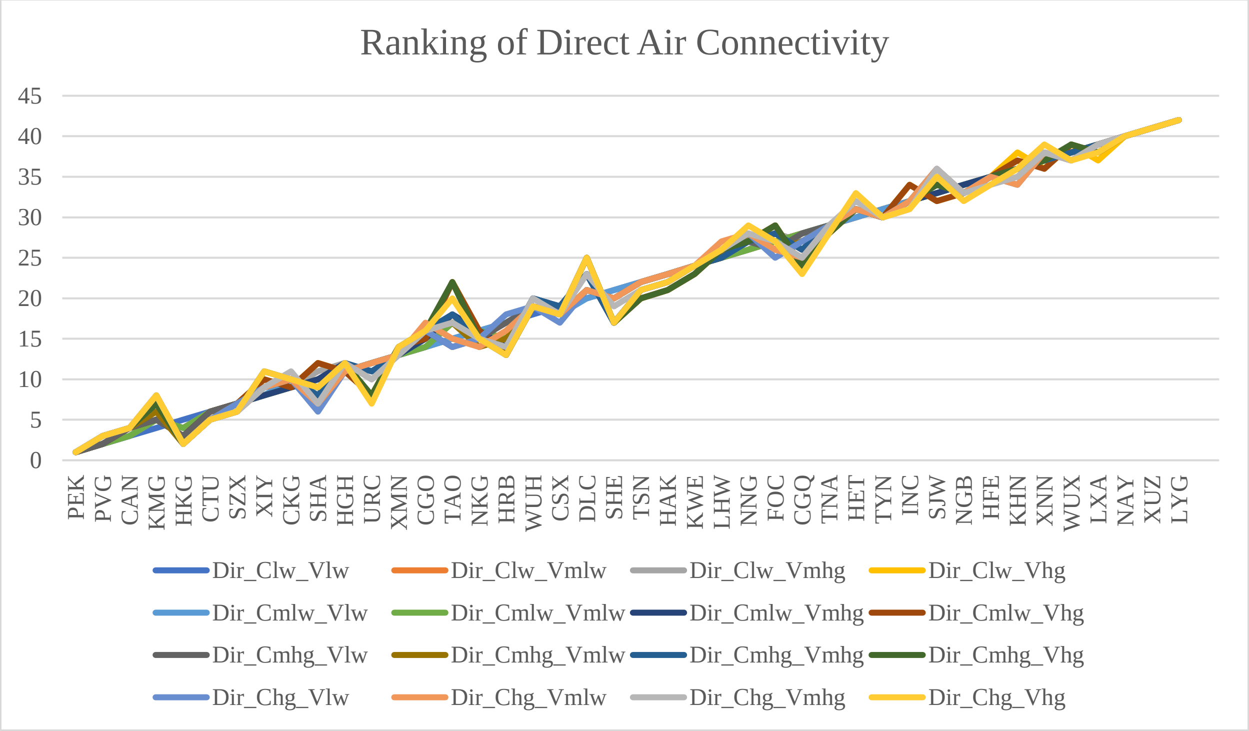

Figure 27 Robust test on domestic airports-ranking

Figure 28 gives the normalized connectivity with China of top 30 international airports. Compared with domestic airports, the connectivity between international airports and China's domestic cities is less robust. Sensitivity of capacity has a slight favor for long-haul routes because airlines tend to serve long-haul routes with large aircraft. Sensitivity of velocity discount strongly support airports that are far away from China.

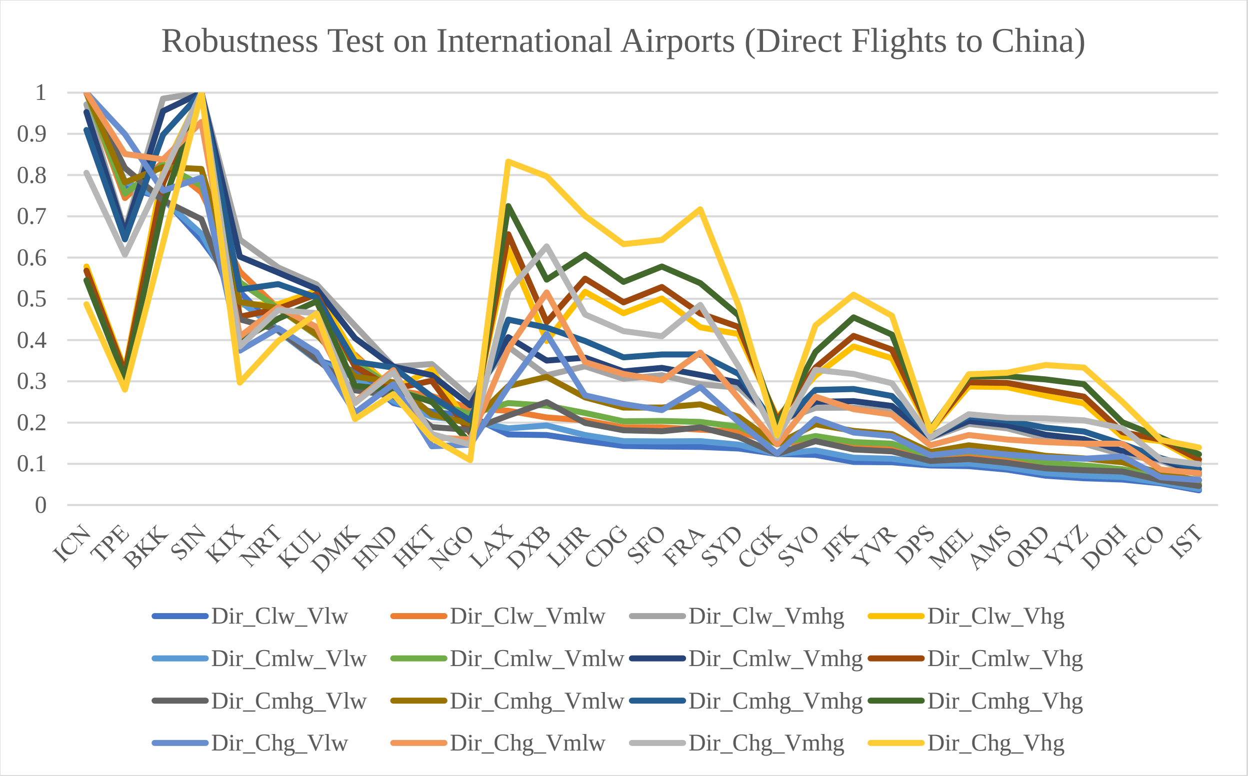

Figure 28 Robustness test on international airports (direct flights to China)

The robustness shows that the weight of different discounting factors does have effect on results. It should be carefully chosen according to the objective before application.

4 Analysis for Drivers of Connectivity

While a lot of research calculates connectivity, studies on the drivers of connectivity, and especially those on Chinese terminals connectivity remain sporadic. Although some literature (e.g., Li and Cai, 2004; Lin, 2012; Wang et al. 2014) has studied the evolution of air transport network of China and revealed a significant improvement in connectivity, the connectivity of individual airports has not been measured using a comprehensive approach that considers both quantity and quality elements. In this Section, we run analysis on the drivers of connectivity[30].

The air connectivity of 69 Chinese airports, considering all the flights from and to these 69 airports for the period 2005-2016, is calculated, including both domestic and international flights. The results are in Appendix 7. These airports accounted for about 95% of the total passenger enplanements in the last few years. For each year, we use the flight data of two periods to construct the connectivity measure: April 16 to April 22, and Oct 16 to Oct 22. We hope that the use of two periods' flight information will give a good representation of that year's connectivity.

4.1 The Methodology and Data for Detecting the Drivers of Air Connectivity

We have obtained the connectivity performance scores for 69 airports (67 cities as Beijing and Shanghai have two airports each). In this section, we will investigate the economic and institutional drivers of the connectivity performance of these cities.[31]

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[30] Only air connectivity is considered as historical schedule data for trains is not available.

[31] The city of Lhasa is excluded from the second-stage regression analysis due to the lack of some macroeconomic indicator data for this city.

Although Burghouwt and Redondi (2013) note that connectivity is an important variable in passengers' route choice and can be used in econometric models as an independent variable, little literature has studied the drivers of air connectivity as a dependent variable, although some studies have mentioned that connectivity is determined by a set of supply and demand components. They include land-use component (the characteristics of land uses at origins and destinations travellers), transport system component, the temporal component and the individual traveller component (e.g., demographic and income information) (Geurs and Van Wee, 2004; Taylor, 2008; Matisziw and Grubesic, 2010). In fact, many connectivity metrics are constructed based on this framework.

A relevant study is carried out by Maertens (2010) who examined the drivers of long haul flight supply at secondary airport in Europe. The author identified internal factors such as airport charges, semi-external factors such as the length of runway, and external factors including economic power, regional importance of inbound tourism, political importance of the catchment, etc. The research suggests that economic power measured by GDP has a significantly positive impact on long haul flight supply. However, the author argued that sufficient runway length is only a condition sine qua non, which does not automatically increase the number of long haul flights. In fact, many long runways at many secondary airports are underutilised and thus not economically viable.

Macroeconomic condition matters. Wittman and Swelbar (2013) reported that in the period 2007-2012, the US air transportation system experienced a series of changes as a result of the global financial crisis, high fuel prices and airlines' profit-focused capacity discipline strategies. Connectivity at medium-hub airports declined the most (15.6%) while large hub airports only lost 3.9% of their connectivity.

The gravity model might also be relevant. Our connectivity of a city (airport) is the aggregate of the connectivity of the city to and from all destinations. The connectivity performance of the city is driven by the economic significance of the city and its major trading partners as well as some impedance and facilitating variables. This is analogous to the gravity model which has been widely used in cross-country empirical analysis of international trade flows. The gravity model has also been applied to air transport to identify the determinants of bilateral air passenger or air cargo flows (Zhang and Zhang, 2016). Although our connectivity measure reflects the aggregate connectivity at an airport/city, which is not a flow between cities, the gravity model can still give us some guidance in revealing the economic drivers and cost/incentive factors for this performance indicator.

Following the above discussion[32], the regression model is specified as follows:

$$Y_{it}=\alpha_0+\alpha_1\ln HHI_{it}+\alpha_2\ln Yield_{it}+\alpha_3 Location_i+\alpha_4\ln Pop_{it}+\alpha_5\ln GDPCapita_{it}+\alpha_6\ln Fixedasset_{it}$$

$$+\alpha_7 Tourist_i+\alpha_8 Hub_i+\alpha_9\ln Runway_i+\alpha_{10}\ln Terminal_{it}+\alpha_{11}\, Spring_{it}+\alpha_{12} HSR_{it}$$

$$+\alpha_{13}\ln Economy_t+\alpha_{14} Crisis_t+\alpha_{15}\, Olympic_{it}+\alpha_{16} Expo_{it}+\tau_i+\varepsilon_{it}$$

where,

- Y_{it} is the connectivity (overall, domestic, and international) for city *i* in year *t*.
- HHI_{it} is the Herfindahl-Hirschman Index (HHI) of city *i* in year *t*. The HHI is calculated using the passenger share of each operating airline at the airport(s) of city *i*.
- $Yield_{it}$ is the average yield of all the flights out of the city *i* in the year *t*. Airline yield is calculated by dividing the airfare with the flight’s flying distance. The passenger number is used as the weight for the average.

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[32] Apart from the factors mentioned above, non-aviation services at airport, such as shopping, car rental, hotel, etc., may also help airports to attract passengers and generate revenue. However, services are not included in the regression model because of data availability and endogeneity.

- $Location_i$ is the sum of the reciprocal of distance from city *i* to its provincial capital city and its distance to the eight most-well connected airports in our sample. It is expected that if a city is closer to a larger city, its air connectivity will be lower.
- Pop_{it} is the population of city *i* in year *t*.
- $GDPCapita_{it}$ is GDP per capita of city *i* in year *t*.
- $Fixedasset_{it}$ is the value of the fixed asset investment of city *i* in year *t*.
- $Tourist_i$ is a dummy variable to control for the tourist cities.
- Hub_i is equal to one if the city's airport is one of the 11 hubs declared by the CAAC in 2010.
- $Runway_{it}$ is the airport runway length in city *i* in year *t*. If a city has multiple runways, the sum of the length of all runways is used.
- $Terminal_{it}$ is the airport terminal size in city *i* in year *t*.
- $Spring_{it}$ is a dummy variable to control for the presence of the low-cost carrier (LCC), the Spring Airlines, in city *i* in year *t*.
- HSR_{it} is a dummy variable to indicate whether city *i* has high-speed rail (HSR) service in year *t*.
- $Economy_t$ is the sum of the GDP of Beijing, Shanghai and Guangzhou in year *t*. This variable is included following the guidance of the gravity model, which says that bilateral trade/passenger flows between two economies are proportional to the size measured by GDP or population of them. Beijing, Shanghai and Guangzhou represents three economic centres in North, East and South China, respectively, which are significant trading partners and travel destinations to almost all Chinese cities. For many airports, the first route that was launched should be the one linking to one of the three cities.
- $Crisis_t$ is the variable to control for the global financial crisis in 2008 and 2009.
- $Olympic_{it}$ is the dummy variable to control for the effect of the 2008 Beijing Olympic game to Beijing.
- $Expo_{it}$ is the variable to control for the effect of the 2010 Shanghai World Expo to Shanghai.

All continuous independent variables are taken logarithm in the estimation. For the panel data regressions (random and fixed-effect models), the connectivity index is also taken the logarithm. We use one-year lagged values of all the time-variant variables for the estimation to avoid potential endogeneity caused by the simultaneity between these variables and the air connectivity.

We assume the error term to be consisted of a time-invariant airport-specific unobservable τ_i, and a white-noise term ε_{it}, which is independent and identically distributed (i.i.d).[33] We adopt both fixed-effect and random-effect. Fixed-effect model help deal with the potential endogeneity problem if the error term τ_i is correlated to any independent variable. However, under this estimation method, the coefficients of all the time-invariant control variables, such as city tourism status, the airport hub status and other time-invariant variables cannot be identified. Instead, the random-effect model is more efficient, and allows the identification of the time-invariant variables' coefficients. But the endogeneity because of the correlation between τ_i and controlled variables will have to be compromised.

Santos Silva and Tenreyro (2006) showed that the Jensen's inequality, $E(log(y)) \neq log\ (E(y))$, had been neglected for a long time in estimating the log-linearized gravity. Under heteroscedasticity (which is often the case in gravity studies and of course this study), parameters of log-linearized gravity models estimated by OLS will be highly misleading, which may distort the interpretation of the models. Santos Silva and Tenreyro (2006) thus recommended the use of the Poisson pseudo-maximum likelihood estimator (PPML) technique. This approach also has the advantage of dealing with the zero-flow problem in data (Zhang et al., 2017). Fally (2015) shows that PPML with fixed effects can produce reliable and consistent results for gravity

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[33] The auto-correlation of the ε_{it} does not affect the estimation consistency and unbiasedness. It may only decrease the estimation efficiency.

models. Therefore, the PPML approach will be used in addition to the panel data estimation techniques. With PPML the level of connectivity is used instead of the logarithmic form.

The airport HHI, and the average yield variables are calculated using the IATA AirportIS data. These are the air ticket booking data on the route and airline basis, with each airline's passenger number, flight flying distance and the average ticket price reported monthly, quarterly and annually.[34] The airport location index is calculated as the sum of reciprocal of the distances to major airports as discussed earlier. The distances between airports are retrieved by the GPS. The city population, GDP, total fixed asset investment data are available in China City Statistical Year Book (2005-2015). The 2015 and 2016 data of some these variables are not available, so our regression analysis only covers a period of 2005-2014. The city tourism status dummy equals one for the cities including Guilin, Haikou, Hangzhou, Huangshan, Kunming, Sanya, Wuyishan, Xi'an, Xiamen, Yichang and Zhangjiajie.[35] The airport runway length and terminal size data can be found in CAAC published statistical data on civil aviation of China. The dummy of Spring Airlines' presence is based on the IATA AirportIS data. The HSR dummy is constructed by referring to the news reports on the opening of HSR services at each city. Table 5 provides the summary statistics of our variables.

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[34] We retrieve the prices of all the fare classes.

[35] We chose these cities as tourism cities by referring to Zhang and Round (2009) and Fu et al. (2015).

Table 5 Descriptive statistics of the variables

Variable	**No. of Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Unit**
Connectivity (overall)	660	952	1,436	2.69	8,971	Unit
Connectivity (domestic)	660	861	1,197	2.69	7,532	Unit
Connectivity (international)	660	91	287	0	2,120	Unit
HHI (1/10000)	660	2,658	1,515	865	9,831	Unit
Airport Average yield	660	0.154	0.08	0.08	1.30	RMB
Location Index	660	0.116	0.031	0.024	0.177	Unit
City Population	660	596	450	52	3,375	Ten thousand
City GDP per capita	660	52,034	42,974	5,303	481,638	RMB
City Fixed Asset Investment	660	17,800,000	17,700,000	344,900	131,000,000	Ten thousand RMB
Tourist	660	0.167	0.373	0	1	Unit
Airport hub status	660	0.197	0.398	0	1	Unit
Runway length	660	34,06	1,750	2,200	14,000	Meter
Terminal size	660	13	22.54	0.2	140.85	Ten thousand m^2
Spring Airlines' share	660	0.009	0.02	0	0.23	Unit
HSR	660	0.152	0.36	0	1.00	Dummy
Economy	660	3.87	1.37	2.13	6.16	Hundred billion RMB

4.2 Results Analysis

4.2.1 Connectivity Results Analysis

The overall connectivity scores (including both domestic and international connectivity) of all the cities under study are listed in Appendix 7. The total connectivity of the 69 airports increased from 40,330 in 2005 to 107,329 in 2016, an increase of 166%. Some small- and medium-sized airports experienced the largest percentage increase. For example, Luzhou witnessed a 37-times increase and Wuxi 17-times. The airports of Beijing, Shanghai, and Guangzhou saw relatively slower growth rate. However, if we look at the absolute change, the top airports, Shanghai Pudong, Beijing, Kunming, Guangzhou, Xi’an, Chongqing, Chengdu, Shenzhen and Hangzhou, all experienced an increase of more than 200 connectivity points each year. The top 10 best connected airports in 2016 and 2005 are reported in Table 6. From 2005 to 2016, Beijing Capital, Guangzhou and Shanghai Pudong airports consistently remained the top three. Xi’an and Chongqing made into the top 10 while in 2016 Haikou and Urumqi dropped out. It should be noted that in 2016 the air connectivity of Shanghai as a city with two mega-airports surpassed Beijing as the best-connected city.

Table 6 Top ranked airports in 2005 and 2016

2016			**2005**		
Rank	**Airport**	**Connectivity**	**Rank**	**Airport**	**Connectivity**
1	Beijing Capital	8,762	1	Beijing Capital	5,643
2	Guangzhou	6,095	2	Guangzhou	3,216
3	Shanghai Pudong	5,693	3	Shanghai Pudong	2,947
4	Kunming	4,805	4	Shanghai Hongqiao	2,368
5	Shenzhen	4,729	5	Shenzhen	2,209
6	Chengdu	4,585	6	Chengdu	1,934
7	Xi’an	4,116	7	Kunming	1,473
8	Shanghai Hongqiao	3,980	8	Haikou	1,155
9	Chongqing	3,800	9	Hangzhou	1,149
10	Hangzhou	3,565	10	Urumqi	1,138

We put the airports into different groups based on their overall connectivity scores: over 3900, 400-3900, below 400. The evolution of the eight best connected airports in 2016 (overall connectivity score is greater than 3900) is presented in Figure 29. Almost all of them experienced very steady growth during 2005-2016. For the airports with connectivity scores between 400 and 3900 in 2016, we can also observe an upward growth pattern throughout the years. In general, we found that the higher the connectivity, the more stable the growth trend. This is especially the case for most provincial capital cities. The evolution of the least connected airports in 2016 is shown in Figure 30. Most of them are small and tourism cities. It can be seen that most of them suffered the loss of connectivity at some stage, indicating the vulnerability of the connectivity of small airports. It has been noticed that the HSR network has been extended to some of these cities including Taizhou, Wuyishan, and Yuncheng, which may have caused the ups and downs of connectivity of these cities. In addition, their closeness and easy access to some large cities via highways may be another factor.

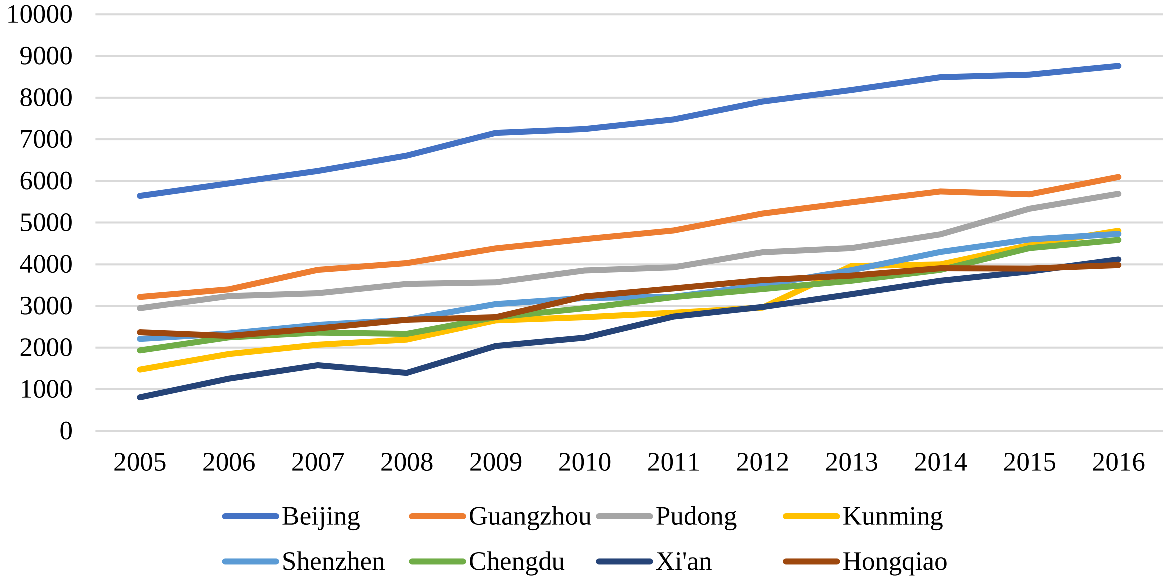

Figure 29 Connectivity of top connected airports 2005-2016

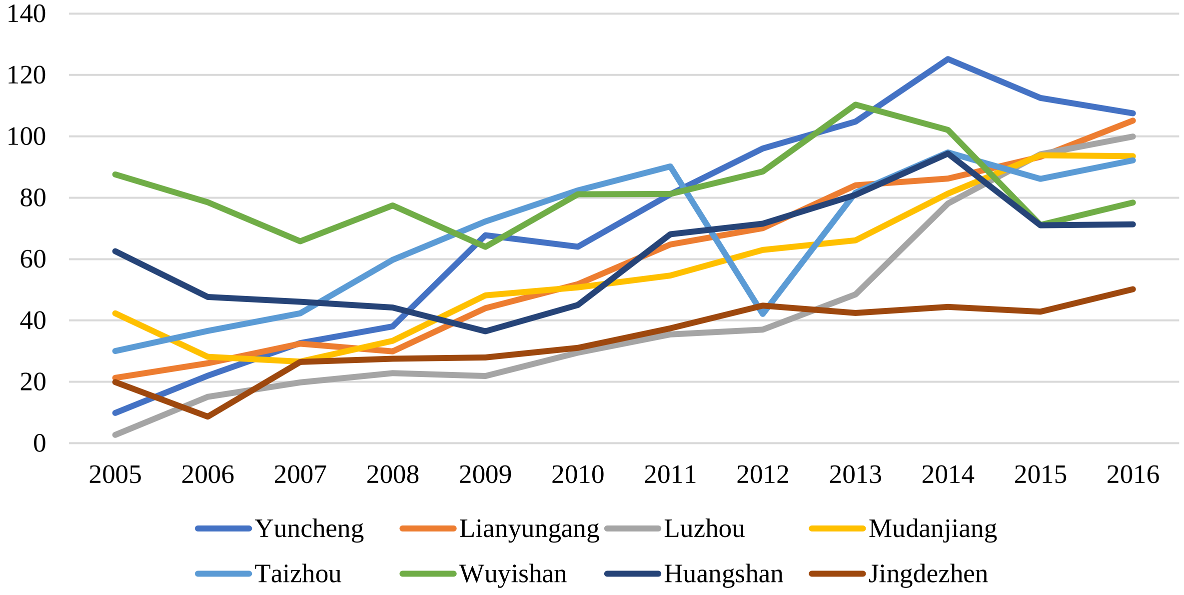

Figure 30 Connectivity of least connected airports 2005-2016

Cities that heavily rely on the tourism industry should be more concerned about the airport connectivity. We examine five cities, Huangshan, Guilin, Sanya, Wuyishan, and Zhangjiajie. Except Guilin, the tourism industry contributes to more than 50% of the GDP for other four cities. Figure 31 shows that apart from Sanya, the situation is worrying for these cities as their airport connectivity performance exhibits stagnant or declining trends in some periods. In fact, Wuyishan and Zhangjiajie recorded negative growth between 2005 and 2016.

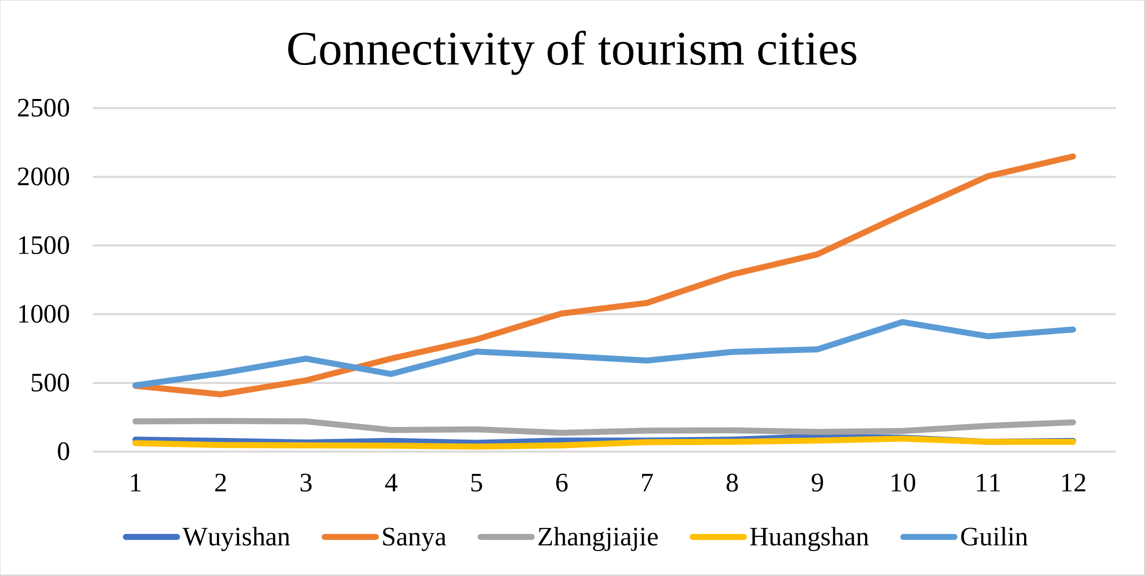

Figure 31 Connectivity of some tourism routes

The Civil Aviation Administration of China (CAAC) has partitioned China into several administrative regions: East China, Central and South China, North China, Northeast China, Southwest China, Northwest China and Xinjiang. Each region is administered by the CAAC regional administration. In this study, we combine Northwest China and Xinjiang. The distribution of the 69 airports is shown in Figure 32. The vast majority of the airports are located in the East, central, and south part of China. The connectivity at the region level can be seen in Figure 33, which clearly shows that East China, and Central & South China have much higher connectivity than other regions. Northeast and Northwest are at the bottom. The air connectivity within each region is shown in Figure 34, which shows how the airports in each region connect to each other. Again, cities are much better connected in East, Central and South China.

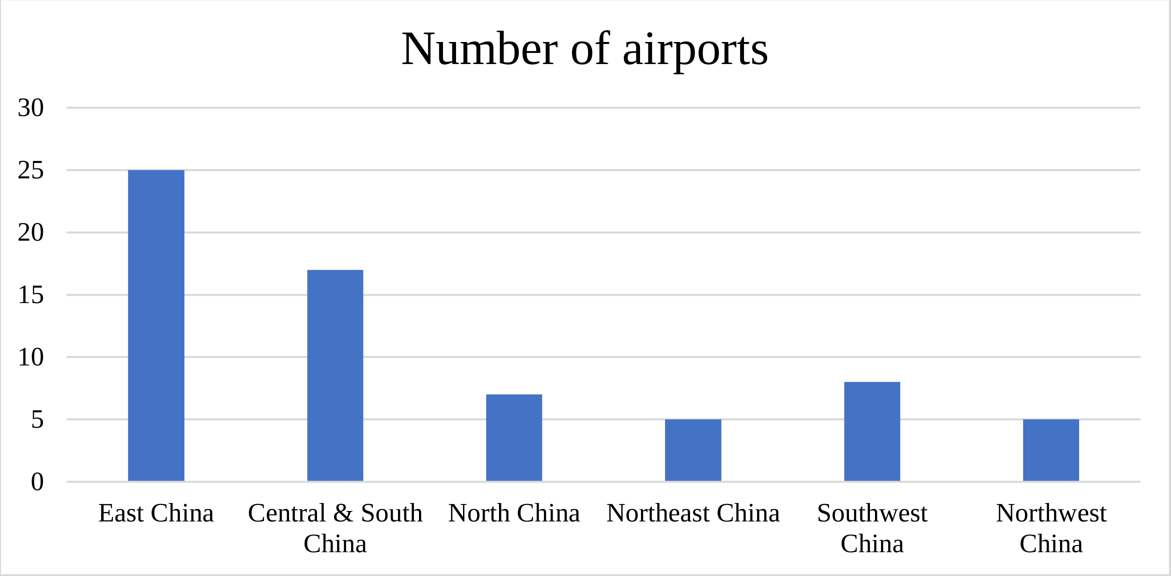

Figure 32 The distribution of airports across regions

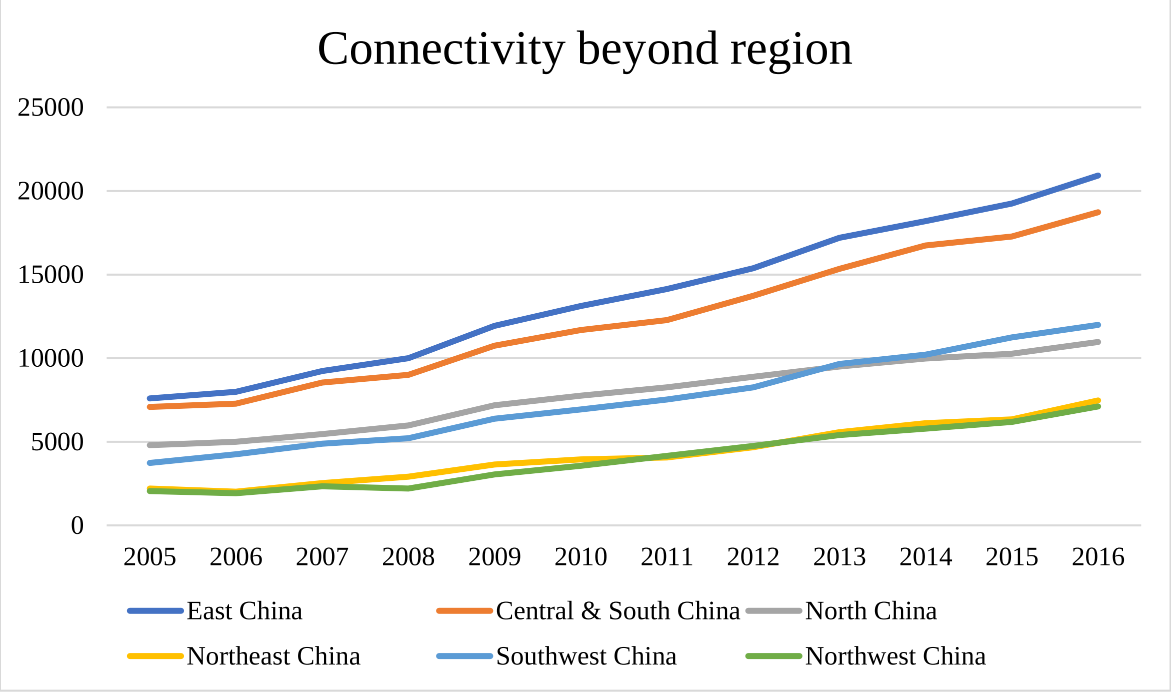

Figure 33 Connectivity to the network outside the region

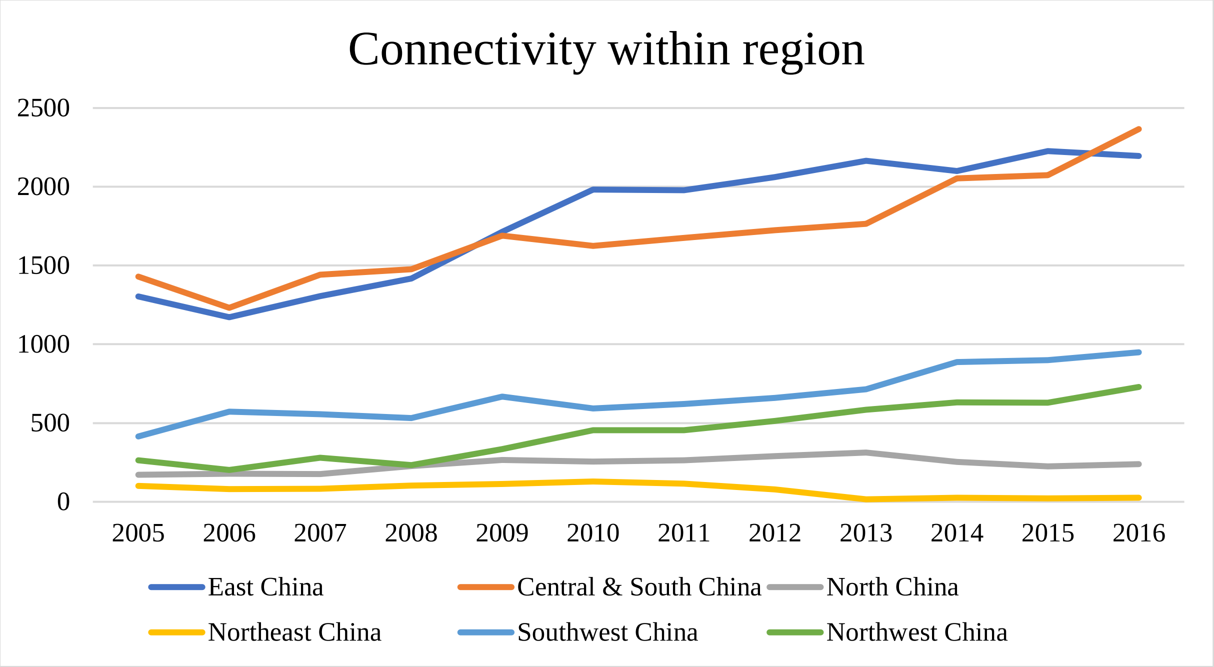

Figure 34 Connectivity inside the region

The domestic connectivity follows the same pattern as the overall connectivity, which is not reported here. Figure 35 shows the top eight cities that have the highest international connectivity in 2016. Shanghai remained the best internationally connected city, followed by Hong Kong, Beijing, and Guangzhou. International connectivity of all other cities is almost negligible. It can be seen that the international connectivity of Shanghai and Beijing were severely affected by the 2008 global financial crisis. Beijing had not restored to its highest historical level by the end of 2016.

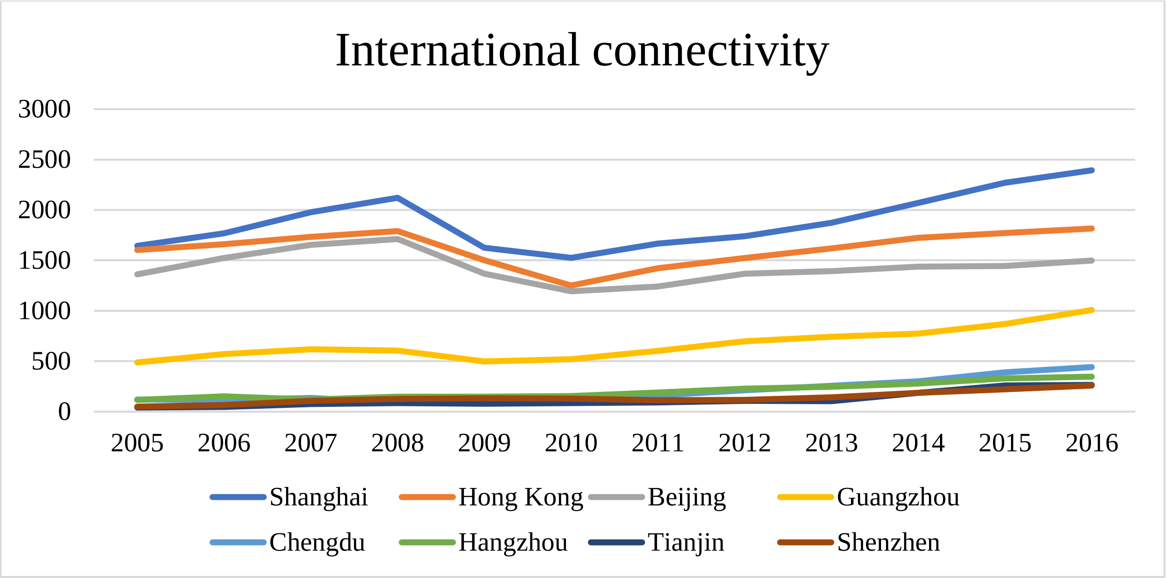

Figure 35 International connectivity of major cities

4.2.2 Regression Results Analysis

The regression results for the overall air connectivity are collated in Table 7. The results are largely consistent across models. As the PPML with fixed effects can produce more efficient estimation results in the presence of the heteroscedasticity problem, our discussion is mainly based on the findings of this model.

According to all regression models, airline competition measured by HHI is conducive to overall air connectivity. Lower HHI indicates that the market has more airlines and more competition, which means that the market is more liberalized. Regression results also show that airports with lower average price have higher level of air connectivity, which means that the price that airports and airline charge is not only important for regulation reasons as discussed in Zhang and Czerny (2012), but it’s also an important factor affecting air connectivity. Zhang and Czerny (2012) discussed that a private and monopolistic airport tend to charge excessive prices to airlines and passengers. Therefore, the regression results show an insight that liberalization benefit air connectivity by both increasing the competition and decreasing the airline price. This is consistent with conclusion of Fu et al. (2010), which showed empirical conclusion that liberalization led to substantial economic and traffic growth. It indicates the deregulation policies observed in Chinese airline market are effective and beneficial in promoting overall air connectivity. Fu et al. (2015) discussed the recent deregulation moves taking place in China, which empower airlines with more autonomy in route entry, network development and competition. Market mechanism for airport slot allocations have also been tried out in Shanghai and Guangzhou airports for a more efficient utilisation of scarce airport capacities. We would expect continuous deregulation in China's air transport sector can further promote the air connectivity.

Table 7 The estimations of overall air connectivity

	Panel data Fixed-effects	**Panel data Random-effects**	**PPML Fixed-effects**	**PPML without fixed effects**
Airport HHI	-0.437***	-0.455 ***	-0.518***	- 0.211 ***
	(0.063)	(0.062)	(0.045)	(0.062)
Airport Average Yield	-0.156***	-0.158***	-0.119***	-0.390***
	(0.029)	(0.028)	(0.032)	(0.093)
Location Index		-6.806**		-3.329***
		(3.419)		(1.014)
City Population	0.121	0.193**	0.097	0.418***
	(0.104)	(0.099)	(0.106)	(0.103)
City GDP per capita	0.009	0.091	-0.074	0.503***
	(0.093)	(0.097)	(0.058)	(0.113)
City Fixed Asset Investment	0.115**	0.105**	0.131***	-0.193**
	(0.049)	(0.048)	(0.036)	(0.087)
Tourist		0.681 **		0.506 ***
		(0.274)		(0.081)
Airport Hub Status		0.794***		0.186***
		(0.245)		(0.067)
Runway Length		1.893***		0.094 **
		(0.502)		(0.057)
Terminal Size	-0.049	0.079	-0.025	0.574***
	(0.071)	(0.103)	(0.040)	(0.032)

Spring Airlines	0.022	0.029	0.013	0.191***
	(0.035)	(0.034)	(0.014)	(0.047)
HSR	-0.020	-0.020	-0.082***	-0.132***
	(0.045)	(0.041)	(0.017)	(0.053)
Economy	0.490***	0.388 ***	0.463***	0.187***
	(0.070)	(0.076)	(0.050)	(0.091)
Global Financial Crisis	-0.098***	-0.088***	-0.084***	-0.152 ***
	(0.019)	(0.019)	(0.015)	(0.051)
Beijing Olympic Games	0.081***	0.059**	0.042*	-0.040
	(0.026)	(0.026)	(0.025)	(0.052)
World Expo	0.088***	0.049**	0.077***	-0.125***
	(0.022)	(0.023)	(0.020)	(0.052)
Constant	-3.173**	-17.154***	-8.179	-3.484**
	(1.549)	(4.507)	(1.569)	(1.922)
No. of Obs	594	549	549	549

Note:
(1). The one-year lag values are used for each time-series control variable.
(2) *, **, *** stand for the significance levels of 10%,5% and 1%.
(3). The same notes also apply to the following Tables 8 and 9.

The random-effects estimations show that the closeness (“location index” variable) to the provincial capitals and to other mega airports can downgrade the airport connectivity, probably as a result of the airport competition and service substantiality. Similar to Bowers et al. (2015), the significantly positive effects of the length of runways, terminal and the amount of fixed asset investment in a city show that investment in airport facilities expansion and surface access to airports could produce the intended results, i.e., improving airport connectivity.

In addition, tourism, hub status, and cities with larger capacity have higher overall air connectivity. Population and GDP per capita also have positive effects as expected. In particular, the economic activities at the mega cities (the “economy” variable), i.e. Beijing, Shanghai, and Guangzhou, contribute to a better overall air connectivity for all our sampled cities. This is because, in China, most small-and-medium sized cities prefer to establish links with the mega-cities, Beijing, Shanghai, and Guangzhou (Li and Cai, 2004; Gong et al., 2017).

Our PPML model (without fixed effects) reveal that the presence of LCC (Spring Airlines) promotes air connectivity. Spring has opened many direct flights to Chinese secondary cities not normally served by the full-service carriers (Fu et al., 2015). It is interesting to see that competition from HSR lowers overall air connectivity. On some short-and-medium haul routes in China, the launching of HSR services has forced airlines to withdraw capacity and reduce destinations (Wan et al.,2016). With plans to build more HSR, we would expect the HSR will impose more severe impacts on the air connectivity in China. Wang et al. (2017) highlights the importance of the coordination between air and HSR developments in China in order to avoid any investment redundancy.

Finally, we find that the global financial crisis adversely affects overall air connectivity in China, which is consistent with the findings in the US air transport market (Wittman and Swelbar, 2013). The Beijing Olympics and Shanghai Expo had the effect of increasing air connectivity of Beijing and Shanghai in the respective years.

Table 8 summarises the regression results for the domestic air connectivity. The results and findings are quite similar to those for the overall air connectivity estimations. The regression results for the international air connectivity are shown in Table 9. It is found that high airline price does not necessarily damage the international air connectivity. This might be because many international airline markets are still regulated by bilateral air service agreements (ASAs), and price competition is less relevant to the level of international connectivity. Our location index variable is also insignificant for the international air connectivity estimation. This is probably because international air services are still concentrated in several major airports, such as Beijing, Shanghai and Guangzhou. The other findings of the international air connectivity are instead very similar to those of our overall and domestic connectivity estimations.

Table 8 The estimations of domestic air connectivity

	Panel data Fixed-effects	**Panel data Random-effects**	**PPML Fixed-effects**	**PPML without fixed effects**
Airport HHI	-0.430***	-0.451***	-0.506***	-0.211***
	(0.065)	(0.063)	(0.044)	(0.063)
Airport Average Yield	-0.165***	-0.168***	-0.153***	-0.460***
	(0.029)	(0.028)	(0.036)	(0.099)
Location Index		-6.778**		-3.403***
		(0.028)		(0.997)
City Population	0.114	0.184**	0.089	0.417***
	(0.102)	(0.097)	(0.100)	(0.113)
City GDP per capita	0.001	0.083	-0.069	0.494***
	(0.096)	(0.099)	(0.057)	(0.113)
City Fixed Asset Investment	0.116**	0.106**	0.105***	-0.211**
	(0.048)	(0.047)	(0.027)	(0.090)
Tourist		0.660**		0.491***
		(0.273)		(0.077)
Airport Hub Status		0.755***		0.093*
		(0.219)		(0.057)
Runway Length		1.777***		0.047
		(0.524)		(0.083)
Terminal Size	-0.051	0.078	-0.032	0.579***
	(0.070)	(0.103)	(0.039)	(0.033)
Spring Airlines	0.023	0.031	0.020	0.184***
	(0.036)	(0.035)	(0.015)	(0.049)
HSR	-0.020	-0.018	-0.078***	-0.121**
	(0.046)	(0.035)	(0.018)	(0.053)
Economy	0.501***	0.399***	0.513***	0.243***
	(0.073)	(0.079)	(0.052)	(0.093)
Global Financial Crisis	-0.096***	-0.087***	-0.092***	-0.166***
	(0.019)	(0.019)	(0.016)	(0.053)
Beijing Olympic Games	-0.004	-0.027	-0.036	-0.095*
	(0.026)	(0.026)	(0.026)	(0.055)
World Expo	0.168***	0.131***	0.157***	-0.086
	(0.022)	(0.023)	(0.022)	(0.055)
Constant	-3.402**	-15.738***	-0.999	-3.335
	(1.606)	(4.522)	(1.053)	(1.858)
No. of Obs	594	594	594	594

Table 9 The estimations of international connectivity

	Panel data Fixed-effects	**Panel data Random-effects**	**PPML Fixed-effects**	**PPML without fixed effects**
Airport HHI	-0.524**	-0.362**	-0.439***	0.071
	(0.224)	(0.193)	(0.173)	(0.110)
Airport Yield	0.113	0.131	0.133	0.256*
	(0.095)	(0.098)	(0.088)	(0.149)
Location Index		-4.217		-3.038
		(4.277)		(2.466)
City Population	0.705**	0.658***	0.177	0.585***
	(0.343)	(0.234)	(0.349)	(0.191)
City GDP per capita	0.038	0.408**	-0.222	1.000***
	(0.197)	(0.203)	(0.160)	(0.278)
City Fixed Asset Investment	-0.018	-0.075	0.368**	-0.057
	(0.140)	(0.126)	(0.163)	(0.089)
Tourist		0.946***		0.831***
		(0.346)		(0.133)
Airport Hub Status		0.309		0.138
		(0.355)		(0.099)
Runway Length		1.131***		0.785***
		(0.430)		(0.107)
Terminal Size	-0.737***	0.696***	0.246	0.610***
	(0.142)	(0.179)	(0.376)	(0.068)
Spring Airlines	-0.045	-0.055	-0.103*	0.219***
	(0.088)	(0.091)	(0.051)	(0.086)
HSR	0.078	-0.001	-0.014	-0.149*
	(0.141)	(0.144)	(0.069)	(0.089)
Economy	0.724***	0.490**	0.162	-0.556***
	(0.235)	(0.227)	(0.113)	(0.203)
Global Financial Crisis	-0.158**	-0.141**	-0.023	-0.026
	(0.062)	(0.064)	(0.063)	(0.095)
Beijing Olympic Games	0.595***	0.588***	0.355***	0.161**
	(0.084)	(0.091)	(0.063)	(0.076)
World Expo	-0.002	-0.094	-0.171***	-0.396***
	(0.055)	(0.058)	(0.066)	(0.075)
Constant	-9.596*	-21.025***	-20.191***	-6.592**
	(5.034)	(5.027)	(5.982)	(3.044)
No. of Obs	594	594	594	594

5 Conclusion

This research has proposed a connectivity model, CUM, to calculate connectivity and centrality involving multiple transport modes and multiple quality dimensions. Numeric results are produced with air and rail schedule data for 2016. A regression analysis on the drivers of connectivity is also conducted.

CUM allows calculation of connectivity across modes and takes into consideration the effect of terminal locations on the connectivity a terminal contributes to the city, which enables the comparison of comprehensive connectivity level between cities. It has also included quality factors that would affect passengers' utility and therefore reveals the connectivity felt by passengers. Furthermore, CUM has no constraint on the data's time span or geographical range. Connectivity can be calculated for a day, a week, a month, or a year, for a city, a country, a continent, or the whole globe, which is useful for government and enterprises to monitor the up-to-date connectivity level of a customized transport network and make strategies accordingly. Besides, CUM also makes it easy to observe connectivity from different angles, terminal-wise, route-wise, city-wise, etc.

The numeric results presented in Section 3 has shown that terminals in mega cities (Beijing, Shanghai, Guangzhou, Hong Kong, etc.) lead in connectivity. PEK, and NKH are the winner of airports and railway stations respectively. PEK is also the winner among all terminals. PVG is very close to PEK in terms of air connectivity. However, PVG's cooperation with railway stations is not as good as PEK, resulting in a lower overall connectivity. SHA and AOH is a good example of air rail cooperation, ranking 4th and 5th in centrality. They are also the top 2 cross-mode hubs. Cooperation in location is a win-win game for both airports and train stations in terms of connectivity. Cooperation of schedules will help improve the connectivity even further.

Connectivity of continental international routes are highly concentrated in the top four airports (PVG, PEK, CAN, and HKG). While, connectivity of short-haul international routes is more distributed. Bangkok International Airport (BKK) is the best-connected foreign airport for China. And United States leads with big advantage to be the best-connected country with China. High level of passenger connectivity also represents high level of interaction and economic dependency with each other. As the world's 1st and 2nd largest economy, US and China are deeply connected.

Rail transport, especially HSR, is recognized as dominant mode for short haul routes against air. However, the numeric results show that rail connectivity is also critical for mid and long-haul routes with distance up to 1500 km. Shanghai, Beijing, Guangzhou, and Nanjing are the most important cities in China's city network. When Shanghai is lost, 9.6% of overall connectivity and 15.1% of direct connectivity in the whole city network will be lost. Hong Kong, Shanghai, Beijing, and Hangzhou, are more resistant of route loss in extreme situations, and therefore are better choices as warehouse, factory, etc., for security reasons.

The regression analysis has shown that airline competition, investment in airport facilities expansion and surface access to airports, tourism, hub status, larger population and higher GDP per capita, economic activities, and presence of LCC help promoting air connectivity in China. However, being close to capital or mega cities downgrades air connectivity. The effect of being close to big airports might well become positive when the capacity of airports in capital and mega cities are in shorter supply. Global financial crisis adversely affects overall air connectivity in China.

The trends and patterns of the evolution of airport connectivity in China clearly demonstrate that China's air transport market is a growth market. For example, major airports including most provincial capital cities experienced steady growth between 2005 and 2016. A number of non-capital cities such as Luzhou, Wuxi, Nantong, Luoyang, Shijiazhuang, Yuncheng and Mianyang increased by more than 10 times during this period.

However, for some tourism cities and small cities, the growth has been stagnant, although our regression results suggest that tourism cities tend to have higher connectivity levels than non-tourism cities, other things been equal. Several solutions can be considered according to our findings. First, tourism and small cities should develop a strategy to attract LCCs and ideally establish partnership with LCCs. Most LCCs are point-to-point airlines and thus the presence of them will increase the number of destinations and thus connectivity. The entry of LCCs is also expected to increase consumer choice airfare affordability, which will in turn lead to higher connectivity. Many studies including Olipra (2012) have confirmed that LCCs influence the development of tourism in smaller cities and less famous destinations. Second, this research shows that infrastructure investment including upgrading and expanding airport facilities including development of passenger terminal facility will likely promote airport connectivity. Many big airports have become congested and many markets have been saturated in terms of frequency, which makes it hard for new airlines to enter these markets. Quite a few new airlines have emerged in China since 2013 and they are also looking for opportunities to grow themselves. A relatively new and modern airport will be a selling point for small airports to increase connectivity. When flight delay, long queues and high parking fees have become the norm at large airports, this implies an opportunity for nearby small airports. For example, the Director of the CAAC has recently announced that some flights from the second- and third-tier cities to Beijing will be shifted to Tianjin and Shijiazhuang in the future and these airports will be linked to Beijing via HSR. This implies that on the one hand, HSR poses a threat to air connectivity, whereas on the other hand it can also be used to mitigate the congestion problem for mega-airports and increase the air connectivity of some cities in the neighbourhood.

At the regional level, connectivity of Northwest China and Northeast China is substantially lower than other parts of China, although the performance of the provincial capitals is quite acceptable. The fundamental reason for the low connectivity in the two regions is the lack of airports and the failure of attracting air services to the non-capital airports. That is why National Development and Reform Commission and the CAAC jointly issued a notice in 2017 on national civil aviation airport network planning in which constructing new airports in West China is a top priority. Compared with Northwest China, Northeast China is more developed. It was the country's heavy industrial base in the planned economy period with a focus on manufacturing, steel, automobile, oil extraction and refining. However, with the shift to a market-oriented economy and the gradual depletion of natural resources, Northeast China has lost its competitive position. In recent year, about two million people moved out of this region each year, which is a severe blow to its stagnant economy and the air transport sector. The central government put forward a strategy to invigorate Northeast China in 2003. However, this strategy has failed to regenerate the economy in the three Northeast provinces. It has been reported that in 2016 both private and government investment contracted in Northeast China (Yao, 2016). Our regression model has shown a significantly positive relationship between fixed asset investment, population and air connectivity. Unless the economic performance improves, we do not expect to see a significant increase in airport connectivity in the next few years for the Northeast China region.

Our results confirm that business cycle affects the airline industry and thus airport connectivity, while large events such as Olympic games and World Expo have the effects of promoting airport connectivity. Although these factors are largely beyond the control of most local governments, the central government should take them into consideration when offering financial assistance and choosing venues for hosting large sports and expo events.

The negative sign of the location index confirms our hypothesis that if there are two airports nearby, some passengers would be attracted to use the larger one. Without the support of local residents and businesses, it is difficult to increase the connectivity of the local airports. Advantages of large airports include cheaper prices and more frequency, which are unbeatable by smaller airports. Education campaign might be needed to convince the passenger that the benefit to them and to the local community is higher than driving hours to the nearest large airport. When the transit service between small airports and big cities in the neighbourhood is improved by using HSR, shuttle bus service, etc., we may expect the small airports to cooperate better with crowded mega airports and achieve progress in connectivity.

A final warning is that although we have attempted to reveal a set of drivers behind the airport connectivity ranking which are undoubtedly useful for policy makers and airport management, the strategy of boosting connectivity should also be examined on a case-by-case basis.

More research will be conducted on CUM and drivers of connectivity in the future. Numeric results involving more quality factors, e.g. cost, and more transport modes, will be useful to understand the overall connectivity and competition position of cities. CUM can be also used to calculate cargo connectivity when the quality factors are substituted by freight-related variables in equation (1).

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Appendices

Appendix 1: List of cities

No	City	No	City	No	City	No	City
1	Beijing	11	Hangzhou	21	Nanchang	31	Taiyuan
2	Changchun	12	Harbin	22	Nanjing	32	Tianjin
3	Changsha	13	Hefei	23	Nanning	33	Urumqi
4	Chengdu	14	Hohhot	24	Ningbo	34	Wuhan
5	Chongqing	15	Hong Kong	25	Qingdao	35	Xiamen
6	Dalian	16	Jinan	26	Shanghai	36	Xi'an
7	Fuzhou	17	Kunming	27	Shenyang	37	Xining
8	Guangzhou	18	Lanzhou	28	Shenzhen	38	Xuzhou
9	Guiyang	19	Lhasa	29	Shijiazhuang	39	Yinchuan
10	Haikou	20	Lianyungang	30	Suzhou	40	Zhengzhou

Appendix 2: List of terminals

No	Station	Type	City	FULL Name
1	PEK	Airport	Beijing	Beijing Capital International Airport
2	NAY	Airport	Beijing	Beijing Nanyuan Airport
3	CGQ	Airport	Changchun	Changchun Longjia International Airport
4	CSX	Airport	Changsha	Changsha Huanghua International Airport
5	CTU	Airport	Chengdu	Chengdu Shuangliu International Airport
6	CKG	Airport	Chongqing	Chongqing Jiangbei Airport
7	DLC	Airport	Dalian	Dalian Zhoushuizi International Airport
8	FOC	Airport	Fuzhou	Fuzhou Changle Airport
9	CAN	Airport	Guangzhou	Guangzhou Baiyuan International Airport
10	KWE	Airport	Guiyang	Guiyang Longdongbao International Airpo
11	HAK	Airport	Haikou	Haikou Meilan International Airport
12	HGH	Airport	Hangzhou	Hangzhou Xiaoshan International Airport
13	HRB	Airport	Harbin	Harbin Taiping International Airport
14	HFE	Airport	Hefei	Hefei Xinqiao International Airport
15	HET	Airport	Hohhot	HET Baita International Airport
16	HKG	Airport	Hong Kong	Hong Kong International Airport
17	TNA	Airport	Jinan	Jinan Yaoqiang International Airport
18	KMG	Airport	Kunming	Kunming Changshui International Airport
19	LHW	Airport	Lanzhou	Lanzhou Zhongchuan International Airport
20	LXA	Airport	Lhasa	Lhasa Gonggar Airport
21	LYG	Airport	Lianyungang	Lianyungang Baitabu Airport
22	KHN	Airport	Nanchang	Nanchang Changbei International Airport
23	NKG	Airport	Nanjing	Nanjing Lukou International Airport
24	NNG	Airport	Nanning	Nanning Wuxu International Airport
25	NGB	Airport	Ningbo	Ningbo Lishe International Airport
26	TAO	Airport	Qingdao	Qingdao Liuting International Airport
27	PVG	Airport	Shanghai	Shanghai Pudong International Airport
28	SHA	Airport	Shanghai	Shanghai Hongqiao International Airport
29	SHE	Airport	Shenyang	Shenyang Taoxian International Airport
30	SZX	Airport	Shenzhen	Shenzhen Bao'an International Airport
31	SJW	Airport	Shijiazhuang	Shijiazhuang Zhengding International Airport
32	TYN	Airport	Taiyuan	Taiyuan Wusu International Airport
33	TSN	Airport	Tianjin	Tianjin Binhai International Airport
34	URC	Airport	Urumqi	Urumqi Diwopu International Airport

No	Station	Type	City	FULL Name
35	WUH	Airport	Wuhan	Wuhan Tianhe International Airport
36	XMN	Airport	Xiamen	Xiamen Gaoqi International Airport
37	XIY	Airport	Xi'an	Xi'an Xianyang International Airport
38	XNN	Airport	Xining	Xining Caojiabao Airport
39	XUZ	Airport	Xuzhou	Xuzhou Guanyin International Airport
40	INC	Airport	Yinchuan	Yinchuan Hedong International Airport
41	CGO	Airport	Zhengzhou	Zhengzhou Xinzheng International Airport
42	VAP	Train Station	Beijing	Beijing North Railway Station
43	BXP	Train Station	Beijing	Beijing West Railway Station
44	BJP	Train Station	Beijing	Beijing Railway Station
45	VNP	Train Station	Beijing	Beijing South Railway Station
46	BOP	Train Station	Beijing	Beijing East Railway Station
47	CRT	Train Station	Changchun	Changchun West Railway Station
48	CCT	Train Station	Changchun	Changchun Railway Station
49	CSQ	Train Station	Changsha	Changsha Railway Station
50	CWQ	Train Station	Changsha	Changsha South Railway Station
51	CNW	Train Station	Chengdu	Chengdu South Railway Station
52	CDW	Train Station	Chengdu	Chengdu Railway Station
53	ICW	Train Station	Chengdu	Chengdu East Railway Station
54	CQW	Train Station	Chongqing	Chongqing Railway Station
55	CUW	Train Station	Chongqing	Chongqing North Railway Station
56	BPW	Train Station	Chongqing	Beibei Railway Station
57	DLT	Train Station	Dalian	Dalian Railway Station
58	DFT	Train Station	Dalian	Dalian North Railway Station
59	FZS	Train Station	Fuzhou	Fuzhou Railway Station
60	FYS	Train Station	Fuzhou	Fuzhou South Railway Station
61	GBQ	Train Station	Guangzhou	Guangzhou North Railway Station
62	GZQ	Train Station	Guangzhou	Guangzhou Railway Station
63	GGQ	Train Station	Guangzhou	Guangzhou East Railway Station
64	IZQ	Train Station	Guangzhou	Guangzhou South Railway Station
65	GIW	Train Station	Guiyang	Guiyang Railway Station
66	KQW	Train Station	Guiyang	Guiyang North Railway Station
67	VUQ	Train Station	Haikou	Haikou Railway Station
68	HZH	Train Station	Hangzhou	Hangzhou Railway Station
69	HGH	Train Station	Hangzhou	Hangzhou East Railway Station

No	Station	Type	City	FULL Name
70	BJB	Train Station	Harbin	Binjiang Railway Station
71	HBB	Train Station	Harbin	Harbin Railway Station
72	XFB	Train Station	Harbin	Xiangfang Railway Station
73	VAB	Train Station	Harbin	Harbin West Railway Station
74	HTB	Train Station	Harbin	Harbin North Railway Station
75	ENH	Train Station	Hefei	Hefei South Railway Station
76	HFH	Train Station	Hefei	Hefei Railway Station
77	HHC	Train Station	Hohhot	Hohhot Railway Station
78	NDC	Train Station	Hohhot	Hohhot East Railway Station
79	JAK	Train Station	Jinan	Jinan East Railway Station
80	JNK	Train Station	Jinan	Jinan Railway Station
81	JGK	Train Station	Jinan	Jinan West Railway Station
82	KMM	Train Station	Kunming	Kunming Railway Station
83	LZJ	Train Station	Lanzhou	Lanzhou Railway Station
84	LAJ	Train Station	Lanzhou	Lanzhou West Railway Station
85	LSO	Train Station	Lhasa	Lhasa Railway Station
86	UKH	Train Station	Lianyungang	Lianyungang East Railway Station
87	NCG	Train Station	Nanchang	Nanchang Railway Station
88	NXG	Train Station	Nanchang	Nanchang West Railway Station
89	NJH	Train Station	Nanjing	Nanjing Railway Station
90	NKH	Train Station	Nanjing	Nanjing South Railway Station
91	NNZ	Train Station	Nanning	Nanning Railway Station
92	NFZ	Train Station	Nanning	Nanning East Railway Station
93	NGH	Train Station	Ningbo	Ningbo Railway Station
94	QHK	Train Station	Qingdao	Qingdao North Railway Station
95	QDK	Train Station	Qingdao	Qingdao Railway Station
96	JXK	Train Station	Qingdao	Jiaozhou Railway Station
97	SHH	Train Station	Shanghai	Shanghai Railway Station
98	SNH	Train Station	Shanghai	Shanghai South Railway Station
99	AOH	Train Station	Shanghai	Shanghai Hongqiao Railway Station
100	SYT	Train Station	Shenyang	Shenyang Railway Station
101	SOT	Train Station	Shenyang	Shenyang South Railway Station
102	SBT	Train Station	Shenyang	Shenyang North Railway Station
103	IOQ	Train Station	Shenzhen	Shenzhen North Railway Station
104	BJQ	Train Station	Shenzhen	Shenzhen East Railway Station

No	Station	Type	City	FULL Name
105	OSQ	Train Station	Shenzhen	Shenzhen West Railway Station
106	NZQ	Train Station	Shenzhen	Futian Railway Station
107	SZQ	Train Station	Shenzhen	Shenzhen Railway Station
108	SJP	Train Station	Shijiazhuang	Shijiazhuang Railway Station
109	VVP	Train Station	Shijiazhuang	Shijiazhuang North Railway Station
110	SZH	Train Station	Suzhou	Suzhou Railway Station
111	OHH	Train Station	Suzhou	Suzhou North Railway Station
112	KAH	Train Station	Suzhou	Suzhou Industry Zone Railway Station
113	TYV	Train Station	Taiyuan	Taiyuan Railway Station
114	TNV	Train Station	Taiyuan	Taiyuan South Railway Station
115	JMP	Train Station	Tianjin	Junliangcheng North Railway Station
116	TXP	Train Station	Tianjin	Tianjin West Railway Station
117	TIP	Train Station	Tianjin	Tianjin South Railway Station
118	FHP	Train Station	Tianjin	Binhai Raiway Station
119	YKP	Train Station	Tianjin	Yujiabao Railway Station
120	TJP	Train Station	Tianjin	Tianjin Railway Station
121	WAR	Train Station	Urumqi	Urumqi Railway Station
122	HKN	Train Station	Wuhan	Hankou Railway Station
123	WCN	Train Station	Wuhan	Wuchang Railway Station
124	WHN	Train Station	Wuhan	Wuhan Railway Station
125	XMS	Train Station	Xiamen	Xiamen Railway Station
126	XKS	Train Station	Xiamen	Xiamen North Railway Station
127	XAY	Train Station	Xi'an	Xi'an Railway Station
128	EAY	Train Station	Xi'an	Xi'an North Railway Station
129	CAY	Train Station	Xi'an	Xi'an South Railway Station
130	XNO	Train Station	Xining	Xining Railway Station
131	UUH	Train Station	Xuzhou	Xuzhou East Railway Station
132	XCH	Train Station	Xuzhou	Xuzhou Railway Station
133	YIJ	Train Station	Yinchuan	Yinchuan Railway Station
134	XPF	Train Station	Zhengzhou	Zhengzhou West Railway Station
135	ZZF	Train Station	Zhengzhou	Zhengzhou Railway Station
136	ZAF	Train Station	Zhengzhou	Zhengzhou East Railway Station

Appendix 3: Terminal connectivity

No	*Station*	*Type*	*Admin City*	*Connectivity*			
				Air	*Rail*	*Across Mode*	***Overall***
1	PEK	Air	Beijing	75227.83	0.00	17225.23	**92453.06**
2	PVG	Air	Shanghai	73653.93	0.00	9023.39	**82677.32**
3	HKG	Air	Hong Kong	67914.57	0.00	8036.81	**75951.37**
4	CAN	Air	Guangzhou	48538.14	0.00	19335.60	**67873.74**
5	NKH	Rail	Nanjing	0.00	18958.53	42542.87	**61501.40**
6	HGH	Rail	Hangzhou	0.00	16459.75	38991.53	**55451.28**
7	SZH	Rail	Suzhou	0.00	13164.05	37945.43	**51109.49**
8	CTU	Air	Chengdu	28933.44	0.00	17773.86	**46707.31**
9	AOH	Rail	Shanghai	0.00	18927.13	27616.24	**46543.37**
10	KMG	Air	Kunming	24056.81	0.00	22244.55	**46301.36**
11	SZX	Air	Shenzhen	24311.56	0.00	19838.17	**44149.73**
12	TJP	Rail	Tianjin	0.00	13629.77	26819.12	**40448.89**
13	URC	Air	Urumqi	19382.82	0.00	20795.04	**40177.86**
14	SJP	Rail	Shijiazhuang	0.00	13384.41	26510.55	**39894.96**
15	CKG	Air	Chongqing	20728.43	0.00	14896.53	**35624.96**
16	UUH	Rail	Xuzhou	0.00	14064.39	21537.16	**35601.56**
17	XMN	Air	Xiamen	20237.85	0.00	15134.88	**35372.73**
18	XIY	Air	Xi'an	21372.38	0.00	12632.68	**34005.07**
19	IZQ	Rail	Guangzhou	0.00	10322.96	22156.06	**32479.02**
20	JGK	Rail	Jinan	0.00	11300.96	20837.73	**32138.69**
21	CCT	Rail	Changchun	0.00	12964.45	19030.65	**31995.10**
22	NGH	Rail	Ningbo	0.00	11985.64	19456.52	**31442.15**
23	HRB	Air	Harbin	17184.18	0.00	13793.71	**30977.89**
24	SBT	Rail	Shenyang	0.00	13559.63	16987.30	**30546.93**
25	NJH	Rail	Nanjing	0.00	10583.80	18379.43	**28963.23**
26	HGH	Air	Hangzhou	21049.38	0.00	7872.80	**28922.18**
27	SHE	Air	Shenyang	17358.21	0.00	11344.54	**28702.75**
28	VNP	Rail	Beijing	0.00	12819.85	15768.74	**28588.59**
29	CWQ	Rail	Changsha	0.00	11759.93	16519.94	**28279.87**
30	WHN	Rail	Wuhan	0.00	10500.88	17296.56	**27797.44**
31	HAK	Air	Haikou	13476.26	0.00	14164.38	**27640.65**
32	TAO	Air	Qingdao	16731.09	0.00	10577.55	**27308.65**
33	DLC	Air	Dalian	16219.65	0.00	10605.47	**26825.12**

No	***Station***	***Type***	***Admin City***	***Connectivity***			
				Air	*Rail*	*Across Mode*	***Overall***
34	OHH	Rail	Suzhou	0.00	7944.63	18115.85	**26060.49**
35	SYT	Rail	Shenyang	0.00	8528.78	16753.34	**25282.11**
36	NNG	Air	Nanning	12801.60	0.00	12099.56	**24901.17**
37	BXP	Rail	Beijing	0.00	12904.98	11967.35	**24872.33**
38	KWE	Air	Guiyang	12808.83	0.00	11959.53	**24768.36**
39	LHW	Air	Lanzhou	13345.98	0.00	11338.31	**24684.28**
40	CUW	Rail	Chongqing	0.00	10908.38	13505.57	**24413.95**
41	JNK	Rail	Jinan	0.00	10386.10	13689.85	**24075.95**
42	FOC	Air	Fuzhou	14355.77	0.00	9669.21	**24024.98**
43	ZZF	Rail	Zhengzhou	0.00	9647.28	14169.57	**23816.84**
44	NXG	Rail	Nanchang	0.00	8802.61	14883.90	**23686.51**
45	ZAF	Rail	Zhengzhou	0.00	9458.96	14088.94	**23547.90**
46	WUH	Air	Wuhan	17093.15	0.00	6299.08	**23392.23**
47	NKG	Air	Nanjing	17320.07	0.00	5874.34	**23194.41**
48	CSX	Air	Changsha	15197.88	0.00	7802.97	**23000.84**
49	SHA	Air	Shanghai	14232.11	0.00	8386.54	**22618.65**
50	CGO	Air	Zhengzhou	15655.53	0.00	6694.21	**22349.74**
51	CGQ	Air	Changchun	13099.79	0.00	8770.05	**21869.84**
52	FZS	Rail	Fuzhou	0.00	7881.48	13964.01	**21845.49**
53	XCH	Rail	Xuzhou	0.00	8884.55	12782.37	**21666.92**
54	IOQ	Rail	Shenzhen	0.00	9128.74	12287.50	**21416.23**
55	SZQ	Rail	Shenzhen	0.00	5097.87	16099.67	**21197.53**
56	ENH	Rail	Hefei	0.00	8565.16	12351.78	**20916.94**
57	TSN	Air	Tianjin	13051.46	0.00	7370.60	**20422.06**
58	WCN	Rail	Wuhan	0.00	7284.11	11418.68	**18702.79**
59	INC	Air	Yinchuan	10013.62	0.00	8391.89	**18405.51**
60	XKS	Rail	Xiamen	0.00	8104.21	10046.96	**18151.17**
61	TIP	Rail	Tianjin	0.00	5877.66	11494.30	**17371.96**
62	ICW	Rail	Chengdu	0.00	7816.02	9541.29	**17357.31**
63	GZQ	Rail	Guangzhou	0.00	8223.34	9021.46	**17244.80**
64	TXP	Rail	Tianjin	0.00	7196.72	9932.96	**17129.67**
65	SHH	Rail	Shanghai	0.00	9697.04	7396.82	**17093.85**
66	TYN	Air	Taiyuan	9134.77	0.00	7455.10	**16589.87**
67	XNN	Air	Xining	8731.52	0.00	7784.52	**16516.03**
68	HET	Air	Hohhot	8610.05	0.00	7765.20	**16375.26**

No	***Station***	***Type***	***Admin City***	***Connectivity***			
				Air	*Rail*	*Across Mode*	***Overall***
69	EAY	Rail	Xi'an	0.00	7714.60	8512.38	**16226.98**
70	VAB	Rail	Harbin	0.00	7574.26	8358.19	**15932.45**
71	HBB	Rail	Harbin	0.00	7567.57	8250.33	**15817.91**
72	XAY	Rail	Xi'an	0.00	7469.57	8148.72	**15618.29**
73	LZJ	Rail	Lanzhou	0.00	7552.01	7928.84	**15480.85**
74	HZH	Rail	Hangzhou	0.00	5984.47	9460.42	**15444.89**
75	WAR	Rail	Urumqi	0.00	9197.00	5826.00	**15023.00**
76	NGB	Air	Ningbo	10053.95	0.00	4899.72	**14953.67**
77	CSQ	Rail	Changsha	0.00	6139.61	8789.48	**14929.09**
78	BJP	Rail	Beijing	0.00	7183.60	7743.04	**14926.63**
79	GIW	Rail	Guiyang	0.00	6862.55	7818.82	**14681.37**
80	CRT	Rail	Changchun	0.00	5483.60	9166.81	**14650.41**
81	HKN	Rail	Wuhan	0.00	6099.49	8127.59	**14227.08**
82	FYS	Rail	Fuzhou	0.00	4200.57	9863.59	**14064.16**
83	KMM	Rail	Kunming	0.00	6736.43	7020.61	**13757.04**
84	TNA	Air	Jinan	8864.36	0.00	4577.36	**13441.72**
85	HFH	Rail	Hefei	0.00	6492.67	6884.55	**13377.21**
86	VVP	Rail	Shijiazhuang	0.00	5132.37	7959.73	**13092.10**
87	KHN	Air	Nanchang	7673.00	0.00	5174.56	**12847.55**
88	HFE	Air	Hefei	9735.66	0.00	3111.03	**12846.69**
89	CDW	Rail	Chengdu	0.00	7090.59	5641.59	**12732.18**
90	LXA	Air	Lhasa	5808.74	0.00	6715.79	**12524.53**
91	QDK	Rail	Qingdao	0.00	5675.38	6785.55	**12460.93**
92	KQW	Rail	Guiyang	0.00	5767.92	6520.25	**12288.18**
93	SNH	Rail	Shanghai	0.00	5270.69	6968.98	**12239.66**
94	TYV	Rail	Taiyuan	0.00	5546.04	6251.55	**11797.59**
95	TNV	Rail	Taiyuan	0.00	4121.13	7520.41	**11641.54**
96	NNZ	Rail	Nanning	0.00	6918.39	4722.75	**11641.15**
97	XNO	Rail	Xining	0.00	6290.57	5216.00	**11506.57**
98	SJW	Air	Shijiazhuang	5280.89	0.00	5806.48	**11087.38**
99	GGQ	Rail	Guangzhou	0.00	4840.37	5577.73	**10418.10**
100	DFT	Rail	Dalian	0.00	4087.71	5511.33	**9599.04**
101	NCG	Rail	Nanchang	0.00	4833.24	4684.13	**9517.37**
102	HHC	Rail	Hohhot	0.00	4660.32	4857.04	**9517.36**
103	NFZ	Rail	Nanning	0.00	4762.32	4747.74	**9510.06**

No	***Station***	***Type***	***Admin City***	***Connectivity***			
				Air	*Rail*	*Across Mode*	***Overall***
104	DLT	Rail	Dalian	0.00	3996.50	5462.63	**9459.13**
105	NDC	Rail	Hohhot	0.00	4630.74	4747.73	**9378.47**
106	YIJ	Rail	Yinchuan	0.00	4730.46	4441.55	**9172.00**
107	JAK	Rail	Jinan	0.00	2741.85	3909.21	**6651.06**
108	QHK	Rail	Qingdao	0.00	3734.11	2510.96	**6245.06**
109	CQW	Rail	Chongqing	0.00	2995.90	3232.18	**6228.09**
110	LSO	Rail	Lhasa	0.00	3057.76	1794.96	**4852.72**
111	BJQ	Rail	Shenzhen	0.00	3501.64	1335.17	**4836.80**
112	UKH	Rail	Lianyungang	0.00	2670.83	2144.03	**4814.86**
113	LYG	Air	Lianyungang	2360.79	0.00	2236.19	**4596.98**
114	VUQ	Rail	Haikou	0.00	2488.76	1899.47	**4388.23**
115	CAY	Rail	Xi'an	0.00	2113.74	2077.98	**4191.72**
116	OSQ	Rail	Shenzhen	0.00	2086.50	1795.74	**3882.24**
117	NAY	Air	Beijing	1751.31	0.00	1800.13	**3551.44**
118	XUZ	Air	Xuzhou	2073.66	0.00	1166.02	**3239.68**
119	NZQ	Rail	Shenzhen	0.00	505.12	2599.26	**3104.38**
120	GBQ	Rail	Guangzhou	0.00	1224.22	1353.22	**2577.44**
121	SOT	Rail	Shenyang	0.00	746.36	1176.70	**1923.06**
122	KAH	Rail	Suzhou	0.00	518.04	871.37	**1389.41**
123	CNW	Rail	Chengdu	0.00	449.89	909.75	**1359.64**
124	LAJ	Rail	Lanzhou	0.00	497.99	820.16	**1318.15**
125	XPF	Rail	Zhengzhou	0.00	548.68	668.66	**1217.34**
126	BPW	Rail	Chongqing	0.00	559.25	644.73	**1203.98**
127	HTB	Rail	Harbin	0.00	573.89	604.29	**1178.17**
128	YKP	Rail	Tianjin	0.00	164.37	861.30	**1025.67**
129	XMS	Rail	Xiamen	0.00	634.06	317.27	**951.33**
130	JMP	Rail	Tianjin	0.00	371.18	467.80	**838.98**
131	FHP	Rail	Tianjin	0.00	569.53	243.33	**812.86**
132	XFB	Rail	Harbin	0.00	594.02	93.29	**687.31**
133	BOP	Rail	Beijing	0.00	380.19	61.49	**441.68**
134	VAP	Rail	Beijing	0.00	177.44	260.94	**438.38**
135	BJB	Rail	Harbin	0.00	339.87	86.75	**426.62**
136	JXK	Rail	Qingdao	0.00	117.12	187.18	**304.29**

Appendix 4: Connectivity of international airports (with China), top 50.

No	*IATA Code*	*Country*	*Connectivity*	*No*	*IATA Code*	*Country*	*Connectivity*
1	BKK	TH	15999.63	26	IST	TR	6278.75
2	SIN	SG	15955.22	27	ORD	US	6077.06
3	ICN	KR	12323.00	28	HND	JP	6052.31
4	KUL	MY	12208.43	29	MEL	AU	5981.90
5	FRA	DE	11861.63	30	YYZ	CA	5905.65
6	SFO	US	11705.79	31	SEA	US	5662.42
7	DMK	TH	11613.43	32	HEL	FI	5294.42
8	LAX	US	11443.80	33	KBV	TH	5273.15
9	NRT	JP	10591.14	34	ADD	ET	5199.93
10	CDG	FR	10494.39	35	EWR	US	5185.78
11	KIX	JP	9853.24	36	AKL	NZ	5071.76
12	TPE	TW	9817.51	37	MUC	DE	5043.62
13	HKT	TH	9674.60	38	CJU	KR	4879.29
14	AMS	NL	8979.78	39	DTW	US	4810.62
15	SYD	AU	8939.75	40	CNX	TH	4790.64
16	YVR	CA	8738.79	41	GMP	KR	4637.21
17	LHR	GB	8329.41	42	DFW	US	4587.44
18	JFK	US	7964.67	43	ZRH	CH	4437.04
19	DXB	AE	7695.06	44	MXP	IT	4368.69
20	SVO	RU	7633.26	45	HNL	US	4189.41
21	DOH	QA	6802.27	46	PUS	KR	4087.90
22	FCO	IT	6467.09	47	MNL	PH	4077.22
23	DPS	ID	6449.95	48	CPH	DK	3973.45
24	NGO	JP	6436.61	49	IAD	US	3932.50
25	CGK	ID	6282.82	50	BOS	US	3918.73

Appendix 5: Connectivity of foreign countries (with China), top 80.

No	*Country*	*Connectivity*	*No*	*Country*	*Connectivity*
1	US	130906.82	41	CZ	2737.77
2	TH	52889.50	42	PK	2696.36
3	JP	50977.87	43	BE	2589.23
4	KR	28980.19	44	GR	2541.56
5	DE	25483.90	45	KE	2238.44
6	AU	23274.81	46	NP	2152.15
7	MY	21973.46	47	KZ	2125.47
8	CA	20092.10	48	UA	1833.40
9	ID	19340.50	49	BD	1789.49
10	RU	19184.89	50	IL	1745.46
11	TW	17166.97	51	NO	1708.08
12	IT	16077.64	52	PT	1700.30
13	SG	15955.22	53	HU	1685.49
14	GB	15069.49	54	JO	1465.81
15	FR	14328.14	55	NG	1418.43
16	IN	13463.61	56	IQ	1401.32
17	VN	13063.69	57	DZ	1334.86
18	AE	11298.23	58	LA	1285.04
19	ES	10073.00	59	HR	1207.73
20	TR	9535.90	60	AZ	1064.28
21	NL	9071.59	61	RO	1030.09
22	QA	6802.27	62	UZ	969.21
23	NZ	6772.18	63	TZ	961.65
24	CH	6514.77	64	MU	950.70
25	PH	6466.71	65	IE	947.44
26	KH	6421.09	66	MA	850.30
27	FI	6276.02	67	MN	813.03
28	ET	5922.31	68	LB	798.91
29	SA	5408.57	69	BH	795.85
30	MX	4818.96	70	GE	739.38
31	DK	4568.51	71	OM	737.06
32	AT	4519.33	72	BY	730.44
33	SE	3956.73	73	RS	724.13
34	LK	3789.62	74	KW	715.29
35	PL	3584.65	75	CY	651.20
36	ZA	3578.83	76	BG	642.79
37	EG	3306.07	77	TN	553.71
38	MM	3147.82	78	BN	518.17
39	MV	3101.07	79	GH	515.26
40	IR	3057.66	80	TM	502.67

Appendix 6: City connectivity with different radiation discount functions

No	City	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
1	Shanghai	177,254	195,426	227,168	259,318	167,088	132,324	229,539	176,157
2	Beijing	161,048	166,171	182,304	198,655	151,626	132,923	189,057	155,540
3	Guangzhou	127,702	153,538	179,989	206,398	129,727	100,861	173,207	137,672
4	Nanjing	110,391	122,060	137,501	154,254	111,140	98,183	166,723	107,240
5	Hangzhou	96,358	131,360	156,344	182,719	113,519	93,109	181,034	105,011
6	Tianjin	95,018	102,048	128,224	155,164	81,760	59,041	137,708	82,040
7	Shenzhen	94,314	174,632	197,810	220,773	152,121	123,347	190,604	162,569
8	Shenyang	82,187	81,371	83,583	85,964	79,510	76,922	90,373	79,992
9	Wuhan	81,333	80,445	84,482	88,877	77,191	72,745	98,231	77,739
10	Suzhou	78,559	154,496	194,180	234,927	124,072	90,366	203,144	121,798
11	Hong Kong	77,407	140,884	169,431	197,808	113,339	79,097	158,457	129,938
12	Jinan	74,322	74,761	82,204	90,405	69,201	61,825	105,794	69,041
13	Chengdu	72,641	71,857	73,994	76,223	69,953	67,244	78,276	70,497
14	Zhengzhou	66,397	62,887	66,804	71,060	59,423	54,729	80,222	61,159
15	Xi'an	65,552	61,529	63,613	65,668	59,104	55,526	66,967	61,300
16	Changchun	63,844	61,690	66,993	72,564	57,076	51,114	73,043	58,279
17	Chongqing	62,994	61,743	64,663	67,744	59,192	55,653	70,869	59,938
18	Changsha	62,953	59,505	63,409	67,485	55,813	50,655	72,096	57,684
19	Shijiazhuang	61,915	70,155	78,416	87,688	65,092	59,251	102,818	61,359
20	Xuzhou	59,593	63,999	69,827	76,528	60,494	56,218	95,737	58,289
21	Harbin	58,583	54,242	58,493	62,826	50,152	44,636	61,194	52,009
22	Fuzhou	57,192	52,039	57,431	63,108	47,001	40,738	64,573	49,578
23	Kunming	54,565	46,896	50,320	53,565	42,644	36,430	49,075	46,780
24	Xiamen	49,545	50,533	53,339	56,403	48,433	45,679	62,686	48,150
25	Urumqi	48,705	46,766	47,604	48,360	45,652	43,913	46,767	46,766
26	Guiyang	47,622	45,652	47,581	49,601	43,793	41,099	52,864	44,884
27	Hefei	44,415	61,219	72,720	85,448	54,121	46,213	102,510	48,402
28	Ningbo	44,016	87,035	111,342	137,049	70,431	52,271	134,314	59,702
29	Nanchang	43,928	46,142	49,952	54,323	43,748	40,749	68,119	42,618

No	City	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
30	Qingdao	42,649	42,153	45,817	49,928	39,386	35,677	62,700	39,696
31	Nanning	42,550	38,186	40,539	42,930	35,599	31,998	44,136	37,841
32	Dalian	41,725	42,924	45,012	47,514	41,764	40,308	58,868	41,070
33	Lanzhou	38,614	29,082	34,801	40,599	24,362	19,169	35,217	27,181
34	Taiyuan	37,204	42,744	47,734	53,304	39,574	35,840	64,222	37,549
35	Hohhot	32,841	33,597	34,716	36,107	33,051	32,389	44,132	32,601
36	Haikou	27,567	23,423	26,029	28,721	20,714	16,965	30,712	22,831
37	Yinchuan	25,383	24,350	25,440	26,592	23,321	21,832	28,981	23,894
38	Xining	25,075	26,088	28,884	31,780	23,751	20,778	31,393	23,784
39	Lhasa	16,134	10,948	12,970	15,079	8,735	6,267	10,957	10,948
40	Lianyungang	8,304	17,279	25,012	33,827	12,812	7,777	53,783	8,763

Appendix 7: Airport connectivity from 2005 to 2016

Airport	*Y2005*	*Y2006*	*Y2007*	*Y2008*	*Y2009*	*Y2010*	*Y2011*	*Y2012*	*Y2013*	*Y2014*	*Y2015*	*Y2016*
Beijing Capital	5,643	5,943	6,240	6,608	7,157	7,243	7,475	7,909	8,187	8,489	8,552	8,762
Guangzhou	3,216	3,395	3,869	4,032	4,383	4,607	4,815	5,219	5,489	5,746	5,680	6,095
Shanghai Pudong	2,947	3,236	3,308	3,529	3,568	3,849	3,924	4,292	4,389	4,721	5,334	5,693
Kunming	1,473	1,845	2,071	2,194	2,653	2,730	2,836	2,957	3,956	4,001	4,456	4,805
Shenzhen	2,209	2,335	2,542	2,669	3,043	3,192	3,219	3,497	3,860	4,296	4,594	4,729
Chengdu	1,934	2,247	2,364	2,333	2,727	2,945	3,211	3,406	3,603	3,868	4,389	4,585
Xi'an	806	1,257	1,579	1,392	2,040	2,240	2,742	2,977	3,280	3,609	3,829	4,116
Shanghai Hongqiao	2,368	2,281	2,464	2,670	2,727	3,232	3,420	3,619	3,727	3,907	3,900	3,980
Chongqing	995	1,119	1,345	1,522	1,928	2,034	2,280	2,746	3,012	3,339	3,582	3,800
Hangzhou	1,149	1,302	1,520	1,683	1,895	2,045	2,139	2,362	2,786	2,960	3,286	3,565
Urumqi	1,138	769	901	845	1,044	1,499	1,703	2,079	2,467	2,508	2,663	3,071
Xiamen	1,019	997	1,186	1,279	1,650	1,734	2,023	2,260	2,609	2,789	2,839	2,965
Harbin	638	583	746	890	1,080	1,130	1,171	1,380	1,643	1,909	2,063	2,508
Nanjing	795	742	1,063	1,185	1,490	1,554	1,624	1,769	1,840	1,900	2,199	2,484
Zhengzhou	508	576	736	797	1,064	1,170	1,186	1,392	1,717	2,043	2,027	2,392
Qingdao	993	918	1,107	1,084	1,327	1,440	1,521	1,685	1,880	2,032	2,267	2,370
Changsha	575	851	1,087	1,150	1,465	1,583	1,566	1,818	1,913	2,063	2,035	2,320
Shenyang	804	789	1,001	1,030	1,199	1,226	1,318	1,436	1,717	1,822	1,825	2,225
Wuhan	780	724	1,061	1,081	1,309	1,368	1,413	1,578	1,799	1,930	2,066	2,200
Dalian	861	767	868	980	1,225	1,383	1,396	1,508	1,623	1,847	1,813	2,157
Sanya	479	417	518	676	816	1,004	1,083	1,288	1,435	1,724	2,004	2,148
Haikou	1,155	746	786	946	957	912	1,114	1,163	1,375	1,514	1,760	2,124
Tianjin	388	389	531	668	826	953	1,007	1,151	1,340	1,535	1,763	2,083
Guiyang	487	550	649	582	785	829	957	1,125	1,293	1,554	1,568	1,736
Nanning	367	384	474	535	714	809	1,027	1,063	1,217	1,365	1,407	1,588
Fuzhou	621	565	623	651	830	909	964	1,080	1,296	1,310	1,455	1,523
Lanzhou	268	308	395	341	456	553	501	628	780	923	1,063	1,495
Changchun	375	325	395	525	670	774	735	911	1,092	1,159	1,304	1,433
Jinan	598	618	704	814	931	994	1,129	1,118	1,189	1,204	1,232	1,393

Airport	Y2005	Y2006	Y2007	Y2008	Y2009	Y2010	Y2011	Y2012	Y2013	Y2014	Y2015	Y2016
Taiyuan	423	384	473	570	712	754	837	936	1,090	1,056	1,123	1,148
Hohhot	181	197	217	224	353	437	563	717	795	824	896	1,077
Wenzhou	446	355	436	470	621	671	695	666	814	833	827	926
Yinchuan	190	179	199	226	381	465	495	582	668	709	823	894
Guilin	482	570	678	565	727	697	663	725	745	943	839	889
Ningbo	428	433	450	483	560	585	622	615	659	824	784	869
Nanchang	325	334	371	413	460	584	611	677	794	810	810	867
Shijiazhuang	78	105	121	154	209	361	472	482	609	647	630	859
Zhuhai	144	109	158	145	208	244	255	275	385	626	634	857
Hefei	216	259	308	324	422	482	554	661	714	732	780	819
Xining	150	112	159	157	208	283	307	387	464	569	526	677
Lijiang	123	186	220	232	270	257	249	315	419	530	550	615
Wuxi	33	78	164	200	226	264	311	343	392	456	490	608
Yantai	183	182	207	213	275	317	281	379	505	496	536	607
Shantou	163	145	167	181	178	196	230	279	376	367	448	543
Lhasa	100	154	184	116	171	215	230	241	289	419	466	516
Quanzhou	90	118	172	254	274	279	287	282	344	344	417	470
Beijing Nanyuan	0	0	113	146	162	242	288	364	437	481	521	461
Baotou	57	54	44	81	113	127	140	185	188	240	236	236
Xuzhou	46	54	74	68	85	97	137	153	168	189	212	225
Zhangjiajie	221	223	219	157	162	137	153	154	143	151	188	214
Changzhou	48	67	76	111	90	87	132	150	213	226	203	209
Mianyang	19	16	21	29	35	50	78	67	92	123	148	206
Zhanjiang	65	58	54	43	57	76	60	64	82	113	148	206
Beihai	57	37	45	29	68	90	94	90	132	155	169	200
Yiwu	39	51	101	72	95	92	110	135	167	168	179	193
Nantong	13	19	32	25	26	31	42	57	105	130	149	189
Yichang	71	86	85	87	90	90	80	103	124	134	132	161
Weihai	32	43	63	62	68	79	97	90	116	85	138	158
Linyi	19	28	33	38	55	82	98	106	115	133	138	153
Liuzhou	15	26	47	44	36	35	71	101	95	88	95	123

Airport	***Y2005***	***Y2006***	***Y2007***	***Y2008***	***Y2009***	***Y2010***	***Y2011***	***Y2012***	***Y2013***	***Y2014***	***Y2015***	***Y2016***
Luoyang	9	23	23	22	41	34	44	92	87	68	82	110
Yuncheng	10	22	33	38	68	64	81	96	105	125	113	108
Lianyungang	21	26	32	30	44	52	65	70	84	86	93	105
Luzhou	3	15	20	23	22	30	35	37	48	78	94	100
Mudanjiang	42	28	27	33	48	51	55	63	66	81	94	94
Taizhou	30	37	42	60	72	82	90	42	82	95	86	92
Wuyishan	88	79	66	77	64	81	81	89	110	102	71	78
Huangshan	63	48	46	44	36	45	68	71	81	94	71	71
Jingdezhen	20	9	26	28	28	31	37	45	42	44	43	50