ESSAYS ON HIGH-SPEED RAIL DEVELOPMENT: REGIONAL DISPARITIES AND IMPACTS ON AIRPORT PERFORMANCE

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Essays on High-speed Rail Development: Regional Disparities and Impacts on Airport Performance

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CERTIFICATE OF ORIGINALITY

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______________________________ (Signed)

Shuli LIU (Name of student)

ABSTRACT

This dissertation consists of three independent but interrelated studies associated with high-speed rail (HSR) development. It aims to provide some policy implications regarding HSR investment.

The first study examines whether cities are getting more equally accessible and connected via HSR in China over the period from 2010 to 2015. Using HSR timetable data, this work incorporates both scheduled travel time and daily train frequency of each origin-destination city pair into three centrality measures, which are widely used to evaluate the importance of nodes in the network, and further quantifies regional inequalities in these centrality measures using Theil's T index. It reveals that as the HSR network expands, cities appear to be more equal in terms of accessibility, but their disparities in connectivity and transitivity depend on the dimension of comparison. In general, although the difference has reduced among economic regions or among megalopolises, small- or medium-sized cities not belonging to any major city cluster are further lagged behind in HSR development. It also finds that the difference between core and non-core cities in the same megalopolises has decreased despite that non-core cities are increasingly relying on core cities to access the other regions.

The second study explores the impacts of HSR development on airport-level passenger traffic by considering not only the position of the airport's city in the HSR network but also the availability of air-HSR intermodal linkage between the airport and HSR station. Following the methods used in the first study, the position of the airport's city is measured by degree centrality and harmonic centrality, which reflect the city's connectivity and accessibility respectively. Employing a sample of 46 airports in China

and 16 airports in Japan over the period of 2007-2015, we conduct panel regression analysis and compare the results between these two Northeast Asian countries. It is observed that as HSR connectivity or accessibility increases, there is, on average, a decline in airports' domestic and total traffic in China but little change in Japan. Meanwhile, there is a strong complementary effect of HSR to feed international flights with the presence of air-HSR intermodal linkage. As a result, some airports may experience a total traffic increase. In China, hub airports tend to gain traffic regardless the availability of air-HSR linkage, while non-hub airports are likely to lose. In Japan, on the other hand, airports with air-HSR linkage tend to gain traffic regardless the hub status. The research also reveals some differentiated impacts of HSR connectivity and accessibility in China.

As a natural extension of the second study, the third study focuses on the association between HSR development and airport technical efficiency. In addition to passenger traffic, HSR development may influence airports' other outputs such as cargo and flight movements and various inputs. Those inputs and outputs collectively determine airports' technical efficiency. With access to a dataset from 2007 to 2015, the study adopts both standard two-stage Data Envelopment Analysis (DEA) and double bootstrap method to evaluate the impact of HSR development on airports' efficiency. In addition, we evaluate the effect of HSR on the labour productivity of airports. The main results suggest that HSR development relates to a decrease in airport efficiency. Airports located in cities that have better positions in the HSR network suffer more efficiency loss than the others. It is also observed that the accessibility of HSR station from the city centre is negatively associated with airports' efficiency. By contrast, good access to the airport from an HSR station is positively correlated with airport efficiency. Furthermore, the study reports different results between China and Japan with respect to the effect of HSR on labour productivity.

PUBLICATIONS ARISING FROM THE THESIS

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CHAPTER 1

INTRODUCTION

This Chapter provides the research background, motivation, research questions, and research design for the dissertation. It firstly introduces the development of high-speed rail (HSR) around the world and illustrates the motivation for the dissertation. It then identifies the research questions and outlines the overall structure of the thesis.

1.1 Background

According to the definition offered by International Railway Union (UIC), HSR is a type of rail transport that allows trains to operate at a speed of 250 km/h on new lines, or 200 km/h on upgraded conventional lines. As the train is powered predominately by electricity, there is a strong consensus among policy makers that this modern mode of transport has substantial economic and environmental benefits to the society. Thus, it is very attractive to countries which aim to cut their emissions in the transport sector.

Figure 1.1 shows the growth trends of HSR lines currently in operation. Originating from Japan where the first HSR line was built to connect Tokyo and Osaka in 1964, HSR has undergone a remarkable growth around the world, particularly in the past decade. Based on UIC's 2020 statistics, there are 21 countries that operate HSR services with a total length of 52,484 kilometers. In addition, there are 24 countries that are constructing or have planned the construction of HSR. In terms of HSR traffic, as shown in Figure 1.2, the total volume of traffic by HSR in 2018 had increased almost four times in comparison with 2008. The growth in HSR traffic is primarily contributed by China where HSR has grown out of nothing to the largest in the world, reaching 680.5 billion passenger-km. By contrast, HSR traffic of major European countries and

Japan which have a long history of HSR has experienced marginal change over the past ten years. A rich body of literature on HSR concentrates on European markets while studies focusing on Northeast Asia have not raised much attention until recent years. These facts make Northeast Asia which accounts for over 80% of the world's total HSR traffic an ideal context to investigate HSR related investments and policies.

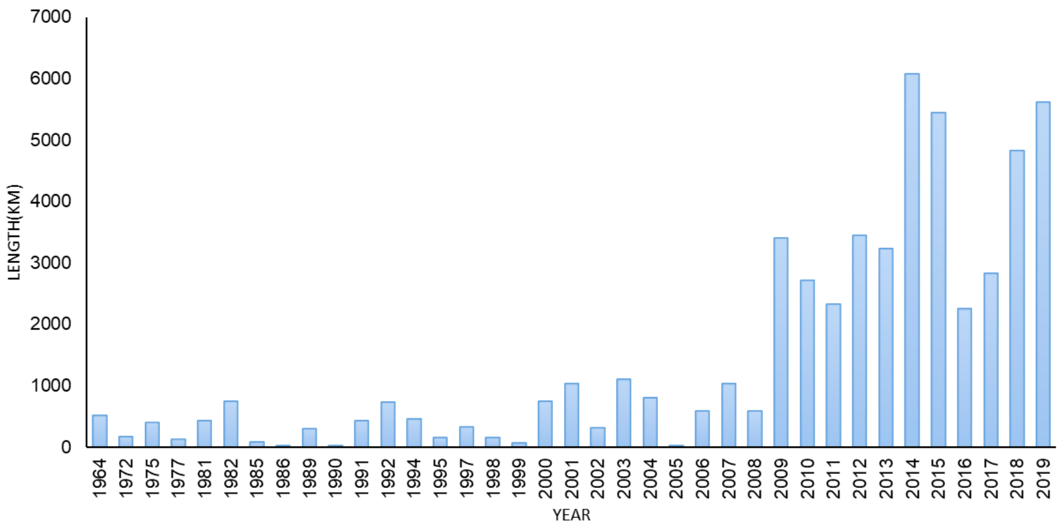

Figure 1. 1 Development of worldwide HSR lines

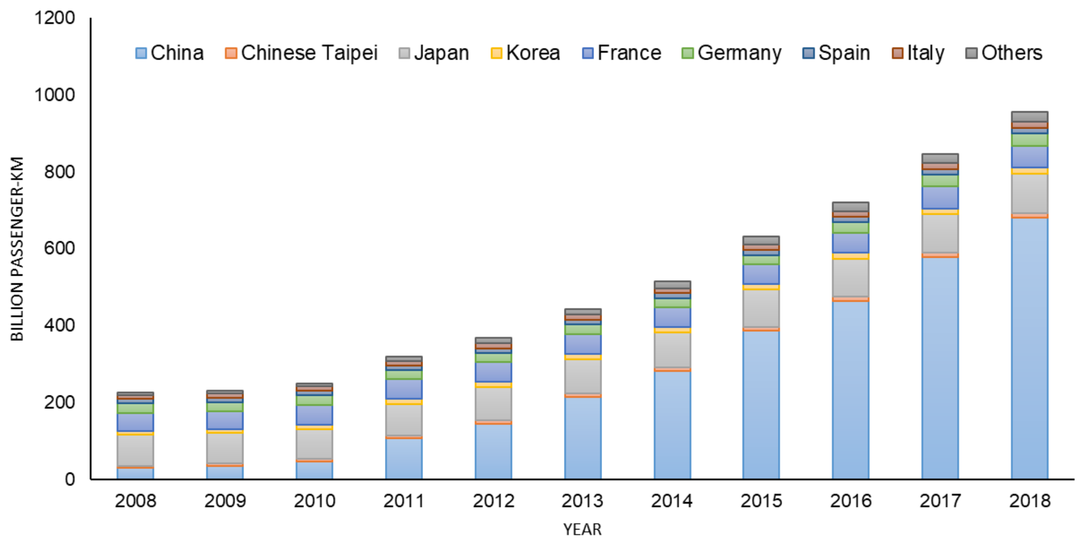

Figure 1. 2 Development of worldwide HSR traffic

1.2 Motivation

The rapid development of HSR is driven by many factors, including regional economic growth and awareness of environmental issues.

A widely supported opinion on HSR investment is that HSR is a catalyst for economic development. This is partly because the construction of HSR could create many job opportunities and the operation of HSR services would stimulate economic activities. It is also because the improvement in connectivity and accessibility between cities would increase the intercity mobility and accelerate the process of urban agglomeration. In reality, cities or regions might be affected differently as their positions in the HSR network are heterogeneous. However, scholars have yet to reach a consensus regarding the equality concerns raised by HSR expansions. On one hand, some existing research reveals an unbalanced growth in the regional economy between HSR-connected small cities and HSR-connected large cities (e.g. Qin, 2017; Diao, 2018). This is possibly because small intermediate cities connected by HSR infrastructures tend to be bypassed by HSR services to guarantee the service quality for metropolises. (Urena et al., 2009; Urena et al., 2009; Moyano and Dobruszkes, 2017; Qin, 2017). On the other hand, some evidence shows that HSR does not contribute to the dispersion of regional development (e.g. Sasaki et al., 1997; Zheng and Khan, 2013; Monzon et al., 2013; Vickerman, 2018; Wang, 2018).[1] Furthermore, literature documents that the position of a city in the HSR network is closely related to the city's economic opportunities (e.g. Chong et al., 2019; Credit, 2019), which indicates that exploring the dynamics of cities' positions in the HSR network may help us better understand the impact of HSR on regional economy. Nonetheless, researchers

[1] For a recent survey of the literature, see Zhang et al. (2019).

have not treated this idea in much detail.

Another popular argument for promoting HSR is to reduce carbon emissions by providing an efficient alternative to air travel. According to the IPCC Fourth Assessment, emissions from the aviation sector are responsible for 2% of global CO2 emissions (Intergovernmental Panel on Climate Change [IPCC] AR4, 2007). Although the proportion is not high, emissions from aviation have grown very fast in the past decade because of the increase in demand for air travel.[2] It is predicted that emissions from aviation, if no action is taken, will triple by 2050 on the 2010 basis (International Civil Aviation Organization [ICAO], 2016). Coping with this challenge has become a matter of urgency for many nations. Given the fact that HSR releases much less emissions per passenger-km than air transport,[3] replacing flights with HSR services may help to mitigate carbon emissions (e.g. Eurocontrol, 2004; Givoni, 2007; Givoni and Banister, 2006; Sun et al., 2017). In practice, some European countries have been encouraging a shift from air travel to HSR for domestic and intra-Europe travel. However, some scholars express doubts about HSR's capability of offsetting the emissions stemming from HSR related infrastructure construction and additional power production, revealing that HSR traffic diverted from aviation should be sufficiently large to achieve a net reduction of emissions (Westin and Kageson, 2012). As a result, it remains unclear whether the benefits of emission reduction could realize with the help of HSR.

To examine the aforementioned issues, the dissertation includes two research topics: (1) equity concerns related to HSR development; and (2) impacts of HSR on airports. Chapter 2 relates to the first topic and Chapter 3&4 study the second topic.

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[2] According to a survey by UN, greenhouse gas (GHG) emission from aviation bunker increase 76.1%.
[3] Europe Environment Agency (2014) reported that CO2 emission by HSR is 14g per passenger-km but by air transport the number raises to 285g per passenger-km.

1.3 Research questions and research design

The following research questions are developed for this thesis:

- Chapter 2: How to represent HSR networks? How to measure the position of a city in the HSR network? Whether cities in the network are getting more equally accessible and connected as the HSR network expands?
- Chapter 3: How does the importance of the airport's city in the HSR network affect the airport's passenger traffic? How does the air-HSR intermodal linkage moderate the effects of HSR on airports?
- Chapter 4: What are the impacts of HSR development on the airport's technical efficiency and productivity? How do the substitute and complementary effects of HSR on air transport determine airport's performance?

Table 1.1 presents the summary of research activities for answering the above questions.

1.4 Thesis outline

The remainder of this dissertation is organized as follows. Chapter 2 studies in detail the questions related to HSR development and regional disparities in the context of China. Chapter 3 explores the impacts of HSR development on airport-level passenger traffic by considering not only the position of the airport's city in the HSR network but also the availability of air-HSR intermodal linkage between the airport and HSR station. Chapter 4 focuses on the association between HSR and airport efficiency. Chapter 5 concludes the key findings and outlines avenues for future research.

Table 1. 1 Scope of research activities of the thesis

Topic	Topic one: Equity issues related to HSR development	Topic two: Impacts of HSR on airports	
Chapter	Chapter 2	Chapter 3	Chapter 4
Core question	Whether cities in the network are getting more equally accessible and connected as the HSR network expands?	How does the importance of the airport's city in the HSR network affect the airport's passenger traffic?	What are the impacts of HSR development on the airport's technical efficiency and productivity?
Methods	Complex network analysis Disparity analysis	Comparative analysis Complex network analysis Panel data models with fixed effects	Comparative analysis Data Envelopment Analysis Bootstrap-Data Envelopment Analysis
Context	China	China and Japan	China and Japan
Data	Chinese HSR timetable (2010-2015)	China HSR timetable (2007-2015) Japan rail timetable (2007-2015) 46 airports in China, 16 airports in Japan	HSR train timetable (2007-2015) Japan rail timetable (2007-2015) 46 airports in China, 16 airports in Japan

Findings	- Cities appear to be more equal in terms of accessibility.
	- Inequalities in connectivity and transitivity depend on the dimensions of comparison.
	  - Small/medium-sized cities not belonging to any major city cluster are further lagged behind in HSR development.
		- HSR development is negatively associated with airport's domestic traffic and total traffic in China but little change in Japan.
		- A good air-HSR linkage mainly facilitates HSR to feed international flights and hence increase international traffic at airports.
		  - Even without air-HSR linkage, hub airports may experience traffic increase.
			- HSR development relates to a decrease in airport efficiency.
			- Airports located in cities that have better positions in the HSR network suffer more efficiency loss than the others.
			- Good access to the airport from an HSR station is positively correlated with airport efficiency

CHAPTER 2

DOES CHINA’S HIGH-SPEED RAIL DEVELOPMENT LEAD TO REGIONAL DISPARITIES? A NETWORK PERSPECTIVE

2.1 Introduction

Transportation planners and policy makers are interested in understanding the impacts of high-speed rail (HSR) development on regional integration or disparities. For example, in China’s 12th and 13th Five-Year Plans for Railway Development issued in 2011 and 2017 respectively, one objective of future HSR development is to reduce regional inequality and promote inter-regional cooperation via the improvement of connectivity between the rich and poor regions. However, it remains unclear how HSR can affect regional economy. In theory, the new economic geography model predicts that regional disparity can increase as a result of transportation infrastructure development (Fujita and Thisse, 1996). This is because reduced transportation cost may reinforce the “siphone effect”, i.e. the tendency of having resources being attracted from small cities to large cities. Furthermore, HSR stations in large cities generally have better locations, since large cities have stronger bargaining power when negotiating with the central planner, and hence they are more attractive for HSR service providers (Zhu et al., 2015; Sun et al., 2020). Empirically, the findings are mixed. Some studies find HSR development increases regional disparity (e.g. Loukaitou-Sideris et al., 2013; Kim and Sultana, 2015; Chen and Haynes, 2017; Diao, 2018), while others find HSR does not contribute to regional dispersion (e.g. Sasaki et al., 1997; Zheng and Khan, 2013; Monzon et al., 2013; Vickerman, 2018; Wang, 2018).[4] For instance, in the context of China, Zheng and Khan (2013) find that HSR

[4] For a recent survey of the literature, see Zhang et al. (2019).

facilitates market integration, leading to reduced disparity between mega cities and nearby second- and third-tier cities. Diao (2018) reveals, on the other hand, that second-tier cities with relatively large population benefit more in attracting investment than small cities and mega cities.

Quantifying the impact of HSR on regional development and testing the underlying mechanisms are empirically challenging. Whether a city is benefited from HSR depends, among others, on how the city is linked to the other cities in the HSR network. Sanchez-Mateos and Givoni (2012) find that only very few cities with good accessibility to metropolis along the newly constructed line in the UK could gain benefits. Scholars have warned that the situation of small cities might even become worse due to the lack of adequate services or inappropriate station design (e.g. Preston and Wall, 2008; Moyano and Dobruszkes, 2017). In fact, being linked to the HSR network is not equivalent to being well-served by HSR. Small intermediate cities on an HSR line are found to be bypassed by HSR services in favor of the metropolises in both Europe (Urena et al., 2009; Moyano and Dobruszkes, 2017) and China (Qin, 2017). As suggested by Qin (2017), this bypassing behavior may weaken the relative economic position of small cities, since small cities are further marginalized while the linkages among large cities are enhanced. To better understand the impact of HSR on regional economy, therefore, we need first to investigate the important question of whether cities in an HSR network are getting more equally accessible and connected as the network expands.

This study focuses on the spatial disparity of HSR development among Chinese cities and the inter-temporal changes of such disparity as the HSR network expands. The objective is to examine whether the gap between cities in terms of HSR service supply has been reduced over time. After recent years of HSR development in China, many small cities have been linked to the HSR network, but it is unclear whether such linkages have helped small cities to catch up with the large ones. As the levels of economic development are highly uneven within China, it is essential to assess the disparity of HSR development among cities in different regions, of different sizes, and in different megalopolises. This approach may shed light on the regional disparity from the viewpoint of provision of HSR services and pave the way for a better understanding of the HSR impact on regional economy. From a planning point of view, an increased disparity in service provision may imply low utilization of HSR infrastructure at small cities. This can serve as a signal for policy makers to seek ways to better utilize the existing infrastructure, instead of further expanding the infrastructure to small cities. Furthermore, policy makers may pay more attention to improve the attractiveness of small cities as a support policy of an overall HSR development.

To address our research questions, we use HSR timetable data over the 2010-2015 period to evaluate a city's status in HSR development from a network perspective. In particular, we employ the weighted degree, betweenness and harmonic centralities to measure, respectively, a city's connectivity, transitivity and accessibility. The degree centrality is weighted by daily service frequency, whereas the betweenness and harmonic centralities are weighed by the generalized travel time that takes into account scheduled travel time and daily train frequency. Then, by calculating the Theil's T indices of these centrality measures across HSR cities, we explore whether inequalities among cities have increased or decreased over the study period. Theil's T index allows us to examine both the disparity within a group and the disparity across city groups, after grouping cities according to geographic regions, city sizes, and megalopolises, respectively. We include all Chinese cities over a certain population threshold in the study, regardless of the availability of HSR stations in the cities. By doing so, we can take into account the impact of having more cities being served by HSR as the network expands. We find that the disparity in accessibility has been gradually reduced as the HSR network expands, but this is not the case for connectivity and transitivity, suggesting that a comprehensive assessment on all three aspects might be necessary during the planning of HSR network and services.

The rest of this chapter is organized as follows. Section 2.2 reviews the related literature. Section 2.3 presents the methodology and describes the data. Section 2.4 compares HSR infrastructure network and service network and explains why the latter is chosen for further analysis. Section 2.5 displays the disparity analysis on the three dimensions, namely, economic regions, tiers of cities, and megalopolises. Section 2.6 concludes the study and discusses policy implications and avenues for further research.

2.2 Related Literature

Our study is most related to the stream of studies that apply complex network theories to measure centralities of cities in Chinese HSR network. This kind of analysis may have different purposes: e.g. quantification of the spatial evolutional pattern (Chen et al., 2018), projection of the growth pattern of future HSR network based on the national railway planning proposal (Xu et al., 2018a), comparison of the configurations of China's HSR system and airline networks (Yang et al., 2018), introduction of an integrated connectivity and accessibility indicator (Xu et al., 2018b), assessment of the robustness of HSR network (Li et al., 2019; Li and Rong, 2020), and examination of the hierarchical impacts of HSR on the city networks (Jiao et al., 2017).

Most of these studies measure centralities based on the HSR infrastructure; as such, they treat all the edges in HSR network equally (no weights are imposed on each edge of the HSR network by service quality). However, infrastructure only provides the potential of offering HSR services but does not capture the actual provision and usage of HSR services (Zhang et al., 2016; Yang et al., 2019). Evidence shows that HSR can positively affect regional economies only if the location of a region and its external factors such as the commuting frequency are effectively matched (Jia et al., 2017). Chen et al. (2018), Jiao et al. (2017), Li et al. (2019) and Li and Rong (2020) are exceptions here,[5] but they either fail to fully utilize the timetable data or focus on another question. For instance, Li et al.(2019) and Li and Rong (2020) employ a comprehensive HSR timetable data that takes into account travel time and passenger flow to explore the volunerability and robustness of HSR nrtwork. Chen et al. (2018) weigh edges by estimated travel time only, while Jiao et al. (2017) only consider service frequency. None of them uses the generalized travel time, which takes into account both scheduled travel time and service frequency, to construct transitivity and accessibility, as well as considers the directional difference in scheduled HSR services.[6] In addition, all of the studies use the closeness centraltiy to measure accessiblity. By contrast, we use the harmonic centrality since this measure can better deal with disconnected networks that are common in the earlier stages of HSR development in China. Moreover, none of the above studies track the disparities in the provision of HSR services as the HSR network expands. This is the most crucial difference between our study and those in the literature.

Our study is also relevant to the measure of regional inequalities in the context of HSR development. The literature mainly adopts three measures, i.e., coefficient of

[5] See also Takebayashi (2015) and Zhu et al. (2018, 2019) who use timetables for HSR and airlines to examine multi-modal connections and connectivity radiations of transportation infrastructure.

[6] According to the train timetables, we find that the numbers of inbound and outbound train services are not necessarily close to each other, especially for the small cities. Large cities tend to have more balanced inbound and outbound services (see Appendix A.1).

variation (e.g. Gutierrez, 2001; Jiao et al., 2014; Kim and Sultana, 2015; Chen and Haynes, 2017; Wang, 2018; Wang and Duan, 2018), Gini coefficient (e.g. Kim, 2000; Chen and Haynes, 2017; Wang et al., 2019) and Theil index (e.g. Cheng and Haynes, 2017), to evaluate disparity. All studies cited above apply the view of New Economic Geography which associates accessibility with regional development. As a result, these studies mainly measure disparity in accessibility. However, we argue that other centrality measures, namely connectivity and transitivity, also deserve investigation. In fact, Jiao et al. (2017) find that changes in connectivity resulted from HSR expansion plays a more vital role in economic development than in time saving, a key element of accessibility. Campante and Yanagizawa-Drott (2018) establish empirically that more and better air connectivity (and network centrality) can contribute to local economic growth.[7] Connectivity improvement brought by HSR is also recognized as a key factor in driving economic growth (Chong et al., 2019). In addition to geographical condition and topography, connectivity is highly affected by policy interventions and the disparity in connectivity is also associated with the inequalities in development opportunities (Rodrigue, 2019). Further, it is evident that transit station proximity is positively correlated with new business creation (Credit, 2019). Therefore, it is essential to comprehensively explore the uneven development of HSR with various centrality measurements.

Among studies measuring disparities in HSR development listd above, our work is most relevant to Jiao et al. (2014) and Chen and Haynes (2017). Jiao et al. (2014) use the coefficient of variation to predict changes in the disparities of Chinese cities' accessibility based on future HSR expansion plans. Therefore, unlike our study, they did not include connectivity and transitivity and they based their assessment on

[7] See also Wong et al. (2019) and Cheung et al. (2020), among others, for the recent studies on airports using various centrality measures.

planned infrastructure network instead of the actual provision of HSR services. Moreover, we explore inequalities not only among different regions and different sizes of cities, but also among five megalopolises which is again not included in Jiao et al. (2014). Although both Chen and Haynes (2017) and our paper use Theil index to assess disparity, the subjects being studied are different. The objective of Chen and Haynes (2017) is to identify the impact of HSR development on regional economic disparity. Thus, they used Theil index to evaluate the inequality of regional economy and then applied panel regression analysis to explain how HSR may potentially associate with regional economic disparity. Unlikely Chen and Haynes (2017), we focus on HSR development *per se* and hence measure the disparities of connectivity, transitivity and accessibility of HSR service provision.

2.3 Methodology

2.3.1 Network representation and data

The topology of a transportation network can vary by taking different views of "space", namely the space of stations, space of stops, or space of changes (Kurant and Thiran, 2006). These three views of space affect how two nodes (cities or stations) are defined as connected and hence the construction of edges. The space of stations reflects the physical infrastructure, i.e. railway tracks. In a space of stations, two stations are considered as connected only if they are directly linked by at least one railway track without going through any other station in between. Both space of stops and space of changes are based on the schedule of train services. In a space of stops, two stations are connected if there exists at least one direct train making two consecutive stops at these stations. In a space of changes, two stations are connected when there exists at least one direct train that stops at both stations regardless the number of stops between these two stations. In other words, two nodes are connected as long as they can be directly reached without changing trains. In this way, all stations served by the same train are fully connected with each other. The space of stations and the space of stops are also called L-space in the literature (e.g. Barthelemy, 2011), while the space of changes is also called P-space.

In this paper, we use L-space (space of stations) to represent HSR infrastructure network and P-space to represent HSR service network.[8] Figure 2.1 distinguishes these two representations of an example HSR network. The P-space emphasizes the accessibility of two nodes and is more effective for reflecting the socio-economic connections of two locations (Lu et al., 2018). As a result, it is very popular in analysing service networks and has been proven to be practical in the analysis of public transport networks (Chatterjee, 2016). In both views of "space", the edges can be weighted to reflect the strength of the links.

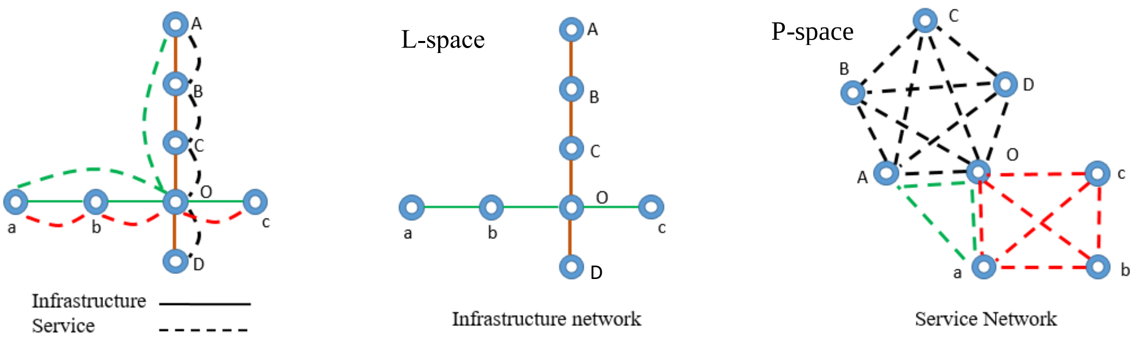


Figure 2. 1 Representations of HSR infrastructure network versus service network

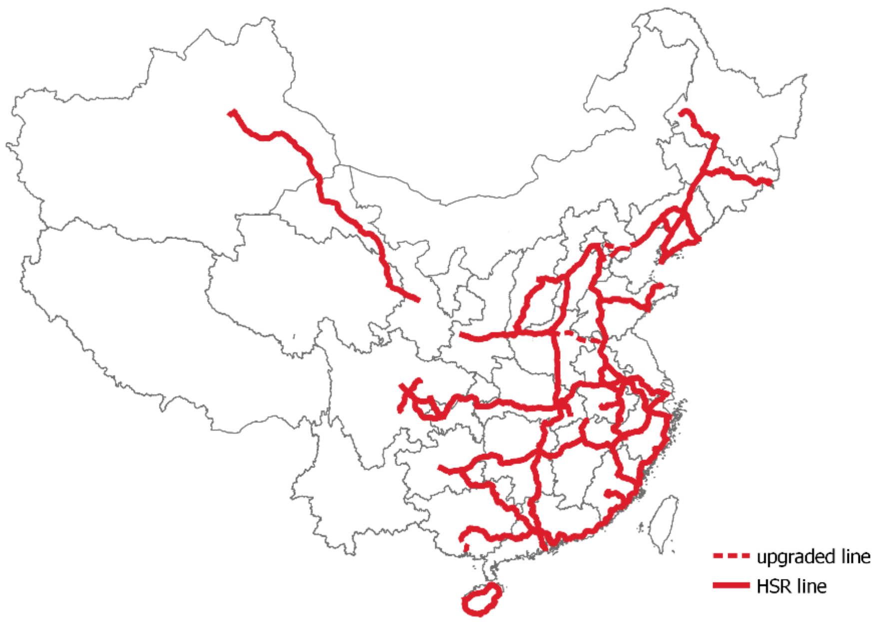
In the HSR infrastructure network, nodes represent cities, and edges are physical railway tracks of two consecutive cities. As shown in Figure 2.1, the solid line segment AB is an edge in the infrastructure network. From A to C, one needs to go through two

[8] Zhang et al. (2016) mentioned that actual passenger flow data is the best to analyse urban networks. Yang et al. (2019) found that timetable data and passenger flow data can generate very different results. However, passenger flow data is not available for our study. Moreover, passenger flow data may reflect the demand for HSR services, while our focus is on the supply, since connectivity, transitivity and accessibility are all referring to passengers' ability to reach other cities instead of demand for travel.

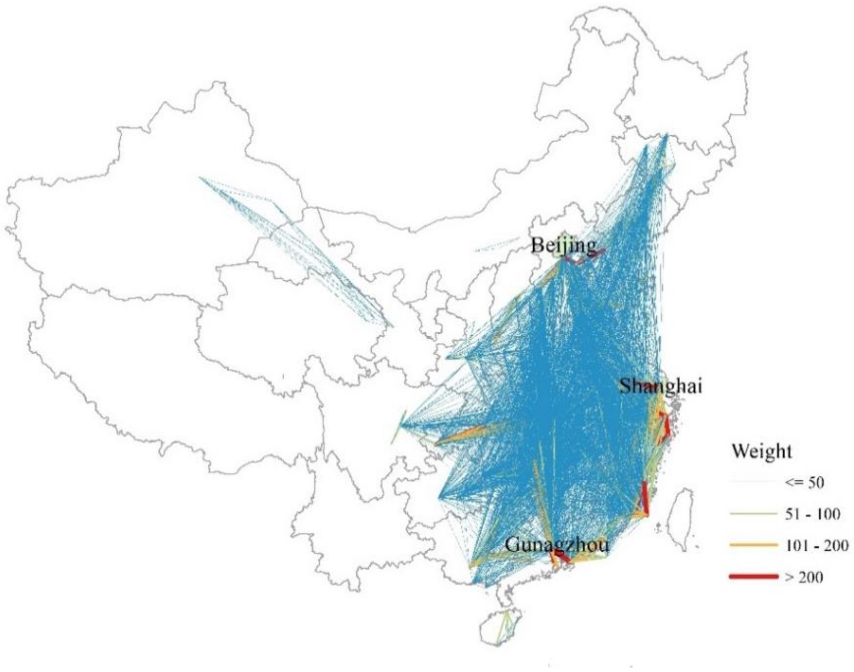
edges, AB and BC. In the HSR service network, nodes represent cities, and edges represent the *existence* of direct rail services between two cities. For example, in the service network of Figure 2.1, the dashed line segment between A and C is one edge despite that there is one stop (B) between A and C, because there is one direct train service which stops at A, B, C, O and D in sequence. To travel from C to b, one needs to go through two edges, i.e. making a train transfer. The black dashed line and green dashed line between A and O represent the same edge (not two different edges), despite that there are two direct trains serving these two nodes.

Our study examines Chinese cities' centralities in the HSR network and inequality in their HSR development during the period of 2010-2015. China's HSR network has experienced remarkable growth since 2008 and the network has reached a total length of 19730 km by 2015, covering 28 out of 31 provincial-level regions in mainland China and forming a grid network consisting of four vertical corridors and four horizontal corridors. This makes China's HSR network the largest in the world in terms of both total length and traffic volume. Figure 2.2 (a)-(b) show the development of HSR network reflected by infrastructure and service respectively by 2015. According to the Medium- and Long-Term Railway Network Plan approved by China's Cabinet and the 13th Five-Year Plan for Railway Development issued by China's National Development and Reform Commission, 80% of the cities with over one million population will be connected by HSR by 2020 and all cities with more than 0.5 million urban population will be linked by HSR by 2025. Therefore, cities with population over 1 million and urban population over 0.5 million in mainland China are all included in our study, resulting in 341 cities being assessed. We include all cities which have been or will potentially be linked into the HSR network, because we consider the individual cities' HSR development and hence the measure of disparity should capture the effect of having an increasing number of cities linked to the HSR system over the study period. Note that the inclusion of cities without HSR stations does not affect the calculation of centralities and these cities will be assigned a value of zero for each centrality indicator.

The HSR infrastructure data is obtained from international union of railways (UIC), while train timetable data is retrieved from China Train Timetable (2010-2015, July editions), and all types of bullet trains (G, C and D) are considered. China Railway Corporation releases several editions of train timetable each year. We choose the July edition mainly for two reasons. First, July editions are the most available throughout our study period. We are not able to obtain a complete collection (from 2010 to 2015) of editions published in the other months. Second, significant changes in the timetable tend to occur in each July because many HSR lines were opened around the 1st of July to celebrate a major public holiday of the country. Demographic and socio-economic data for each city is obtained from CEIC China database. We focus on cities, and hence multiple stations in one city are merged into one station. We consider the infrastructure network as undirected whereas the service network directed as intensity and quality of train services from one city to the other are not necessarily the same in the return direction.



(a) Mainland China's infrastructure network by 2015



(b) Mainland China's service network by 2015 (Weight represents service frequency)

Figure 2. 2 Development of HSR network in mainland China by 2015

2.3.2 Centrality measures

Our paper focuses on the microscopic properties of China's HSR network. Thus, we use centrality, a fundamental concept in network analysis, to capture the importance of a node in the HSR network.[9] Among various centrality measures, degree, betweenness and closeness are the most popular indices in transportation studies. These three measures can be interpreted respectively as the connectivity (Mishra et al., 2012), transitivity and accessibility (Jiao et al., 2017; Wang et. al, 2011) of a node in the HSR network. However, Opsahl et al. (2010) argued that closeness centrality may not work in a network composed by multiple disconnected components (subgraphs), which is the case of China's HSR network, especially in the early stage of its development. In particular, the closeness centrality may overstate the accessibility of nodes in small subgraphs disconnected from the larger main subgraph (See Appendix A.2 for an example). Therefore, in this study we use harmonic centrality proposed by Marchiori and Latora (2000) as a transformation of closeness centrality. As the HSR connections between cities are highly heterogeneous, all the three centrality measures in our study are weighted.[10] The following provides the detailed definitions of the three measures.

The degree of a node, i.e. city in our case, is the number of other nodes that can be directly connected (Freeman,1978; Newman, 2010). Degree is an effective measure of the importance of a node. The larger the degree centrality, the more central the city is. In an undirected graph (e.g. HSR infrastructure network), the weighted degree centrality of city i is defined as:

$$C_D^I(i) = \sum_{i \neq j \in N} a_{ij} w_{ij} \tag{1}$$

where N is the set of cities in the HSR network. a_{ij} equals to 1 when there exists a direct connection via HSR, i.e. an edge in L-space, between city i and city j, and

[9] This is also done in, e.g., Liu et al. (2019).

[10] In transportation systems, the weights can be ridership, travel cost, geodesic distance and so on.

equals to 0 otherwise. The weight w_{ij} is the number of rail tracks that directly link city i and city j.

In a directed graph (e.g. HSR service network), degree can be separated into in-degree and out-degree. In-degree is the number of inbound links whereas out-degree counts the number of outbound links. Givoni and Banister (2012) argued that service frequency, safety, and reliability are more important than speed in affecting the experience with HSR. Traditional topology measures treat all links equally without taking into account the strengths of each link. This treatment may overstate the importance of cities that have many weak links while understate the importance of cities that have fewer but much stronger links. In this study, we use daily service frequency to weight the degree of city i in the HSR service networks. Then, the weighted degree centrality of city i in the service network is formalized as:

$$C_D^S(i) = \sum_{i \neq j \in N} a_{ij} w_{ij} + \sum_{i \neq j \in N} a_{ji} w_{ji} \tag{2}$$

where a_{ij} indicates the presence of direct HSR service from city i to city j (i.e. outbound links), i.e. an edge pointing from i to j in P-space, and a_{ji} indicates the presence of direct HSR service from city j to city i (i.e. inbound links). Again, a_{ij} and a_{ji} equal to 1 when the corresponding HSR service exists and 0 otherwise. w_{ij} and w_{ji} are the number of daily train services from city i to city j and from city j to city i respectively. They capture the strength of the outbound and inbound services of city i respectively. This weighted degree centrality is also called strength in the literature.

Harmonic centrality captures the average level of convenience that one can travel from a node to all the other nodes in the network. Nodes with higher harmonic centrality can access to the whole network more quickly and hence harmonic centrality reflects the accessibility of a node in a given network. In the infrastructure network, it is defined as:

$$C_H^I(i) = \sum_{i \neq j \in N} \frac{1}{d(i,j)} \tag{3}$$

where

$$d(i,j) = \min_{p \in P_{ij}} \sum_{k \in p} e_k$$

Here, $d(i,j)$ is the length of the shortest path between city *i* and city *j*. To see this, note that P_{ij} is the set of paths linking city *i* and city *j*. A particular path *p* consists a serious of edges which form the path. Each edge k along path *p* is considered as an element of path *p*. In the literature, in many cases e_k indicates the presence of the edge *k* along a path and hence is assigned a value of 1. Therefore, the length of shortest path in fact counts the smallest number of edges needed to link city *i* and city *j*. In our study, each edge is weighted by the estimated travel time along the edge. That is, e_k equals to the ratio of rail distance of this edge and planned operating speed. In this way, we capture not only the number of edges involved in a path but also the quality of the edges (in the form of the travel time). Note that C_H^I is the sum of the reciprocals of $d(i,j)$. That is, the longer the travel time between cities *i* and *j*, the lower the value of the harmonic centrality. In the directed service network, the formula is rewritten as:

$$C_H^S(i) = \sum_{i \neq j \in N} \frac{1}{d(i,j)} + \sum_{i \neq j \in N} \frac{1}{d(j,i)} \tag{4}$$

where

$$d(i,j) = \min_{p \in P_{ij}} \sum_{k \in p} e_k \, , d(j,i) = \min_{p \in P_{ji}} \sum_{k \in p} e_k$$

where $e_k = t_k + \frac{18}{w_k}$. That is, each directional edge k is weighted by the generalized travel time which is the sum of the average scheduled in-vehicle time along the edge

(t_k) and the estimated maximum waiting time between two train services on this edge. According to the schedule data, the daily operating time of HSR services in China is 18 hours and thus the ratio of 18 hours and service frequency, w_k, is a proxy of maximum waiting time, assuming services are evenly distributed throughout the operating time. Thus, the length of each path captures both the number of trains to change to move from city i to city j and the generalized travel time of each train ride. In both infrastructure and service networks, we assume $d(i, j) = +\infty$ and its inverse becomes zero when there exists no path linking city i and city j (i.e., $P_{ij} = \emptyset$). This case occurs when city i and city j belong to two disconnected subgraphs.

The betweenness centrality of a node measures the extent to which a node lies on the shortest paths between two other nodes (Freeman, 1978; Newman, 2010). Nodes on the shortest paths of many origin-destination pairs tend to be more powerful in the network as they determine the bottleneck of the network. For infrastructure network, the betweenness of city i is written as:

$$C_B^I(i) = \sum_{j \neq i \neq k \in N} \frac{\delta_{jk}(i)}{\delta_{jk}} \tag{5}$$

where δ_{jk} is the number of shortest paths between city j and city k, and $\delta_{jk}(i)$ is the number of shortest paths between city j and city k that pass city i. The identification of shortest path between nodes in the network is discussed below when defining harmonic centrality. For directed service network, the formula is rewritten as:

$$C_B^S(i) = \sum_{j \neq i \neq k \in N} \frac{\delta_{jk}(i)}{\delta_{jk}} + \sum_{j \neq i \neq k \in N} \frac{\delta_{kj}(i)}{\delta_{kj}} \tag{6}$$

To measure the overall centrality of one city, we generate an aggregated centrality indicator by first standardizing the three centrality measures and then taking the linear combination of the standardized indicators. The formula of the aggregated indicator is:

$$A(i) = \omega_1 \left[\frac{C_D(i) - \mu_{C_D}}{\sigma_{C_D}}\right] + \omega_2 \left[\frac{C_B(i) - \mu_{C_B}}{\sigma_{C_B}}\right] + \omega_3 \left[\frac{C_H(i) - \mu_{C_H}}{\sigma_{C_H}}\right] \quad (7)$$

where μ and σ indicate the mean and standard deviation of the corresponding centrality measure. ω_1, ω_2 and ω_3 are weights for each centrality measure. In this paper, we assume a city's capability of connectivity, transitivity and accessibility are equally important. Thus, we set $\omega_1 = \omega_2 = \omega_3 = 1$.

2.3.3 Disparity measures

Measures of regional inequality have been well documented in literature and can be classified into three groups: dispersion indices, Lorenz curve indices, and entropy indices. Coefficient of variation is a popular dispersion index which is defined as the ratio of the standard deviation over the mean, and Gini coefficient is a popular indicator based on Lorenz curve. However, both indicators cannot be easily decomposed. The main advantage of entropy indices, such as Theil's T index, is that the total disparity can be decomposed into the between-group and within-group disparities. This feature is particularly useful when identifying the sources of inequality. For example, it can be used to distinguish whether the inequality mainly occurs between large and small cities or within cities with similar size.[11] Since the objective of this research is to examine the disparities among regions, tiers of cities, and megalopolises, Theil's T index fits this purpose better.

Theil's T index (Theil, 1967) is defined as:

[11] One weakness of Theil's T index is that it cannot be directly compared across populations with different sizes. However, this is not a problem in our study. We do not compare inequality between different groups of cities. Rather, our focus is to assess the inter-temporal changes in inequality among cities belonging to the same group. That is, we are interested in which group of cities has experienced increased inequality, but not which group of cities has experienced high inequality than the other groups.

$$T = \frac{1}{n}\sum_{i=1}^{n}\frac{x_i}{\mu}\ln\left(\frac{x_i}{\mu}\right) \tag{8}$$

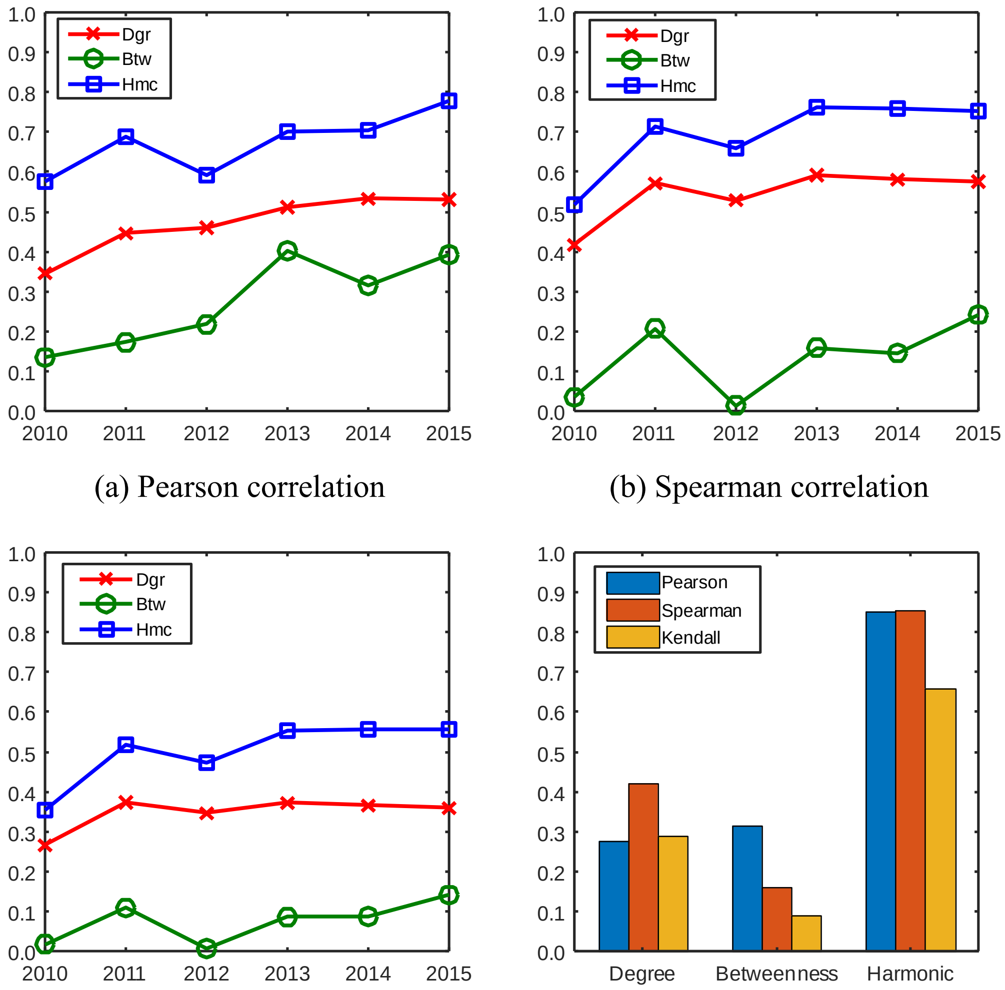
where n is the number of cities included in measuring the inequality, x_i is the centrality measure for city i, and μ is the average centrality measure of all the n cities. Equation (8) can be decomposed into between-group inequality (T_B) and with-in group inequality (T_W):

$$T_B = \sum_{j=1}^{m} s_j T_j\,, \qquad T_W = \sum_{j=1}^{m} s_j \ln\frac{\bar{x}_j}{\mu}, \qquad \text{where} \quad s_j = \frac{n_j}{n}\frac{\bar{x}_j}{\mu} \tag{9}$$

In equation (9), m is the number of groups, n_j is the number of cities in group j, T_j is the Theil's T index of group j, and $\bar{x}_j$ is the average centrality measure of group j.

2.4. Infrastructure network versus service network

In this section, we explore whether infrastructure network and service network generate similar assessment on a city's centrality in the HSR network. We calculate, for each centrality measure, the correlation between these two network representations. Figure 2.3 (a)-(c) presents three correlation coefficients, Pearson, Spearman and Kendall, over the time. All three centrality measures obtained from service networks appear to have weak correlations with those derived from infrastructure networks. This is especially the case for degree and betweenness, as their correlation coefficients are in most of the cases below 0.5. Harmonic centralities of these two types of networks have a stronger correlation with a coefficient mostly ranging from 0.5 to slightly over 0.7. After pooling the centrality measures over the time, the correlation coefficient of harmonic centrality is substantially improved, exceeding 0.8 in the case of Pearson and Spearman correlations (Figure 2.3 (d)). These inter-temporal correlations are weaker when the degree and betweenness centralities are in concern.

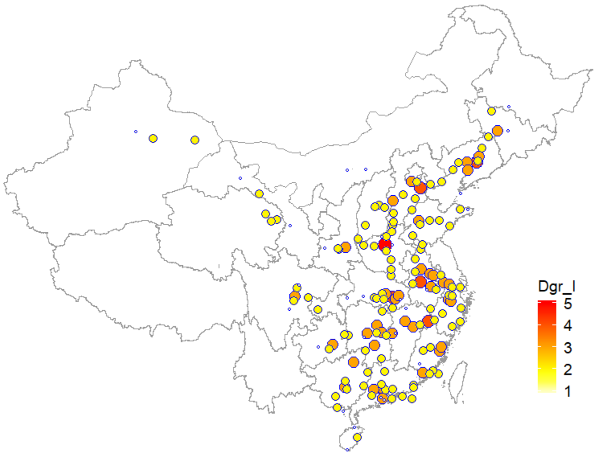


(a) Pearson correlation (b) Spearman correlation

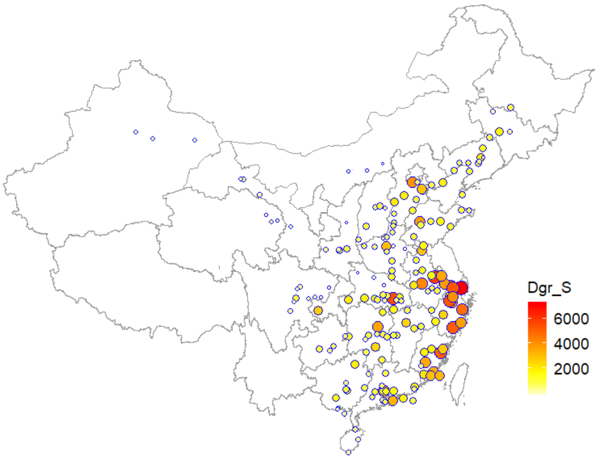
(c) Kendall correlation (d) All periods pooled

Figure 2.3 Correlations between centralities obtained from infrastructure network and service network

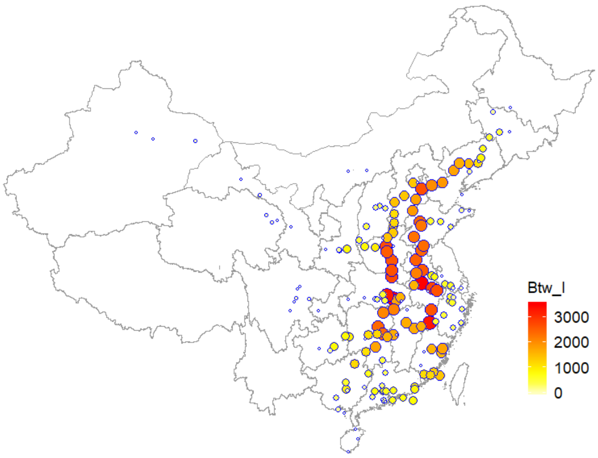
Figure 2.4 shows centralities of individual cities in 2015 based on infrastructure network and service network respectively. Centralities, esp. degree and betweenness, in the service network show stronger variations across cities than in the infrastructure network. This is because centrality measures in the infrastructure network does not incorporate service frequency and scheduled travel time which vary significantly across edges and nodes. In addition, rankings of cities also differ in these two networks. Specifically, the five cities with the highest degree centrality are Shanghai, Nanjing, Wuhan, Hangzhou and Guangzhou in service network, whereas they are Wuhan, Nanjing, Chengdu, Zhuzhou and Shangrao in infrastructure networks. The top-5 cities in terms of betweenness are Wuhan, Zhengzhou, Beijing, Tianjin and Changsha in service network, while Wuhan, Tianjin, Shangrao, Jinan and Changsha are the top-5 cities in infrastructure network. In terms of harmonic centrality, the top-5 cities are Wuhan, Zhengzhou, Changsha, Nanjing and Hangzhou in service networks, whereas only Wuhan and Hangzhou appear in the top-5 list of infrastructure network.



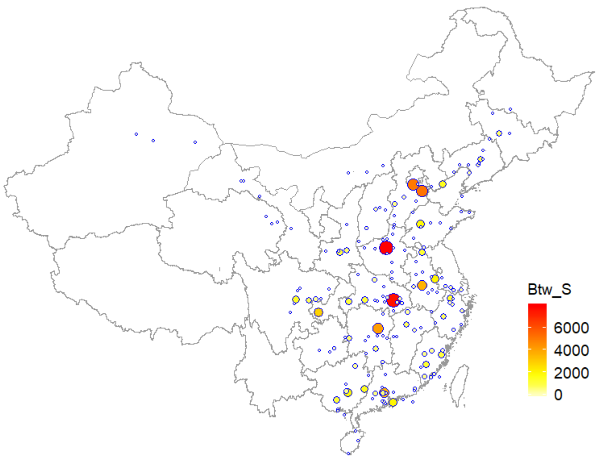
(a) Degree-Infrastructue



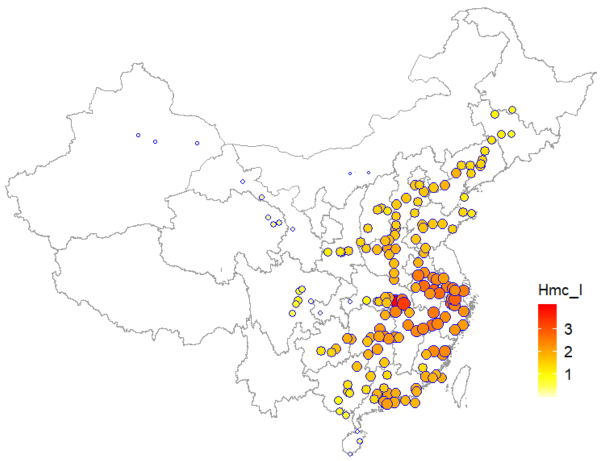
(b) Degree-Service



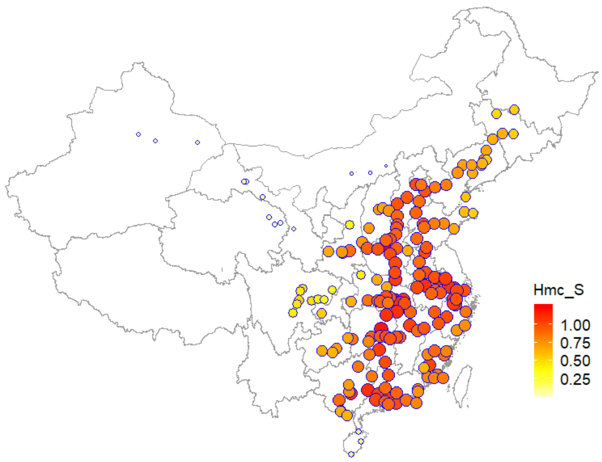
(c) Betweenness-Infrastructue



(d) Betweenness-Service



(e) Harmonic-Infrastructue



(f) Harmonic-Service

Figure 2. 4 Comparison between HSR infrastructure network and service network in 2015 (Cities without HSR are excluded from the figure.)

According to Figure 2.4, we can observe a number of differences with respect to the spatial distributions of centralities between infrastructure and service networks. For example, in the infrastructure network, cities with the highest degrees (red and orange dots) are scattered throughout the country, but in the service network, these cities are concentrated in Yangtze River Delta. Similarly, many cities along the Beijing-Shanghai line and the Beijing-Guangzhou line can achieve high betweenness in the infrastructure network, but only a handful of cities, mostly located in central China, can achieve high transitivity in the service network in terms of transitivity. Both networks have similar patterns in the spatial distribution of harmonic centrality, but there is some slight difference. In the service network, there is a much clearer polarization of strong and weak cities. Although the service network has a lot more cities with high accessibility than the infrastructure network, the rest of the cities in the service network have much lighter colors, indicating a much larger difference between the strong and weak cities. In the infrastructure network, however, although only a few cities enjoy high accessibility, the difference between strong and weak cities is much milder, as majority of the cities have medium level accessibility.

Table 2.1 shows that centralities obtained from infrastructure networks have weak association with cities' demographic and economic characteristics. Centralities obtained from service networks, especially degree and betweenness, have stronger association with economic activities. Harmonic centrality of service network appears to have a weaker linkage with population and GDP. A possible explanation is that harmonic centrality is considerably driven by the physical location of the city in the network. Cities with locational advantages, such as those located in Central China, generally have high values of harmonic centrality despite their lower levels of economic activities compared with cities in East China. Taken together, the centrality measures from service networks are more consistent with the level of development of individual cities and better reflect the true importance of a city in the HSR network. This is consistent with the preference of flow approach (service network) over node approach (infrastructure network) in characterizing urban networks (Yang et al., 2019). Thus, discussions in the next section are based on the centralities generated from service networks.

Table 2. 1 Correlation between centrality measures and population or GDP

	Degree		Betweenness		Harmonic	
	Infrastructure	Service	Infrastructure	Service	Infrastructure	Service
Population	0.286	0.469	0.206	0.435	0.222	0.298
GDP	0.364	0.685	0.276	0.545	0.373	0.417
GDP per capita	0.242	0.414	0.175	0.239	0.321	0.326

2.5. Disparity analysis

Figure 2.5 shows the overall disparities among all the studied cities. Theil's T index of harmonic centrality (Hmc) have decreased over time, suggesting that cities are becoming more equal in terms of accessibility. On the contrary, cities appear to be more unequal regarding betweenness centrality (Btw) which reflects a city's transitivity, indicating that metropolises' capability of channelling traffic between different HSR train services has been enhanced. As a result, the inequality in aggregate measure (Agg) remains almost unchanged with a slight increase. The remainder of Section 2.5 will focus on the inequalities within and between different economic regions, tiers of cities, and megalopolises.

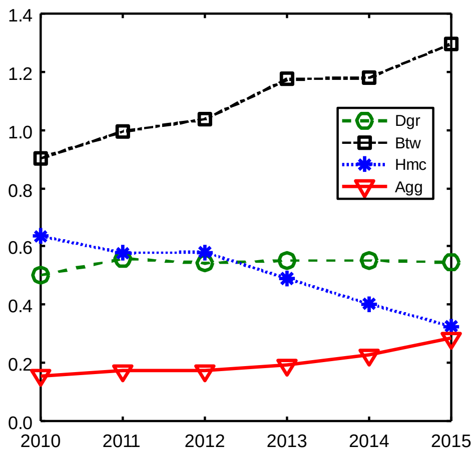


Figure 2. 5 Overall disparity of all sampled cities (Theil's T index)

2.5.1 Disparities by economic regions

Based on the socio-economic status of different provinces, the State Council of China divides the country into four major regions, namely East, Central, Northeast, and West. Figure 2.6 shows the geographical location of each region. Following this standard, we examine the inter-temporal changes in inequalities of HSR development (more precisely, provision of HSR services) within these four regions as well as inequalities between these regions.

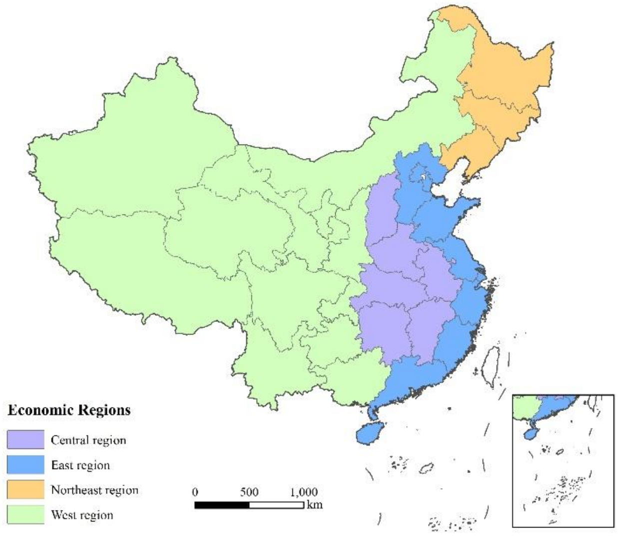


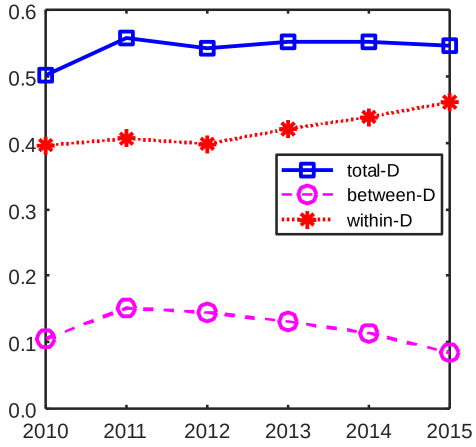
Figure 2. 6 Four economic regions of China

Table 2.2 presents the mean values of the centralities across all studied cities in each region during the study period. All four regions have seen a considerable growth in centrality values. However, the east and central regions dominate the development of HSR in this period. Among the three centrality measures, betweenness is the most sensitive to opening of new HSR lines and is not necessarily increasing throughout the period. The impact of the system-wide deceleration of HSR trains after the 'Wenzhou train collision' happened in 2011 can be immediately seen, as there is a decrease in the average harmonic centrality values in all the regions in the following year.

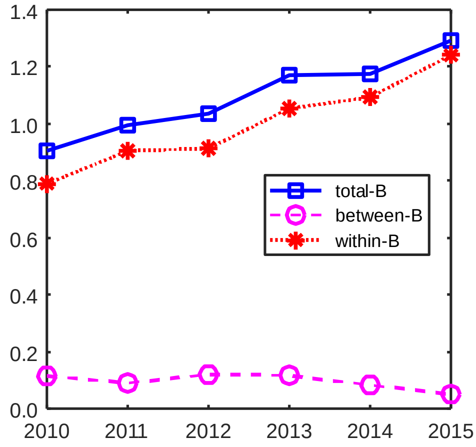
Table 2. 2 Mean centrality values by economic regions

Region (number of cities)		2010	2011	2012	2013	2014	2015
East (126)	Dgr	164.07	398.59	378.71	547.09	787.85	1057.62
	Btw	420.8	486.9	504.5	831.5	1081.0	1230.6
	Hmc	0.1251	0.2615	0.2449	0.3643	0.5027	0.7160
	Agg	0.3711	0.4163	0.4196	0.4889	0.5760	0.6243
Central (91)	Dgr	76.73	115.49	117.15	222.44	378.73	701.54
	Btw	217.8	288.5	268.8	453.0	744.8	1394.9
	Hmc	0.1056	0.1933	0.1803	0.3528	0.5028	0.8146
	Agg	0.2626	0.2610	0.2592	0.3870	0.4864	0.6399
Northeast (39)	Dgr	16.59	34.44	36.59	171.08	264.18	307.85
	Btw	36.6	82.5	66.3	309.6	238.4	305.2
	Hmc	0.0363	0.0850	0.0786	0.2269	0.2883	0.3690
	Agg	0.0792	0.1072	0.1048	0.2559	0.2813	0.2782
West (85)	Dgr	8.55	10.96	12.38	17.60	68.64	215.95
	Btw	11.4	39.0	12.6	23.5	192.0	569.7
	Hmc	0.0093	0.0245	0.0148	0.0238	0.1238	0.2829
	Agg	0.0214	0.0313	0.0200	0.0254	0.1146	0.2205

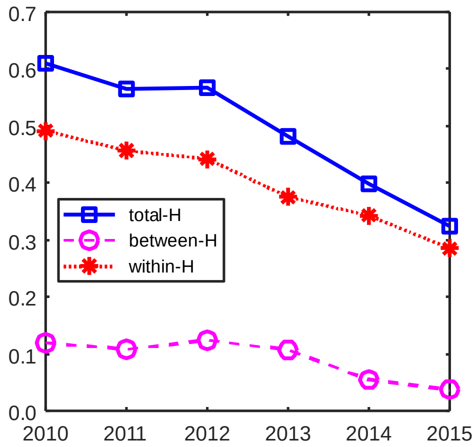
By applying Theil's T index, we decompose the total inequality across all cities sampled into between-region inequality and with-region inequality (Figure 2.7). Disparity among cities within the same region is much stronger than the disparity between different regions. As a result, the trend of total disparity of each centrality measure is mainly driven by the trend of within-region disparity. That is, although the disparity between different regions tends to decrease, the total disparity may not decrease. In particular, the four regions show a trend of convergence in HSR development. Among cities in the same region, as more cities are connected to the HSR network, the inequality in accessibility (harmonic) has been quickly reduced, but the inequalities in connectivity (degree) and transitivity (betweenness) appear to increase. This implies that although cities are getting more inter-connected with each other, the provision of HSR service is progressively concentrated in only a few cities of a region.



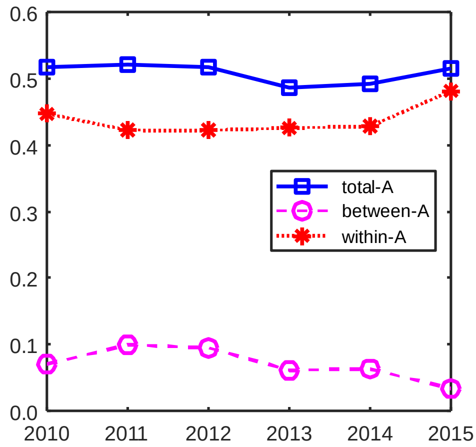
(a) Degree



(b) Betweenness



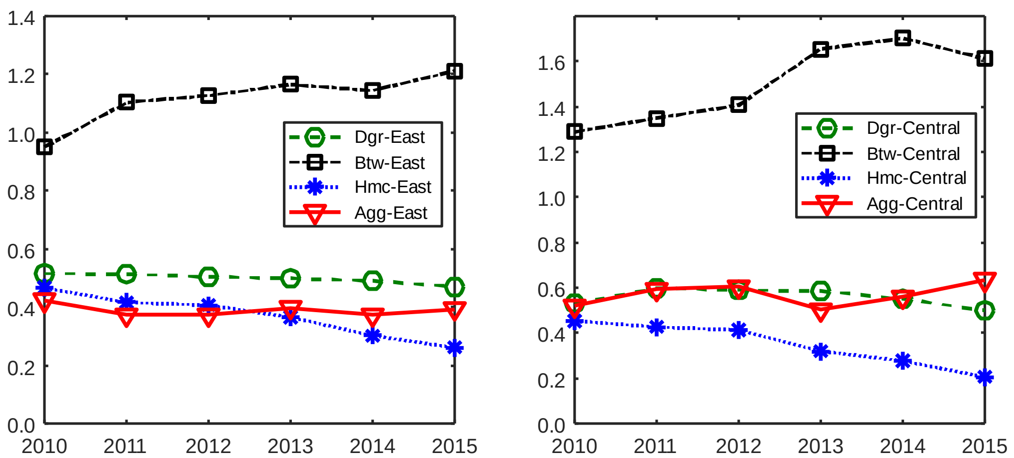
(c) Harmonic



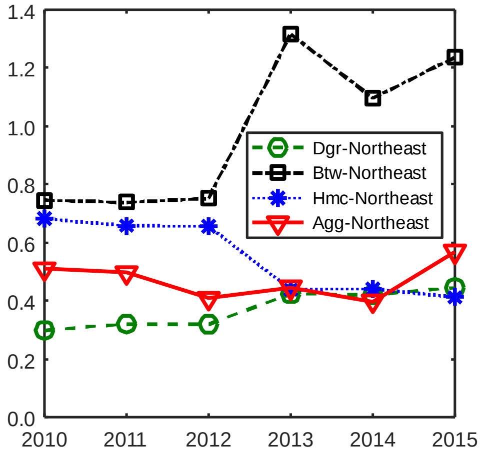
(d) Aggregate

Figure 2. 7 Between-region and within-region disparity: Theil's T index 2010-2015

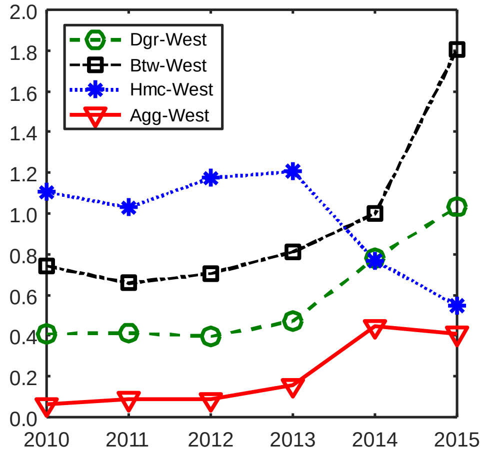
The within-region disparity shown in Figure 2.7 is the average disparity across all the four regions. However, the inter-temporal variations of individual regions may differ (Figure 2.8). Aggregating all the three centralities, the inequalities within the East, Central and Northeast regions remain stable, whereas the inequality within the West has experienced a notable increase. This is mainly contributed by the widening inequality in degree centralities of cities in the West. In particular, the inequalities in degree centralities have barely changed within the East and Central regions and slightly increased in the Northeast region, whereas the inequality in the West has been almost doubled. Unlike small cities in the East, those in the West are left behind probably because of lower service frequency. Given that small cities in the West have lower levels of urbanization and economic activities, they are bypassed by many HSR trains. On the other hand, every region sees a convergent trend in harmonic centralities and a divergent trend in betweenness centralities among its cities. That is, each region has been increasingly relying on a few large cities to channel inter-city traffic. These large cities include Beijing, Tianjin, Nanjing, Hangzhou and Guangzhou in the East, Wuhan, Zhengzhou and Changsha in the Central, Shenyang and Changchun in the Northeast, and Chengdu and Chongqing in the West. This observation is consistent to the National Urban Hierarchical Plan (2006-2020) in which cities nominated as the national central cities are expected to lead regional development and radiate their impacts to others in the country. Thus, these cities may have advantages over the others in gaining national resources including transportation services.



(a) East (b) Central



(c) Northeast



(d) West

Figure 2. 8 Within-region disparities by regions

In addition, it is worth noting that the Northeast and the West regions have experienced more dramatic changes in within-region disparities than the other two regions. This could partially be attributed to the opening of new HSR lines in the Northeast, e.g. Harbin-Dalian line at the end of 2012, and in the West, e.g. Chongqing-Lichuan segment at the end of 2013. These two regions are the least developed in terms of HSR services and therefore opening of new lines affects inequality within these two regions more than the other well-developed regions. For example, the Harbin-Dalian line make more cities in the Northeast to be accessible by HSR, leading to reduced inequality of accessibility, but it also strengthens the bridging role of Shenyang between the Northeast and the other parts of China, as Harbin-Dalian line and Qinhuangdao-Shenyang line join in Shenyang. Similarly, the transitivity of Changchun is also enhanced since Changchun-Jilin line and Harbin-Dalian line join in Changchun. Therefore, Shenyang and Changchun experienced a significant increase in betweenness centrality whereas the values of the other cities remained unchanged, contributing to the increase in with-region disparity. In the West region, the increased inequality in transitivity and connectivity could be caused by the enhanced roles of several metropolises in long-haul services after opening of new lines. For instance, the

Chongqing-Lichuan segment is the final piece of the Shanghai-Wuhan-Chengdu corridor, one of the east-west HSR corridors in China, and hence its opening completes this corridor by linking the west and east rail segments. As a result, Chongqing and Chengdu, being the two major cities on the west segment of the corridor, are served by new direct long-haul HSR trains linking the east part of China. Meanwhile, the topography and landform of the West region limit the operating speed of HSR. To reduce the travel time between large cities in the west and other parts of China, newly added long-haul HSR services may bypass small and medium cities in the west. Consequently, small cities enjoyed relatively marginal improvement in HSR services, and their residents may find it more convenient to transfer at Chongqing and Chengdu when traveling to the East region.

2.5.2 Disparities by city tiers

Several studies argue that smaller intermediate cities are more likely to be bypassed by HSR services in favour of the metropolises, and as a result HSR has intensified the polarization between small and large cities (Urena et al., 2009; Moyano and Dobruszkes, 2017). In this section, we investigate the disparities between and within different tiers of cities. We classify all the selected cities into three tiers based on their total and permanent urban population sizes.[12] This classification incorporates the standard set by the Ministry of Housing and Urban-Rural Development of China. In particular, tier 1, tier 2 and tier 3 denote large, medium and small cities respectively.

Table 2.3 presents the average centrality values of each tier of cities. Although

[12] Tier 1 includes cities with total population over 5 million and permanent urban population over 1 million. Tier 2 includes cities with total population in the range of 3-5 million and permanent urban population over 0.5 million. Tier 3 includes cities with total population in the range of 1-3 million and permanent urban population below 0.5 million.

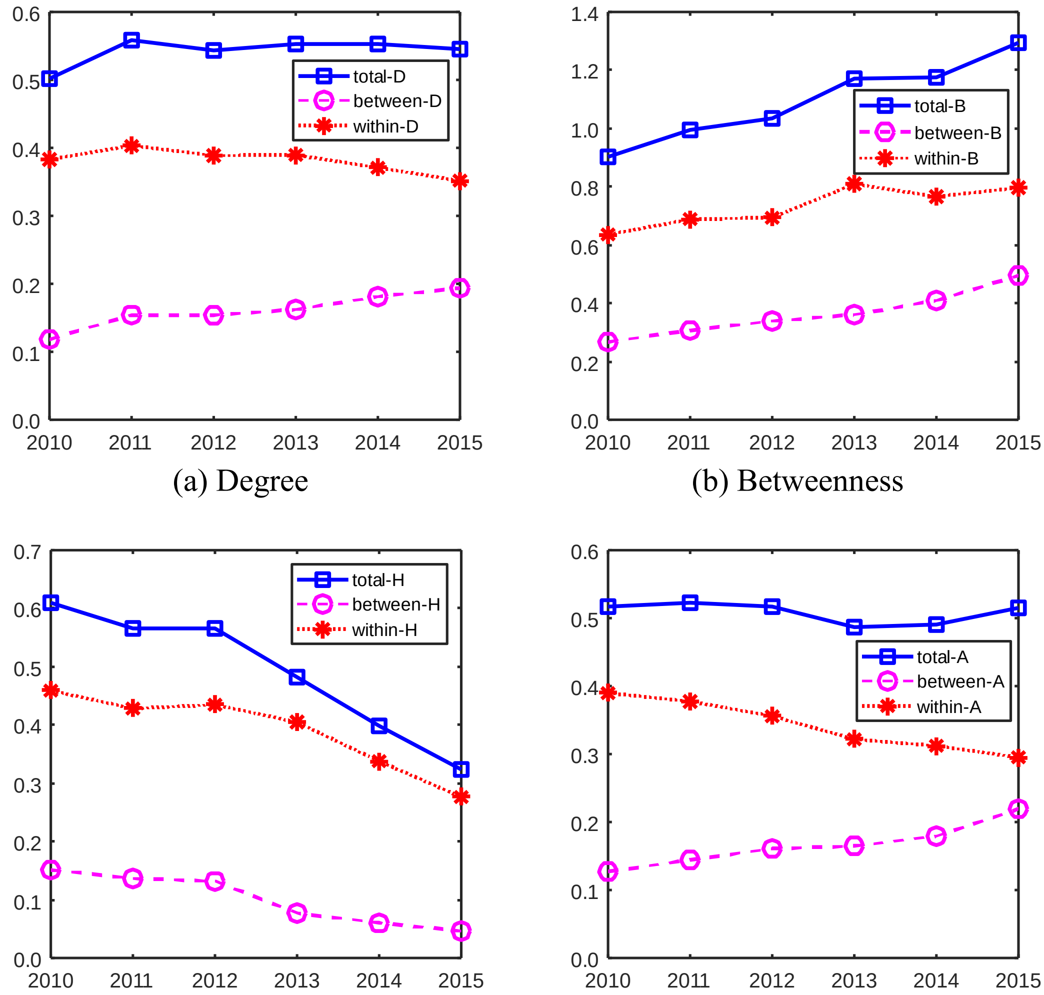
cities of tier 1 are clearly much better-developed in HSR than those of the other two tiers, which is consistent with Xu et al. (2018) and Sun et al. (2020), medium and small cities have experienced faster growth since 2013. For example, during this six-year period, the average aggregated indicator of tier 1 cities has increased by 0.4 times, while those of tier 2 cities and tier 3 cities have increased by 1.2 and 3.1 times respectively. This is expected as more medium and small cities are connected by HSR over the time. Based on the growth rates, while the development of tier 2 cities is mostly contributed by the increase in degree, the most remarkable development of tier 3 cities is the dramatic increase in betweenness.

Table 2. 3 Mean centrality values by tiers of cities

Tier (number of cities)		2010	2011	2012	2013	2014	2015
Tier 1 (49)	Dgr	397.86	875.10	834.45	1240.06	1747.53	2408.12
	Btw	2137.4	3005.8	2961.2	4367.2	6383.4	9658.0
	Hmc	0.2495	0.4790	0.4380	0.6332	0.8315	1.1371
	Agg	0.9615	0.9409	0.9457	1.1046	1.2590	1.3643
Tier 2 (68)	Dgr	64.97	156.04	151.68	272.99	450.76	726.50
	Btw	127.4	109.8	102.8	285.0	367.4	536.7
	Hmc	0.0969	0.2116	0.1968	0.3478	0.5028	0.7796
	Agg	0.2474	0.2855	0.2775	0.3662	0.4614	0.5531
Tier 3 (224)	Dgr	22.84	42.48	43.10	80.43	149.95	268.13
	Btw	0.1	1.4	0.6	2.3	34.2	62.6
	Hmc	0.0392	0.0807	0.0747	0.1527	0.2496	0.4199
	Agg	0.0635	0.0737	0.0769	0.1290	0.1874	0.2606

Figure 2.9 shows the variation in disparities between and within city tiers. As reflected by the aggregated indicator, the inequality between different tiers has been increasing, but it has been offset by a decrease in inequality within each city tier. Similar pattern is also observed in degree centrality. In terms of betweenness, both within-tier and between-tier disparities have increased, whilst the within-tier disparity has been mitigated slightly since 2013. In contrast, there is a clear trend of convergence in harmonic centrality both between different tiers and within the same tier. In general,

although medium and small cities are gradually catching up with large cities in terms of accessibility, they are still increasingly disadvantaged in terms of connectivity and transitivity.

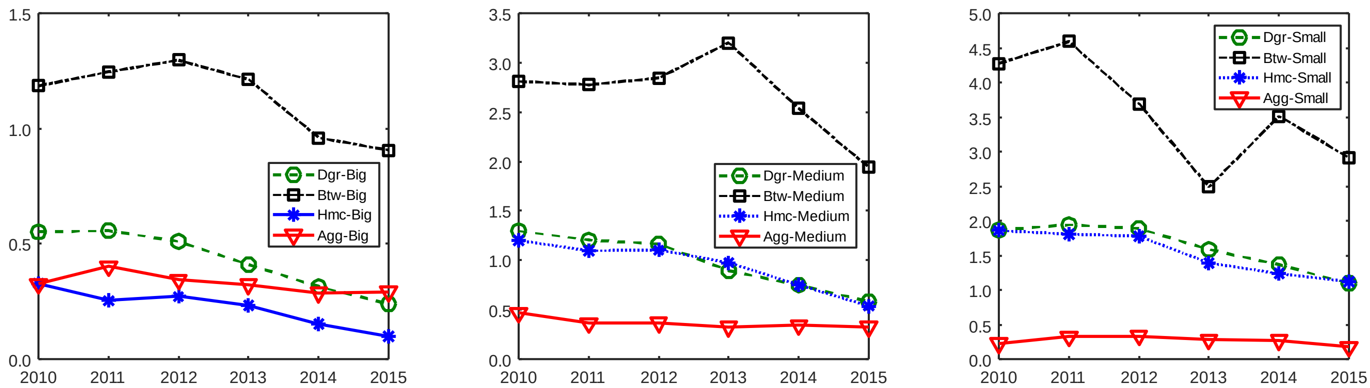


(a) Degree (b) Betweenness

(c) Harmonic (d) Aggregate

Figure 2. 9 Between-tier and within-tier disparities: Theil's T index 2010-2015

Figure 2.10 reports the changes in within-tier inequalities of tier 1, tier 2 and tier 3 cities respectively. In general, HSR development among tier1 cities is more balanced, while the development in tier 2 and tier 3 cities is not quite equal. This is because small cities are not the main target of HSR network planning. Provision of HSR services in small cities is commonly a by-product of linking large cities. As a result, small cities which are luckily located along the routes linking large cities are much better served by HSR than the others. As large cities are concentrated in the east part of China, small cities in the East China are much stronger than those in the West in terms of HSR development. However, as the HSR network expands to the west part of China, more medium and small cities in the West China are connected. As a result, for each of the three tiers, among cities belong to the same tier, there seems to be a convergent trend, especially in degree and harmonic centralities (Figure 2.10). The inequality in betweenness within each tier also shows a decreasing trend, but it has experienced substantial increase and decrease in various years until 2014, especially for tier 2 and tier 3 cities. These variations lead to the increasing pattern of average within-tier disparity during 2010-2013 (Figure 2.9 (b)) and little change in the within-tier inequality of aggregated indicator of all the three tiers.



(a) Tier 1 (b) Tier 2 (c) Tier 3

Figure 2. 10 Within-tier disparities by tiers of cities

2.5.3 Disparities by megalopolises

Megalopolis (officially termed as a "city cluster" in China) is defined as a region that results from the coalescence of a chain of metropolitan areas (Gottmann, 1957). Consequently, megalopolis is a highly developed urban spatial form in the process of industrialization and urbanization. According to China's new urbanization plan, i.e.

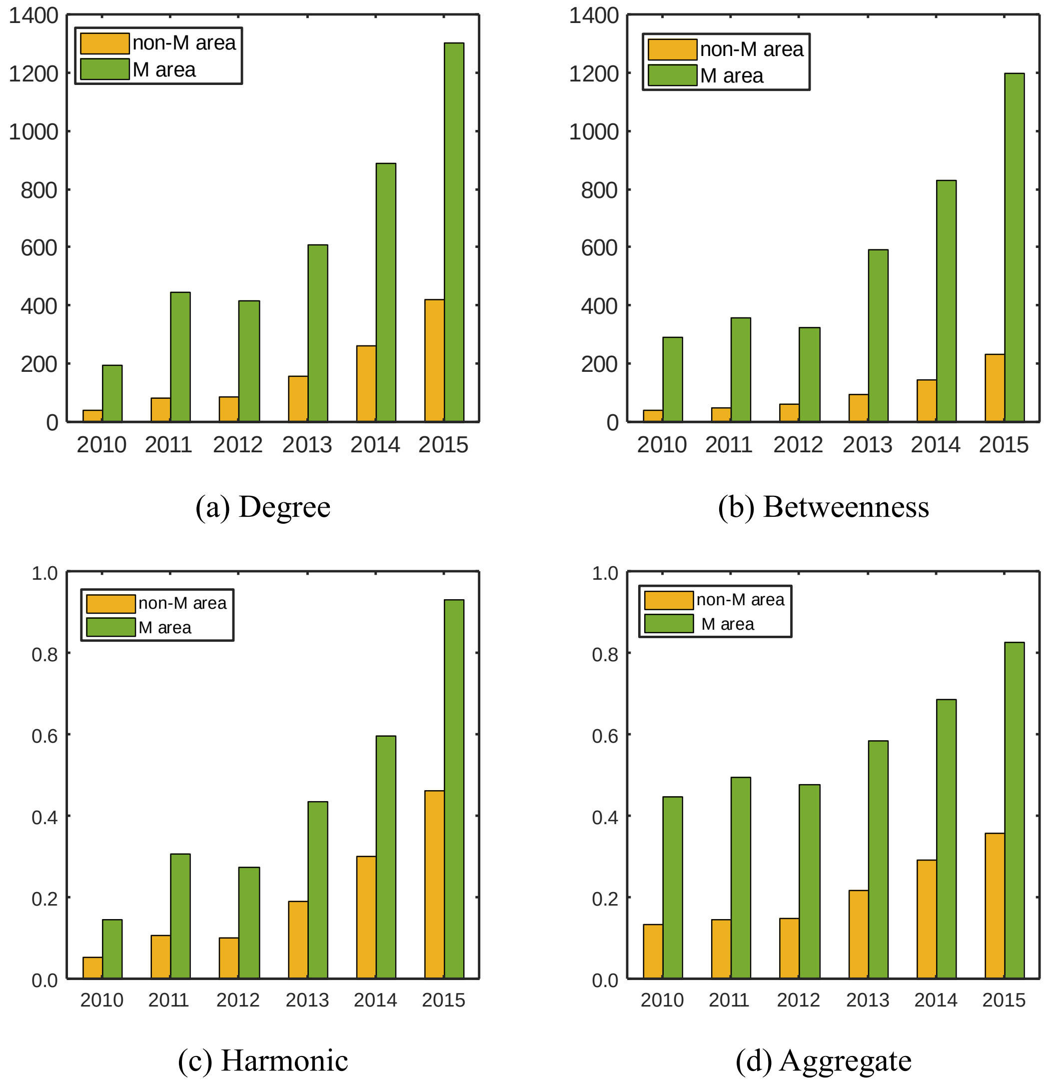
the New-Type Urbanization Plan (2014-2020), the Chinese government gives priority to the development of five world-class city clusters, namely Yangtze River Delta (YRD), Pearl River Delta (PRD), Jing-Jin-Ji (JJJ), Middle-Yangtze River (MYR), and Cheng-Yu Region (CY). These five megalopolises account for 40% of China's population but only 11% of the nation's land (Table 2.4), and they play a key role in Chinese economy, accounting for 55% of China's GDP. According to the new urbanization plan, these megalopolises have the highest priority over the other cities in developing through the integration of public resources, together with enhanced connections among cities within the megalopolises via tight and efficient transportation links, such as highways and HSR. Thus, it is relevant to compare cities in these megalopolises with others as well as HSR development in these megalopolises.

Table 2. 4 Economic and population sizes of the five megalopolises (Source: China index academy)

Megalopolis	Land area (km^2)	2016 GDP (1000 billion CNY)	2015 population (10 million)	GDP per capita (1000 CNY)	GDP Density (10,000 CNY / km^2)
Pearl River Delta	5.5	6.8	58.74	115.6	12346
Yangtze River Delta	21.2	14.7	150	97.5	6949
Jing-Jin-Ji	21.5	7.5	110	67.5	3499
Middle-Yangtze River	34.5	7.1	120	56.8	2049
Cheng-Yu Region	24.0	4.8	98.19	49.1	2007
China total	963.4	74.4	1370	54.0	772

Figure 2.11 compares the average centralities between cities belong to the five megalopolises (M-area) and those not belonging to any of the five megalopolises (nonM-area). Clearly, megalopolises are better served by HSR than non-megalopolises, as these five megalopolises contribute over 50% of the total HSR services. The non-megalopolises' share of HSR services has increased by about 10%, but in terms of centrality measures, the gap between megalopolises and non-megalopolises has been widened during the study period. This finding is somewhat consistent to the new

urbanization plan.



(a) Degree (b) Betweenness

(c) Harmonic (d) Aggregate

Figure 2. 11 Mean centrality values: megalopolises versus non-megalopolises

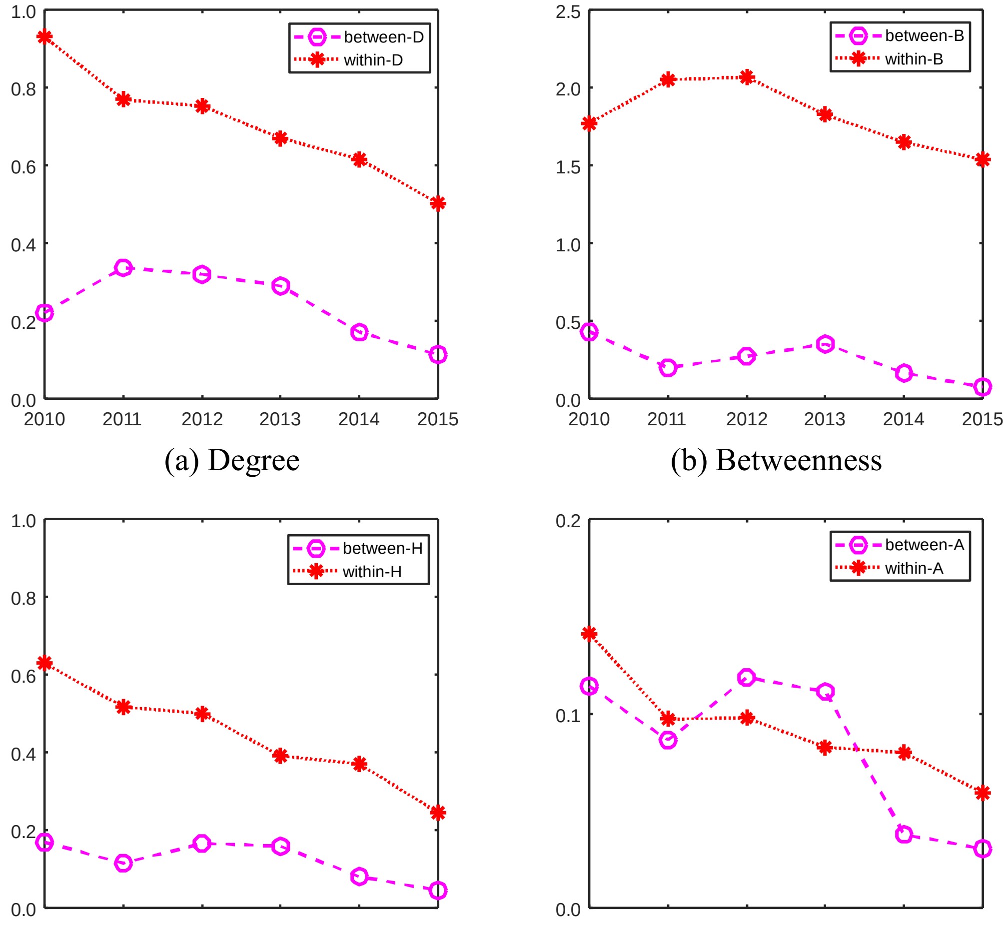
Table 2.5 lists the evolution of average HSR centralities in each megalopolis. Yangtze River Delta performs the best in connectivity, Jing-Jin-Ji achieves the best in transitivity, and Pearl River Delta surpassed Middle-Yangtze River in 2015 and became the most accessible region. Cheng-Yu Region experienced a significant growth after 2014 even though it performs the worst among the five megalopolises.

Table 2. 5 Mean centrality values by megalopolises

Megalopolis (number of cities)		2010	2011	2012	2013	2014	2015
Yangtze River Delta (26)	Dgr	391	941	879	1276	1555	2087
	Btw	1033.7	1306.5	1184.4	2327.2	1943.5	2032.4
	Hmc	0.2342	0.4217	0.3900	0.5650	0.6501	0.9445
	Agg	0.7704	0.7774	0.7681	0.9052	0.8668	0.9333
Pearl River Delta (9)	Dgr	227	673	563	671	1026	1376
	Btw	69.2	324.3	325.9	321.1	1269.4	1935.2
	Hmc	0.1260	0.3978	0.3648	0.4577	0.7289	1.1890
	Agg	0.3759	0.6205	0.5945	0.5777	0.8039	0.9806
Jing-Jin-Ji (13)	Dgr	171	400	404	684	1123	1405
	Btw	1551.0	1115.8	985.3	2086.2	4259.4	5345.6
	Hmc	0.1762	0.4252	0.3929	0.6205	0.7854	0.9791
	Agg	0.5806	0.6428	0.6339	0.8086	0.9663	0.9588
Middle-Yangtze River (28)	Dgr	132	179	177	330	621	995
	Btw	436.6	597.8	589.4	973.5	1334.2	2379.8
	Hmc	0.1419	0.2524	0.2308	0.4836	0.6819	1.0389
	Agg	0.3892	0.3708	0.3660	0.5425	0.6748	0.8843
Cheng-Yu Region (16)	Dgr	28	36	36	45	161	320
	Btw	2.0	138.9	1.5	1.6	485.6	1579.6
	Hmc	0.0102	0.0598	0.0174	0.0190	0.1457	0.3922
	Agg	0.0343	0.0835	0.0288	0.0265	0.1592	0.3327

On average, both between-megalopolis disparity and within-megalopolis disparity have a decreasing trend (Figure 2.12), especially in terms of connectivity and accessibility. Another interesting observation from Figure 2.12 (d) is that the aggregated indicator has very low Theil’s T indexes throughout the period. This implies that cities belonging to these megalopolises have balanced HSR development overall, although some may be stronger in connectivity while others may be stronger in transitivity or accessibility. For each megalopolis, the within-megalopolis inequality has been reduced comparing 2015 with 2010 (Figure 2.13). However, the inequality within Cheng-Yu Region experienced a substantial increase in 2014 in all the three centrality measures. This is caused by the opening of Chongqing-Lichuan line which greatly improved the position of Chongqing and Chengdu, the two largest cities of the

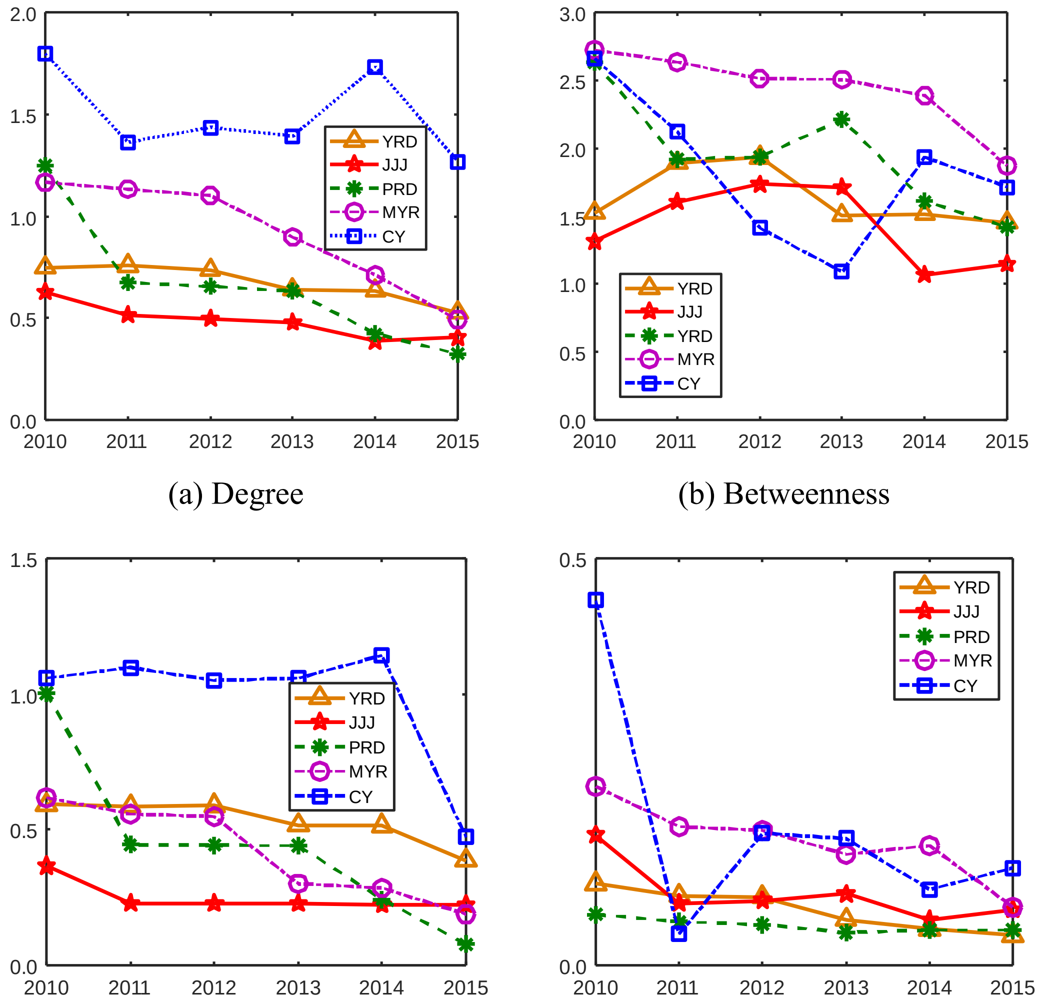
Cheng-Yu Region, while the other cities in the region are only marginally improved. In the Pearl River Delta, the within-megalopolis inequality in betweenness experienced a jump in 2013. This is because the extension of Guangzhou-Zhuhai line at the end of 2012 has weakened the transit function of intermediate cities, such as Foshan and Zhongshan, but strengthened the transitivity of Guangzhou, the largest city in Pearl River Delta.



(a) Degree (b) Betweenness

(c) Harmonic (d) Aggregate

Figure 2. 12 Between-megalopolis and within-megalopolis disparities: Theil's T index 2010-2015



(c) Harmonic (d) Aggregate

Figure 2. 13 Within-megalopolis disparities by megalopolises: 2010-2015

The final question is whether cities in a megalopolis play different roles in the HSR network. That is, some cities may specialize in connecting to the outside regions (out-region connection) while others are mainly linked to cities within the same megalopolis (intra-region connection). To do so, we calculate the "out-region" ("intra-region") centrality values by only taking into account HSR services which link a city with other cities outside (inside) of its own megalopolis. The corresponding Theil's T indices of each megalopolis are shown in Table 2.6. The Theil's T indices of all the centrality measures calculated based on "intra-region" services have decreased comparing 2010 and 2015, suggesting that cities within the same megalopolis have become increasingly similar in their ability to connect with each other by HSR. This again conforms to the new urbanization plan. However, the Theil's T indices based on "out-region" services tend to increase. In fact, only Jing-Jin-Ji and Yangtze River Delta see a reduced inequality in "out-region" connectivity and accessibility. Cities in all the other three megalopolises become more divergent in terms of reaching cities outside of their own megalopolises. In other words, inter-regional HSR services become more concentrated in a few core cities in these three megalopolises, and other non-core cities have to rely more on core cities to access cities in other megalopolises. This is consistent to the increased inequality of "out-region" betweenness in all megalopolises. In fact, our data suggest that in each megalopolis, intra-region connections have grown much faster than out-region connections during the period. In conclusion, as China's HSR network expands, core cities of each megalopolis start to play a major role in bridging the megalopolis and other regions, which gradually weakened non-core cities' capability of reaching other regions directly. Nevertheless, non-core cities have achieved stronger connection with core cities in the same megalopolis in terms of higher frequency and shorter travel time.

Table 2. 6 Disparity by megalopolises: intra-region versus out-region HSR services

megalopolis	Degree				Betweenness				Harmonic				Aggregate			
	Intra-region		Out-region		Intra-region		Out-region		Intra-region		Out-region		Intra-region		Out-region	
	2010	2015	2010	2015	2010	2015	2010	2015	2010	2015	2010	2015	2010	2015	2010	2015
JJJ	0.367	0.184	0.241	0.185	0.845	0.065	0.498	0.737	0.203	0.084	0.148	0.084	0.467	0.395	0.446	0.431
YRD	0.230	0.191	0.153	0.128	0.287	0.232	0.730	0.794	0.161	0.096	0.115	0.045	0.389	0.304	0.413	0.582
PRD	0.298	0.263	0.267	0.302	0.698	0.365	0.517	0.699	0.140	0.138	0.055	0.115	0.434	0.256	0.458	0.479
MYR	0.513	0.264	0.377	0.504	0.495	0.329	0.992	1.475	0.355	0.105	0.198	0.297	0.687	0.424	0.506	0.559
CY	0.786	0.330	0.012[a]	1.210	0.562	0.316	0.038	0.250	0.416	0.188	0.010	0.510	0.754	0.568	0.263	0.283

a. Cheng-Yu Region was not connected to cities outside by HSR until 2011. Thus, we report the out-region service disparity in 2011 for CY.

2.6. Concluding remarks

In this paper, we have examined whether cities in China are getting more equally served by HSR as the HSR network expands. Using HSR timetable data, our research explored Chinese cities' spatial disparities in connectivity, transitivity and accessibility in the HSR network. We emphasized on the intertemporal trend of these disparities from 2010 to 2015 during which the four-by-four grid network of China's HSR was formed. While the literature focuses mainly on the impact of HSR on regional economy and on whether HSR reduces or increases spatial disparity in economic development, our focus is HSR development per se instead of its economic impact. We view that a better understanding on how cities are served by HSR can shed light on their economic development.

The answer to our research question is complex and depends on the dimensions in concern. There are three main insights as summarized in Table 2.7. First, the difference between the economic regions has been reduced in all the three centrality measures. However, within each region, the inequalities tend to increase except for accessibility and the east region. Second, between the cities of different sizes, the disparities in connectivity and transitivity have increased, whilst the inequalities among cities in the same tiers have reduced, especially among large cities (Tier 1). Third, the disparities between and within the five megalopolises have both been reduced after pooling all HSR services together. However, when distinguishing HSR services within the megalopolis and those linking to cities outside of the megalopolis, we found that the reduced disparity mainly applies to HSR services within each megalopolis. Nevertheless, non-core cities have been further falling behind in connecting to cities outside of their own megalopolises. The only exceptions are JJJ and YRD in "out-region" connectivity and accessibility. In sum, interconnections among core metropolises have been increasingly enhanced as well as the importance of core metropolises in the HSR network. Cities nearby these core metropolises also benefit in HSR development by being more tightly connected to these core metropolises and other cities in the same region. Meanwhile, these non-core cities in major clusters are increasingly relying on core metropolises to access other parts of the country, showing a sign of specialization among core and non-core cities in the same cluster. However, small/medium-sized cities not belonging to any major city cluster appear to be further lagged behind in HSR development.

Table 2. 7 Summary of inter-temporal changes in disparities

Classification		Degree	Betweenness	Harmonic	Aggregate
Economic regions	Between	↓	↓	↓	↓
	Within	↑ East and Central (no change)	↑	↓	↑ East (no change)
City tiers	Between	↑	↑	↓	↑
	Within	↓	↓	↓	↓ Tier 2 and Tier 3 (no change)
Megalopolises	Between	↓	↓	↓	↓
	Within	↓	↓	↓	↓
	Intra-region	↓	↓	↓	↓
	Out-region	↑ JJJ &YRD (↓)	↑	↑ JJJ &YRD (↓)	↑

Our study revealed the differentiated impacts on a city's HSR connectivity, transitivity and accessibility. Naturally, as more small cities are linked to the HSR network, the disparity in accessibility will be reduced. However, despite being weighted by the generalized travel time, accessibility is less effective, compared with connectivity and transitivity, in distinguishing the real status of HSR development among highly diverse cities.

Findings of this research provide several insights for policy makers. First, although many small and weak cities have been linked to HSR network and their HSR accessibilities have been improved, it is still difficult for them to catch up with large cities in connectivity and transitivity, as the large cities have developed in an even faster pace. The enlarged gap in the supply of HSR services may be attributed to insufficient opportunities. In other words, it is questionable whether these small cities have been benefited from HSR. Therefore, small cities in remote regions should pay much more attention to increasing their attractiveness (via, for example, industrial upgrading) in addition to building railroads and stations. This point is relevant to China’s future HSR expansion plan. According to the plan, an increasing number of small cities in the central and western parts of China will be linked to the HSR system. Considering these cities’ relative low attractiveness and low population density, together with the region’s complex geographical conditions which raises difficulty in constructing HSR and achieving high operating speed, a serious cost-benefit analysis comparing the development of HSR infrastructure with other options, such as air transport, is warranted, before such heavy investment is materialized (see also Wang et al., 2017). As HSR connectivity is expected to remain at a low level at these small cities, the utilization of such expensive infrastructure will be a cause for concern.

Second, except YRD and JJJ, all the other megalopolises have experienced an increase in the disparities of out-region connectivity, transitivity, and accessibility. This increasing reliance of non-core cities on core cities to reach outside opportunities might be unavoidable in the short term. However, these non-core cities should also plan ahead so as to improve their own attractiveness. On the other hand, the reduction of both the intra-region and out-region disparities in Yangtze River Delta and Jing-Jin-Ji may imply more balanced development opportunities among cities in these two megalopolises.

Third, the substantial increase in the disparity of transitivity (betweenness centrality) may be a warning signal for the potential risk of the HSR system or for the existing scheduling approach. Although having passengers transfer at a few large stations is an efficient way of routing passengers between small cities (similar to the hub-and-spoke system in air transport), it increases the vulnerability of the system when the main transfer point is in trouble. The recent outbreak of novel coronavirus (COVID-19) in the city of Wuhan is a good example. As Wuhan has the highest transitivity among all the cities we studied (Table A.3), the city's position in the HSR network plays an important role in spreading the epidemic across China.

This paper has two major limitations which can lead to two avenues for future studies. First, caution should be taken when interpreting our results as we only include HSR in the picture. In fact, introduction of HSR services may be accompanied with reduction in other services, such as inter-city coaches, conventional trains and short/medium haul flights. Evidence shows that conventional trains suffer the most from the modal substitution of HSR, leading to the reduced service levels on conventional lines (Givoni and Dobruszkes, 2013).[13] In the case of China, for example, the inauguration of Beijing-Shanghai HSR line resulted in a reduction of 47 conventional trains which had served many small cities. The recent opening of Datong-Xi'an line has, for instance, led to the termination of several conventional routes that

[13] The deterioration of conventional train services can be caused by various reasons. For example, conventional trains and high-speed trains may share the same track with the latter having a higher priority than the former. Consequently, the expansion of HSR services would leave less infrastructure available for conventional trains. There can also be a natural adjustment on the supply of conventional services due to a shift of demand from conventional trains to HSR.

served small cities. Even though these cities used to be served frequently by conventional trains, they tend to be bypassed by HSR of which the primary focus is on large cities. The deterioration of conventional trains may widen the gap between small and large cities in terms of accessing rail services. As a result, excluding conventional trains would likely cause an underestimation on the disparities among regions. Similarly, although harmonic centrality can be interpreted as a city's accessibility via HSR alone, it is different from the concept of accessibility in measuring a city's capacity and potential to access markets and resources. The latter would be better measured by considering all possible modes of transportation.

Second, it would be useful to investigate the economic drivers underlying these disparity impacts by HSR in the spirit of the recent work on connectivity at Chinese airports (e.g. Zhang et al., 2017). The new urbanization plan might be a driver, but the plan may also be inspired by the evolving HSR service network. The key is to understand the mechanism behind the flows of capital and human resources and the changing relationships between cities (see detailed discussion in Zhang et al., 2019). For example, what we observe might be a net outcome of both agglomeration and spill-over effects of HSR. That is, while HSR facilitates metropolises to attract more resources from other smaller cities, it also helps with diverting certain activities to nearby cities by offering a tight connection between the metropolises and the nearby cities.

CHAPTER 3

IMPACT OF HIGH-SPEED RAIL NETWORK DEVELOPMENT ON AIRPORT TRAFFIC AND TRAFFIC DISTRIBUTION: EVIDENCE FROM CHINA AND JAPAN[14]

3.1 Introduction

By 2018, high-speed rails (HSR) have been operated in 16 countries and regions, achieving an extensive track length of over 40,000 kilometers (km) worldwide (International Union of Railways [UIC], 2018). Evidence of air traffic reduction on short/medium-haul routes (less than 800-1000km) facing direct competition from HSR has been well documented in the context of Northeast Asia such as China (Chen, 2017; Fu et al., 2012; Wan et al., 2016; Wang et al., 2018; Zhang et al., 2017; Zhang and Zhang, 2016), Japan (Clever and Hansen, 2008; Demizu et al, 2017; Fu et al., 2014; Kojima et al., 2017; Wan et al., 2016), and South Korea (Park and Ha, 2006), as well as in Europe (e.g. Albalate et al, 2015; Behrens and Pels, 2012; Clewlow et al, 2014; Dobruszkes, 2011; Dobruszkes et al., 2014; Jiménez and Betancor, 2012). Such substitution effect of HSR has been in fact welcomed by some policy makers for two major reasons. First, HSR may replace some flights, release airport slots, and alleviate airport capacity shortage (Jiang and Zhang, 2014) especially when it is infeasible to expand airport capacity to cope with demand surge. Second, replacing flights with HSR services may help to mitigate carbon emissions, as HSR releases much less greenhouse gas per passenger-km than air transport (e.g. Eurocontrol, 2004; Givoni, 2007; Givoni and Banister, 2006; Sun et al., 2017). As a result, some European

[14] This chapter has been published. Liu, S., Wan, Y., Ha, H.-K., Yoshida, Y., & Zhang, A. (2019). Impact of high-speed rail network development on airport traffic and traffic distribution: Evidence from China and Japan. *Transportation Research Part A, 127*, 115-135

countries have been encouraging the air-HSR intermodal transport such that HSR can replace air transport to feed long-haul or international flights (Commission of the European Communities, 2001).

Despite abundant route-level studies, it is the amount of traffic reduction at an airport or in the entire air transport system that matters to airport congestion mitigation and emission reduction. First, with mixed empirical evidence on HSR's impacts on long-haul air routes, one may not rule out the possibility of an overall increase in air traffic. For example, Bilotkach et al. (2010) find significant positive impact on flight frequency after pooling a sample of short-haul and long-haul European routes together in a regression analysis. Based on a case study of five European city-pair markets, Dobruszkes (2011) found that in markets where HSR is less competitive than air in terms of travel time, air services continued growing despite the entry of HSR. Studies on domestic air transport markets in China have revealed an increase in airline seat capacity on routes over 800km (Wan et al., 2016) and an increase in passenger numbers on routes over 1000km (Zhang et al., 2018) after the introduction of parallel HSR services. Second, HSR may increase air traffic by expanding airports' catchment with air-HSR intermodal transport (Jiang and Zhang, 2014; Vespermann and Wald, 2011; Xia and Zhang, 2017). In theory, Avenali et al. (2018) prove that the provision of air-HSR intermodal services may substantially increase traffic in air routes fed by HSR and hence increase total traffic at hub airports if air and HSR are not close substitutes. Takebayashi (2016, 2018) models two competing gateway hub airports linked by HSR. He shows numerically that the congestion at the heavily congested airport may not be reduced if HSR and the congested airport collaborates (Takebayashi, 2016). Moreover, under some conditions, even reducing airport charges at the less congested airport may not attract passengers away from the congested airport via air-HSR intermodal transport (Takebayashi, 2018). Third, facing with HSR competition, airlines may be forced to develop new routes with little HSR threat, e.g. international routes. In capacity constrained airports, released runway capacity are very likely taken by longer-haul flights, leading to more rather than less emission (Givoni and Dobruszkes, 2013). As a reaction to the expansion of HSR operations, China Southern Airlines, one of the “Big Three” Chinese airlines, planned to increase the share of international routes in its network from 18.5% to 40% (CAPA, 2011). As predicted by Jiang and Zhang (2016), airlines may give priority to hubbing and increase international coverage at their hub airports.

Therefore, empirical studies on HSR’s impact at the airport level are essential, but to our knowledge, very little attention has been devoted to this and we only find three related studies. Clewlow et al. (2014) study the association between the presence of HSR and airport-level domestic, intra-EU, and total traffic in Europe. Castillo-Manzano et al. (2015) estimate the impact of Spain’s HSR network expansion on the number of domestic passengers at Madrid-Barajas airport. Zhang et al. (2018) quantify the “complementary” effect of HSR on airports’ passenger enplanement in East Asia and Central Europe. This “complementary” effect is captured by introducing a policy variable, air-HSR integration, which is defined as the availability of on-site HSR services at the airport. All of these three studies use simple measures of HSR operations, such as a dummy variable indicating the existence of HSR service (Clewlow et al., 2014), the number of HSR passengers in the railway system (Castillo-Manzano et al., 2015) and a dummy variable indicating the practice of air-HSR integration (Zhang et al., 2018). These approaches ignore airports’ heterogeneous positions in an HSR network. In particular, airports located at the margin of the HSR network might face much weaker HSR impacts than those located at the center of HSR network. This is because in the latter case either a larger share of airport traffic is facing direct competition from HSR or a larger number of passengers can be fed into the airports by air-HSR intermodal transport. Thus, it is essential to measure individual airport city's capability to reach other cities via the HSR system.

This study contributes to the existing literature by investigating the impact of HSR development on airport-level traffic in a more comprehensive way. That is, we consider not only the airport-HSR station linkage but also the position of the airport in the entire HSR network, together with airport hub status. This allows us to achieve the followings. First, we are the first to take a network view of HSR development by associating air transport with the city's connectivity and accessibility to other cities in the HSR network. Second, we capture not only airport traffic increase due to HSR's feeding, but also traffic reduction due to HSR network development. Third, unlike Zhang et al. (2018) who examined the different impacts of air-HSR integration alone on hub and non-hub airports, we compare the joint impacts of HSR network development and air-HSR linkage on hub and non-hub airports. Fourth, we not only study total passenger traffic, but also investigate the impacts on domestic and international traffic separately. Another major contribution of our study is to compare the effects of HSR in China and Japan. This provides a better understanding on how different development stages of HSR could influence the results, which might provide important insights for future HSR development and airport capacity planning.

In terms of methodology, we fit econometric models with two sets of annual data over the period of 2007-2015. One consists of 46 airports in China and the other consists of 16 airports in Japan. A series of regression analysis is conducted to establish the relationship between domestic, international and total airport traffic and abovementioned factors. We apply two concepts widely used in the complex network theory, degree centrality and harmonic centrality, to measure an airport city's position in the HSR network. Degree centrality is used to measure an airport city's connectivity to other cities via HSR services, while harmonic centrality is used to measure an airport city's proximity, or so-called accessibility as defined by Wang et al. (2011), to all the other cities in the HSR network via HSR services.

Our findings reveal that a good connection between the airport and HSR station may bring an extra positive impact on airport traffic in spite of the traffic reduction associated with improved HSR connectivity and accessibility. This moderation effect mainly comes from the increase in international traffic. As a result, a net increase in airport passenger traffic may occur. Such net traffic increase is more likely to be achieved by adding HSR connections than by improving proximity to other cities in the HSR network, and is more likely to occur at hub airports than at non-hub airports.

The rest of this chapter is organized as follows. Section 3.2 briefly compares China and Japan's HSR development and network structures, defines two measures of an airport city's position in an HSR network by applying the concepts of degree centrality and harmonic centrality, and then develops the econometric specifications for regression analysis. Section 3.3 describes the data used in the research and the construction of variables. Regression results and main research findings are reported in Section 3.4. Section 3.5 provides concluding remarks and policy implications.

3.2 Methodology

3.2.1 HSR development in China and Japan

In this paper, we conduct a comparative study about the impact of HSR on airport traffic in China and Japan. We select these two countries for three major reasons. First, these two countries account for nearly 80% of the world's total HSR traffic in terms of passenger-kilometers.[15]

Second, China and Japan are underlying very different stages of HSR development. Figure 3.1 and 3.2 show the development of HSR network in China and Japan respectively during our sampling period (2007-2015) as well as the locations of our sampled airports. In China, even though the construction of the first HSR line was completed in 2003,[16] the HSR service was not provided until 2007 when the government implemented its sixth railway speed up campaign. However, over the sampling period, China's HSR network has grown out of almost nothing and expanded into the largest HSR system in the world, achieving a total length of 19730 km, encompassing 27 out of 31 provinces (Figure 3.1). Japan, on the other hand, inaugurated its first HSR (Shinkansen) service connecting Tokyo and Osaka in October 1964, just in time for the Tokyo Olympics, shaving 2.5 hours off the 513 km journey. After that, due to the public's affirmative response to these fast train services, the Shinkansen system experienced an impressive expansion between 1970s and 1990s. The main structure of Japan's network was established in 1990s and since then there was little change until 2004. Recent expansion projects since 2010 are relatively minor, since they only involve three branch lines linking to the peripheral regions (Figure3. 2). In other words, China was in the emerging and rapid development stages over our study period while Japan was in the matured stage with only some minor refinement in its HSR system. As much longer time has elapsed for the civil aviation markets in Japan to respond to HSR development, we are expecting a much milder impact in Japan than in China.

[15] Calculated by the authors based on HSR traffic data from International Union of Railways.

[16] Qinhuangdao-Shenyang passenger-dedicated line between Qinhuangdao and Shenyang is the first newly built HSR in China. The construction of this line started on August 1999 and finished on October 2003.

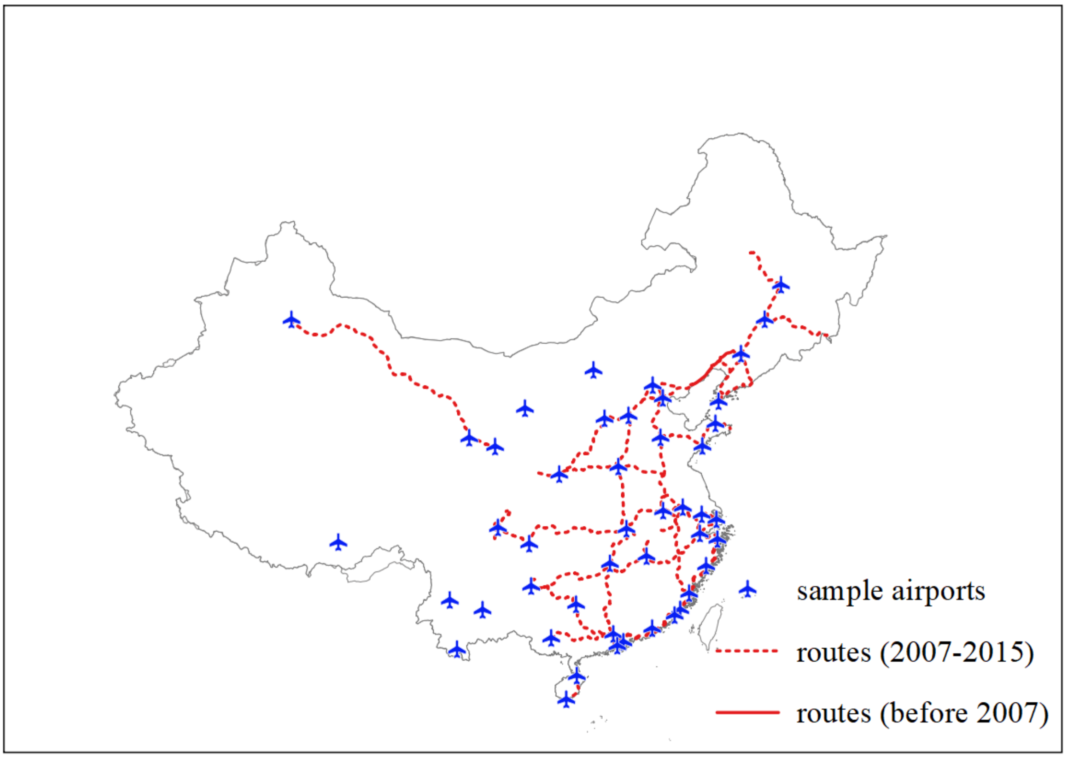


Figure 3. 1 HSR development in China over 2007-2015

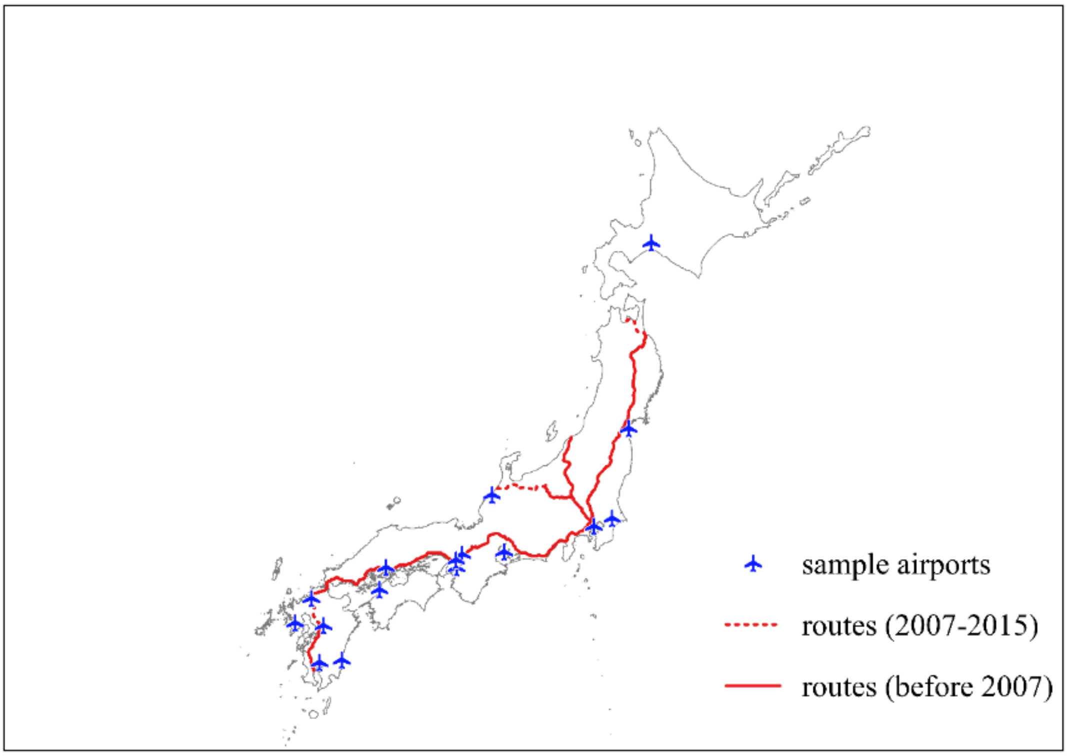


Figure 3. 2 HSR development in Japan over 2007-2015

Third, China and Japan have very different HSR infrastructure network due to the territorial difference between these two countries. By the end of 2015, China's HSR has developed into a network of four vertical corridors and four horizontal corridors together with many branch lines (Figure 3.1). Therefore, China's HSR network appears to be a grid without a clear central node. Japan's network is simpler, and Tokyo is the obvious central node (Figure 3.2). This tree or star-like structure is quite common in other countries with significant HSR development due to the small geographic scope that needs to be covered by the HSR system. This difference in network structure can cause a variation in the correlation among different centrality measures discussed in Section 3.2.2. In general, degree and harmonic centralities are more likely to have stronger correlation in the tree or star-like structure than in the grid-like structure. In other words, differentiated results between connectivity and accessibility are more likely to generate differentiated results in the context of China.

3.2.2 Centrality Measures

Centrality, developed by Freeman (1978), is a fundamental concept in network analysis to evaluate the importance of a node in a network. Among various measures of centrality, degree centrality and closeness centrality are the most commonly used to analyze transportation networks. Degree centrality can be interpreted as a node's connectivity in the network and closeness centrality may be interpreted as a node's accessibility by others in the network (e.g. Jiao et al., 2017; Wang et al., 2011; Wong et al., 2019). However, closeness centrality does not behave well in networks with disconnected components.[17] Therefore, given that HSR network is not fully connected

[17] Closeness centrality is associated with the inverse of the sum of distances from the node in concern to all the other nodes in the network. As the distance (or travel time) between nodes in disconnected components of a network is infinite, the closeness centrality will be zero for all the nodes in the network.

in its early stage of development, especially in China, following Boldi and Vigna (2014), we use the natural modification of closeness centrality, i.e. harmonic centrality, proposed by Marchiori and Latora (2000). Both centralities can be calculated based on the information of the HSR infrastructure network, i.e. the physical HSR tracks. However, infrastructure only tells the potential of improving accessibility and its full potential may be achieved only when adequate services are provided (Moyano et al., 2018) and the quality of the service is as important as the infrastructure (Moyano et al., 2019). Thus, in this study, centralities are calculated based on HSR service schedule data. This is especially important because some small HSR stations have very limited HSR services.

Degree is a straightforward centrality measure that quantifies the number of neighbors a node has. A node with high degree centrality has direct connections to many other nodes in the network. In this study, we use degree centrality to indicate the connectivity of an airport city to other cities in the HSR network. The degree centrality of airport city *i* is defined as:

$$C_D(i) = \sum_{j=1}^{N} a_{ij} \tag{1}$$

where a_{ij} indicates the connection between airport city *i* and prefecture-level HSR stations j. Thus, $a_{ij} = 1$ if there is a direct HSR service between nodes *i* and j, and $a_{ij} = 0$ otherwise. *N* denotes the total number of prefecture-level HSR stations in the networks. We define that two cities are directly connected via HSR service as long as passengers can travel from one city to the other without changing the trains. In addition, if a city pair is only served in one direction but not in the other, we assume these two cities are not directly connected.

Harmonic centrality comes from the idea of taking the harmonic mean of the node-pair distances. The harmonic centrality of airport city *i* is defined as:

$$C_H(i) = \sum_j^N \frac{1}{d(i,j)} \tag{2}$$

where $d(i,j)$ is the shortest distance (travel time in this study) between airport city *i* and prefecture-level HSR station *j* by using the HSR services and we set $d(i,j) = \infty$ if there is no direct HSR service between *i* and *j*. Although distance is widely used to measure $d(i,j)$, travel time may be more appropriate in the case of HSR network, because the maximum operating speed varies across different HSR lines (Wang et al., 2018). The shortest trip time is chosen to construct $d(i,j)$, whenever there exist multiple schedules between two cities and hence different scheduled trip times.

3.2.3 Model specifications

Throughout the analysis, we treat airports in China and those in Japan as two samples. We conduct regression analysis for each sample to characterize the relationship between airport-level passenger traffic and various HSR related variables, including the centrality measures defined in Section 3.2.1 and the intermodal linkage between the airport and HSR station. Eq. (3) is the main empirical model:

$$\begin{aligned} PXG_{it} = {} & \alpha_0 + \alpha_1 HSR_{it}^{Centrality} + \alpha_2\ AirHSR_{it} + \alpha_3\left(HSR_{it}^{Centrality} \times AirHSR_{it}\right) \\ & + \gamma_1 POP_{it} + \gamma_2 GDP\_POP_{it} + \gamma_3 LCC_{it} + \gamma_4 FuelPrice_{it} + \gamma_5 Compete_{it} \\ & + \gamma_6 Year2008_{it} + \gamma_7 Year2009_{it} + \gamma_8 Year2011_{it} + \mu_i + \epsilon_{it} \end{aligned} \tag{3}$$

where PXG_{it} is passenger throughput at airport *i* in year *t*. $HSR_{it}^{Centrality}$ is one of the HSR centrality measure, degree (SDgr) or harmonic (SHmc), of the city where airport *i* locates in year *t*. $AirHSR_{it}$ is a binary variable that equals to 1 if there is an intermodal linkage between airport *i* and an HSR station in year *t*. We include an interactive term between the centrality index and air-HSR intermodal linkage, $HSR_{it}^{Centrality} \times AirHSR_{it}$, to capture the possible feeding effect of HSR because of the convenient transfer between the airport and HSR station, and we expect the coefficient of this interactive term to be positive. We control for population size (POP), real GDP per capita (GDP_POP), low-cost carrier operation (LCC) and jet fuel price (FuelPrice). In addition, we also include airport competition (Compete) and demand shocks indicated by Year2008 (for China sample), Year2009 (for both China and Japan sample) and Year 2011 (for Japan sample) as control variables. Detailed construction of these control variables is described in Section 3.3. u_i is the airport fixed effect to control for unobservable airport-specific characteristics.[18] ϵ_{it} refers to the error term of airport *i* at time *t*. In this study, all variables are measured on the annual basis.

Route-level studies in the literature have revealed the relevance of origin-destination market distance to the impact of HSR on air services (refer to Dobruszkes and Givoni, 2013, for a literature review on some earlier studies). Although HSR has lower speed than air transport, the station access time and pre-departure processing time of HSR are in general shorter than air. Together with lower vulnerability to bad weather, HSR can have advantage over air in short-haul markets. According to Dobruszkes et al.'s (2014) EU-wide study, the impact of HSR travel time on air services diminishes sharply between 2 and 2.5 hours of HSR travel time, suggesting that there is a cutoff somewhere around a rail distance of 500km below which the impact of HSR on airlines is most remarkable. In China, HSR provides extensive long-haul services due to the country's large geographic scope and its ticket price is substantially lower than air. As a result, these two modes can compete in markets up

[18] We estimated both fixed effect and random effect models. The Hausman test rejects the hypothesis that there is no difference between fixed effect estimator and random effect estimator. Therefore, random effect model may produce inconsistent estimations and is not applied in this study.

to 1000km, which has been confirmed by several recent studies in China (e.g. Wan et al., 2016; Zhang et al., 2017; Zhang et al., 2018). Inspired by these findings, we incorporate the role of distance into the study by constructing three sub-measures of degree centrality for each airport *i*. Taking the city of airport *i* as the center, we divide all the other cities in the HSR network into three zones according to their HSR route distance to airport city i: HSR dominant zone (0-500km), HSR subdominant zone (500-1000km) and HSR non-dominant zone (over 1000km). Then, for each zone, we construct one sub-measure of degree centrality by considering cities in the respective zone only. That is, airport i's degree centrality of the HSR dominant zone is the summation of a_{ij} across all *j* belonging to this zone. Subsequently, these three sub-measures are named as SDgr0-500, SDgr500-1000 and SDgr1000+, respectively. In the case of Japan, since the HSR service between Tokyo and Hakata is the only one that exceeds 1000km and is relevant to airports in our sample, we merge HSR non-dominant zone into subdominant zone by adding SDgr 500-1000 and SDgr 1000+ together and creating variable, SDgr 500+, for Japan. The correlation between airport traffic and degree centrality may deteriorate as we move from HSR dominant zone to HSR non-dominant zone.

Albalate et al. (2015) suggest that HSR has differentiated impacts on hub and non-hub airports and the availability of on-site HSR station may play a role in hub airport traffic. Therefore, to distinguish the HSR's effects on hub and non-hub airports, we extend Eq. (3) into Eq. (4) by incorporating the hub status of airport and introducing a three-way interaction term $HSR_{it}^{Centrality} \times AirHSR_{it} \times Hub_{it}$ to identify whether or not hub airports benefit more from the linkage between HSR stations and airports. Hub_{it} is a dummy variable that indicates the hub status of airport *i* at time *t*. In this study, we consider Beijing, Shanghai, Guangzhou and Shenzhen as hubs for China, and Haneda, Narita, Kansai and Itami as hubs for Japan.

$$\begin{aligned} PXG_{it} = {} & \beta_0 + \beta_1 HSR_{it}^{Centrality} + \beta_2 AirHSR_{it} + \beta_3 Hub_{it} + \beta_4 (HSR_{it}^{Centrality} \\ & \times AirHSR_{it}) + \beta_5 (HSR_{it}^{Centrality} \times Hub_{it}) + \beta_6 (AirHSR_{it} \times Hub_{it}) \\ & + \beta_7 (HSR_{it}^{Centrality} \times AirHSR_{it} \times Hub_{it}) + \delta_1 POP_{it} + \delta_2 GDP\_POP_{it} \\ & + \delta_3 LCC_{it} + \delta_4 FuelPrice_{it} + \delta_5 Compete_{it} + \delta_6 Year2008_{it} \\ & + \delta_7 Year2009_{it} + \delta_8 Year2011_{it} + \mu_i + \epsilon_{it} \end{aligned} \tag{4}$$

In addition to using total passenger traffic as the dependent variable, to better understand how different types of traffic are associated with HSR development, we also fit models similar to Eq. (3) and Eq. (4) by replacing the dependent variable with domestic passenger traffic or international passenger traffic, respectively. Given that HSR tends to substitute air transport in domestic short-haul markets, most of the studies in the literature exclude international traffic. However, to assess HSR's role as a complement and feeder to air transport, it is essential to consider the international markets where HSR tends to have limited access.

3.3. Data and variable construction

We consider all major Chinese mainland and Japanese airports with annual throughput over two million passengers in 2015. That is, there are 48 relevant Chinese airports covering all the provincial capitals and sub-provincial cities in mainland China and 18 Japanese airports from majority of large cities in Japan. Among the 48 Chinese airports, Shanghai Pudong Airport (PVG) and Shanghai Hongqiao Airport (SHA) are merged into one airport entity (SHPV) because both airports are operated under the same authority and only aggregated international passenger traffic data are available for these two airports. Beijing Nanyuan Airport (NAY) is excluded due to lack of detailed information. In the case of Japan, Naha Airport (OKA) and Ishigaki Airport (ISG) are removed since they are located on Ishigaki Island which is not served by HSR. As a result, we have in our panel dataset 46 Chinese airports and 16 Japanese airports covering the period of 2007-2015. Locations of these sample airports are shown in Figures 1 and 2. These airports on average account for 92.2% of China's total passenger traffic and 81.7% of Japan's total passenger traffic. During the sampling period, 41 out of the 46 airport cities in China started HSR services and 12 airport cities in Japan are served by the Shinkansen system (Appendix B.1).

Various data sources are used to obtain airport-level traffic data. In the case of China, there is no single accurate data source which provides consistent information about total, domestic and international traffic of all the sampled Chinese airports. Thus, total passenger traffic (PAX) data is obtained directly from Statistical Data on Civil Aviation of China (2007-2015). China's Port-of-Entry Yearbook provides the number of international passengers using the airport as the point of entry in the previous year and therefore this information in the 2008-2016 versions is extracted to measure international passenger traffic (PAX_International). Domestic passenger traffic (PAX_Domestic) in China is estimated by subtracting the international passenger traffic from total passenger traffic of each Chinese airport.[19] The total, domestic and international passenger traffic data for airports in Japan is available from Japanese Ministry of Land, Infrastructure, Transport and Tourism. Table 3.1 summarizes the descriptive statistics of total, domestic and international traffic, variable of interest and control variables.

[19] Another possible source of domestic traffic data is Statistical Data on Civil Aviation of China, but this source only includes traffic data for major (not all) route segments. We have conducted robustness check for domestic traffic with this data source and the main results persist.

Table 3. 1 Descriptive statistics of all the variables

	China					Japan				
Variable	**Obs**	**Mean**	**Std.**	**Min**	**Max**	**Obs**	**Mean**	**Std.**	**Min**	**Max**
Dependent variable										
PXG (millions)	414	12.712	16.208	0.700	99.189	144	12.564	16.433	1.717	75.255
PXG_Domestic (millions)	414	11.051	12.267	0.681	67.363	144	9.133	14.307	1.143	64.994
PXG_International (millions)	414	1.660	4.422	0	32.359	144	3.431	7.118	0	31.104
Variable of interest										
SDgr	414	18.384	23.866	0	113	144	22.208	20.387	0	68
SDgr0-500	414	5.715	6.184	0	26	144	18	15.799	0	53
SDgr500-1000 or SDgr500+ [a]	414	6.290	8.540	0	43	144	4.208	5.174	0	17
SDgr1000+	414	7.217	12.614	0	67	-	-	-	-	-
SHmc	414	0.079	0.081	0	0.319	144	0.229	0.237	0	0.790
AirHSR	414	0.082	0.275	0	1	144	0.375	0.486	0	1
Control variable										
POP (millions)	414	7.446	5.571	0.465	30.166	144	5.091	4.031	1.104	13.515
GDP_POP (10 thousands in CNY or millions in JPY)	414	4.393	2.081	0.601	11.449	144	4.248	1.309	3.068	7.857
LCC	414	0.085	0.279	0	1	144	0.604	1.111	0	4
FuelPrice (100$ per barrel in 2000 USD)	414	1.029	0.232	0.657	1.276	144	1.029	0.232	0.657	1.276
Compete	414	0.565	1.057	0	6	144	0.979	0.780	0	2
Year2008	414	0.111	0.315	0	1	-	-	-	-	-
Year2009	414	0.111	0.315	0	1	144	0.111	0.315	0	1
Year2011	-	-	-	-	-	144	0.111	0.315	0	1

Note: a. SDgr500+ applies to the case of Japan only.

As mentioned in Section 3.2, there are three variables of interest: HSR connectivity of airport city (degree centrality, SDgr), HSR accessibility of airport city (harmonic centrality, SHmc) and air-HSR intermodal linkage (AirHSR). SDgr and SHmc are calculated based on HSR timetables, namely National Rail Timetable of China (July edition, 2007-2015) published by Ministry of Railways of China and JR Timetable of Japan (March edition, 2007-2015) provided by Japan Railways Group. Since there are several editions of timetables each year, July edition is chosen for China and March edition is chosen for Japan. This is because majority of the newly opened

HSR lines are launched around July 1st or December 31st in China and March in Japan during our observation period. Moreover, since HSR services started close to the end of a calendar year may have limited impacts on that year's air transport, we follow Wan et al. (2016) and assume that the "effective" start year of a particular new HSR service is one year after the actual start year if this service starts in the fourth quarter of a year. In calculating centralities, we consolidate all the stations into one when there are multiple HSR stations in a city.

Table 3.2 lists average SDgr and SHmc for each sampled airport across the sampling period, including connectivity to HSR dominant zone (SDgr 0-500), subdominant zone (SDgr 500-1000) and non-dominant zone (SDgr 1000+). One observation is that SDgr and SHmc provide similar but still different information. In China, Beijing, Shanghai, Wuhan, Nanjing, Wuxi, Zhengzhou and Hangzhou are the best connected to other cities via HSR. Each of them has an average SDgr over 40 during our observation period. Wuxi, Zhengzhou, Wuhan, Nanjing, Changsha and Hangzhou have higher values in SHmc. Cities with high SHmc tend to be located near the physical center of the HSR infrastructure network, since this SHmc reflects the distance from one node to all the other nodes in the HSR network, but this is not the case for cities with high SDgr, e.g. Beijing and Shanghai. In Japan, where HSR network structure looks like a line, Tokyo and Osaka are found to be the most important cities in both SDgr and SHmc. In general, connectivity and accessibility measures are highly correlated, and thus, we only include one of them in each regression analysis to avoid multi-collinearity issues. Consistent with our discussion in Section 3.2.1, this correlation is stronger in Japan (0.96) than in China (0.90) probably due to different network structure, which might explain the slightly differentiated impacts of connectivity and accessibility in China (refer to Appendix B.2 for the pairwise correlations among all centrality indicators).

Table 3. 2 Average HSR centralities over 2007-2015 period for each sampled airport city

China							Japan					
City	Airport code	SDgr	SDgr 0-500	SDgr 500-1000	SDgr 1000+	SHmc	City	Airport code	SDgr	SDgr 0-500	SDgr 500+	SHmc
Beijing	PEK	59.89	13.11	21.78	25.00	0.13	Tokyo	HND	62.67	46.78	15.89	0.77
Shanghai	SHPV	55.22	14.67	17.89	22.67	0.16	Tokyo	NRT	62.67	46.78	15.89	0.77
Wuhan	WUH	48.11	16.22	21.56	10.33	0.18	Osaka	ITM	35.11	31.00	4.11	0.26
Nanjing	NKG	45.00	15.78	15.78	13.44	0.18	Osaka	KIX	35.11	31.00	4.11	0.26
Wuxi	WUX	41.67	13.56	13.67	14.44	0.20	Fukuoka	FUK	30.78	22.11	8.67	0.23
Zhengzhou	CGO	40.89	16.56	18.22	6.11	0.19	Kobe	UKB	30.11	25.00	5.11	0.28
Hangzhou	HGH	40.67	15.44	14.78	10.44	0.16	Hiroshima	HIJ	26.11	22.56	3.56	0.26
Changsha	CSX	35.67	11.56	13.22	10.89	0.16	Nagoya	NGO	26.00	21.00	5.00	0.28
Jinan	TNA	35.22	13.22	12.33	9.67	0.15	Sendai	SDJ	21.11	21.11	0.00	0.27
Tianjin	TSN	32.78	9.11	12.33	11.33	0.14	Kagoshima	KOJ	12.89	9.56	3.33	0.12
Shijiazhuang	SJW	26.89	10.44	8.67	7.78	0.14	Kumamoto	KMJ	11.11	9.44	1.67	0.17
Nanchang	KHN	26.33	11.44	9.11	5.78	0.14	Komatsu	KMQ	1.67	1.67	0.00	0.02
Hefei	HFE	25.22	10.22	10.11	4.89	0.14	Sapporo	CTS	0.00	0.00	0.00	0.00
Fuzhou	FOC	24.89	6.22	8.33	10.33	0.10	Miyazaki	KMI	0.00	0.00	0.00	0.00
Ningbo	NGB	24.67	8.67	9.33	6.67	0.11	Matsuyama	MYJ	0.00	0.00	0.00	0.00
Guangzhou	CAN	24.44	7.00	5.22	12.22	0.12	Nagasaki	NGS	0.00	0.00	0.00	0.00
Qingdao	TAO	24.22	4.22	8.89	11.11	0.09						
Wenzhou	WNZ	21.22	6.22	9.22	5.78	0.09						
Shengyang	SHE	21.11	8.67	5.33	7.11	0.11						
Shenzhen	SZX	21.00	4.56	4.56	11.89	0.10						
Xiamen	XMN	18.33	4.33	6.00	8.00	0.08						
Quanzhou	JJN	18.11	4.89	6.78	6.44	0.09						
Xian	XIY	16.89	4.00	6.00	6.89	0.09						
Changchun	CGQ	15.89	6.11	4.33	5.44	0.08						
Taiyuan	TYN	15.56	4.89	7.11	3.56	0.10						
Harbin	HRB	15.00	3.44	5.22	6.33	0.06						
Chongqing	CKG	12.00	1.89	1.56	8.56	0.04						
Chengdu	CTU	11.56	3.22	0.67	7.67	0.04						
Guiyang	KWL	9.33	2.33	2.00	5.00	0.04						
Nanning	NNG	9.33	2.00	1.67	5.67	0.04						
Dalian	DLC	7.89	2.44	2.89	2.56	0.03						
Guilin	KWE	7.00	0.67	1.56	4.78	0.02						
Jieyang	SWA	6.44	2.22	1.67	2.56	0.04						
Yantai	YNT	2.22	0.33	1.11	0.78	0.02						
Zhuhai	ZUH	1.11	1.11	0.00	0.00	0.08						
Urumqi	URC	0.89	0.11	0.11	0.67	0.00						
Xining	XNN	0.89	0.44	0.11	0.33	0.01						
Lanzhou	ZGC	0.89	0.33	0.22	0.33	0.00						
Haikou	HAK	0.56	0.56	0.00	0.00	0.00						
Sanya	SYX	0.56	0.56	0.00	0.00	0.00						
Hohhot	HET	0.11	0.11	0.00	0.00	0.00						
Yinchuan	INC	0.00	0.00	0.00	0.00	0.00						
Jinghong	JHG	0.00	0.00	0.00	0.00	0.00						
Kunming	KMG	0.00	0.00	0.00	0.00	0.00						
Lijiang	LJG	0.00	0.00	0.00	0.00	0.00						
Lhasa	LXA	0.00	0.00	0.00	0.00	0.00						

Notes: To save space, we show the average centrality values only. Centrality values of individual years are available upon request. Cities are listed in descending order of their average connectivity (SDgr).

Zhang et al. (2018) use on-site HSR service to capture the complementary traffic feeding effect of HSR. They ignore the cases where on-site HSR services are not available but a convenient transfer between the airport and an HSR station in the city is available. Even without on-site HSR, air-HSR intermodal services may still be desirable when passengers have limited flight choices at other airports or air-to-air connections are not convenient. The latter is very likely the case in China due to severe flight delays at busy airports and cumbersome flight connecting procedures in general. The easiness to transfer between the airport and HSR station can be measured by the access time between HSR station and airport. However, as historical data of this access time is not available, we construct a dummy variable, AirHSR, instead to reflect the availability of a convenient and reliable connection between these two modes, including on-site or nearby HSR stations. Therefore, AirHSR equals to one if:

(1) The airport and HSR station are connected by any form of urban rail transit[20] with an exclusive right-of-way and separated from other road traffic of which the trip time is no more than 30 minutes; or

(2) The HSR station is located nearby the airport terminal (e.g. Shanghai Hongqiao Airport and Changchun Longjia Airport) or inside the airport terminal (e.g. Chengdu Shuangliu Airport and Guiyang Longdongpu Airport).

Otherwise, AirHSR equals to zero. Related information is obtained from various channels including news articles and airports' official websites. Control variables are constructed in the following ways.

- Population (POP): Larger population size in the airport's catchment area tends to generate higher air travel demand. This variable is measured by the number

[20] Compared with cars and buses, this form of transit is more reliable and is less likely to be influenced by traffic congestion and other exogenous factors, which is quite important for passengers who are connecting between the flight and HSR ride.

of permanent residents in an airport's catchment area. In the case of China, we define the catchment area of an airport as the city where the airport locates, and in the case of Japan, the catchment area is the prefecture in which the airport is situated.

- Real GDP per capita (GDP_POP): It is expected that higher GDP per capita implies higher income of a region and hence associates with higher air travel demand. The variable is constructed by taking the ratio between the real GDP in 2007 base and the population in an airport's catchment area. Population and real GDP data are gathered from National Bureau of Statistics of China and Cabinet of Japan.
- Low-cost carrier operation (LCC): Inspired by Albalate and Fageda (2016), we use the number of low-cost carriers using the airport as their base to capture the influence of low-cost carriers on airport traffic. The relevant information is captured by examining news and airport reports. We expect that LCC will be positively associated with airport passenger traffic.
- Jet fuel price (FuelPrice): As jet fuel accounts for a substantial share of airlines' operating costs, it can affect airfares and hence travel demand (Ito and Lee, 2005). Therefore, jet fuel price is widely used as a control variable for air traffic volume. Clewlow et al. (2014) find that airport traffic can experience a substantial decrease as the jet fuel price increases and thus we expect a negative coefficient of this variable. Jet fuel price data is collected from IATA Fact Sheet (Fuel) 2018.
- Airport competition (Compete): This variable aims to capture the relationship between an airport's traffic and the presence of other airports nearby, which could be the outcome of airport competition. Following Bel and Fageda (2010),

we use number of airports located within a radius of 100km as a proxy for the "upper level" of potential competition among airports (Adler and Liebert, 2014).[21] To focus on airports which do have a potential to compete, we only take into account rival airports with an annual passenger number over 2 million in 2015. Most studies (e.g. Bel and Fageda, 2010; Adler and Liebert, 2014; Randrianarisoa et al. 2015) use a cutoff of 150,000 passengers per year as this figure is used by Eurostat to distinguish main and small commercial airports. Considering the higher population density in China and Japan, we plot the distribution of traffic among airports and reveal that 2 million is a more reasonable cutoff in our context.

- Demand shocks (Year2008, Year2009, Year2011): We use several dummy variables to indicate years when exogenous events occurred and might substantially affect air transport demand. Years 2008 and 2009 are selected for airports in China and years 2009 and 2011 are chosen for airports in Japan. Year 2008 controls for the effect of Beijing Olympic Games in China. Year 2009 controls for the effect of global financial crisis which started near the end of 2008 and had most substantial impact on air transport in 2009. Year 2011 controls for the effect of Tohoku earthquake and tsunami in Japan.

3.4. Regression results

3.4.1 Analysis based on the main model

This section reports the regression results based on Eq. (3) for China and Japan

[21] More rigorous measures of airport competition intensity can be constructed by considering alternative origin-destination routes offered by rival airports nearby. This method requires more detailed route-level information which is not available for this study.

respectively. Table 3.3 presents the results for China, using total passenger traffic as the dependent variable. The estimated coefficients of control variables follow our expectation. Population and real GDP per capita are both positively correlated with airport traffic with a high level of statistical significance across all models, suggesting that airports located in more developed cities induce more air travel demand. Both jet fuel price and airport competition negatively correlate with airport traffic. Airport traffic is positively correlated with the status of a low-cost carrier base. Although the coefficients are not statistically significant, major multinational events such as 2008 Olympic Games might have some positive impact on airport traffic and global financial crisis (captured by Year2009) seems to have some negative effect as well.

Columns (1)-(5) in Table 3.3 show the average effect of HSR connectivity and accessibility without differentiating airports with and without air-HSR intermodal linkage. Columns (1)-(4) present the results using SDgr, SDgr0-500, SDgr500-1000 and SDgr1000+, respectively, as the centrality measures. On average, airport traffic in China is negatively correlated with the airport city's HSR accessibility but the relationship with HSR connectivity is highly affected by the distance. Columns (2) and (3) suggest that increasing connectivity to HSR dominant zones and sub-dominant zones may associate with statistically significant reduction in airport traffic. In particular, adding one direct HSR connection to cities within 500km implies a reduction of 0.267 million passengers per year. Whilst, there will be a much milder drop in passenger throughput (0.131 million per year) if the airport city adds one HSR connection to a city located within 500-1000km. However, connectivity to the HSR non-dominant zone has little correlation with airport total traffic (column 4), which may contribute to the statistically insignificant coefficient of SDgr in column (1). This finding indicates that the impact of HSR deteriorates in its service distance, which is consistent with the earlier route-level studies in China (e.g. Wan et al., 2016; Chen, 2017). Column (5) reports results using SHmc as the centrality measure. The negative coefficient of SHmc suggests that improving the proximity of the airport city to the other cities by HSR may on average resulting in a decline in airport passenger traffic.

Table 3. 3 Regression results based on Eq.(3) (DV = total passenger traffic, China)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HSR zones		0-500	500-1000	1000+			0-500	500-1000	1000+	
POP	5.076*** (0.353)	5.301*** (0.331)	5.301*** (0.336)	4.702*** (0.349)	5.066*** (0.339)	4.862*** (0.339)	5.033*** (0.324)	5.021*** (0.331)	4.620*** (0.334)	4.835*** (0.330)
GDP_POP	1.973*** (0.244)	2.292*** (0.225)	2.217*** (0.224)	1.598*** (0.233)	2.035*** (0.246)	1.874*** (0.234)	2.104*** (0.221)	2.022*** (0.221)	1.607*** (0.224)	1.888*** (0.239)
LCC	2.468*** (0.815)	2.266*** (0.799)	2.197*** (0.806)	2.486*** (0.815)	2.462*** (0.814)	1.682** (0.788)	1.755** (0.782)	1.717** (0.789)	1.572** (0.792)	1.759** (0.795)
FuelPrice	-2.935*** (0.800)	-3.189*** (0.689)	-3.316*** (0.711)	-1.724** (0.828)	-2.910*** (0.747)	-2.394*** (0.770)	-2.731*** (0.675)	-2.788*** (0.698)	-1.561** (0.792)	-2.440*** (0.728)
Compete	-6.211*** (1.394)	-6.774*** (1.370)	-5.697*** (1.378)	-6.224*** (1.394)	-6.468*** (1.397)	-5.177*** (1.340)	-5.932*** (1.334)	-4.930*** (1.3449)	-5.210*** (1.341)	-5.630*** (1.356)
Year2008	0.455 (0.502)	0.457 (0.476)	0.548 (0.482)	0.071 (0.510)	0.385 (0.488)	0.258 (0.481)	0.319 (0.462)	0.386 (0.4694)	0.001 (0.487)	0.210 (0.473)
Year2009	-0.719 (0.505)	-0.795 (0.487)	-0.780 (0.490)	-0.438 (0.508)	-0.772 (0.506)	-0.518 (0.483)	-0.598 (0.473)	-0.576 (0.477)	-0.333 (0.485)	-0.595 (0.489)
SDgr	-0.017 (0.012)	-0.267*** (0.063)	-0.131*** (0.034)	0.027 (0.021)		-0.028** (0.012)	-0.262*** (0.060)	-0.123*** (0.034)	-0.012 (0.021)	
SHmc					-7.642* (4.372)					-9.162** (4.254)
AirHSR						0.630 (0.958)	1.307 (1.076)	1.486 (0.919)	0.909 (0.871)	1.046 (1.096)
SDgr × AirHSR						0.069*** (0.018)	0.205** (0.098)	0.152** (0.067)	0.121*** (0.031)	
SHmc × AirHSR										16.903** (6.911)
Constant	-27.06*** (2.390)	-28.34*** (2.194)	-29.20*** (2.315)	-24.39*** (2.339)	-26.86*** (2.257)	-26.17*** (2.291)	-26.72*** (2.144)	-27.49*** (2.273)	-24.48*** (2.245)	-25.54*** (2.192)
Airport FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	414	414	414	414	414	414	414	414	414	414
R^2	0.426	0.425	0.435	0.421	0.426	0.442	0.437	0.446	0.437	0.438

Note: Standard errors are in parentheses. *p < 0.1, ** p < 0.05, ***p < 0.01.

Columns (6)-(10) in Table 3.3 report the estimations by following Eq. (3) exactly to take into account air-HSR intermodal linkage and its interaction with SDgr or SHmc. Coefficients of the interaction term are all positive and statistically significant. It suggests that a good connection between airport and HSR station may bring an extra positive impact on airport traffic in spite of the traffic reduction associated with improved HSR connectivity and accessibility. Moreover, this moderation effect also depends on distance, because the coefficients of the interaction term have a decreasing magnitude as one moves from column (7) to column (9). This finding is consistent to Zhang et al. (2018).

A similar regression analysis is conducted in the case of Japan and the results are presented in Table 3.4. Without considering the role of air-HSR linkage, we observe no statistically significant relationship between HSR centralities and airport traffic (columns 1-4). Even after controlling for air-HSR linkage (columns 5-8), the coefficients of SDgr and SHmc are not statistically significant. This can be partially explained by the fact that HSR network has been highly developed in Japan since the 1990s and hence the competition between HSR and air transport has reached a certain equilibrium years ago. As discussed in Section 3.2.1, the relatively minor expansion in Japanese HSR system during the sampling period is not substantial enough to break this equilibrium. This can be seen from the data (Appendix B.3), as many Japanese airport cities in the sample have limited inter-temporal variation in HSR connectivity and accessibility. This result is consistent with the conclusion made by Castillo-Manzano et al. (2015) that as time passes by and new lines are added, the air-HSR substitution rate diminishes after reaching its maximum. However, we still reveal an important role of air-HSR intermodal linkage from the coefficients of the interaction terms in columns (5), (6) and (8), while the one in column (7) is not statistically significant.

Table 3. 4 Regression results based on Eq. (3) (DV = total passenger traffic, Japan)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HSR zones		0-500	500+			0-500	500+	
POP	3.491 (2.219)	3.304 (2.220)	3.894* (2.216)	3.515 (2.216)	2.429 (2.215)	2.544 (2.168)	4.244* (2.432)	2.491 (2.300)
GDP_POP	2.204** (1.005)	2.110*** (1.002)	2.576** (1.013)	2.203** (1.009)	1.872* (0.982)	1.964** (0.960)	2.713** (1.106)	2.008** (1.011)
LCC	1.524*** (0.357)	1.528*** (0.355)	1.610*** (0.358)	1.530*** (0.356)	1.234*** (0.393)	1.223*** (0.383)	1.562*** (0.396)	1.609*** (0.392)
FuelPrice	-1.389** (0.567)	-1.359** (0.566)	-1.267** (0.570)	-1.385** (0.567)	-1.473*** (0.550)	-1.318** (0.539)	-1.246** (0.581)	-1.410** (0.563)
Compete	2.438** (1.155)	2.482** (1.151)	2.578** (1.151)	2.446** (1.155)	-4.512* (2.611)	-2.548 (1.926)	2.679 (2.665)	-2.827 (3.088)
Year2009	-0.902* (0.470)	-0.882* (0.470)	-0.901* (0.467)	-0.904* (0.470)	-0.907** (0.455)	-0.829* (0.447)	-0.886* (0.475)	-0.905* (0.467)
Year2011	-1.337*** (0.367)	-1.358*** (0.365)	-1.234*** (0.367)	-1.333*** (0.366)	-1.432*** (0.359)	-1.432*** (0.351)	-1.239*** (0.371)	-1.348*** (0.367)
SDgr	0.013 (0.030)	0.035 (0.035)	-0.131 (0.100)		-0.018 (0.030)	-0.022 (0.037)	-0.134 (0.119)	
SHmc				0.904 (2.343)				-1.104 (2.543)
AirHSR					-6.922*** (2.257)	-6.570*** (1.864)	0.425 (1.120)	-3.207* (1.743)
SDgr×AirHSR					0.225*** (0.070)	0.253*** (0.067)	-0.041 (0.226)	
SHmc×AirHSR								11.457* (5.831)
Constant	-16.48 (12.88)	-15.56 (12.87)	-19.68 (12.96)	-16.54 (12.881)	-2.49 (13.34)	-5.35 (12.705)	-22.17 (15.477)	-5.42 (14.079)
Airport FE	Y	Y	Y	Y	Y	Y	Y	Y
N	144	144	144	144	144	144	144	144
R^2	0.734	0.733	0.731	0.735	0.746	0.766	0.724	0.775

Note: Standard errors are in parentheses. *p <0.1, ** p<0.05, ***p<0.01;

3.4.2 Net effects by air-HSR intermodal linkage

Although air-HSR intermodal linkage may moderate the negative impact of HSR expansion in both China and Japan, it is unclear whether this moderation effect can offset the traffic reduction and eventually lead to a positive correlation between airport traffic and HSR centralities. Thus, we calculate the "net effect" of HSR connectivity and accessibility by taking partial derivative of Eq.(3) with respect to the corresponding HSR centrality measure. That is, the net effect of a particular HSR centrality can be written as:

$$\frac{\partial PXG_{it}}{\partial HSR_{it}^{Centrality}} = \alpha_1 + \alpha_3 AirHSR_{it}$$

Table 3.5 presents such net effects and their statistical significance by distinguishing airports with and without air-HSR intermodal linkage. The top part of Table 3.5 is for total passenger traffic in China and Japan. To shed some lights on the possible reasons for different results regarding total passenger traffic, we conduct similar regression analysis for domestic and international passenger traffic. In the middle and bottom parts of Table 3.5, we present the "net effect" from these models to facilitate the comparison with total passenger traffic and to save space. The details of the model estimation are available in Appendix B.4.

Table 3. 5 Net effects on passenger traffic by air-HSR linkage

Dependent variable	HSR centrality	AirHSR	China		Japan	
			Net effect	Std. Err.	Net effect	Std. Err.
Total Passenger	SDgr	0	-0.028**	0.012	-0.018	0.030
		1	0.041**	0.020	0.206***	0.067
	SDgr0-500	0	-0.262***	0.061	-0.021	0.036
		1	-0.057	0.114	0.231***	0.061
	SDgr500-1000	0	-0.123***	0.034	-0.134	0.119
	SDgr500+[a]	1	0.029	0.072	-0.176	0.204
	SDgr1000+	0	-0.012	0.021	-	-
		1	0.109***	0.031	-	-
	SHmc	0	-9.162**	4.254	-1.104	2.543
		1	7.740	7.615	10.352*	5.337
Domestic Passenger	SDgr	0	-0.025***	0.010	-0.015	0.018
		1	-0.007	0.016	0.037	0.040
	SDgr0-500	0	-0.217***	0.049	-0.014	0.022
		1	-0.254***	0.092	0.048	0.038
	SDgr500-1000	0	-0.095***	0.027	-0.095	0.069
	SDgr500+[a]	1	-0.073	0.058	-0.134	0.119
	SDgr1000+	0	-0.014	0.017	-	-
		1	0.023	0.026	-	-
	SHmc	0	-7.605**	3.456	-1.109	1.502
		1	-9.573	6.187	2.556	3.152
International Passenger	SDgr	0	-0.003	0.004	-0.002	0.022
		1	0.048***	0.007	0.169***	0.049
	SDgr0-500	0	-0.044**	0.021	-0.007	0.026
		1	0.197***	0.040	0.182***	0.045
	SDgr500-1000	0	-0.028**	0.012	-0.038	0.088
	SDgr500+[a]	1	0.102***	0.025	-0.042	0.151
	SDgr1000+	0	0.002	0.007	-	-
		1	0.085***	0.010	-	-
	SHmc	0	-1.556	1.441	0.005	1.872
		1	17.314***	2.580	7.796**	3.929

Note: a. SDgr500+ applies to the case of Japan only. *$p < 0.1$, ** $p < 0.05$, ***$p < 0.01$.

In China, raising HSR *accessibility* by 0.01 (about 12.6% of the average SHmc) implies a net reduction of 0.092 million passengers at airports without air-HSR linkage but it has no statistically significant relationship with total traffic at airports with air-HSR linkage. An increase in HSR *connectivity* implies a net decrease in total traffic at airports without a good linkage to HSR stations but a net increase in total traffic at airports with air-HSR linkage. In a word, HSR accessibility and connectivity generate different net effects. A comparison between domestic and international traffic reveals the underlying reasons. In particular, when there is air-HSR linkage, HSR connectivity to all the three zones, SDgr0-500, SDgr500-1000 and SDgr1000+, are positively correlated with international passengers. Meanwhile, only SDgr0-500 has a statistically significant negative relationship with domestic passengers. As a result, the positive impact on international passengers dominates, leading to a net increase in airport traffic. HSR accessibility, on the other hand, measures the overall closeness of the airport city to other cities by HSR. Thus, high accessibility suggests high connectivity to cities within the HSR dominant zone (SDgr0-500) relative to cities located in other zones. As a result, cities with high HSR accessibility suffers too much domestic traffic reduction which cannot be offset by an increase in international passengers, leading to a net reduction in total airport traffic. The above also explains why the positive effect of air-HSR linkage on total traffic is mainly driven by adding HSR connection to cities over 1000km away (i.e. increasing SDgr1000+), instead of cities within 1000km, because when adding connectivity to cities within 1000km, the negative impacts on domestic passengers offsets the positive impacts on international passengers.

In Japan, HSR accessibility and connectivity tend to generate similar net impacts though the level of statistical significance is lower with HSR accessibility. This is consistent with the higher correlation between SDgr and SHmc in Japan than in China as mentioned in Section 3.3. Increasing HSR accessibility may raise airport traffic when the airport has air-HSR linkage but has little impact otherwise. Similar conclusion can be drawn on increasing HSR connectivity with only one exception:

connections to cities located over 500km away are not associated with airport traffic regardless the availability of air-HSR intermodal linkage. In fact, neither domestic traffic nor international traffic is associated with HSR connectivity or accessibility when the airport has no air-HSR linkage. Whilst, as air-HSR intermodal linkage facilitates HSR to feed international flights, international traffic becomes positively correlated with several HSR centrality measures.

A closer look at the magnitudes of the net effects reveals another interesting difference between China and Japan. Taking SDgr as an example, when there is no air-HSR linkage, the net effect of SDgr is -0.028 in China and -0.018 (not statistically significant) in Japan. When there exists air-HSR linkage, the coefficient is 0.041 in China and 0.206 in Japan. A similar pattern can be observed for the net effects of SHmc. Thus, in summary, compared with Japan, HSR network development in China has a stronger substitution effect, causing much milder total traffic increase when air-HSR linkage is provided.

3.4.3 Role of airport hub status

This section distinguishes hub and non-hub airports in the analysis by fitting Eq. (4). Again, the details about model estimation are available in Appendix B.5. By taking partial derivative of Eq.(4) with respect to HSR centrality, the net effect of HSR network development depends on not only the hub status but also the air-HSR linkage and it can be written as:

$$\frac{\partial PXG_{it}}{\partial HSR_{it}^{Centrality}} = \beta_1 + \beta_4 AirHSR_{it} + \beta_5 Hub_{it} + \beta_7 AirHSR_{it} \times Hub_{it}$$

Table 3.6 reports the net effects in the context of China by distinguishing airport hub status as well as the availability of air-HSR linkage. The upper part of Table 3.6

reports the net effects of increasing SDgr and the lower part reports the net effects of increasing SHmc. Each number under the column of "net effect" represents the amount of such net effects for different scenarios. An airport will fall into one of the four scenarios: (1) non-hub airport without air-HSR linkage (AirHSR = 0 and Hub = 0), (2) hub airport without air-HSR linkage (AirHSR = 0 and Hub = 1), (3) non-hub airport with air-HSR linkage (AirHSR = 1 and Hub = 0) and (4) hub airport with air-HSR linkage (AirHSR = 1 and Hub = 1). Therefore, the number 0.052 in the first "net effect" column means that if SDgr increases by one, an average hub airport without air-HSR linkage will have 0.052 million more passengers.

Table 3. 6 Net effects on passenger traffic by air-HSR linkage and hub status (China)

HSR centrality	Scenario		Total Passenger		Domestic Passenger		International Passenger	
	AirHSR	Hub	Net effect	Std. Err.	Net effect	Std. Err.	Net effect	Std. Err.
SDgr	0	0	-0.023**	0.011	-0.023**	0.010	0.0007	0.002
	0	1	0.052**	0.022	0.010	0.020	0.041***	0.005
	1	0	-0.030	0.021	-0.035*	0.019	0.005	0.004
	1	1	0.160***	0.032	0.046	0.029	0.113***	0.007
SHmc	0	0	-8.666**	3.863	-7.393**	3.417	-1.273	0.802
	0	1	12.616	11.842	1.467	10.47	11.14***	2.460
	1	0	-17.56**	7.580	-17.75***	6.705	0.189	1.574
	1	1	67.83***	16.97	3.731	15.01	64.10***	3.526

Note: $*p < 0.1$, $** p < 0.05$, $***p < 0.01$.

Table 3.6 reveals the differentiated impacts on hub and non-hub airports. In general, both HSR connectivity and accessibility tend to have negative or statistically insignificant net effects on non-hub airports. This negative impacts are particularly strong in domestic markets and there is no substantial increase in international traffic even when air-HSR linkage is provided. On the contrary, both centrality measures tend to positively correlate with international and total traffic at hub airports with little impact on domestic traffic. In other words, HSR network development enlarges the traffic difference between hub and non-hub airports by draining traffic from non-hub airports and adding traffic to hub airports, and as a result further concentrates passenger traffic at a few large airports. Provision of air-HSR linkage is likely to enhance the feeder role of HSR for hub airports in the sense that hub airports with air-HSR linkage enjoy substantially more traffic increase than those without air-HSR linkage. However, air-HSR linkage does not always benefit non-hub airports and the net impact depends on the centrality indicator in concern. In particular, if SDgr increases, the total traffic change at non-hub airports with air-HSR linkage is statistically insignificant. However, if SHmc increases, these airports may experience more traffic loss comparing with the case without air-HSR linkage. Consequently, as HSR connectivity or accessibility improves, hub airports with air-HSR linkage would experience the highest level of traffic increase, followed by hub airports without air-HSR linkage. Nevertheless, non-hub airports *without* air-HSR linkage would experience the strongest traffic reduction if HSR connectivity increases while non-hub airports *with* air-HSR linkage would experience the strongest traffic reduction if HSR accessibility improves.

Table 3.7 reports the net effects of HSR connectivity and accessibility in the context of Japan. One major difference between China and Japan is that in Japan, the main results are driven by the air-HSR linkage instead of hub status. That is, non-hub airports with good air-HSR linkage can also experience an increase in international traffic and consequently an increase in total traffic. Regarding hub airports, although those with air-HSR linkage may experience substantial traffic increase driven mainly by international traffic, those without air-HSR linkage may experience little traffic increase due to loss of domestic passengers. Therefore, in Japan, the only noteworthy net effect comes from the traffic increase at airports with air-HSR linkage, and such effect can be stronger for hub airports. Airports without air-HSR linkage experience little traffic change regardless their hub status. This finding is consistent with the international air passenger traffic flow survey conducted by the Ministry of Land, Infrastructure and Transport (MLIT) of Japan in 2012. According to the survey, Narita Airport indeed attracts good amount of international air passenger traffic via Shinkansen, i.e., about 3.5% of its total international air passengers. Fukuoka and Sendai are two representative non-hub airports of which 10.1% and 7.7% of international passengers access the airports via Shinkansen, respectively. Both airports have good air-HSR linkage and Fukuoka's Shinkansen (HSR) station is a major terminal of two Shinkansen lines (Sanyo and Kyushu Shinkansen lines). Sendai is also the hub of the Shinkansen line that goes through the region.

Table 3. 7 Net effects on passenger traffic by air-HSR linkage and hub status (Japan)

HSR centrality	Scenario		Total Passenger		Domestic Passenger		International Passenger	
	AirHSR	Hub	Net effect	Std. Err.	Net effect	Std. Err.	Net effect	Std. Err.
SDgr	0	0	-0.009	0.030	-0.011	0.018	0.002	0.022
	0	1	-0.044	0.039	-0.056**	0.023	0.012	0.029
	1	0	0.166**	0.076	0.038	0.045	0.127**	0.055
	1	1	0.189***	0.071	0.0007	0.042	0.188***	0.052
SHmc	0	0	-0.969	2.475	-0.909	1.466	-0.059	1.817
	0	1	-5.885	4.422	-7.088***	2.619	1.202	3.246
	1	0	11.335**	5.201	2.789	3.081	8.546**	3.818
	1	1	21.467**	8.535	-0.539	5.055	22.01***	6.266

Note: *$p < 0.1$, ** $p < 0.05$, ***$p < 0.01$.

3.5. Concluding remarks and policy implications

We are the first to quantify HSR's impacts on airport-level traffic by considering the position of an airport city in the HSR network. That is, we believe that the impact of HSR does not rest on its introduction but on the importance of the city in the HSR network. Degree centrality (HSR connectivity) and harmonic centrality (HSR accessibility) are both introduced to measure such importance. The former measures the amount of connections between the airport city and other cities via the HSR system, while the latter measures the closeness of an airport city to all the other cities in terms of HSR travel time. A series of econometric models are estimated by including different HSR centrality measures, air-HSR intermodal linkage, airport hub status and interactions between these variables as key variables of interest. We use two samples of panel data, one for China and one for Japan, to make comparison between these two countries.

Similar to Albalate et al. (2015) and Zhang et al. (2018), in addition to the substitutional effect on airport traffic, we observe a strong complementary feeding effect of HSR on airports allowing for convenient transfer between airport terminals and HSR stations. However, we also find that this feeding effect diminishes in the distance from the airport city to other cities directly reachable by HSR. That is, if HSR mainly connects an airport city with cities located very far away, the catchment of the airport may not be effectively expanded as those living in distance may not perceive air-HSR intermodal service as viable. Thus, even if it is easy to travel between the HSR station and the airport, the amount of feeding traffic will be low. A good air-HSR linkage mainly facilitates HSR to feed international flights and hence increase international traffic at airports. Since airlines in China and Japan face little competition from HSR in international markets, consequently, some airports may experience total traffic increase as HSR connectivity or HSR accessibility increases while others may experience traffic reduction. In particular, hub airports tend to enjoy a higher level of complementary effect from air-HSR intermodal services than non-hub airports, which is consistent with Zhang et al. (2018)'s finding.

We also observe some difference in China and Japan. First, HSR connectivity and accessibility have little impact on domestic air traffic in Japan but they have a strong negative impact on domestic air traffic in China. Consequently, in China, on average, airports with air-HSR linkage experienced much milder air traffic increase than those in Japan. Second, the importance of hub status and air-HSR linkage differs in these two countries. In fact, even without air-HSR linkage, hub airports in China may experience traffic increase though at a lower level than those with air-HSR linkage. This result echoes Albalate et al. (2015)'s finding. However, in contrast to Albalate et al. (2015)'s finding, our results suggest that in China non-hub airports are more negatively affected by HSR even with air-HSR linkage. In a word, HSR development seems to drain traffic from non-hub airports and add traffic to hub airports, exaggerating the uneven traffic distribution among airports, regardless of the availability of air-HSR linkage. In Japan, on the other hand, air-HSR linkage plays a more important role than hub status in terms of adding airport traffic after improving the city's centrality in the HSR network. Finally, although HSR connectivity and accessibility have similar impacts in Japan, they affect Chinese airports differently. In particular, when air-HSR linkage is available, adding HSR connectivity is more likely to achieve a net traffic increase than improving HSR accessibility in China.

Policy makers may learn several lessons about promoting air-HSR intermodal services from these findings. First, air-HSR intermodal services in many cases may help with feeding traffic to the airport. Therefore, the benefit of congestion mitigation and emission reduction at busy airports may not realize with the help of HSR. In fact, traffic reduction is most likely to occur in small airports which already have too little traffic. In China, hub airports, such as Beijing, Shanghai and Guangzhou, are already very congested. Therefore, to alleviate airport congestion and achieve a better (more even) traffic distribution among large and small airports, it might be a good idea to discourage air-HSR intermodal connection at large, hub airports, while encouraging this investment at small, regional airports. Second, caution should be taken when the policy makers plan to boost their airport traffic by investing in air-HSR intermodal service alone, since small airports with low level of international flight connectivity may risk more severe traffic loss if the air-HSR linkage is added. As shown by Takebayashi (2018), to relieve congestion at large airport by diverting traffic to samller airports using HSR, the key is still to develop local demand for international travel around the smaller airports and build up connectivity to international destinations. This is difficult to achieve by regional airports located in cities with very low income and low growth potential. Thus, investment in intermodal services may not be desirable at these cities. The policy makers may invest air-HSR linkage at airports which have the potential to be converted into international gateway hubs.

Finally, our findings may have implications related to China's current plan to expand its HSR network into eight west-east corridors and eight north-south corridors. Based on The 2016-2030 Mid-to-Long-Term Railway Network Plan, Xu et al. (2018) projected that enormous new HSR lines will be invested in the low-income, low population-density central/western China by 2030. As a result, cities in these regions will expect substantial increase in HSR connectivity and accessibility in the future. Chongqing, Hefei and Chengdu will become the top three based on the connectivity-accessibility index. If this projection is correct, one may expect a much more difficult life for the air transport sector in China in the future, since airports in central/western China are relatively weak and in fact, none of the primary hub airports in China are located in this region. Although the Civil Aviation Administration of China and China Railway Corporation signed an agreement in May 2018 to cooperate in air-HSR intermodal infrastructure development, benefit of promoting air-HSR cooperation in the central/western region is questionable. International air travel demand in the less developed central/western China is quite low but the complementary effect of HSR is the most substantial for international traffic. Moreover, cities like Hefei and Chengdu in central/western China will have very high accessibility but relatively low connectivity by 2030, so very likely the substitution effect of HSR may outweigh the complementary effect. According to Wang et al. (2017), low-density corridors in the central/western China can be much better served by LCCs than HSR due to higher operational flexibility and cost efficiency. Thus, instead of fully executing the 2016-2030 HSR expansion plan, HSR and air transport should take a more coordinated approach to plan for future development of an integrated inter-city transportation system, so that each mode can serve the markets at its best and avoid overinvestment

CHAPTER 4

DOES HIGH-SPEED RAIL DEVELOPMENT AFFECT AIRPORT PRODUCTIVITY? EVIDENCE FROM NORTHEAST ASIA

4.1 Introduction

Airports play a vital role in boosting national and local economies. According to a recent report carried out by InterVISTAS, European airports generate a total of 675 billion euros in GDP each year, accounting for about 4.1% of GDP of Europe (InterVISTAS, 2015a). A similar report conducted in Asia-Pacific region shows that aviation activities contribute to approximate 1.4% of the region's total employment and 3% of the region's total GDP (InterVISTAS, 2015b). Over the past decade, the demand for air travel has experienced a substantial growth, leading to a doubling in passengers numbers carried in 2007 (ICAO, 2018). The latest IATA forecast predicts that the worldwide air passenger number will continue to grow with a 3.5% compound annual growth rate, reaching 8.2 billion in 2037 (IATA, 2018), which will bring immense pressure on existing airport infrastructures.

To cope with this surging demand, some governments have been increasing or planned to enlarge their airports' capacity by expanding existing infrastructures or constructing new facilities. Opponents criticize these investments with the opinion that, in addition to environmental concerns, the available facilities have not been effectively utilized. On the other hand, the rapid development of high-speed rail (HSR) around the world, in particular in Northeast Asia, may cancel out the positive effects related to the investments in airports' capacity expansion and influence airports productivity.

In theory, an airport's productivity associates with many variables, including its inputs (e.g., runway, terminal, and labor supply) and outputs (e.g., passenger, cargo, and aircraft movements).These variables jointly determine the airport's productivity. The inputs, in particular capital input, of an airport cannot be easily adjusted compared with the outputs which are very sensitive to exogenous environments. This may lead to the fact that the dynamic of an airport's productivity is mainly driven by the changes in its outputs. For example, HSR may play a role in affecting an airport's productivity by influencing the airport's outputs such as passenger traffic and aircraft movement. To date, although several attempts have made to examine the impacts of HSR on airports' passenger traffic (e.g., Clewlow et al., 2014; Zhang et al., 2018; Liu et al., 2019), aircraft movements (e.g., Dobruszkes, 2011; Dobruszkes et al., 2014), very few studies investigate the effects of HSR on airport productivity. Results about the impacts of HSR are not consistent even among literature on passenger traffic and aircraft movements. Dobruszkes (2011) and Dobruszkes et al. (2014) reveal that a decline in the number of passenger traffic does not necessarily result in a decrease in the number of flights for some given routes. On thses routes, airlines may arrange more flights per day using smaller airplnaes to compete with HSR. A real-world case is Guiyang-Guangzhou Air Express, the service promoted by Guiyang airport in 2014, which provides cheaper and more flights per day to confront the competition from HSR. Such kind of express services are very popular on HSR affected routes. As a result, the output of an airport captured by its total aircraft movements on all routes may not be negatively influenced as passnger traffic be. Additionally, HSR development may also affect airports' other output such as cargo throughput and variable inputs, for example, employee. These situations make the impacts of HSR on airport productivity more complicated.

With access to a dataset from 2007 to 2015, we first employ data envelopment analysis (DEA) to assess the efficiency of 62 airports in two main Northeast Asian countries: China and Japan. Then, the obtained efficiency scores are used as dependent variables for the second-stage regression analysis to examine the effects of HSR on airport efficiency. Regarding our main explanatory variables, we primarily use two variables to measure HSR development and introduce two variables to capture the effect of the substitutability and complementarity between HSR and air transport on airport productivity. Some scholars question the application of standard two-stage DEA approach because it lacks a well-defined data generation mechanism and there exists unknown serial correlation of the first-stage DEA efficiency estimates (Simar and Wilson, 2007). Thus, we further estimates our results by adopting double bootstrap method. Furthermore, given that the input elements of most sample airports have changed marginally except employee during our study period, we also look into the effects of HSR on the larbor productivity at airports, which is measured by the work load units per employee and the aircraft movements per employee.

We reveal that HSR development relates to a decrease in the technical efficiency of airports. Airports located in cities that have better positions in the HSR network suffer more efficiency loss than the others. We also find that the accessibility advantage of HSR stations from the city center is negatively associated with airport performance. By contrast, good access to an airport from its corresponding HSR station is positively correlated with airport efficiency, in particular to the airports in China. Further, it is evident that HSR development is likely to decrease the labor productivity at Chinese airports, but the development of HSR in Japan is reported to increase the labor productivity at airports when the labor productivity is measured by the aircraft movements per employee.

The contributions of this research are twofold. First, we examine the impacts of HSR development on airport technical efficiency, which have received scant attention in the literature. Second, to our knowledge, our study is the first to explore the impacts of HSR on the labor productivity at airports. Research findings from this study may be of interest to policy makers. We summarize two policy implications from the paper. First, decision makers should take into account the comprehensive effects of HSR on airport when they decide to expand their existing infrastructures. Instead of constructing new infrastructures, improving the current facilities at airports with advanced technologies and reducing the ground access cost may help airports fully utilize their resources. Second, in the case of China, given that reducing the access time between HSR stations and airport terminals may help the airport gain efficiency, it would be a good idea to promote air-HSR intermodal linkage.

The rest of this paper is organized as follows. Section 2 presents the literature review. Section 3 provides the methodology applied in the paper. Section 4 describes the construction of research data. Section 5 reports the empirical findings and Section 6 concludes.

4.2 Literature review

This study relates to literature using DEA method to evaluate airport efficiency. The application of DEA has a long history and has gained vast popularity in the field of transportation in recent years. Cavaignac and Petiot (2017) conduct a compresensive bibliometric survey and reveal that, during the period of 1989 and 2016, more than 460 articles associated with the application of DEA in transport sector were published, among which over 110 focus on airports. Cavaignac and Petiot (2017) only provides the basic statistics of the published studies without involving the details of them. To our knowledge, Libert and Niemeier (2013) is the only literature that thoroughly reviews the application of DEA in airport benchmarking by providing fundamental information such as the selection of DEA model, the choice of inputs and outputs, and the context of investigation. However, almost all the articles reviewed in Libert and Niemeier (2013) were published before 2010. In our study, we follow the standard of Libert and Niemeier (2013) and review the literature published after 2010 on assessing airport technical efficiency with DEA model. Table 4.1 shows the summary of our review.

As depicted in the table, majority of the recent literature concentrates in countries in Europe and the Asia-Pacific region. A common practice in literature is to use output-oriented DEA model which is based on the assumption that the primary goal of airports is to maximize their outputs with the current level of inputs. Variable returns to scale (VRS) model appears to be more popular than constant returns to scale (CRS). The major rationale behind this is that their study samples consist of airports of different sizes (e.g. Adler and Liebert, 2014; D'Alfonso et al, 2015). VRS models is used so that small sized airports are not benchmarked against large sized airports. In this study, we follow the majority of existing studies and adopt output-oriented VRS model. With repsect to the data for the assessment of airport efficiency, output variables such as passenger volume, cargo throughput, and aircraft movements are the most preffered; but the selection of input variables largely depends on the availability of data, nonthelethess, employee, runway and terminal appears more frequently.

The heterogeneity of technical efficiecy among airports can be attributed to other factors which influence the inputs and outputs of airports. Thus, our researh is also relevant to the studies exploreing the determinants of airport technical efficiency. To date, airport technical efficiency has been associated with many internal factors such as airport ownership (e.g., Oum et al., 2008; Martini et al, 2013; Adler and Liebert, 2014), airport hub status (e.g., Yuen and Zhang, 2009; Gitto and Mancuso, 2012; Tsui et al., 2014a), low cost carriers (e.g., Chang et al., 2013; Coto-Millan, et al., 2014) as well as many external factors, for example, economic regulation (e.g., Curi et al., 2011; Assaf and Gillen, 2012; Adler et al., 2015), the curruption of local government (e.g., Yan and Oum, 2014; Randrianarisoa et al., 2015), and airport competition (e.g., Yuen and Zhang, 2009; Scotti et al., 2012; Adler and Liebert, 2014; Merkert and Mangia, 2014; D'Alfonso et al., 2015). Note that the competition here mainly referes to the pressure from neighbouring airports. In fact, HSR, as an effective alternative to air services in the domestic market, could bring competition to airports in two aspects. One is that HSR can have a traffic redistribution effect on airport, i.e., some primary hub airports with good air connectivity may win traffic from smaller airports that has limited air routes may lose traffic after the introduction of HSR, which in some cases could intensify the competition between airports (Liu et al., 2019; Zhang et al., 2019). The other is HSR itself may be a strong rival through attracting passengers who used to travel by airplane. As a result, all these aspects will influence airport technical efficiency. We only find one study in the literature investigating the impacts of HSR on airport efficiency in the context of Italy (Galli et al., 2020). Our research is fundamentally different from Galli et al (2020) by taking into account HSR conncetivity and accessibility rather than using a dummy to indicate the presence of HSR.

Table 4. 1 Summary of studies on the application of DEA in airport benchmarking ((2010-2020) reverse chronological order)

Research	Sample	Methodology		Variables for productivity measures	
		Model	Account for observed heterogeneity	Inputs	Outputs
Chaouk et al. (2020)	59 European and Asia-Pacific airports (2009, 2015)	Output-oriented CRS; Output-oriented VRS.	Two-stage approach with Tobit regression; Bootstrap with truncated regression.	Number of employees; Number of runways; Terminal size; Number of gates.	Passenger traffic; Cargo throughput; Aircraft movements; Non-aeronautical revenues.
Karanki & HoonLim (2020)	59 US airports (2009-2016)	Output-oriented CRS; Output-oriented VRS.	Bootstrap with truncated regression.	Number of employees; Number of gates; Terminal size; Operational costs.	Work unit load; Non-aeronautical revenues.
Ngo & Tsui (2020)	11 New Zealand airports (2006-2017)	Slack-Based Measure DEA-Window Analysis.	Two-stage approach with Tobit regression.	Runway lengths; Operational costs; Labor costs.	Aircraft movements; Aeronautical revenues; Non-aeronautical revenues.
Galli et al. (2019)	31 Italian airports (2003-2014)	Output-oriented CRS.	Bootstrap with truncated regression.	Number of employees; Number of runways.	Passenger traffic; Cargo throughput; Aircraft movements.
Jiang et al. (2019)	110 Chinese airports (2003-2014)	Output-oriented VRS; Three-stage DEA.	-	Terminal size; Runway lengths.	Passenger traffic; Cargo throughput; Aircraft movements.
Ennen & Batool (2018)	12 Pakistani airports (2012)	Input-oriented DEA with restrictions on the weights of inputs and outputs.	-	Number of employees; Number of runways; Number of taxiways; Terminal size.	Passenger traffic; Cargo throughput; Aircraft movements.

Fragoudaki & Giokas (2016)	38 Greek airports. (2011)	Output-oriented VRS.	Two-stage approach with Tobit regression.	Runway lengths; Terminal size; Apron size.	Passenger traffic; Cargo throughput; Aircraft movements.
Gutierrez & Lozano (2016)	21 European airports (2011)	Output-oriented VRS.	-	Number of gates; Number of parking spaces; Runway size; Number of routes; Number of airlines.	Passenger traffic; Cargo throughput; Aircraft movements.
Orkcu et al. (2016)	21 Turkish airports (2009-2014)	Output-oriented VRS; Malmquist-DEA.	Bootstrap with truncated regression.	Number of runway; Runway lengths; Terminal size.	Passenger traffic; Cargo throughput; Aircraft movements.
Lai et al. (2015)	24 Worldwide airports (2010)	Output-oriented VRS; Analytic hierarchy process; Assurance region DEA.		Number of employees; Number of gates; Number of runways; Terminal size; Runway lengths; Operational cost;	Passenger traffic; Cargo throughput; Aircraft movements; Total revenues.
Merkert & Assaf (2015)	30 International airports (2013)	Output-oriented VRS Bootstrap.	Two-stage approach with Tobit regression; Bootstrap with truncated regression.	Runway lengths; Terminal size; Full time equivalent.	Passenger traffic; Cargo throughput; Aircraft movements.
D'Alfonso et al. (2015)	34 Italian airports (2010)	Output-oriented VRS.	Two-stage approach with location scale non-parametric regression.	Number of employees; Number of runways; Number of gates; Number of terminals; Number of check-in desks; Airport size.	Passenger traffic; Cargo throughput; Aircraft movements.

Ulku (2015)	41 Spanish and 32 Turkish airports (2009-2011)	Input-oriented VRS.	-	Runway size; Operational costs; Labor costs.	Passenger traffic; Cargo throughput; Aircraft movements; Aeronautical revenues.
Adler & Liebert (2014)	48 European airports and 3 Australian airports (1998-2007)	Input-oriented VRS.	Robust cluster regression.	Labor costs; Operational costs; Runway capacity.	Passenger traffic; Cargo throughput; Aircraft movements; Non-aeronautical revenues.
Ahn & Min (2014)	23 Worldwide airports (2006-2011)	Non-oriented VRS; Non-oriented CRS; Malmquist index.	-	Passenger terminal size; Cargo terminal size; Runway lengths; Airport size.	Passenger traffic; Cargo throughput; Aircraft movements.
Coto-Millan, et al. (2014)	35 Spanish airports (2009-2011)	Input-oriented VRS; Input-oriented CRS; Malmquist-DEA.	Two-stage approach with Tobit regression.	Labor costs; Operational costs; Value of fixed assets.	Passenger traffic; Cargo throughput; Aircraft movements.
Merkert & Mangia (2014)	35 Italian and 46 Norwegian airports (2007–2009)	Input-oriented VRS; Input-oriented CRS; Input-oriented NIRS.	Bootstrap with truncated regression.	Number of employees; Number of runways; Runway lengths Terminal size; Runway size; Apron size; Airport size.	Passenger traffic; Cargo throughput; Aircraft movements.

Scotti et al. (2014)	44 US airports (2005-2009)	Output-oriented CRS; Directional distance function approach.	Two-stage approach with Tobit regression.	Number of gates; Runway lengths; Terminal size; Airport size; Operational costs.	Passenger traffic; Cargo throughput; Aircraft movements.
Tsui et al. (2014a)	21 Asia-Pacific airports (2002-2011)	Output-oriented VRS.	Two-stage approach with Tobit regression.	Number of employees; Number of runways; Terminal size; Runway lengths.	Passenger traffic; Cargo throughput; Aircraft movements.
Tsui et al. (2014b)	11 New Zealand airports (2009-2011)	Input-oriented VRS; Slack-based DEA; Malmquist-DEA.	Bootstrap with truncated regression.	Number of runways; Operating costs.	Passenger traffic; Aircraft movements; Total revenues.
Adler et al. (2013)	43 European airports (1998-2007)	Output-oriented VRS; Network DEA.	-	Labor costs; Operational costs; Runway capacity; Terminal capacity.	Passenger traffic; Cargo throughput; Aircraft movements. Aeronautical revenues; Non-aeronautical revenues;
Chang et al. (2013)	41 Chinese airports (2008)	Output-oriented VRS; Output-oriented CRS; Output-oriented NIRS.	Bootstrap with truncated regression.	Terminal size; Runway size; Operating hours.	Passenger traffic; Cargo throughput; Aircraft movements.
Ha et al. (2013)	12 Northeast Asian airports (1994-2011)	Output-oriented VRS; Output-oriented CRS.	Two-stage approach with Tobit regression.	Number of employees; Terminal size; Runway lengths.	Work load unit.
Martini et al. (2013)	33 Italian airports (2005-2008)	Output-oriented VRS; Directional distance function approach.	Bootstrap with truncated regression.	Number of parking spaces; Number of baggage claims; Runway lengths; Terminal size.	Work load unit; Aircraft movements; Local air pollution; Noise levels.

Assaf & Gillen (2012)	73 International airports (2003-2008)	Output-oriented VRS; Semiparametric Bayesian stochastic frontier model.	Two-stage approach with Truncated regression; Bootstrap with truncated regression.	Number of employees; Number of runways; Terminal size; Operational costs.	Passenger traffic; Aircraft movements. Non-aeronautical revenues;
Barros et al. (2012)	27 French airports (2000-2008)	Output-oriented CRS.	Bootstrap with truncated regression.	Number of employees; Passenger terminal size; Runway size.	Passenger traffic; Total freight volume; Total mail volume; Aircraft movements.
Gitto & Mancuso (2012)	28 Italian airports (2000-2006)	Output-oriented CRS; Bootstrap.	Bootstrap with truncated regression.	Number of employees; Terminal size; Runway size.	Passenger traffic; Cargo throughput; Aircraft movements.
Merkert & Mangia (2012)	46 Norwegian airports (2007–2009)	Input-oriented VRS; Input-oriented CRS; Input-oriented NIRS.	Bootstrap with truncated regression.	Number of employees; Number of runways; Runway lengths Terminal size; Runway size; Apron size; Airport size.	Passenger traffic; Cargo throughput; Aircraft movements.
Perelman & Serebrisky, (2012)	21 Latin American airports (2000-2007)	Output-oriented VRS; Output-oriented CRS; Malmquist-DEA.	-	Number of employees; Number of runways; Terminal size.	Passenger traffic; Cargo throughput; Aircraft movements.
Wanke (2012)	63 Brazilian airports (2009)	Output-oriented VRS Bootstrap.	-	Number of runways; Number of parking spaces; Number of parking places; Runway lengths; Terminal size; Apron size; Airport size.	Passenger traffic; Cargo throughput; Aircraft movements.

Curi et al. (2011)	18 Italian airports (2000-2004)	Output-oriented CRS Bootstrap.	-	Number of employees; Number of runways; Terminal size.	Passenger traffic; Cargo throughput; Aircraft movements.
Lozano & Gutierrez (2011)	39 Spanish airports (2006 and 2007)	Non-oriented VRS; Slacks-based DEA.	-	Number of apron stands; Number of gates; Number of check-in desks; Number of bag belts; Runway size.	Passenger traffic; Cargo throughput; Aircraft movements.
Tsekeris (2011)	39 Greek airports (2007)	Output-oriented VRS; Output-oriented CRS.	-	Runway lengths; Terminal size; Apron size; Operating hours.	Passenger traffic; Cargo throughput; Aircraft movements.

Note. VRS = Variable returns to scale; CRS = Constant returns to scale; NIRS = Non-increasing returns to scale.

4.3 Research methodology

In this section, we first introduce the standard two-stage DEA approach and the double bootstrap DEA procedure developed by Simar and Wilson (2007), both of which are used to explore the effects of exogenous factors on airport technical efficiency. We then specify the econometric model for examining the effects of HSR on the labor productivity at airports.

4.3.1 Two-stage DEA

Two-stage procedure is a method wherein efficiency is assessed in the first stage and then the resulting efficiency scores are regressed on some exogenous variables in the second stage. In this study, we calculate the efficiency of airports by DEA which is a non-parametric approach for the identification of efficiency frontiers. Compared to parametric efficiency measures such as stochastic frontier analysis (SFA), DEA allows the use of multiple inputs and outputs without imposing assumptions about the specification of a functional form for the frontier and the probability distribution of the error terms (Cummins and Xie, 2016).

DEA model can be either output-oriented or input-oriented depending on the strategies for improving the performances of insufficient decision-making units (DMUs). Output-oriented model attempts to maximize the outputs while retaining the level of inputs unchanged. On the contrary, input-oriented model seeks to minimize inputs without influencing the level of outputs. In this paper, we follow Gitto et al. (2010) and Galli et al. (2020) and employ output-oriented model. There are also two main reasons. First, it is infeasible to cut the costly infrastructures without years of rigorous planning even though an airport can lay off its employee in the short run.

Second, this study aims to provide decision makers at airports with a view that enables them to verify how far the airports' outputs can be increased with currently available inputs.

In general, DEA has two main types of models, i.e., BCC model (Banker et al., 1984) and CCR model (Charnes et al., 1978). BCC model also refers to variable returns to scale (VRS) model and CCR models is also known as constant returns to scale (CRS) model. The difference between VRS and CRS lies in the assumption regarding returns to scale. CRS model assumes that any change in inputs should result in a proportionate change in outputs while VRS supposes that a proportionate change in all inputs will not produce a proportionate change in outputs, allowing either increasing or decreasing returns to scale. The CRS assumption is only appropriate when all decision-making units (DMUs) are operating at an optimal scale (Charnes et al., 1978). Conversely, the VRS assumption is suitable when DMUs are not operating at an optimal scale, which is usually the case when DMUs are facing imperfect competition, government regulations, etc. In fact, the latter situation is more appropriate to reflect the real case of airport competition, we therefore use output-oriented VRS DEA model for the assessment of efficiency in the first stage. Suppose that we have n DMUs and each DUM consumes m different inputs to produce s different outputs. Then the efficiency score of each DMU can be obtained by solving the following linear programming problem (Cooper et al., 2004):

$$Max \;\; \theta$$

subject to:

$$\sum_{j=1}^{n} \lambda_i x_{ij} \;\le\; x_{io}, \qquad i = 1,2,\ldots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \theta y_{ro}, \qquad r = 1,2, \dots, s \tag{1}$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0, \qquad j = 1,2, \dots, n$$

where θ is the efficiency score, x_{ij} denotes the consumption of input i by DMU j, y_{rj} is the production of output r by DMU j, x_{io} and y_{ro} respectively represent the input i and output r of DMU o, which is the DMU under evaluation. The DMU lies on the efficient frontier when its efficiency score equals to 1. Higher scores indicates less efficient

DEA model mainly focuses on measuring efficiency without explaining the efficiency differentials resulting from environmental variables. To quantify the effects of HSR on airport efficiency, the obtained efficiency scores are then carried over to the Tobit regression analysis using the following models:

$$\theta_{it}{}^{*} = \beta_0 + \beta_1 HSR_{it} + \mathbf{X}_{it}\boldsymbol{\gamma} + \delta_i + \epsilon_{it} \tag{2}$$

$$\theta_{it} = \begin{cases} \theta_{it}{}^{*}, & if \ \theta_{it}{}^{*} > 1 \\ 1, & Otherwise \end{cases}$$

where $\theta_{it}{}^{*}$ stands for the observed efficiency score for airport *i* in year *t*, HSR_{it} captures the development of HSR in the city where airport *i* is located in year *t*. $\mathbf{X}_{it}$ is the vector of control variables. δ_i is airport dummy and ϵ_{it} is error term.

$$\theta_{it} = \beta_0 + \beta_1 HSR_{it} + \beta_2 HSR\_SE_{it} + \beta_2 HSR\_CE_{it} + \mathbf{X}_{it}\boldsymbol{\gamma} + \delta_i + \epsilon_{it} \tag{3}$$

where HSR_SE_{it} and HSR_CE_{it} measure the HSR's capability to substitute and complement air transport respectively.

4.3.2 Bootstrap DEA

Simar and Wilson (2007) question the application of conventional two-stage approach for two reasons. First, the traditional procedure fails to describe the coherent data generation process (DGP) which would make the regression in the second stage sensible. Second, the standard method may make the inference invalid by including DEA efficiency scores that are serially correlated. The authors proposed a double bootstrap procedure to deal with these concerns and the novel approach has been widely used in recent studies. Similar with the standard two-stage DEA, there are also two typical stages in Simar and Wilson (2007). In the first stage, it corrects the bias in the DEA efficiency scores by bootstrap procedure. Then, the bias-corrected efficiency scores are regressed on environmental variables using a second bootstrap procedure applied to the truncated regression. We include the brief procedures in the appendix (Appendix C.2) and refer the audience to Simar and Wilson (2007) for the details of the procedures. The proposed algorithm can be easily performed with existing software such as *FEAR* package in R and STATA.

However, the assumption about DGP in Simar and Wilson (2007) is restrictive because it does not include a two-sided noise term. As a result, the preference for truncated regression rather than Tobit in the second stage is less appropriate (Banker and Natarajan, 2008). In addition, the approach proposed by Simar and Wilson (2007) assumes that the exogenous factors only affect the inefficient processes but not the frontier, which should be tested further (Simar and Wilson, 2011). Thus, in this paper, we apply both standard two-stage procedure and Simar and Wilson (2007) method to obtain robust estimations. Note that the econometric models for the double bootstrap procedure are the same with those of the standard two-stage approach.

4.3.3 HSR effect on airport's labor productivity

Labor and capital are two most important inputs at airports. However, the investment in airport capital infrastructures normally requires years of planning and the adjustments of the facilities are not easy. In fact, only a few airports expanded their terminals or built new runways during our study period. Nonetheless, most airports adjusted their numbers of employees annually to cope with market dynamics, meaning that airport efficiency reflected by labor productivity may be differently affected by HSR. As a complement to our efficiency analysis, we identify the effects of HSR development on the labor productivity at airports. In this study, we use two common measures to assess the efficiency of labor use at airports. One measure is based on work-unit loads (WLU) per employee, which calculates the volumes of passenger and cargos handled by per worker. The calculation of WLU follows Ha et al. (2013). The other measure is the aircraft movements per employee. Similar to the econometric models for airport's efficiency, the specifications for airport's labor productivity are:

$$\ln(L_{it}) = \beta_0 + \beta_1 \ln(HSR_{it}) + \mathbf{X}_{it}\boldsymbol{\gamma} + \delta_i + \epsilon_{it} \tag{4}$$

$$\begin{aligned}\ln(L_{it}) = \beta_0 + \beta_1 \ln(HSR_{it}) + \beta_2 \ln\left({HSR_{SE}}_{it}\right) + \beta_2 \ln\left({HSR_{CE}}_{it}\right) \\ + \mathbf{X}_{it}\boldsymbol{\gamma} + \delta_i + \epsilon_{it}\end{aligned} \tag{5}$$

where L_{it} is the labor productivity of airport *i* in year *t*.

4.4 Data and variable construction

There are more than 200 civil airports[22] in mainland China with a total passenger traffic of 914.8 million by the end of 2015 (CAAC, 2015) and 87 airports in Japan with passenger throughput of 277.7 million at the same period. Considering the availability of data, this paper only involves airports that have an annual passenger of over two billion by 2015. Specifically, we take into account 48 Chinese airports and 18 Japanese airports over the time period from 2007 to 2015. Among the 48 Chinese airports, Shanghai Hongqiao Airport (SHA) and Shanghai Pudong Airport (PVG) are merged into one airport entity (SHPV) because both airports are operated under the same authority and hence only aggregated data of the employee are available for them. Beijing Nanyuan Airport (NAY) is excluded due to a lack of employee data. In the case of Japan, Naha Airport (OKA) and Ishigaki Airport (ISG) are removed since they are located on Ishigaki Island which is not possible to be connected by HSR. As a result, our estimation is based on 46 Chinese airports and 16 Japanese airports. Our sample airports account for 92.2% of China's total air passenger traffic and 81.7% of Japan's total air passenger traffic, 97.7% of China's total freight throughput and 90.3% of Japan's total freight throughput, 77% of China's total aircraft movements and 74.8% of Japan's total aircraft movements, and cover majority of large cities in China and Japan.

As discussed in the literature review section, this paper includes three input factors, i.e., runway lengths which is defined by the total lengths of all the runways of an airport, terminal size which is the sum of passenger and cargo terminal areas, and employee. As for output variables, we consider passenger throughput, cargo

[22] 206 out of the 210 commercial airports have regular service.

throughput and aircraft movements. The data for input and output variables are collected from various sources, including Statistical Data on Civil Aviation of China (2008-2016), Japanese Ministry of Land, Infrastructure, Transport and Tourism (MILT, 2007-2015), airports' annual reports, news articles, and the authors' direct contact with airports' managers. Table 4.2 and 4.3 present the descriptive statistics for the input and output variables.

Table 4. 2 Descriptive statistics of input and output variables for Chinese airports

Variable	Observation	Mean	Std.	Min	Max
Outputs (000)					
Passengers	414	12711.51	16208.01	699.88	99188.94
Cargo	414	242.01	558.85	1.28	3708.83
Flight Movements	414	107.35	118.08	7.07	705.77
Inputs					
Runway length (m)	414	4125.12	2518.95	2400	21700
Terminal Size (m^2)	414	143700	245000	3500	1414000
Employee	414	1953.21	1378.47	320	7136

Table 4. 3 Descriptive statistics of input and output variables for Japanese airports

Variable	Observation	Mean	Std.	Min	Max
Outputs (000)					
Passengers	144	12563.88	16432.51	1717.10	75254.95
Cargo	144	295.41	532.58	0	2254.42
Flight Movements	144	94.88	91.91	14.37	438.54
Inputs					
Runway length (m)	144	4228.69	2183.73	2500	11000
Terminal Size (m^2)	144	201660.2	288871.1	17052	1177700
Employee	144	160.65	185.78	4	773

Control variables used in the regression analysis are listed and explained in Table 4.4.[23] We control the population and real GDP per capita of the airport's hinterland. In this study, we follow Liu et al. (2019) and define the hinterland of an airport as the municipality or prefecture-level city where the airport locates for the case of China and the prefecture in which the airport is situated for the case of Japan. For each airport

[23] Since the basic econometric specification for the standard two-stage DEA approach and the double bootstrap DEA procedure are the same, the control variables used in these two methods are the same.

in our sample, its population is the number of its hinterland's permanent residents. The real GDP per capita of each airport shows its hinterland's real GDP, using 2007 as the base year, divided by its hinterland's population. In addition, we also control airport's characteristics such as privatization, hub status, and runway structures which are known to influence airport performance. Some other external factors of an airport also relate to the changes in demand. Thus, we include *jet fuel price* and *compete* to capture the external factors that may affect airport performance. Data for *jet fuel price* is obtained from IATA Fact Sheet (Fuel) 2018. *Compete* is a dummy variable to indicate whether the airport has competitors within a radius of 100 km. Further, we control exogenous events that cause large demand shocks, for example, Beijing Olympic Games in 2008, global financial crisis in 2009[24], and Tohoku earthquake and tsunami in 2011. We present the descriptive statistics for all independent variables in Appendix C.1.

Table 4. 4 Description of control variables

Variable	Labels	Definition
Population	POP	The total population of an airport's hinterland as a proxy for the market size of the airport.
GDP per capita	GDP_POP	The real GDP per capita of an airport's hinterland as a proxy for the market size of the airport
Privatization	Private	Dummy variable. It equals to 1 if an airport is fully or partially private.
Hub status	Hub	Dummy variable. It equals to 1 if an airport is an international hub (Beijing, Shanghai, Guangzhou, Haneda, Narita, Kansai).
Runway structure	RwyStructure	Dummy variable. It equals to 1 if two runways are too close to each other (< 460m) or have intersections (Guangzhou, Haneda, Shanghai et al.)
Jet Fuel Price	Fuel	Aviation jet fuel price which is measured by US 100 dollar/bbl (Base = 2000).

[24] The global financial crisis started in 2008 but had most obvious on the aviation sector in 2009.

Competition	Compete	Number of airports within a 100km radius of the airport.
Beijing Olympic games	Olympic	Dummy variable. Year 2008 = 1
Global financial crisis	Crisis	Dummy variable. Year 2009 = 1
Tokoku earthquake and tsunami	Disaster	Dummy variable. Year 2011 = 1

Regarding the HSR related independent variables in the equations in Section 3, we include HSR_{it}, HSR_SE_{it}, and HSR_CE_{it}. HSR_{it} is used to measure the development of HSR on air transport. We construct this variable in four ways, namely HSR connectivity, HSR accessibility, integrated HSR connectivity and accessibility and HSR dummy. The first three measures take into account the heterogeneous levels of HSR development among different cities while the last measure only indicates the presence of HSR. We assume the value of these measures equals to 0 when there is no HSR stations in the city where the airports locate. The calculation is based on HSR service data which is obtained from China Train Timetable (2007-2015) and Japan Railway Timetable (2007-2015). The details of the methods can be found in Liu et al. (2019) and Liu et al. (2020). It is worth noting that passengers can still access to HSR by other transportation modes when there is no HSR station in the city that the airport locates. This depends on the relative convenience in travelling to HSR stations from the city center. Thus, we introduce HSR_SE_{it}. HSR_SE_{it} reflects the substitution of air transport by HSR and is estimated by the advantage of HSR station over airport in the convenience of accessing to/from city center. It is formulated as:

$$HSR\_SE_{it} = \frac{AirtoCity_{it}}{HSRtoCity_{it}} \tag{6}$$

where $AirtoCity_{it}$ is the road distance from airport i to its city center and $HSRtoCity_{it}$ denotes the road distance from HSR station in the city that airport i

locates to the city center. If there is no HSR station in the city, we choose the nearest HSR station to the airport instead. We take the average distance when there are multiple HSR stations in the city.

HSR_CE_{it} indicates the complementarity of HSR on air transport, which is approximated by taking the reciprocal of the road distance between airport i and its nearest HSR station. Again, we calculate the mean value of the distance when there are multiple HSR stations in airport i's city. It is expressed as:

$$HSR\_CE_{it} = \frac{1}{AirtoHSR_{it}} \tag{7}$$

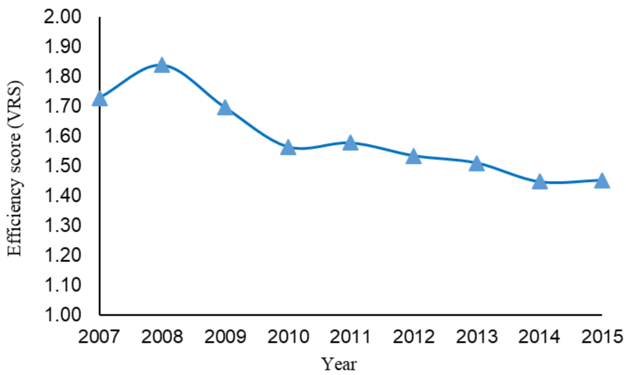
4.5 Empirical results

4.5.1 Airport technical efficiency

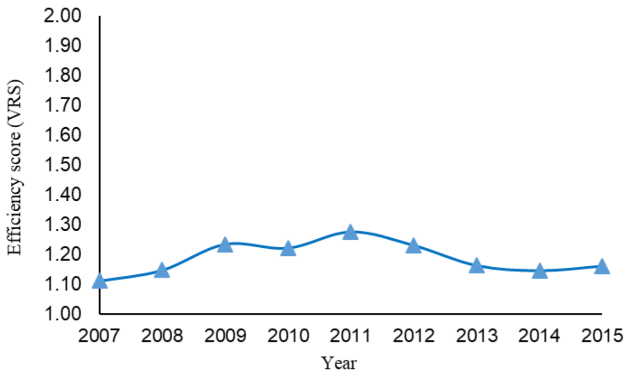
Airport in different countries have their unique characteristics associated with the country, therefore, the comparison of airport efficiency across countries is less meaningful without reasonable assumption (Merkert and Mangia, 2014). Since there are many differences between China and Japan, for example, national territories, cultural backgrounds, and average years of schooling, which are important factors in determining the investment in airports infrastructures and the level of airports' management, we pool all years from 2007 to 2015 together and calculate the efficiency scores of airports in these two countries separately.

The average efficiency score of Chinese airports and Japanese airports over the 2007-2015 period is 1.781 and 1.248 respectively under VRS estimation, indicating that airports in China, on average, can improve their outputs by 43.8% and Japanese airport, on average, can increase their outputs by 19.8% to reach the efficient frontiers with their current levels of inputs.[25]

Figure 4.1 (a)-(b) show the overall trend of airport efficiency in China and Japan. Chinese airports appear to become more technically efficient during our observation period. However, there was a loss in efficiency in 2008 among airports in China. This is because the economic recession[26] and the holding of Beijing Olympic Games. By contrast, Japanese airports seem to be more stable than their counterparts in China. The technical efficiency fell to its lowest level in 2011 because of the Tohoku earthquake and tsunami.



(a) Chinese airports



(b) Japanese airports

Figure 4. 1 Trend of overall airport efficiency during the 2007-2015 period

[25] Scores of 1 imply technically efficient. Higher score indicates relatively less efficient.
[26] Note that the crisis seems to have little impact on Japan in 2008 but its impact becomes more obvious in 2009 which is different from China.

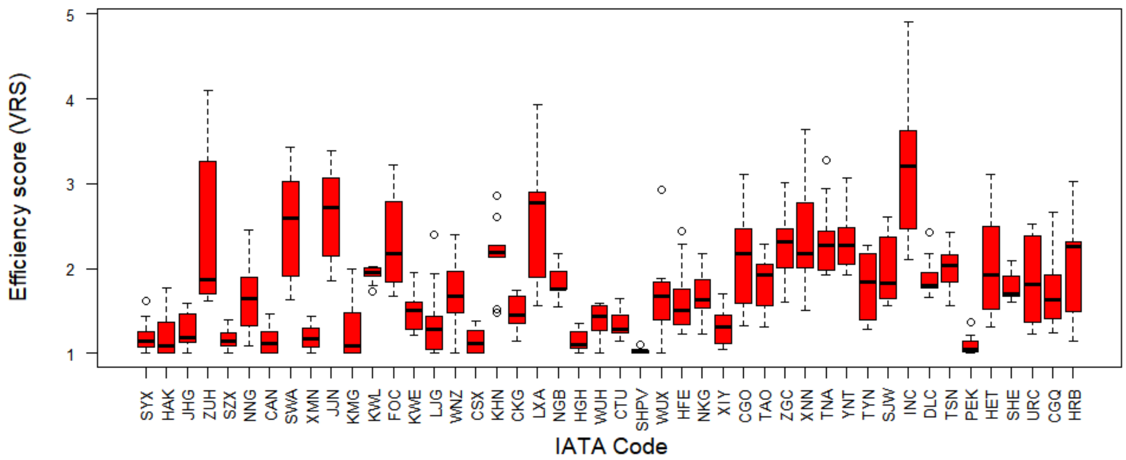


Figure 4. 2 Boxplot distribution of Chinese airports' efficiency scores between 2007 and 2015[27]

Figure 4.2, sorted by the ascending order or airports' latitudes, shows the distribution of efficiency scores across the 46 airports in China. We observe that airports in the southern part of China, on average, are more technically efficient than those in the north. We also find that Shanghai (SHPV), Beijing (PEK), Shenzhen (SZX), and Guangzhou (CAN) airports have lower median values and little inter-quartile ranges of efficiency scores, indicating that these airports are the most efficient and stable ones during our study period. On the other hand, airports located near those most efficient airports are far from efficient, for example, Wuxi (WUX), Tianjin (TSN), Zhuhai (ZUH), and Chaoshan (SWA). One possible explanation for this phenomenon is that large airports tend to be more attractive in a multi-airport system.

Similarly, we plot the distribution of efficiency scores for the 16 Japanese airports in Figure 4.3. The figure based on the ascending order of airports' longitudes shows that most airports with low efficiency are situated along Tokaido Shinkansen which is the busiest HSR line in Japan. It also reveals that airports in the west, on average,

[27] Please refer to Table B.1 in the appendix for the name of airport.

performs better than those in the east where the HSR lines are more densely distributed.

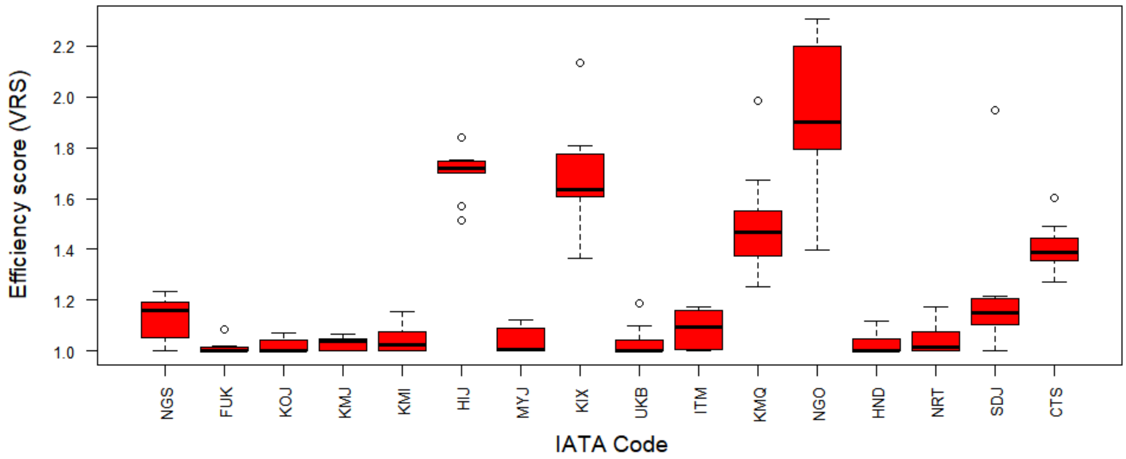


Figure 4. 3 Boxplot distribution of Japanese airports' efficiency scores between 2007 and 2015[28]

As shown in table 4.5, the average yearly efficiency score of Chinese airports ranges between 1.034 (Shanghai airport group, SHPV) and 3.204 (Yinchuan airport, INC). According to the overall change rate which is the average annual efficiency change rate, airports with the most significant improvement in efficiency include Zhuhai (ZUH), Harbin (HRB), Hohhot (HET), Changchun (CGQ), and Chaoshan (SWA) airports. The scores of these airports drop by over 10% every year on average, meaning that the resources in these airports are utilized increasingly efficient. For example, the efficiency score of Harbin airport decreased from 3.021 in 2007 to 1.142 in 2015, achieving an above-average performance. On the contrary, the efficiency performance of Wuxi (WUX) and Wenzhou (WNZ) airports experienced a notable decrease by having their average yearly growth rates in their efficiency scores of more than 5%. Given that Wuxi and Wenzhou have very important positions in the HSR network, this drop might be partially attributed to the decline in airport throughputs

[28] Please refer to Table B.1 in the appendix for the name of airport.

resulting from the development of HSR.

Table 4. 5 Summary statistics of efficiency scores for Chinese airports over 2007-2015

IATA Code	Mean	Std.	Average Yearly Change (%)
CAN	1.165	0.055	-4.95
CGO	2.098	0.450	-8.83
CGQ	1.752	0.233	-10.28
CKG	1.458	0.049	-5.97
CSX	1.150	0.070	-3.62
CTU	1.348	0.061	0.30
DLC	1.914	0.183	-4.40
FOC	2.341	0.057	-8.68
HAK	1.230	0.172	-7.86
HET	2.075	0.034	-11.63
HFE	1.638	0.030	2.28
HGH	1.147	0.004	-4.11
HRB	2.015	0.204	-13.45
INC	3.204	1.019	-7.68
JHG	1.276	0.135	3.63
JJN	2.651	0.228	-5.18
KHN	2.155	0.033	-3.36
KMG	1.282	0.021	-0.08
KWE	1.510	0.052	-5.91
KWL	1.931	0.068	-0.13
LJG	1.386	0.035	-1.15
LXA	2.550	0.825	-8.86
NGB	1.830	0.039	-4.50
NKG	1.704	0.039	-5.14
NNG	1.682	0.119	-5.82
PEK	1.101	0.264	-0.72
SHE	1.798	0.071	-3.01
SHPV	1.034	0.073	-0.14
SJW	1.976	0.452	0.36
SWA	2.537	0.162	-10.17
SYX	1.214	0.123	-6.59
SZX	1.172	0.007	0.88
TAO	1.815	0.168	-5.99
TNA	2.355	0.239	-7.34

TSN	1.987	0.166	-5.91
TYN	1.782	0.090	-5.22
URC	1.846	0.086	-8.98
WNZ	1.676	0.000	5.27
WUH	1.381	0.415	1.48
WUX	1.691	0.593	8.84
XIY	1.319	0.056	-0.11
XMN	1.194	0.260	-0.19
XNN	2.436	0.166	-8.74
YNT	2.389	0.410	-1.90
ZGC	2.244	0.384	-3.64
ZUH	2.489	0.587	-14.90
Overall	1.781	0.195	-4.18

According to table 4.6, the average efficiency scores of Japanese airports vary from 1.015 (Fukuoka airport, FUK) to 1.946 (Chubu airport, NGO). Major airports such as Haneda, Narita, and Osaka operate at high level of efficiency, whereas Kansai airport with an average score of 1.669 is reported as one of the least efficient airports in our Japanese sample. In addition, we observe that the efficiency of Japanese airports has stagnated over time. The losses in efficiency is particularly outstanding for Komatsu airport (KMQ), Kansai airport (KIX), Chubu airport (NGO), and Sendai airport (SDJ), all of which lose efficiency by more than 2% per year on average.

Table 4. 6 Summary statistics of efficiency scores for Japanese airports over 2007-2015

IATA Code	Mean	Std.	Average Yearly Change (%)
CTS	1.409	0.099	-0.634
FUK	1.015	0.027	0.055
HIJ	1.700	0.099	1.685
HND	1.030	0.046	0.095
ITM	1.095	0.075	-1.056
KIX	1.669	0.234	4.755
KMI	1.050	0.056	0.114
KMJ	1.032	0.025	0.032
KMQ	1.518	0.212	6.805
KOJ	1.026	0.030	0.090

MYJ	1.040	0.052	0.105
NGO	1.946	0.305	4.153
NGS	1.137	0.083	1.820
NRT	1.051	0.066	0.385
SDJ	1.213	0.286	2.683
UKB	1.039	0.065	0.221
Overall	1.248	0.072	1.199

In both China and Japan, we find that large airports, in general, are more technically efficient. This phenomenon is consistent with existing literature which focuses on other countries, for example, Italy (Curi et al., 2011; D'Alfonso et al., 2015) and UK (Assaf, 2009). The finding suggests that small airports in China and Japan have more spare capacity and could improve their productivity with their current levels of inputs. On top of this, we identify that the development of airports in China is more unbalanced than in Japan according to the distribution of the airports' efficiency scores.

4.5.2 The impact of HSR on airport efficiency

We now turn our focus to the regression analysis which examines the effects of HSR development on the technical efficiency of airports in China and Japan. In this section, we discuss and compare the results obtained from the two-stage DEA approach and the double bootstrap DEA procedure.

Table 4.7 reports the parameter estimation of Equation (2) using standard two-stage approach for Chinese airports. Column (1) to (4) employ various indices to estimate the development of HSR, namely, connectivity (1), accessibility (2), integrated connectivity and accessibility (3), and HSR dummy (4). All variables denoting HSR are positive and statistically significant but the one in column (4) which is not significant and negative. In fact, using a dummy variable may not be able to reflect the true effects of HSR on airports. One reason is that it treats all airports equally without identifying the heterogeneous positions of cities in the HSR network. Another reason is that the measure does not consider factors (e.g., travel time and frequency) related to the competition between HSR and air transport. Hence, the results showed in column (4) is for reference only. Estimates in column (1), (2) and (3) suggest that HSR development is negatively correlated with airport efficiency. More specifically, increasing the connectivity and accessibility of a city in the HSR network relates to losses in the technical efficiency of airports located in that city. The degree of reduction in efficiency can be approximated by the magnitude of increase in efficiency score, indicating that higher value of efficiency scores associates with lower efficiency. In addition, most of the estimates for control variables satisfy our expectation. For example, GDP per capita and the hub status of an airport are reported to be positively correlated with airport efficiency, but airport competition and global financial crisis appear to reduce airport efficiency. However, the coefficients on Olympic are positive, meaning that hosting 2008 Olympic Games did not help Chinese airports improve efficiency in that year, which is opposite to our hypothesis. This phenomenon might be attributed to the intense security measures in place during the Olympic Games and in addition to a series of natural disasters such as Chinese winter storms and Sichuan earthquake occurred in the first half of 2008.

Table 4. 7 Results using two-stage DEA (China)

China	(1) Connectivity	(2) Accessibility	(3) Integrated	(4) Dummy
POP	-0.012	0.037	0.003	0.084*
	(0.051)	(0.051)	(0.051)	(0.049)
GDP_POP	-0.354***	-0.306***	-0.343***	-0.240***
	(0.035)	(0.036)	(0.036)	(0.029)
Privatize	0.087	0.058	0.072	0.062
	(0.191)	(0.193)	(0.192)	(0.193)
Hub	-1.330**	-1.732***	-1.417**	-2.260***
	(0.622)	(0.636)	(0.634)	(0.612)
Fuel	0.241**	0.058	0.171	-0.068
	(0.112)	(0.106)	(0.111)	(0.095)
Compete	0.437**	0.493**	0.485**	0.401
	(0.195)	(0.200)	(0.197)	(0.201)
RwyStructure	0.135***	0.143***	0.140***	0.137***
	(0.025)	(0.025)	(0.025)	(0.025)
Olympic	0.186***	0.253***	0.217***	0.269***
	(0.069)	(0.068)	(0.069)	(0.068)
Crisis	0.168**	0.137*	0.162**	0.089
	(0.069)	(0.071)	(0.070)	(0.070)
HSR	0.009***	1.549**	0.439***	-0.102
	(0.001)	(0.615)	(0.111)	(0.069)
Constant	2.817***	2.295***	2.530***	2.357***
	(0.624)	(0.625)	(0.623)	(0.631)
Airport Dummy	Yes	Yes	Yes	Yes
N	414	414	414	414
LR chi2	529.11	512.55	521.45	508.38
Log likelihood	-172.92	-181.20	-176.75	-183.29

Note. Standard errors are in parentheses. **p <0.1; **p<0.05; ***p<0.01.*

Table 4.8 reports the estimation results of Equation (3), which takes into account the substitutability and complementarity between HSR and air travel, using standard two-stage method for airports in China. Again, we use the estimates in the first three columns to interpret our findings. As shown in the table, the coefficient of HSR_CE is negative and statistically significant, meaning that improving the accessibility between airport and HSR station may help increase the technical efficiency of the airport. This is because easy access to airports from HSR stations may facilitate the cooperation between HSR and air transport, which accordingly bring more traffic to the airport. On the other hand, we observe that airport productivity is likely to decrease because of the substitution of air travel by HSR despite the fact that the coefficient is not consistently significant across all columns. In other words, airports that are more difficult to access from the city center than their relevant HSR stations normally experience substantial reductions in efficiency. Estimates for all the other variables are consistent with the baseline model (Equation (2)).

Table 4. 8 Results with HSR substitutability and complementarity using two-stage DEA (China)

China	(1) Connectivity	(2) Accessibility	(3) Integrated	(4) Dummy
POP	-0.014	0.035	0.0001	0.089*
	(0.050)	(0.051)	(0.051)	(0.049)
GDP_POP	-0.357***	-0.309***	-0.348***	-0.236***
	(0.035)	(0.036)	(0.036)	(0.029)
Privatize	0.128	0.099	0.118	0.060
	(0.191)	(0.194)	(0.193)	(0.193)
Hub	-1.390**	-1.750***	-1.441**	-2.326***
	(0.615)	(0.633)	(0.627)	(0.611)
Fuel	0.289**	0.092	0.220*	-0.061
	(0.112)	(0.106)	(0.112)	(0.095)
Compete	0.362*	0.430**	0.408**	0.389*
	(0.196)	(0.200)	(0.198)	(0.201)
RwyStructure	0.132***	0.141***	0.138***	0.136***
	(0.024)	(0.025)	(0.025)	(0.025)
Olympic	0.152**	0.226***	0.182***	0.264***
	(0.069)	(0.069)	(0.069)	(0.068)
Crisis	0.160**	0.129*	0.154***	0.087
	(0.069)	(0.070)	(0.070)	(0.070)
HSR	0.010***	1.972***	0.523***	-0.159
	(0.001)	(0.648)	(0.115)	(0.109)
HSR_SE	0.020**	0.011	0.015*	0.014
	(0.009)	(0.009)	(0.009)	(0.009)
HSR_CE	-3.232**	-3.209**	-3.611**	0.238
	(1.372)	(1.454)	(1.420)	(1.974)
Constant	2.984***	2.428***	2.710***	2.354***
	(0.623)	(0.626)	(0.623)	(0.629)
Airport Dummy	Yes	Yes	Yes	Yes
N	414	414	414	414
LR chi2	536.48	517.66	528.50	510.57
Log likelihood	-169.24	-178.64	-173.23	-182.19

Note. Standard errors are in parentheses. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

Similar to the above analysis carried out for Chinese airports, we present the estimation results for Japanese airports in table 4.9 and 4.10. Table 4.9 reports the estimates by following our baseline model (equation (2)). Compared with the case of

China, in which the estimate for HSR dummy is not consistent with the other three measures of HSR, all variables related to the development of HSR in Japan appear to be positive and statistically significant, indicating that the development of HSR in Japan is negatively correlated with airport efficiency. Nonetheless, our explanation focuses on HSR measured by connectivity (column (1)), accessibility (column (2)), and integrated connectivity and accessibility (column (3)). Specifically, adding one more HSR connections to the city that an airport locates implies an increase of 0.007 in the airport's efficiency score, resulting in a maximum of 0.69% drop in airport efficiency. Likewise, the coefficient on HSR accessibility is equal to 0.630, which means a one-unit increase in the HSR accessibility may decrease airport efficiency by up to 38.6%. Table 4.10 presents the results from estimating equation (3). The coefficients on HSR_SE in column (1)-(3) are all statistically significant at p =0.01 level while those on HSR_CE show no statistical significance with airport efficiency, which reflects the substitution effects of HSR on air transport is more significant than complementary effects in the context of Japan. This arises partly because the shift in passengers from airplanes to bullet trains in Japanese domestic markets where HSR stations are easier to get to. Airports in Japan, in general, require relatively longer access time than HSR stations. Furthermore, we observe that the characteristics of an airport' hinterland show positive correlation with the airport's efficiency and the 2011 earthquake and tsunami severely affect airport performance.

Table 4. 9 Results using two-stage DEA (Japan)

Japan	(1) Connectivity	(2) Accessibility	(3) Integrated	(4) Dummy
POP	-0.507**	-0.491*	-0.499*	-0.455*
	(0.246)	(0.249)	(0.247)	(0.246)
POP-GDP	-0.454***	-0.460***	-0.458***	-0.460***
	(0.109)	(0.109)	(0.109)	(0.106)
Privatize	-0.114	-0.111	-0.113	-0.101
	(0.093)	(0.093)	(0.093)	(0.091)
Fuel	0.079	0.082	0.080	0.094
	(0.066)	(0.066)	(0.066)	(0.065)
Compete	0.866	0.869	0.867	0.849
	(48.32)	(48.248)	(48.25)	(46.99)
Crisis	0.080	0.079	0.080	0.079
	(0.051)	(0.051)	(0.051)	(0.050)
Disaster	0.123***	0.123***	0.123***	0.127***
	(0.039)	(0.039)	(0.039)	(0.038)
HSR	0.007**	0.630**	0.264**	0.278***
	(0.003)	(0.277)	(0.115)	(0.083)
Constant	4.788	4.716	4.756	4.527
	(48.34)	(48.27)	(48.27)	(47.01)
Airport Dummy	Yes	Yes	Yes	Yes
N	144	144	144	144
LR chi2	267.63	267.78	267.84	273.73
Log likelihood	50.25	50.32	50.36	53.30

Note. Standard errors are in parentheses. *$p < 0.1$; **$p<0.05$; ***$p<0.01$.
Hub and *RwyStructure* are omitted due to multi-collinearity.

Table 4. 10 Results with HSR substitutability and complementarity using two-stage DEA (Japan)

Japan	(1) Connectivity	(2) Accessibility	(3) Integrated	(4) Dummy
POP	-0.455*	-0.454*	-0.455*	-0.492*
	(0.238)	(0.238)	(0.238)	(0.251)
GDP_POP	-0.457***	-0.457***	-0.457***	-0.455***
	(0.101)	(0.101)	(0.101)	(0.100)
Privatize	-0.105	-0.105	-0.105	-0.105
	(0.086)	(0.087)	(0.087)	(0.086)
Fuel	0.140**	0.140**	0.140**	0.142**
	(0.064)	(0.064)	(0.064)	(0.064)
Compete	0.769	0.769	0.769	0.774
	(22.71)	(22.72)	(22.71)	(22.79)
Crisis	0.089*	0.089*	0.089*	0.088*
	(0.047)	(0.047)	(0.047)	(0.047)
Disaster	0.123***	0.124***	0.124***	0.125***
	(0.036)	(0.036)	(0.036)	(0.035)
HSR	0.0004	0.012	0.011	4.454
	(0.004)	(0.508)	(0.185)	(8.641)
HSR_SE	0.074***	0.074***	0.074***	-0.124
	(0.017)	(0.017)	(0.017)	(0.386)
HSR_CE	-2.752	-2.650	-2.736	-99.90
	(3.538)	(4.514)	(3.992)	(188.85)
Constant	4.552	4.543	4.548	4.990
	(22.75)	(22.76)	(22.75)	(22.85)
Airport Dummy	Yes	Yes	Yes	Yes
N	414	414	414	414
LR chi2	286.66	286.65	286.65	286.91
Log likelihood	59.76	59.76	59.76	59.89

Note. Standard errors are in parentheses. **p <0.1; **p<0.05; ***p<0.01.*
Hub and *RwyStructure* are omitted due to multi-collinearity.

As mentioned in the methodology section, typical two-stage DEA method lacks a well-defined data generation mechanism and there exists unknown serial correlation of the first-stage DEA efficiency estimates. We address these issues by conducting further analysis with Simar and Wilson (2007) DEA double bootstrap procedure. Table 4.11 and 4.12 report the estimates for airports in China and table 4.13 and 4.14 present the results for Japanese sample. It appears that our main findings on the effects of HSR development on airport efficiency are consistent across different approaches. However, there are a few differences between these two methods. First, the coefficients on HSR have larger values when using double bootstrap approach to estimate our baseline model, indicating that the standard two-stage DEA method may underestimate the impacts of HSR. Figure 4.4 and 4.5 show the difference between the bias-corrected efficiency score and original DEA efficiency score for airports in China and Japan respectively. As shown in the figures, the efficiency score of airports in cities that have HSR stations is larger than airports in cities without HSR stations. Second, in the case of China, the complementarity between HSR and air travel becomes more significant and important in affecting airport efficiency. By contrast, HSR_SE which reflects the substitutability between HSR and air transport becomes less significant as a factor impacting airport efficiency. Third, in the case of Japan, the estimates for both HSR_SE and HSR_CE are improved. Notably, the complementarity between HSR and air transport is likely to improve the efficiency of Japanese airports.

Table 4. 11 Results using double bootstrap procedure (China)

China	(1) Connectivity	(2) Accessibility	(3) Integrated	(4) Dummy
POP	-0.039	0.010	-0.028	0.094
	(0.076)	(0.075)	(0.076)	(0.071)
GDP-POP	-0.495***	-0.453***	-0.491***	-0.366***
	(0.045)	(0.045)	(0.046)	(0.038)
Privatize	-0.063	-0.065	-0.064	-0.057
	(0.354)	(0.373)	(0.357)	(0.378)
Hub	-2.163**	-2.607**	-2.176**	-3.653***
	(0.994)	(1.006)	(1.025)	(0.976)
Fuel	0.178	-0.001	0.114	-0.181
	(0.148)	(0.138)	(0.140)	(0.122)
Compete	0.550*	0.525*	0.573*	0.295
	(0.312)	(0.312)	(0.303)	(0.328)
RwyStructure	0.266***	0.278***	0.273***	0.275***
	(0.039)	(0.039)	(0.039)	(0.043)
Olympic	0.287***	0.350***	0.315***	0.376***
	(0.084)	(0.083)	(0.083)	(0.081)
Crisis	0.173**	0.143	0.167*	0.082
	(0.087)	(0.089)	(0.087)	(0.083)
HSR	0.011***	2.104***	0.547***	-0.150*
	(0.002)	(0.772)	(0.142)	(0.088)
Constant	3.480***	3.156***	3.267***	3.531***
	(1.003)	(1.018)	(0.976)	(1.081)
Airport Dummy	Yes	Yes	Yes	Yes
N	414	414	414	414
Wald chi2	795.14	737.10	841.71	732.23

Note. Standard errors are in parentheses. **p <0.1; **p<0.05; ***p<0.01.*

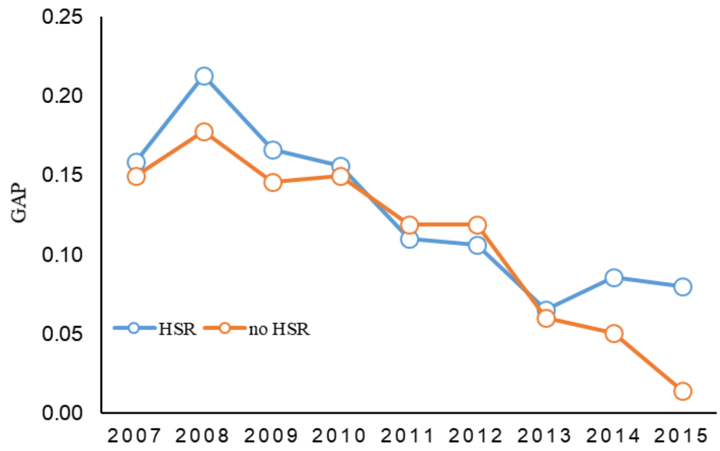


Figure 4. 4 Difference between bootstrap efficiency score and typical DEA score (China)

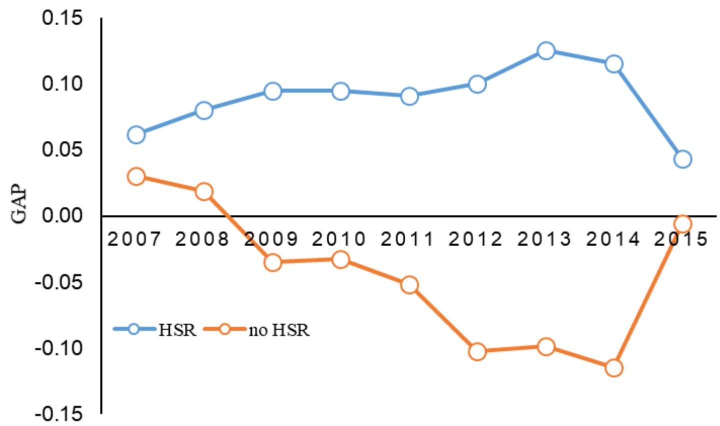


Figure 4. 5 Difference between bootstrap efficiency score and typical DEA score (Japan)

Table 4. 12 Results with HSR substitutability and complementarity using double bootstrap procedure (China)

China	(1) Connectivity	(2) Accessibility	(3) Integrated	(4) Dummy
POP	-0.039	0.008	-0.035	0.096
	(0.074)	(0.076)	(0.070)	(0.075)
GDP_POP	-0.498***	-0.473***	-0.506***	-0.356***
	(0.043)	(0.047)	(0.047)	(0.039)
Privatize	0.018	0.016	0.037	-0.051
	(0.373)	(0.390)	(0.385)	(0.354)
Hub	-2.274**	-2.678**	-2.224**	-3.707***
	(0.973)	(1.057)	(0.966)	(1.047)
Fuel	0.234	0.050	0.187	-0.180
	(0.143)	(0.134)	(0.143)	(0.124)
Compete	0.393	0.349	0.400	0.251
	(0.303)	(0.317)	(0.316)	(0.336)
RwyStructure	0.262***	0.281***	0.275***	0.272***
	(0.038)	(0.040)	(0.038)	(0.041)
Olympic	0.243***	0.307***	0.262***	0.370***
	(0.082)	(0.086)	(0.082)	(0.085)
Crisis	0.164*	0.133	0.158*	0.076
	(0.086)	(0.088)	(0.085)	(0.087)
HSR	0.013***	3.245***	0.730***	-0.169
	(0.002)	(0.887)	(0.146)	(0.128)
HSR_SE	0.020*	0.010	0.016	0.010
	(0.011)	(0.010)	(0.010)	(0.011)
HSR_CE	-5.302***	-6.708***	-6.704***	-0.925
	(1.906)	(2.158)	(2.011)	(2.518)
Constant	3.854***	3.635***	3.714***	3.599***
	(0.994)	(1.012)	(1.001)	(1.065)
Airport Dummy	Yes	Yes	Yes	Yes
N	414	414	414	414
Wald chi2	833.53	803.24	798.83	770.46

Note. Standard errors are in parentheses. *$p < 0.1$; **$p<0.05$; ***$p<0.01$.

Table 4. 13 Results using double bootstrap procedure (Japan)

Japan	(1) Connectivity	(2) Accessibility	(3) Integrated	(4) Dummy
POP	-0.688	-0.750	-0.716	-0.627
	(0.463)	(0.500)	(0.458)	(0.460)
GDP-POP	-0.597***	-0.629***	-0.615***	-0.561***
	(0.160)	(0.162)	(0.165)	(0.158)
Privatize	-0.590	-0.577	-0.569	-0.484
	(0.482)	(0.519)	(0.491)	(0.464)
Fuel	0.157	0.173	0.162	0.194
	(0.103)	(0.103)	(0.104)	(0.103)
Compete	-0.221	-0.183	-0.210	-0.178
	(0.262)	(0.221)	(0.242)	(0.192)
Crisis	0.107	0.110	0.107	0.112
	(0.077)	(0.078)	(0.076)	(0.076)
Disaster	0.166***	0.164***	0.165***	0.176***
	(0.059)	(0.059)	(0.059)	(0.056)
HSR	0.028***	2.416***	0.962***	0.573***
	(0.007)	(0.661)	(0.269)	(0.151)
Constant	7.316***	7.699***	7.504***	6.764**
	(2.724)	(2.927)	(2.738)	(2.706)
Airport Dummy	Yes	Yes	Yes	Yes
N	144	144	144	144
Wald chi2	327.87	324.81	319.23	299.74

Note. Standard errors are in parentheses. **p <0.1; **p<0.05; ***p<0.01.*
Hub and *RwyStructure* are omitted due to multi-collinearity.

Table 4. 14 Results with HSR substitutability and complementarity using double bootstrap procedure (Japan)

Japan	(1) Connectivity	(2) Accessibility	(3) Integrated	(4) Dummy
POP	-0.473	-0.531	-0.493	-0.681
	(0.431)	(0.423)	(0.437)	(0.431)
GDP_POP	-0.588***	-0.618***	-0.615***	-0.570
	(0.142)	(0.153)	(0.144)	(0.149)
Privatize	-0.464	-0.484	-0.481	-0.458
	(0.420)	(0.411)	(0.414)	(0.381)
Fuel	0.215**	0.216**	0.215**	0.223**
	(0.100)	(0.096)	(0.095)	(0.097)
Compete	0.309	1.150**	0.760*	4.707***
	(0.333)	(0.522)	(0.425)	(0.987)
Crisis	0.126*	0.127*	0.125*	0.121*
	(0.068)	(0.068)	(0.069)	(0.068)
Disaster	0.170***	0.163***	0.165***	0.177***
	(0.053)	(0.052)	(0.052)	(0.053)
HSR	0.007	1.492	0.435	8.169***
	(0.012)	(1.154)	(0.469)	(0.943)
HSR_SE	0.085***	0.085***	0.083***	-0.278***
	(0.023)	(0.024)	(0.023)	(0.061)
HSR_CE	-10.57*	-17.17**	-13.42**	-184.9***
	(5.611)	(7.659)**	(6.690)	(17.19)
Constant	5.524**	5.118**	5.286**	2.654
	(2.471)	(2.462)	(2.519)	(2.512)
Airport Dummy	Yes	Yes	Yes	Yes
N	144	144	144	144
Wald chi2	341.28	343.67	349.52	5350.77

Note. Standard errors are in parentheses. **p <0.1; **p<0.05; ***p<0.01.*
Hub and *RwyStructure* are omitted due to multi-collinearity.

4.5.3 The impact of HSR on airport's labor productivity

The findings in this section focus on using HSR connectivity and accessibility as a proxy for the development of HSR.

Table 4.15 presents the impacts of HSR development on the labor productivity at Chinese airports, measured by WLU per employee. Column (1) and (2) report results from estimating equation (4). HSR connectivity and accessibility are reported to have negative and statistically significant effects on airport labor productivity. Specifically, a 1% increase in HSR connectivity decreases labor productivity by approximately 0.1% (Column (1)). Column (2) shows a similar elasticity for HSR accessibility. Column (3) and (4) include the substitution and complementary effects of HSR on air transport, as specified in equation (5). We find that improving the access to airport terminal from HSR station may substantially increase the labor productivity of the airport. On the other hand, compared with the impact of HSR complement, we observe that HSR substitution is more significant in affecting the efficiency of labor use at Chinese airports even though the magnitude is smaller.

Similarly, we calculate the WLU per employee for each airport in Japan and regress the results on our main variables of interest. Table 4.16 shows the estimation results. We observe no evidence that there are substantially changes in labor productivity at Japanese airports as a result of HSR development (Column (1) and (2)). There is also no indication that the WLU per employee increases because of the complementary relationship between HSR and air transport and decreases due to the substitution effects of HSR on air travel (Column (3)).

Table 4. 15 Labor productivity (WLU) estimates for Chinese airports

China	(1)	(2)	(3)	(4)
Ln(POP)	0.738	0.634	0.697	0.590
	(0.278)***	(0.276)**	(0.275)**	(0.273)**
	[0.361]**	[0.332]*	[0.371]	[0.340]*
Ln (GDP_POP)	0.998	0.928	0.924	0.856
	(0.117)***	(0.110)***	(0.119)***	(0.112)***
	[0.242]***	[0.230]***	[0.244]***	[0.238]***
Privatization	-0.199	-0.134	-0.206	-0.144
	(0.119)*	(0.119)	(0.117)*	(0.117)
	[0.092]**	[0.073]*	[0.087]**	[0.071]**
Ln(Fuel)	-0.130	-0.107	-0.128	-0.106
	(0.054)**	(0.053)**	(0.054)**	(0.053)**
	[0.050]**	[0.048]**	[0.051]**	[0.050]**
Compete	-0.077	-0.102	-0.038	-0.067
	(0.094)	(0.095)	(0.094)	(0.096)
	[0.078]	[0.088]	[0.111]	[0.120]
RwyStructure	-0.113	-0.118	-0.142	-0.150
	(0.114)	(0.114)	(0.112)	(0.113)
	[0.133]	[0.145]	[0.124]	[0.134]
Olympic	-0.049	-0.070	-0.039	-0.058
	(0.050)	(0.050)	(0.050)	(0.050)
	[0.035]	[0.035]*	[0.035]	[0.035]
Crisis	-0.051	-0.061	-0.031	-0.047
	(0.048)	(0.048)	(0.049)	(0.050)
	[0.031]	[0.033]*	[0.029]	[0.032]
Ln(HSR)	-0.098	-0.117	-0.094	-0.108
	(0.026)***	(0.034)***	(0.026)***	(0.034)***
	[0.036]**	[0.039]***	[0.034]**	[0.040]**
Ln(HSR_SE)			-0.124	-0.123
			(0.043)***	(0.043)***
			[0.047]**	[0.050]**
Ln(HSR_CE)			0.188	0.167
			(0.074)**	(0.075)**
			[0.091]**	[0.095]*
Constant	3.783	3.539	4.726	4.452
	(0.522)***	(0.556)***	(0.614)***	(0.653)***
	[0.693]***	[0.643]***	[0.789]	[0.744]***
Airport Dummy	Yes	Yes	Yes	Yes
N	261	261	261	261
R-square	0.513	0.507	0.531	0.525

Note. Standard errors are in parentheses. Robust standard errors clustered by airport are reported in brackets. **p <0.1; **p<0.05; ***p<0.01.*

Hub are omitted due to multi-collinearity.

Table 4. 16 Labor productivity (WLU) estimates for Japanese airports[29]

Japan	(1)	(2)	(3)
Ln(POP)	1.925	2.071	2.099
	(1.269)	(1.253)	(1.255)*
	[1.752]	[1.777]	[1.857]
Ln(GDP_POP)	1.111	1.108	1.118
	(0.436)**	(0.440)**	(0.440)**
	[0.581]*	[0.587]*	[0.59]*
Privatization	-0.013	-0.012	-0.013
	(0.085)	(0.085)	(0.085)
	[0.010]	[0.011]	[0.011]
Ln(Fuel)	-0.036	-0.035	-0.041
	(0.053)	(0.053)	(0.054)
	[0.030]	[0.032]	[0.030]
Compete	0.286	0.283	0.282
	(0.095)***	(0.095)***	(0.095)***
	[0.042]***	[0.042]***	[0.045]***
Crisis	-0.045	-0.044	-0.044
	(0.047)	(0.047)	(0.047)
	[0.045]	[0.045]	[0.045]
Disaster	-0.098	-0.099	-0.100
	(0.035)***	(0.036)***	(0.035)***
	[0.035]**	[0.035]**	[0.035]**
Ln(HSR)	-0.018	-0.108	
	(0.023)	(0.272)	
	[0.037]	[0.383]	
Ln(HSR_SE)			-0.114
			(0.130)
			[0.195]
Ln(HSR_CE)			0.210
			(0.258)
			[0.381]
Constant	4.874	4.672	5.483
	(1.968)**	(1.949)**	(2.195)**
	[2.623]*	[2.676]	[3.001]*
Airport Dummy	Yes	Yes	Yes
N	144	144	144
R-square	0.230	0.227	0.231

Note. Standard errors are in parentheses. Robust standard errors clustered by airport are reported in brackets. **p <0.1; **p<0.05; ***p<0.01.*
Hub and *RwyStructure* are omitted due to multi-collinearity.

[29] Compared with the case of China, there are very marginal changes in the expansion of HSR networks in Japan during our study period. In such situation, there exist multi-collinearity between Ln(HSR) and the other two variables: Ln(HSR_SE) and Ln(HSR_CE). Therefore, Ln(HSR) is omitted in column (3).

We next examine the effects of HSR development on the aircraft movements per employee which is another measure of labor productivity at airports. In table 4.17, we report the estimates for our samples in China. Again, column (1) and (2) show the impacts of HSR connectivity and accessibility on the labor productivity at airports. We reveal that the aircraft movements per workforce appear to be negatively influenced by the development of HSR. In terms of scale we estimate the aircraft movements per workforce at Chinese airports decreases by 0.07% from a 1% increase in HSR connectivity, and by 0.1% from a 1% improvement in HSR accessibility of the airports' corresponding cities. There is no dramatic difference between these measures. Column (3) and (4) take into account the substitution and complementary effects of HSR on air travel. The estimated impacts of HSR remain almost unchanged. However, compared with labor productivity measured by WUL, the productivity captured by aircraft movements per employee is less likely to increase with the help of reducing the travel time between an airport and its relevant HSR station. On the flip side, we still find evidence that the disadvantages of an airport in terms of access to/from the city center are likely to reduce its labor productivity even though the coefficient on HSR_SE is somewhat smaller and less statistically significant ($p < 0.1$).

Table 4. 17 Labor productivity (Aircraft movements) estimates for Chinese airports

China	(1)	(2)	(3)	(4)
POP	0.250	0.173	0.210	0.133
	(0.247)	(0.244)	(0.246)	(0.242)
	[0.394]	[0.360]	[0.392]	[0.357]
GDP_POP	0.664	0.623	0.610	0.577
	(0.104)***	(0.097)***	(0.106)***	(0.100)***
	[0.224]***	[0.218]***	[0.228]**	[0.229]**
Privatization	-0.144	-0.091	-0.147	-0.097
	(0.105)	(0.105)	(0.104)	(0.104)
	[0.098]	[0.078]	[0.091]	[0.072]
Fuel	-0.097	-0.081	-0.097	-0.084
	(0.048)**	(0.047)*	(0.048)**	(0.047)*
	[0.043]**	[0.040]*	[0.042]**	[0.041]**
Compete	-0.089	-0.111	-0.067	-0.094
	(0.083)	(0.084)	(0.084)	(0.085)
	[0.059]	[0.061]*	[0.064]	[0.069]
RwyStructure	-0.081	-0.081	-0.105	-0.105
	(0.101)	(0.101)	(0.100)	(0.100)
	[0.139]	[0.148]	[0.130]	[0.139]
Olympic	-0.041	-0.058	-0.034	-0.050
	(0.045)	(0.044)	(0.044)	(0.044)
	[0.031]	[0.030]*	[0.031]	[0.031]
Crisis	-0.032	-0.043	-0.026	-0.041
	(0.042)	(0.043)	(0.044)	(0.045)
	[0.029]	[0.032]	[0.032]	[0.035]
HSR	-0.079	-0.101	-0.074	-0.096
	(0.023)***	(0.030)***	(0.023)***	(0.030)***
	[0.033]**	[0.035]***	[0.031]**	[0.036]**
HSR_SE			-0.090	-0.088
			(0.038)**	(0.038)**
			[0.047]*	[0.050]*
HSR_CE			0.113	0.094
			(0.066)*	(0.066)
			[0.089]	[0.093]
Constant	2.721	2.473	3.348	3.052
	(0.463)***	(0.491)***	(0.548)***	(0.579)***
	[0.717]***	[0.648]***	[0.630]***	[0.664]***
Airport Dummy	Yes	Yes	Yes	Yes
N	261	261	261	261
R-square	0.303	0.301	0.321	0.320

Note. Standard errors are in parentheses. Robust standard errors clustered by airport are reported in brackets. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

Hub are omitted due to multi-collinearity.

In table 4.18, using aircraft movement per employee as dependent variable, we show the estimates for airports in Japan. The first two columns report that airports which have better positions, measured by connectivity and accessibility, in the HSR network experience substantial increases in their labor productivity. The elasticities of HSR connectivity and accessibility are 0.041 (robust standard error 0.020) and 0.68 (robust standard error 0.203) respectively. Again, similar to column (3) in table 4.16 where labor productivity is measured by WLU per employee, the coefficients on HSR_SE and HSR_CE are statistically insignificant, suggesting that the aircraft movements per workforce at Japanese airports may not be impacted by the coopetition between HSR station and airport terminal.

Table 4. 18 Labor productivity (Aircraft movements) estimates for Japanese airports

Japan	(1)	(2)	(3)
POP	3.887	3.751	3.729
	(1.161)***	(1.131)***	(1.140)***
	[2.202]*	[2.132]*	[2.045]*
GDP_POP	1.987	1.900	1.942
	(0.399)***	(0.397)***	(0.399)***
	[0.445]***	[0.461]***	[0.435]***
Privatization	0.109	0.103	0.111
	(0.077)	(0.077)	(0.077)
	[0.010]***	[0.009]***	[0.010]***
Fuel	0.025	0.024	0.031
	(0.049)	(0.048)	(0.049)
	[0.038]	[0.038]	[0.045]
Compete	0.374	0.374	0.378
	(0.087)***	(0.086)***	(0.086)***
	[0.057]***	[0.056]***	[0.054]***
Crisis	0.056	0.057	0.055
	(0.043)	(0.042)	(0.043)
	[0.052]	[0.053]	[0.054]
Disaster	-0.052	-0.057	-0.051
	(0.032)	(0.032)*	(0.032)
	[0.032]	[0.032]*	[0.031]
HSR	0.046	0.680	
	(0.021)**	(0.245)***	
	[0.020]**	[0.203]***	
HSR_SE			-0.002
			(0.118)
			[0.277]
HSR_CE			0.112
			(0.235)
			[0.546]
Constant	-1.640	-1.363	-0.831
	(1.801)	(1.759)	(1.994)
	[2.919]	[2.830]	[3.800]
Airport Dummy	Yes	Yes	Yes
N	144	144	144
R-square	0.355	0.370	0.365

Note. Standard errors are in parentheses. Robust standard errors clustered by airport are reported in brackets. **p <0.1; **p<0.05; ***p<0.01.*
Hub and *RwyStructure* are omitted due to multi-collinearity.

To summarize, we draw four main conclusions from this section. First, using the standard two-stage method may underestimate the impacts of HSR on airport efficiency. Second, in both China and Japan, the increase in HSR connectivity and accessibility appears to be negatively associated with airport efficiency. Third, the complementarity between HSR and air travel is found to have a positive and significant impact on the technical efficiency of Chinese airports. By contrast, in the case of Japan, the substitution of air transport by HSR is more notable in affecting airport efficiency. Finally, the development of HSR is likely to decrease the labor productivity at Chinese airports, but HSR development in Japan is revealed to increase the labor productivity at airports when measured by the aircraft movements per employee.

4.6 Conclusion

In a global environment, an inadequate provision of air services is regarded as a bottleneck to economic development. Hence, expanding the capacity of air transport, in particular the expansion of airport capacity, has been seen as a necessary prerequisite for the growth of local and national economies (Gibbons and Wu, 2019). The investments on these expansions are massive and have not always proved a success. For example, due to a lack of rational planning and rigorous analysis, many of newly constructed or expanded European airports over the past 15 years have been remaining empty or unused, leading to a waste of taxpayers' money by 666 million euros[30]. It is evident that the development of HSR network in Europe together with the overlap of catchment areas among neighboring airports jointly result in this situation. Up to now, there is a rich body of literature investigating the impacts of competition from

[30] https://www.worldfinance.com/inward-investment/europes-dead-airports-a-big-waste-of-taxpayers-money

neighboring airports on airport performance. However, little attention has been paid to the influence by HSR. Aiming at filling the research gap, this study explores the effects of HSR development on the performance of airports in the context of Northeast Asia where HSR traffic accounts for over 80% of the world.

The study contributes to better understanding of the impacts of HSR on airport from the viewpoint of airport performance and productivity. Our analysis has shown that even though majority of our sample airports exhibit increases in efficiency between 2007 and 2015, HSR development associates with a decrease in airport technical efficiency. We also reveal that using two-stage DEA method may underestimate the effects of HSR on the performance of airports. In the case of China, our estimation on airport efficiency are consistent with those on labor productivity, indicating that the impacts of HSR on airport outputs outperforms those on inputs. Notably, on the other hand, we do not observe such consistency in the case of Japan where HSR development appears to be negatively correlated with airport technical efficiency but increases labor productivity measured by aircrafts movements per workforce. This is likely because the fact that the increases in flights with small airplanes in Japanese domestic markets to compete with HSR.

We also evaluate the influences of the potential substitution and complementary effects of HSR on air travel on airport performance. Results indicate that shortening the travel cost to airport from its nearest HSR station may help Chinese airports gain technical efficiency and WLU productivity but is less likely to improve the labor productivity measured by aircraft movements per employee. In addition, reducing the travel time from airport relative to HSR station to city center may increase the WLU productivity at Chinese airports. By contrast, these effects only work for airport technical efficiency in the context of Japan. In another words, labor productivity at

Japanese airports appears not to be affected by the coopetition between HSR station and airport terminal.

Our study could be of interest to decision makers as the research provides empirical evidence that help them understand the role of HSR development in airport performance. In addition to many other concerns, decisions on airport expansions should also take into account the effects of HSR development. For airports which city has good positions in the HSR network, it might not be a good idea to substantially expand their existing infrastructures only if the airport is an international hub. Instead of expansion, which may lead to a loss in efficiency, the airport may gain benefits by reducing the travel cost between airport and city center/HSR station.

Due to the limitation of research data, we only investigate the impacts of HSR on airport technical efficiency. As a complement to this research, in the future, it would be interesting to study the effects of HSR on the cost efficiency of airports.

CHAPTER 5

CONCLUSION

In this dissertation, we investigate two topics related to HSR development. The first topic aims partly at responding to the concerns about regional disparities as a result of HSR development. The second topic focuses on the interaction between HSR and airport. We propose one question for the former topic and two questions for the latter and explore these questions in three studies. This chapter provides the summary of key findings, contributions, limitations, and the direction for future research.

We firstly examine whether cities in the HSR network are getting more equally connected and accessible as the HSR network expands. We measure HSR development by three variables: connectivity, transitivity, and accessibility. There are three main insights from the study. First, it is evident that, in China, cities appear to be more equally served by HSR in terms of accessibility. By contrast, results obtained from transitivity index indicate that small cities, in particular those not belonging to any major city clusters, are fallen further behind the large ones due to inadequate provision of services. Second, even though the gap between different economic regions has been decreased in all HSR measures, the inequalities in connectivity and transitivity between cities which are located in the same peripheral regions such as the western and northeast part of China show trends toward divergence. Third, on one hand, both the difference between the five major city clusters and the variance between cities within the same city cluster have been reduced; on the other hand, we reveal that non-core cities in major city clusters are increasingly relying on core megalopolises to access to other parts of the country.

From the first study, it is evident that there are heterogeneities among cities' positions in the HSR network. These heterogeneities may lead to the fact that airports located in different cities can be influenced variously by HSR development.

We then identify the impacts of HSR development on airport passenger traffic and compare the difference of effects between China and Japan, which are at different stages of HSR development. We obtain three major findings from the research. First, HSR development has little negative impacts on the domestic air passenger traffic in Japan but has strong negative and statistically significant effects on the domestic air passenger traffic in China. Second, we observe a strong complementary effect of HSR on airport which allows for convenient transfer between airport terminals and HSR stations. This complementary effect diminishes as the distance from the city where the airport locates to other cities directly reachable by HSR increases. Third, a good air-HSR linkage mainly facilitates HSR to feed international flights and hence increases international passenger traffic at airports. However, there exists difference between China and Japan regarding the importance of hub status and air-HSR linkage. In China, the hub status of an airport is more dominant than air-HSR linkage in determining the positive effects of HSR on airport. In Japan, on the contrary, air-HSR linkage plays a more important role.

As a complement to the impacts of HSR on airport, we further estimate the effects of HSR development on airport technical efficiency and the labour productivity at airports. Again, we draw three key conclusions from the study. First, HSR development is reported to be negatively associated with airport technical efficiency in both China and Japan. These negative effects are also observed on the labour productivity at airports in China. However, HSR expansion appears to improve the labour productivity at airports in Japan. Second, the potential complementary effects between HSR and air travel are more statistically significant in impacting the technical efficiency of Chinese airports. Conversely, in the case of Japan, the prospective substitution effects between HSR and air transport are more notable in determining airport efficiency. Third, reducing the cost of travelling between airport and city centre and the cost of trip between HSR station and airport terminals may help improve the labour productivity at Chinese airports but has no significant influence on the labour productivity of airports in Japan.

This thesis contributes to the literature and practice by providing empirical evidences on the concerns about HSR expansion. The first study sheds light on the regional disparities from the viewpoint of the provision of HSR services and paves the way for a better understanding the impacts of HSR on regional economy. The second study, to the best of our knowledge, is the first to quantify the impacts of HSR on airport-level traffic by taking into account the positions of cities where airports locate in the HSR network. The third study explores for the first time the association between HSR development and the labour productivity at airports and help us better evaluate the impacts of HSR on airports from the perspective of airport efficiency.

However, there is a major limitation related to the first topic. In the study, we only consider HSR without incorporating conventional trains, which may cause an underestimation on the disparities among cities as a results of HSR development. Intuitively, if conventional rail is involved in the study, disparities between small cities and large cities will likely be increased. This is because, in order to encourage passenger to travel by HSR, some conventional rail services have been deteriorated or even cancelled, widening the gap between small cities and large cities in terms of accessing rail services. Other transport modes such as coaches and air flights should also be taken into account. Nonetheless, in addition to the difficulty in accessing relevant data, we argue that our treatment is acceptable since HSR and other modes of transport are very different in terms of speed, service quality as well as price. Incorporating all transport modes requires to fundamentally change the research methodology.

Each topic of the thesis opens avenues for future research. For the first topic, it would be an interesting direction to identify the association between HSR development and the interdependence of major cities, which are reflected by investment flows, labour mobility, and academic collaborations and so on. For the second topic, future research could investigate the changes in airport service quality (e.g., on-time performance, passenger complaints) resulting from HSR network development.

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APPENDICES

Appendix A: Appendix for Chapter 2

A.1 Difference between inbound and outbound HSR services

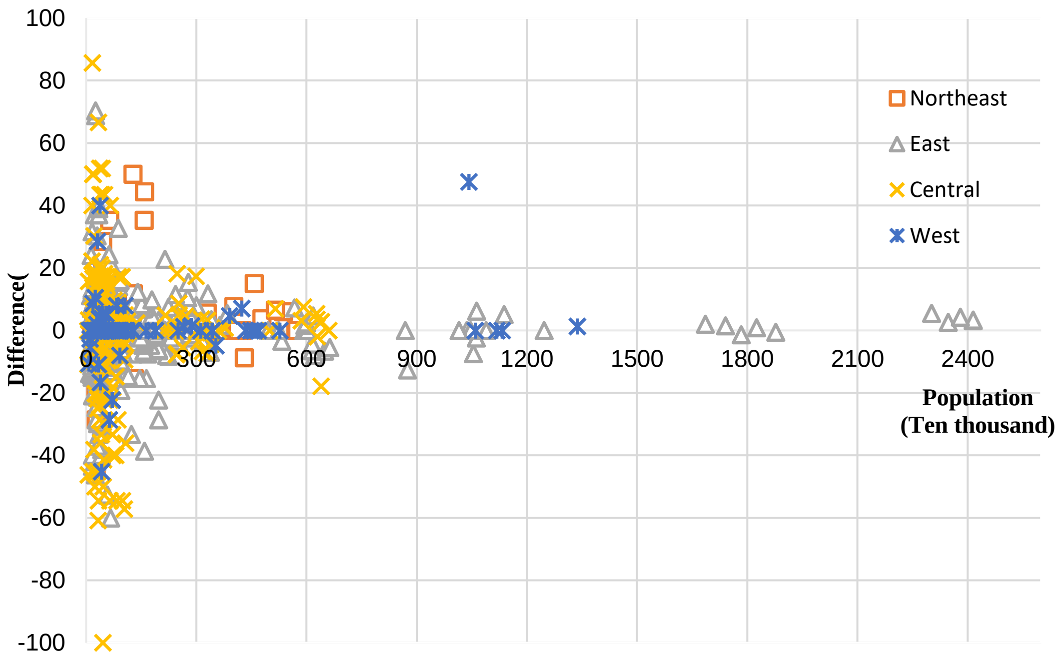


Figure A. 1 Comparison of inbound and outbound HSR services (2010-2015)

A.2 Difference of closeness and harmonic centralities in a disconnected network

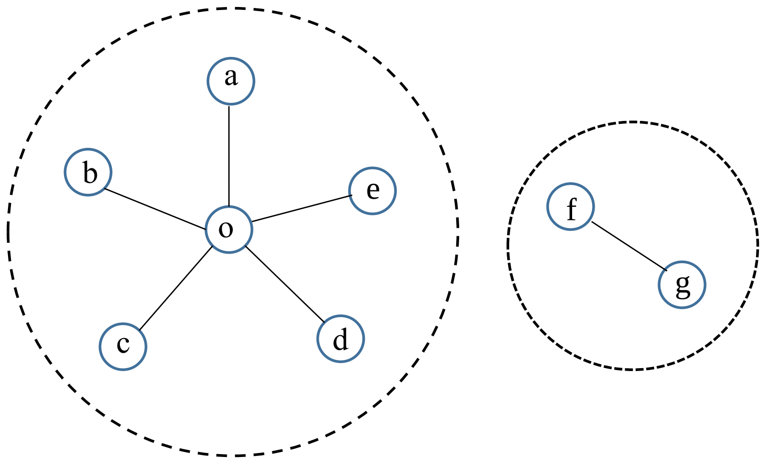


Figure A. 2 An example of a disconnected network

Closeness centrality may not be applicable to the network that consists of several disconnected components. Figure A.2 shows an example of disconnected network. In this case, closeness centrality can be inaccurate in measuring accessibility. This is because most nodes in the larger subgraph need to go through more edges to reach the other nodes in the same subgraph than nodes f and g in the smaller subgraph. For example, node a needs to go through one edge to reach node o but two edges to reach nodes b, c, d and e. Whist, node f only needs to go through one edge to reach g. As a result, nodes g and f in the smaller subgraph appear to have a larger closeness than nodes in the larger subgraph (Table A.1). Obviously, this does not reflect the true situation that nodes in the larger subgraph is in fact more accessible. Harmonic centrality in Table A.1 reflects the true accessibility better.

Table A. 1 Network analysis of the disconnected network

	a	b	c	d	e	o	f	g
a	-	2	2	2	2	1	Inf	Inf
b	2	-	2	2	2	1	Inf	Inf
c	2	2	-	2	2	1	Inf	Inf
d	2	2	2	-	2	1	Inf	Inf
e	2	2	2	2	-	1	Inf	Inf
o	1	1	1	1	1	-	Inf	Inf
f	Inf	Inf	Inf	Inf	Inf	Inf	-	Inf
g	Inf	Inf	Inf	Inf	Inf	Inf	1	-

(a) Distance matrix

	Farness	Closeness	Harmonic
a	Inf	1/9	3
b	Inf	1/9	3
c	Inf	1/9	3
d	Inf	1/9	3
e	Inf	1/9	3
o	Inf	1/5	5
f	Inf	1/1	1
g	Inf	1/1	1

(b) Accessibility measure

A.3 Comparison of our results with Jiao et al. (2017)

Table A.2 compares our city-level rankings with those of Jiao et al. (2017). Since both studies employ the same data source (China railway timetable), all major rail hubs such as Shanghai, Beijing, Guangzhou, Wuhan, and Nanjing are on the top-20 lists of both studies. Nonetheless, only 60% of the cities on our list appear on Jiao et al. (2017)'s list when degree centrality is in concern, and the level of similarity in terms of closeness (harmonic) and betweenness centralities are 65%. This low level of similarity might be contributed by three major differences. First, when calculating degree centrality, Jiao et al. (2017) also take service frequency into account, but their approach is equivalent to taking the geometric mean of unweighted degree and strength, while our degree centrality is equivalent to strength.[31] Our approach is more likely to upgrade cities with fewer connections but higher HSR service frequencies. Second, when generating the other two centralities, we incorporate both in-vehicle travel time and service frequency while Jiao et al. (2017) only take service frequency into account. As the in-vehicle time vary significantly across edges depending on geographical locations and types of HSR services provided, ignoring this feature can substantially change the results. Third, Jiao et al. (2017) use closeness centrality to measure accessibility, while we use harmonic centrality.

[31] The formula of Jiao et al. (2017)'s degree centrality can be rewritten into $C_D(i) = \sqrt{(\sum_{j\neq i} a_{ij})(\sum_{j\neq i} w_{ij})}$. The strength of node i is defined as $\sum_{j\neq i} w_{ij}$.

Table A. 2 Comparison of city-level rankings in year 2014

Rank	Jiao et al. (2017)			Our analysis		
	Degree	Accessibility - closeness	Betweenness	Degree	Accessibility - harmonic	Betweenness
1	Shanghai	Shanghai	Beijing	Shanghai	Wuhan	Wuhan
2	Beijing	Nanjing	Wuhan	Nanjing	Nanjing	Zhengzhou
3	Nanjing	Beijing	Guangzhou	Wuhan	Wuxi	Tianjin
4	Wuhan	Wuhan	Zhengzhou	Hangzhou	Changzhou	Nanjing
5	Zhengzhou	Zhengzhou	Shenyang	Wenzhou	Suzhou	Beijing
6	Guangzhou	Hangzhou	Shanghai	Guangzhou	Zhenjiang	Huzhou
7	Hangzhou	Guangzhou	Hangzhou	Fuzhou	Hangzhou	Guangzhou
8	Xuzhou	Suzhou	Xi'an	Suzhou	Huzhou	Jinan
9	Suzhou	Xuzhou	Jinan	Ningbo	Shanghai	Qinhuangdao
10	Shijiazhuang	Changsha	Nanjing	Wuxi	Ezhou	Fuzhou
11	Wuxi	Wuxi	Chengdu	Beijing	Zhengzhou	Ningbo
12	Changsha	Shijiazhuang	Tianjin	Shaoxing	Jinan	Shenzhen
13	Jinan	Changzhou	Harbin	Jinan	Yixing	Shenyang
14	Tianjin	Tianjin	Shijiazhuang	Shenzhen	Xianning	Hangzhou
15	Shenyang	Jinan	Xuzhou	Changzhou	Guangzhou	Chongqing
16	Changzhou	Zhenjiang	Changsha	Tianjin	Beijing	Hefei
17	Hengyang	Shenyang	Nanchang	Putian	Hefei	Xuzhou
18	Zhenjiang	Hengyang	Baoji	Xiamen	Tianjin	Sanming
19	Zhuzhou	Xi'an	Shenzhen	Hefei	Huanggang	Changsha
20	Xi'an	Bengbu	Lanzhou	Xuzhou	Shaoxing	Shijiazhuang
Similarity				60%	65%	65%

Appendix B: Appendix for Chapter 3

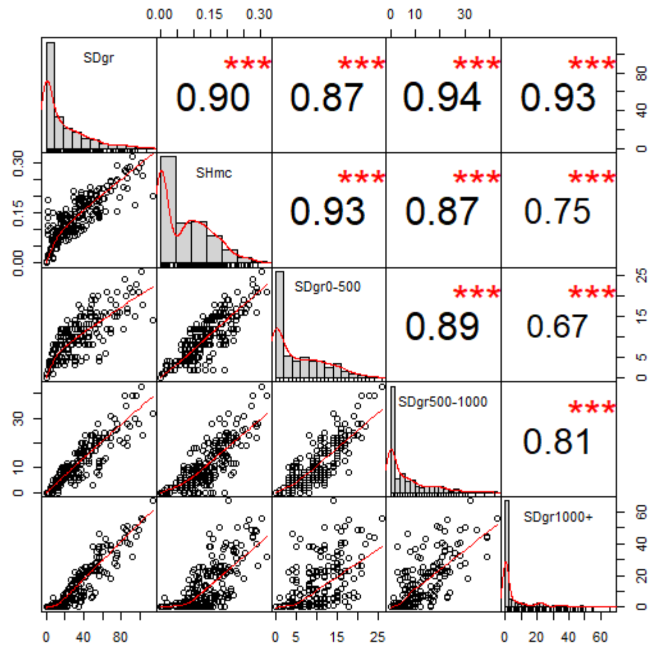
B.1 List of sample airports and HSR service commencement years

Table B. 1 List of sample airports and HSR service commencement years

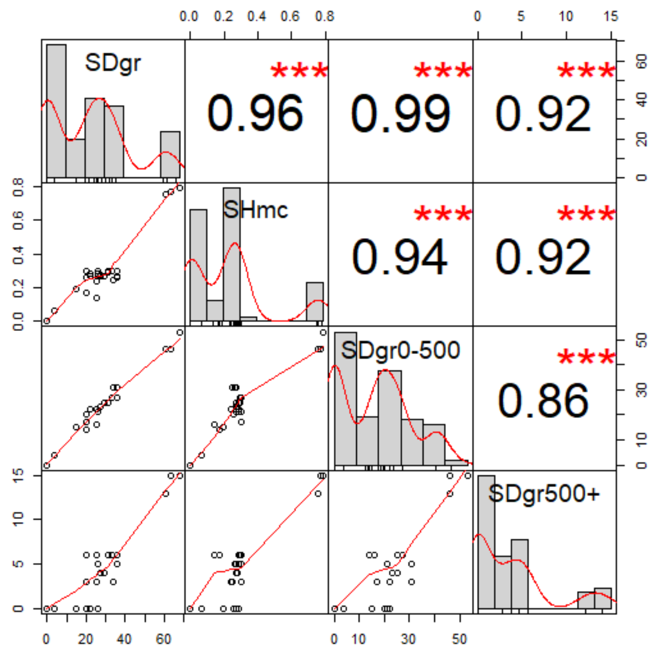
Code	Airport	City	HSR Service	Code	Airport	City	HSR Service
CAN	Guangzhou Baiyun Airport	Guangzhou	2007	CTS	New Chitose Airport	Sapporo	-
CGO	Zhengzhou Xinzheng Airport	Zhengzhou	2007	FUK	Fukuoka Airport	Fukuoka	1975
CGQ	Changchun Longjia Airport	Changchun	2007	HIJ	Hiroshima Airport	Hiroshima	1975
CKG	Chongqing Jiangbei Airport	Chongqing	2010	HND	Haneda Airport	Tokyo	1964
CSX	Changsha Huanghua Airport	Changsha	2007	ITM	Osaka Airport	Osaka	1964
CTU	Chengdu Shuangliu Airport	Chengdu	2010	KIX	Kansai Airport	Osaka	1964
DLC	Dalian Zhoushuizi Airport	Dalian	2013	KMI	Miyazaki Airport	Miyazaki	-
FOC	Fuzhou Changle Airport	Fuzhou	2009	KMJ	Kumamoto Airport	Kumamoto	2011
HAK	Haikou Meilan Airport	Haikou	2011	KMQ	Komatsu Airport	Komatsu	-
HET	Hohhot Baita Airport	Hohhot	2015	KOJ	Kagoshima Airport	Kagoshima	2004
HFE	Hefei Xinqiao Airport	Hefei	2008	MYJ	Matsuyama Airport	Matsuyama	-
HGH	Hangzhou Xiaoshan Airport	Hangzhou	2007	NGO	Chūbu Airport	Nagoya	1964
HRB	Harbin Taiping Airport	Harbin	2007	NGS	Nagasaki Airport	Nagasaki	-
INC	Yinchuan Hedong Airport	Yinchuan	-	NRT	Narita Airport	Tokyo	1964
JHG	Xishuangbanna Gasa Airport	Jinghong	-	SDJ	Sendai Airport	Sendai	1982
JJN	Quanzhou Jinjiang Airport	Quanzhou	2009	UKB	Kobe Airport	Kobe	1972
KHN	Nanchang Changbei Airport	Nanchang	2007				
KMG	Kunming Changshui Airport	Kunming	2016				
KWE	Guilin Liangjiang Airport	Guilin	2014				
KWL	Guiyang Longdongpu Airport	Guiyang	2015				
LJG	Lijiang Sanyi Airport	Lijiang	-				
LXA	Lhasa Gongga Airport	Lhasa	-				
NGB	Ningbo Lishe Airport	Ningbo	2009				
NKG	Nanjing Lukou Airport	Nanjing	2007				
NNG	Nanning Wuxu Airport	Nanning	2014				
PEK	Beijing Capital Airport	Beijing	2007				
SHE	Shenyang Taoxian Airport	Shenyang	2007				
SHPV	Shanghai Pudong Airport	Shanghai	2007				
SJW	Shijiazhuang Zhengding Airport	Shijiazhuang	2007				
SWA	Jieyang Chaoshan Airport	Jieyang	2014				
SYX	Sanya Fenghuang Airport	Sanya	2011				
SZX	Shenzhen Baoan Airport	Shenzhen	2007				
TAO	Qingdao Liuting Airport	Qingdao	2007				
TNA	Jinan Yaoqiang Airport	Jinan	2007				
TSN	Tianjin Binhai Airport	Tianjin	2007				
TYN	Taiyuan Wusu Airport	Taiyuan	2009				
URC	Urumqi Diwopu Airport	Urumqi	2015				
WNZ	Wenzhou Longwan Airport	Wenzhou	2009				
WUH	Wuhan Tianhe Airport	Wuhan	2007				
WUX	Sunan Shuofang Airport	Wuxi	2007				
XIY	Xian Xianyang Airport	Xian	2007				
XMN	Xiamen Gaoqi Airport	Xiamen	2009				
XNN	Xining Caojiapu Airport	Xining	2015				
YNT	Yantai Penglai Airport	Yantai	2015				
ZGC	Lanzhou Zhongchuan Airport	Lanzhou	2015				
ZUH	Zhuhai Jinwan Airport	Zhuhai	2011				

Data source: UIC High-speed rail database

B.2 Pairwise correlation coefficient between connectivity and accessibility



China



Japan

Figure B. 1 Pairwise correlation coefficient between connectivity and accessibility

B.3 Changes of centrality measures at sampled Japanese airports

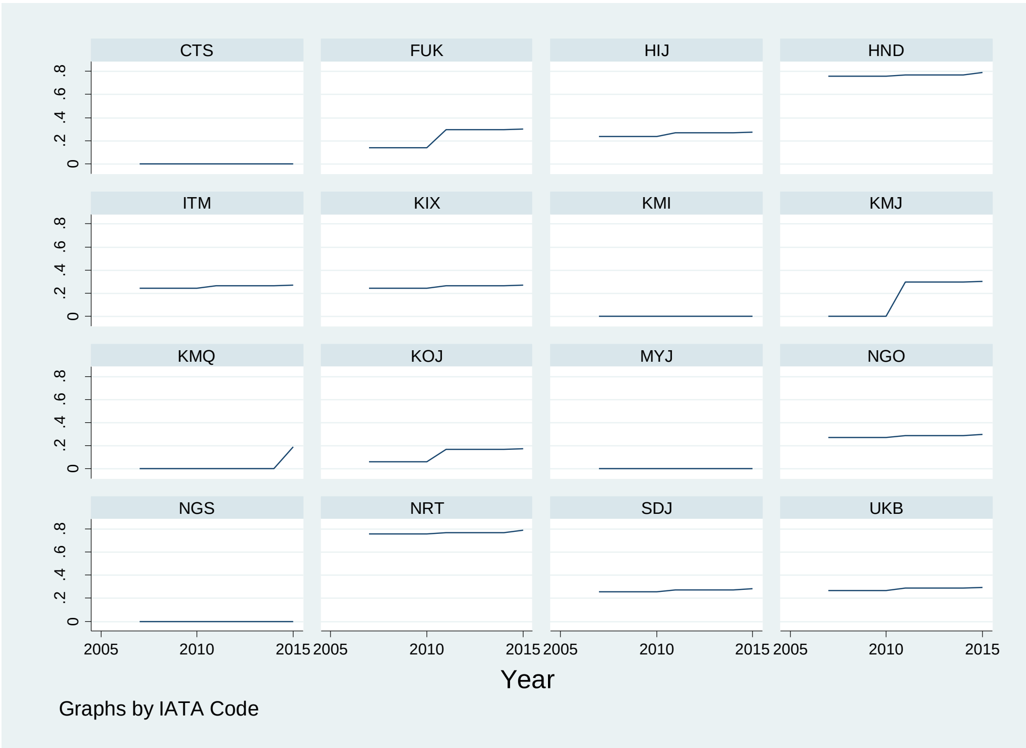


Figure B. 2 Changes of centrality measures at sampled Japanese airports

B.4 Regression analysis on domestic and international traffic

Table B. 2 Regression results based on Eq.(3) (DV = domestic passenger traffic, China)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HSR zones		0-500	500-1000	1000+			0-500	500-1000	1000+	
POP	3.698*** (0.280)	3.805*** (0.262)	3.785*** (0.267)	3.444*** (0.278)	3.643*** (0.269)	3.591*** (0.277)	3.705*** (0.263)	3.654*** (0.269)	3.390*** (0.275)	3.540*** (0.268)
GDP_POP	1.888*** (0.193)	2.070*** (0.179)	1.986*** (0.178)	1.626*** (0.185)	1.904*** (0.195)	1.823*** (0.191)	1.982*** (0.179)	1.881*** (0.180)	1.610*** (0.184)	1.819*** (0.194)
LCC	2.444*** (0.645)	2.294*** (0.634)	2.251*** (0.641)	2.496*** (0.649)	2.449*** (0.645)	2.061*** (0.645)	1.974*** (0.634)	1.987*** (0.641)	2.063*** (0.651)	2.135*** (0.646)
FuelPrice	-2.314*** (0.633)	-2.286*** (0.546)	-2.345*** (0.566)	-1.554** (0.659)	-2.153*** (0.592)	-2.123*** (0.630)	-2.177*** (0.547)	-2.135*** (0.568)	-1.516** (0.651)	-2.051*** (0.591)
Compete	-4.545*** (1.104)	-5.025*** (1.086)	-4.155*** (1.096)	-4.579*** (1.111)	-4.810*** (1.108)	-4.063*** (1.096)	-4.665*** (1.082)	-3.818*** (1.093)	-4.085*** (1.103)	-4.437*** (1.102)
Year2008	0.156 (0.398)	0.083 (0.377)	0.146 (0.383)	-0.077 (0.406)	0.043 (0.387)	0.098 (0.394)	0.070 (0.375)	0.093 (0.381)	-0.086 (0.401)	0.033 (0.384)
Year2009	-0.527 (0.400)	-0.536 (0.386)	-0.514 (0.390)	-0.353 (0.405)	-0.550 (0.401)	-0.430 (0.395)	-0.449 (0.383)	-0.416 (0.388)	-0.296 (0.399)	-0.461 (0.397)
SDgr	-0.021** (0.010)	-0.222*** (0.050)	-0.102*** (0.027)	0.001 (0.016)		-0.025** (0.010)	-0.217*** (0.049)	-0.095*** (0.027)	-0.014 (0.017)	
SHmc					-7.696** (3.467)					-7.605** (3.456)
AirHSR						1.128 (0.784)	2.005** (0.872)	1.340* (0.747)	1.075 (0.717)	2.004** (0.890)
SDgr × AirHSR						0.017 (0.015)	-0.036 (0.079)	0.022 (0.054)	0.038 (0.025)	
SHmc × AirHSR										-1.967 (5.615)
Constant	-19.58*** (1.893)	-20.05*** (1.740)	-20.60*** (1.841)	-17.72*** (1.863)	-19.05*** (1.790)	-19.02*** (1.875)	-19.38*** (1.738)	-19.72*** (1.848)	-17.58*** (1.847)	-18.36*** (1.781)
N	414	414	414	414	414	414	414	414	414	414
R^2	0.438	0.436	0.446	0.432	0.436	0.446	0.440	0.451	0.442	0.442

Note: Standard errors are in parentheses. Airport dummies are omitted to save space. *$p < 0.1$, ** $p < 0.05$, ***$p < 0.01$.

Table B. 3 Regression results based on Eq.(3) (DV = international passenger traffic, China)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HSR zones		0-500	500-1000	1000+			0-500	500-1000	1000+	
POP	1.377***	1.495***	1.516***	1.258***	1.423***	1.270***	1.328***	1.367***	1.229***	1.294***
	(0.130)	(0.124)	(0.125)	(0.127)	(0.126)	(0.116)	(0.113)	(0.117)	(0.113)	(0.111)
GDP_POP	0.084	0.221**	0.230***	-0.028	0.131	0.050	0.121	0.140*	-0.003	0.068
	(0.090)	(0.085)	(0.083)	(0.084)	(0.091)	(0.080)	(0.077)	(0.078)	(0.076)	(0.081)
LCC	0.023	-0.027	-0.054	-0.010	0.013	-0.379	-0.218	-0.270	-0.491*	-0.375
	(0.301)	(0.301)	(0.301)	(0.297)	(0.301)	(0.269)	(0.273)	(0.281)	(0.269)	(0.269)
FuelPrice	-0.620**	-0.903***	-0.971***	-0.169	-0.756***	-0.270	-0.553**	-0.653***	-0.044	-0.388
	(0.295)	(0.259)	(0.266)	(0.301)	(0.277)	(0.263)	(0.235)	(0.248)	(0.269)	(0.246)
Compete	-1.666***	-1.749***	-1.542***	-1.644***	-1.657***	-1.114**	-1.267***	-1.112**	-1.124**	-1.193**
	(0.515)	(0.515)	(0.515)	(0.508)	(0.518)	(0.458)	(0.466)	(0.478)	(0.455)	(0.459)
Year2008	0.299	0.373**	0.401**	0.149	0.341**	0.161	0.248	0.293*	0.088	0.177
	(0.185)	(0.179)	(0.180)	(0.185)	(0.181)	(0.164)	(0.161)	(0.167)	(0.165)	(0.160)
Year2009	-0.191	-0.259	-0.266	-0.084	-0.222	-0.088	-0.148	-0.160	-0.036	-0.133
	(0.186)	(0.183)	(0.183)	(0.185)	(0.187)	(0.165)	(0.165)	(0.169)	(0.165)	(0.165)
SDgr	0.004	-0.045*	-0.028**	0.025***		-0.003	-0.044**	-0.028**	0.002	
	(0.004)	(0.023)	(0.013)	(0.007)		(0.004)	(0.021)	(0.012)	(0.007)	
SHmc					0.054					-1.556
					(1.621)					(1.441)
AirHSR						-0.497	-0.697*	0.145	-0.166	-0.957**
						(0.327)	(0.376)	(0.327)	(0.296)	(0.371)
SDgr × AirHSR						0.051***	0.242***	0.130***	0.083***	
						(0.006)	(0.034)	(0.023)	(0.010)	
SHmc × AirHSR										18.871***
										(2.341)
Constant	-7.48***	-8.28***	-8.60***	-6.67***	-7.81***	-7.15***	-7.33***	-7.76***	-6.90***	-7.18
	(0.884)	(0.826)	(0.865)	(0.852)	(0.837)	(0.783)	(0.749)	(0.809)	(0.763)	(0.742)
N	414	414	414	414	414	414	414	414	414	414
R^2	0.310	0.314	0.321	0.304	0.313	0.346	0.347	0.346	0.338	0.344

Note: Standard errors are in parentheses. Airport dummies are omitted to save space. *p < 0.1, ** p < 0.05, ***p < 0.01.

Table B. 4 Regression results based on Eq.(3) (DV = domestic passenger traffic, Japan)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HSR zones		0-500	500+			0-500	500+	
POP	5.095*** (1.313)	5.053*** (1.320)	5.394*** (1.295)	5.078*** (1.312)	4.359*** (1.339)	4.383*** (1.332)	5.127*** (1.414)	4.271*** (1.359)
GDP_POP	1.527** (0.595)	1.481** (0.596)	1.783*** (0.592)	1.526** (0.597)	1.348** (0.594)	1.348** (0.590)	1.721*** (0.643)	1.359** (0.597)
LCC	0.892*** (0.211)	0.884*** (0.211)	0.957*** (0.209)	0.887*** (0.211)	0.999*** (0.238)	0.986*** (0.235)	1.072*** (0.230)	1.084*** (0.231)
FuelPrice	-0.568* (0.336)	-0.570* (0.336)	-0.456 (0.333)	-0.570* (0.336)	-0.573* (0.332)	-0.546 (0.331)	-0.454 (0.338)	-0.563* (0.332)
Compete	-4.357*** (0.683)	-4.366*** (0.684)	-4.243*** (0.673)	-4.363*** (0.683)	-5.099*** (1.578)	-4.711*** (1.183)	-3.264** (1.549)	-5.168*** (1.824)
Year2009	-0.602** (0.279)	-0.595** (0.279)	-0.586** (0.273)	-0.600** (0.278)	-0.610** (0.275)	-0.589** (0.275)	-0.581** (0.276)	-0.606** (0.275)
Year2011	-0.973 (0.217)	-0.987** (0.217)	-0.906*** (0.214)	-0.976** (0.217)	-0.947*** (0.217)	-0.955*** (0.216)	-0.883*** (0.216)	-0.934*** (0.216)
SDgr	-0.008 (0.017)	0.0004 (0.020)	-0.129** (0.058)		-0.015 (0.018)	-0.014 (0.022)	-0.095 (0.069)	
SHmc				-0.549 (1.387)				-1.109 (1.502)
AirHSR					-2.400* (1.364)	-2.400** (1.145)	-0.386 (0.651)	-1.776* (1.029)
SDgr×AirHSR					0.053 (0.042)	0.062 (0.041)	-0.038 (0.131)	
SHmc×AirHSR								3.665 (3.444)
Constant	-18.62** (7.627)	-18.38** (7.656)	-21.21** (7.576)	-18.57** (7.627)	-13.14 (8.065)	-13.70 (7.807)	-20.50** (8.998)	-12.86 (8.316)
N	144	144	144	144	144	144	144	144
R^2	0.365	0.365	0.365	0.365	0.368	0.370	0.374	0.369

Note: Standard errors are in parentheses. Airport dummies are omitted to save space. *p <0.1, ** p<0.05, ***p<0.01.

Table B. 5 Regression results based on Eq.(3) (DV = international passenger traffic, Japan)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HSR zones		0-500	500+			0-500	500+	
POP	-1.604 (1.639)	-1.748 (1.640)	-1.500 (1.654)	-1.562 (1.639)	-1.930 (1.620)	-1.839 (1.585)	-0.882 (1.802)	-1.780 (1.693)
GDP_POP	0.676 (0.743)	0.629 (0.740)	0.793 (0.756)	0.677 (0.746)	0.523 (0.718)	0.616 (0.701)	0.991 (0.819)	0.649 (0.744)
LCC	0.631** (0.264)	0.644** (0.262)	0.652** (0.267)	0.642 (0.263)	0.234 (0.287)	0.237 (0.280)	0.490* (0.293)	0.523* (0.288)
FuelPrice	-0.821* (0.419)	-0.789* (0.418)	-0.810* (0.426)	-0.815* (0.419)	-0.901** (0.402)	-0.771* (0.394)	-0.791* (0.430)	-0.846** (0.414)
Compete	6.795*** (0.853)	6.849*** (0.850)	6.821*** (0.859)	6.810*** (0.854)	0.586 (1.908)	2.163 (1.408)	5.944*** (1.975)	2.340 (2.273)
Year2009	-0.299 (0.348)	-0.286 (0.347)	-0.315 (0.349)	-0.304 (0.348)	-0.297 (0.333)	-0.239 (0.327)	-0.305 (0.352)	-0.299 (0.343)
Year2011	-0.363 (0.271)	-0.370 (0.269)	-0.328 (0.274)	-0.357 (0.271)	-0.486* (0.263)	-0.477* (0.257)	-0.355 (0.275)	-0.414 (0.270)
SDgr	0.020 (0.021)	0.035 (0.026)	-0.002 (0.075)		-0.002 (0.022)	-0.007 (0.026)	-0.038 (0.088)	
SHmc				1.454 (1.733)				0.005 (1.872)
AirHSR					-4.522*** (1.650)	-4.169*** (1.363)	0.812 (0.830)	-1.431 (1.283)
SDgr×AirHSR					0.171*** (0.051)	0.190*** (0.049)	-0.003 (0.167)	
SHmc×AirHSR								7.791* (4.293)
Constant	2.14 (9.521)	2.82 (9.512)	1.53 (9.675)	2.03 (9.526)	10.64 (9.754)	8.34 (9.287)	-1.66 (11.467)	7.43 (10.365)
N	144	144	144	144	144	144	144	144
R^2	0.285	0.342	0.266	0.274	0.355	0.425	0.472	0.443

Note: Standard errors are in parentheses. Airport dummies are omitted to save space. *p <0.1, ** p<0.05, ***p<0.01.

B.5 Regression analysis with airport hub status

Table B. 6 Regression results based on Eq.(4) (China)

	Total		Domestic		International	
	(1)	(2)	(3)	(4)	(5)	(6)
POP	3.764*** (0.335)	3.983*** (0.326)	3.170*** (0.299)	3.202*** (0.288)	0.593*** (0.075)	0.780*** (0.067)
GDP_POP	1.940*** (0.215)	1.987*** (0.222)	1.835*** (0.191)	1.852*** (0.196)	0.105** (0.048)	0.134*** (0.046)
LCC	2.302*** (0.727)	2.349*** (0.738)	2.262*** (0.649)	2.433*** (0.653)	0.039 (0.163)	-0.084 (0.153)
FuelPrice	-2.356*** (0.700)	-2.568*** (0.673)	-2.066*** (0.624)	-2.137*** (0.595)	-0.289* (0.157)	-0.430*** (0.139)
Compete	-3.953*** (1.231)	-4.624*** (1.249)	-3.546*** (1.098)	-4.022*** (1.105)	-0.407 (0.276)	-0.601** (0.259)
Year2008	0.106 (0.438)	0.157 (0.434)	0.020 (0.391)	0.025 (0.384)	0.085 (0.098)	0.131 (0.090)
Year2009	-0.597 (0.437)	-0.648 (0.445)	-0.462 (0.390)	-0.500 (0.394)	-0.134 (0.098)	-0.148 (0.092)
SDgr	-0.023** (0.011)		-0.023** (0.010)		0.0007 (0.002)	
SHmc		-8.666** (3.863)		-7.393** (3.417)		-1.273 (0.802)
AirHSR	1.640* (0.962)	2.199** (1.047)	1.662* (0.858)	2.246** (0.926)	-0.021 (0.216)	-0.046 (0.217)
Hub	-1.192 (1.926)	-1.881 (2.235)	-0.041 (1.718)	-0.164 (1.977)	-1.151*** (0.432)	-1.717*** (0.464)
SDgr × AirHSR	-0.007 (0.020)		-0.011 (0.018)		0.004 (0.004)	
SDgr × Hub	0.075*** (0.020)		0.033* (0.018)		0.041*** (0.004)	
SHmc × AirHSR		-8.901 (7.005)		-10.36* (6.197)		1.462 (1.455)
SHmc × Hub		21.282* (11.017)		8.861 (9.746)		12.421*** (2.288)
AirHSR × Hub	2.292 (2.258)	-2.547 (3.456)	0.033 (2.014)	1.100 (3.057)	2.258*** (0.507)	-3.647*** (0.717)
SDgr × AirHSR × Hub	0.116*** (0.039)		0.048 (0.035)		0.067*** (0.008)	
SHmc × AirHSR × Hub		64.122*** (20.443)		12.628 (18.085)		51.494*** (4.246)
Constant	-19.39*** (2.231)	-20.28*** (2.1517)	-16.46*** (1.990)	-16.27*** (1.903)	-2.931*** (0.501)	-4.01*** (0.446)
N	414	414	414	414	414	414
R^2	0.502	0.482	0.476	0.467	0.555	0.465

Note: Standard errors are in parentheses. Airport dummies are omitted to save space. *p <0.1, ** p<0.05, ***p<0.01.

Table B. 7 Regression results based on Eq.(4) (Japan)

	Total		Domestic		International	
	(1)	(2)	(3)	(4)	(5)	(6)
POP	3.438	3.975*	4.670***	4.652***	-1.232	-0.676
	(2.313)	(2.296)	(1.374)	(1.360)	(1.694)	(1.685)
GDP_POP	1.891*	1.951**	1.277**	1.280**	0.614	0.671
	(0.982)	(0.984)	(0.583)	(0.583)	(0.719)	(0.722)
LCC	1.033**	1.078**	1.004***	1.016***	0.028	0.062
	(0.431)	(0.432)	(0.256)	(0.256)	(0.316)	(0.317)
FuelPrice	-1.475***	-1.449***	-0.597**	-0.588*	-0.878**	-0.861**
	(0.548)	(0.548)	(0.325)	(0.324)	(0.401)	(0.402)
Compete	-5.838**	-13.408***	-5.331***	-7.111**	-0.507	-6.296*
	(2.791)	(4.912)	(1.657)	(2.909)	(2.043)	(3.606)
Year2009	-0.886*	-0.871*	-0.608**	-0.602**	-0.277	-0.269
	(0.454)	(0.454)	(0.269)	(0.269)	(0.332)	(0.333)
Year2011	-1.431***	-1.412***	-0.917***	-0.916***	-0.514*	-0.496*
	(0.359)	(0.359)	(0.213)	(0.212)	(0.263)	(0.263)
SDgr	-0.009		-0.011		0.002	
	(0.030)		(0.018)		(0.022)	
SHmc		-0.969		-0.909		-0.059
		(2.475)		(1.466)		(1.817)
AirHSR	-6.403***	-5.307***	-2.419*	-2.114*	-3.984**	-3.192**
	(2.297)	(1.868)	(0.016)	(1.107)	(1.682)	(1.372)
Hub			(omitted)			
SDgr × AirHSR	0.176**		0.050		0.125**	
	(0.081)		(0.048)		(0.059)	
SDgr × Hub	-0.034		-0.044***		0.009	
	(0.027)		(0.016)		(0.020)	
SHmc × AirHSR		12.305**		3.699		8.605**
		(5.681)		(3.365)		(4.171)
SHmc × Hub		-4.916		-6.178***		1.262
		(3.792)		(2.246)		(2.783)
AirHSR × Hub			(omitted)			
SDgr × AirHSR × Hub	0.057		0.006		0.051	
	(0.046)		(0.027)		(0.033)	
SHmc × AirHSR × Hub		15.047***		2.849		12.197***
		(5.503)		(3.259)		(4.040)
Constant	-6.03	-2.12	-13.74*	-11.91	7.71	9.78
	(13.562)	(13.737)	(8.055)	(8.137)	(9.931)	(10.085)
N	144	144	144	144	144	144
R^2	0.724	0.583	0.364	0.344		

Note: Standard errors are in parentheses. Airport dummies are omitted to save space. *p <0.1, ** p<0.05, ***p<0.01.

Appendix C: Appendix for Chapter 4

C.1 Descriptive statistics for independent variables

Table C. 1 Descriptive statistics of input and output factors for Chinese airports

Variable	Obs	Mean	Std.	Min	Max
HSR Connectivity	414	18.384	23.866	0	113
HSR Accessibility	414	0.079	0.081	0	0.319
HSR Dummy	414	0.616	0.487	0	1
Sbs	414	2.605	3.573	0.004	28.769
Cpl	414	0.024	0.022	0.001	0.093
POP (10^6)	414	7.446	5.571	0.465	30.166
GDP-POP (10^4RMB)	414	4.393	2.081	0.601	11.449
Privatize	414	0.285	0.452	0	1
Hub	414	0.065	0.247	0	1
Fuel	414	1.029	0.232	0.657	1.276
Compete	414	0.565	1.057	0	6
RwyStructure	414	0.034	0.181	0	1
Olympic	414	0.111	0.315	0	1
Crisis	414	0.111	0.315	0	1

Table C. 2 Descriptive statistics of input and output factors for Japanese airports

Variable	Obs	Mean	Std.	Min	Max
HSR Connectivity	144	22.208	20.387	0	68
HSR Accessibility	144	0.229	0.237	0	0.790
HSR Dummy	144	0.667	0.473	0	1
Sbs	144	6.768	8.190	0.028	30.706
Cpl	144	0.424	0.058	0.002	0.238
POP (10^6)	144	5.091	4.031	1.104	13.515
GDP-POP (10^6JPY)	144	4.248	1.301	3.068	7.857
Privatize	144	0.215	0.412	0	1
Hub	144	0.215	0.412	0	1
Fuel	144	1.029	0.232	0.657	1.276
Compete	144	0.979	0.780	0	2
RwyStructure	144	0.125	0.332	0	1
Olympic	144	0.111	0.315	0	1
Crisis	144	0.111	0.315	0	1

C.2 Simar and Wilson (2007) method Algorithm 2

[1] Calculate the DEA output-oriented efficiency score $\hat{\delta}_i = \hat{\delta}(x_i, y_i | \hat{\wp}) \forall\ i = 1, \dots, n$ for each DMU using the original data.

[2]Use maximum likelihood to estimate $\widehat{\boldsymbol{\beta}}$ of $\boldsymbol{\beta}$ and $\widehat{\sigma_\varepsilon}$ of σ_ε in the truncated regression of $\hat{\delta}_i$ on z_i

[3]Loop over the next four steps ([3.1]-[3.4]) L_1 times to obtain n sets of bootstrap estimates $\mathcal{B}_i = \{\hat{\delta}_{ib}^*\}_{b=1}^{L_1}$

[3.1] For each $i = 1, \dots, m,$ draw ε_i from the $N\ (0, \widehat{\sigma_\varepsilon}^2)$ distribution with left truncation at $1 - \boldsymbol{z_i}\widehat{\boldsymbol{\beta}}$

[3.2] For each $i = 1, \dots, m,$ compute $\delta_i^* = \boldsymbol{z_i}\widehat{\boldsymbol{\beta}} + \varepsilon_i$

[3.3] Construct a pseudo data set $(\boldsymbol{x_i^*}, \boldsymbol{y_i^*})$, where $\boldsymbol{x_i^*} = \boldsymbol{x_i}, \boldsymbol{y_i^*} = \boldsymbol{y_i}\, \hat{\delta}_i / \delta_i^*$

[3.4] Compute $\widehat{\delta_\iota}^* = \hat{\delta}(\boldsymbol{x_i}, \boldsymbol{y_i} | \hat{\wp}^*)\ \forall\ i = 1, \dots, n$, where $\hat{\wp}^*$ is obtained by replacing **Y, X** with $Y^* = [y_1^* \dots y_n^*], X^* = [x_1^* \dots x_n^*]$.

[4] For each DUM $i = 1, \dots, n$, compute the bias -corrected estimator $\hat{\hat{\delta}}_i$ by $\hat{\hat{\delta}}_i = \hat{\delta}_i - \widehat{bias}_i$, where $\widehat{bias}_i$ is the bootstrap estimator of the bias obtained from $\widehat{bias}_i = \left(\frac{1}{L_1}\sum_{l=1}^{L_1} \hat{\delta}_{ib}^*\right) - \hat{\delta}_i$

[5]Use maximum likelihood to estimate the truncated regression of $\hat{\hat{\delta}}_i$ on $\boldsymbol{z_i}$, yielding $(\widehat{\widehat{\boldsymbol{\beta}}}, \widehat{\widehat{\boldsymbol{\sigma}}})$

[6] Loop over the next three steps (6.1-6.3) L times to obtain a set of bootstrap estimates $\mathcal{L} = \{(\hat{\beta}^*, \widehat{\sigma_\varepsilon}^*)_b\}_{b=1}^{L_2}$:

[6.1]For each $i = 1, \dots, m,$ draw ε_i from the $N\ (0, \hat{\hat{\sigma}})$ distribution with left truncation at $1 - \boldsymbol{z_i}\widehat{\widehat{\boldsymbol{\beta}}}$

[6.2]For each $i = 1, \dots, m,$ compute $\delta_i^{**} = z_i\widehat{\widehat{\boldsymbol{\beta}}} + \varepsilon_i$

[6.3]Use the maximum likelihood method to estimate the truncated regression of δ_i^{**} on z_i, yielding estimates $(\widehat{\widehat{\boldsymbol{\beta}}}^*, \hat{\hat{\sigma}}^*)$

[7]Use the bootstrap values in $\mathcal{L}$ and the original $\hat{\hat{\beta}}, \hat{\hat{\sigma}}$ to construct estimated confidence intervals for each element of $\boldsymbol{\beta}$ and for σ_ε.