The Implications of High-speed Rail for Chinese Cities: Connectivity and Accessibility

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Investigating the implications of high-speed rail network for Chinese cities based on the connectivity and accessibility measures

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Abstract: Based on China's latest national railway network planning proposal, the connectivity and accessibility indices of China's high-speed railway network (CHSRN) in different time periods are computed to evaluate the implications of the high-speed rail (HSR) for different cities. An overall index for measuring the connectivity-accessibility of cities on CHSRN is proposed based on three indicators: a) the Beta index reflecting the connectivity of the HSR, b) the number of reachable counties by HSR within the 500-km domain of a city, to reflect the location-based accessibility of the HSR, and c) the population of the reachable places by HSR within the 500-km domain of a city, to reflect the potential-based accessibility of the HSR. Finally, the differences in the normalized connectivity-accessibility levels of different categories of cities are qualified to measure the impact of China's future national HSR network on the potential development of cities. It is found that "Mid-to-Long-Term Railway Network Plan (Revised in 2016)", if fully realized, would profoundly change the

HSR connectivity/accessibility of different cities. Most notably, cities in the Yangtze River Delta would suffer the most whereas cities of the central and western regions would gain the most. This could potentially contribute to, or bring about new changes in the socioeconomic landscapes in China. The main contribution of this paper is twofold. Firstly, an overall index to evaluate the comprehensive connectivity and accessibility levels of the HSR network is designed. Secondly, this paper also investigates how to qualify the impact of the future HSR network on different tiers of cities in different time periods according to the change of the overall connectivity/accessibility index.

Keywords: high-speed rail; HSR; accessibility; connectivity; implication; China

1. Introduction

Investments in the construction of national transport infrastructure, particularly railways, are closely associated with the socioeconomic development of a country (Chen et al., 2016). For example, the transcontinental railway had remade and even transformed the US in the 19th century. In recent decades, high-speed rails (HSRs) have received increasing attention. This attention is the result of HSRs' numerous favorable and desirable attributes (i.e., hedonic values), such as high speed, high frequency, travel time reliability, and relatively low fare (compared with other transport modes, especially flights); and the spillover effects of these railways. For example, building and maintaining an HSR can generate new job opportunities and facilitate the establishment of a large and considerably integrated market. In populous developing economies, such as China and India, HSR could be the most cost-effective means of long-distance travel for intercity passengers[1]. The aforementioned desirable attributes and spillover effects mainly explain the reason for the increase in the number of HSR lines being constructed in China and other countries in recent years.

The introduction of HSR will substantially change and even revolutionize the transport mode choice and trip distribution of millions of passengers (Shyr and Hung, 2010). Therefore, the analysis of the impact of HSR on cities on the existing railway network is of immense importance. Such impact can be either realized ones or forecasted ones. The current study focuses on the latter and assumes that from the perspectives of connectivity and accessibility, "winners" and "losers" will emerge from the construction or planned construction of HSRs. Thus, we propose an integrated connectivity–accessibility index and define the "winner" as the city that achieves a higher index value than others because of the introduction of new HSR lines, whereas the "loser" is the city with a relatively small change in its index value. Understandably, the winners and losers cannot easily be detected using conventional techniques, such as eyeballing, buffer analysis, and statistical analysis. Instead, they should be investigated from a considerably broad view using sophisticated methods.

Our existing knowledge and online search have enabled us to determine that different

[1] Heated debates have emerged on (1) which mode can better serve the public and meet future travel demands, that is, HSR or magnetic levitation (Maglev) train, and (2) whether HSR can maintain its significance in the future. A few studies (e.g., Lee et al., 2006; Nishijima et al., 2013) have listed a few advantages of the Maglev train over HSR, such as the unmatched advantage in speed, reduction in guide-way construction and maintenance costs, reduction in the greenhouse gas emissions, and improvement of economic viability. Yet, despite over 80 years of development, Maglev transport systems are in operation only in limited areas in three countries, namely, Japan, South Korea, and China, partially because of the huge construction costs involved.

strategies have been implemented on winners and losers based on the connectivity and accessibility indices before and after completing a national HSR plan. This study uses China's HSR experience and plans as an example to analyze the winners and losers from HSR constructions or planned constructions in four different time periods between 2007 and 2030. Thus, this research provides a new approach in appraising HSR constructions and plans, compares the time-dependent connectivity and accessibility indices of cities on China's HSR network (CHSRN), discusses the trend of these indices at the city level, and studies how planned constructions influence the connectivity and accessibility indices of the different categories of cities and regions. By quantifying future changes in the connectivity and accessibility indices at the city and regional levels in advance, cities and regions could implement proactive measures to respond to such changes. Moreover, this study conducts a performance persistence analysis to reflect the evolution of winners and losers, more specifically, the relationship between past and future performances.

Similar to the current study, Moyano et al. (2018) used cross-sectional data and effectively identified the winner and loser of the city on the Spanish HSR network based on two accessibility indicators (i.e., location- and schedule-based measures). However, they focused more on which HSR stations benefit more from the "service provision" compared with "potential accessibility". By contrast, our study uses longitudinal data (which can measure "change") and compares the connectivity–accessibility levels in different periods in China to identify and evaluate the winners and losers. In view of the extensive scale of CHSRN, the mileage of which is approximately 100 times that of the HSR lines in other countries, we further discuss the performance persistence of the winning/losing status of the city on the HSR network based on the results of a nonparametric method.

The main contributions of this study include (1) filling the research lacuna by adding a reliable empirical study of the largest HSR market in terms of connectivity and accessibility; (2) devising a new methodology that can be easily and efficiently employed in other regions to identify the winners and losers emerging from the HSR constructions from the perspectives of connectivity and accessibility; and (3) employing the proposed analytical framework to uncover the change in connectivity–accessibility stemming from the HSR planning in China.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the methodology and related background information. Section 4 details an empirical case of China, in which the connectivity and accessibility indices are used to show how the past and future HSR constructions have influenced or would influence different cities, city categories, and regions. Section 5 provides the discussion and conclusion.

2. Literature review

2.1 Accessibility and connectivity of transport networks

2.1.1 Accessibility of transport networks

Accessibility is an important dimension of transport networks. Numerous approaches and measures have been used to quantify the accessibility of transport networks (Tong et al., 2015; Martínez et al., 2016). The accessibility measures of transport networks can be divided into three categories: location-, potential-, and transport capacity-based.

Location-based accessibility (LBA) focuses on the ease of reaching a node in a transport network. As such, a few scholars also call LBA “local accessibility”, “access”, and “to-transit accessibility” (Geurs and van Wee, 2004; Matisziw and Grubesic, 2010; Moniruzzaman and Páez, 2012). The calculation of LBA is often based on the average travel time or cost to reach a station on a transport network (Karou and Hull, 2014). In many existing studies, LBA is also perceived as the gravity-based accessibility, which has a few analogues, including the floating catchment area-based accessibility (Luo and Whippo, 2012; McGrail and Humphreys, 2014; Xu et al., 2015), spatial interaction-based accessibility (Saghapour et al., 2016), and cumulative opportunity accessibility (Páez et al., 2012)

Potential-based accessibility (PBA) reflects the fullest degree that a transport infrastructure can be used or the possible (or maximum) amount of travel demand that a transport network can serve (Gutiérrez, 2001; Moniruzzaman and Páez, 2012; Páez et al., 2012; Cui et al., 2016; Saghapour et al., 2016). PBA could be equivalent to a service area or passenger demand of this area on a transport network. The PBA measurement is typically based on Hansen (1959), who defined PBA as a function of the travel demand of an area and the travel cost to this area from other locations. The travel cost can be measured by time, distance, or money by applying the pre-specified decay functions. In existing literature, PBA is also called “regional accessibility”, “locational access” (Edmond et al., 1993; Straatemeier, 2008; Matisziw and Grubesic, 2010; Páez et al., 2012; Caschili and De Montis, 2013), and “by-transit accessibility” (Moniruzzaman and Páez, 2012).

Transport capacity-based accessibility (TCA) measures the ease of travel or the activity that can occur on a transport network under given conditions or environmental inputs. That is, TCA evaluates how easy transport activities can be carried out or how much demand (i.e., goods or people) can be transported with a given infrastructure, level of service (LOS), and schedule or timetable imposed on a transport network (Fransen et al., 2015). Moreover, TCA is commonly analyzed with the user behavior (Caschili and De Montis, 2013). The utility-based method is frequently adopted to determine the effect of passenger behavior on TCA of a network (Nassir et al., 2016). TCA with consideration of the schedule or timetable of a transport service has been frequently applied to analyze the LOS of public transit networks (Silva, 2013; Xu et al., 2015). Theoretically, the difference between PBA and TCA is that the former calculates the amount of the "possible" maximal demand that requires the use of certain infrastructure on the network. By contrast, the latter emphasizes the "revealed" capability of an infrastructure under the constraints of existing environmental inputs or service provisions.

2.1.2 Connectivity of transport networks

In transport studies, connectivity is another common index to evaluate the LOS of a transport network. Connectivity measures the "ease" degree of connection or communication from a node to another on a network (Suau-Sanchez and Burghouwt, 2012; Cheng and Chen, 2015). A host of scholars have provided different approaches to measure connectivity and these approaches are mainly based on graph theory. Sokol (2009) defined the connectivity of transport network (CTN) as the ease with which people, materials, and information can be moved from one location to another. He recommended using CTN of that nature to evaluate the LOS of a regional transport network. Kaplan et al. (2014) formulated the transit connectivity via in-vehicle time, access/egress times, waiting time, service reliability, frequency, and "seamless" transfers along multimodal paths on a transit network. In their measure, transit connectivity is weighted based on the type of travel time on the path between the origin and destination (Kaplan et al., 2014). Mishra et al. (2012) proposed a measure to determine connectivity in multimodal transit networks; this measure integrated routes, schedules, socioeconomic, demographic, and spatial activity patterns. A few studies (e.g., Chin et al., 2008; Suau–Sanchez and Burghouwt, 2012; Blair et al., 2013; Hadas, 2013; van Wee, 2016) regarded connectivity as one of the essential indices for evaluating PBA.

Taaffe et al. (1996) and Rodrigue (2013) explained that two indices can be used to evaluate the connectivity of a transport network: one for the entire network and the other for an individual node on the network. A concrete example of the former is the beta index, which is calculated as the ratio of links (or connections and arcs) to nodes (vertices) (Xie and Levinson, 2009). A concrete example of the latter is given by Sokol (2009), who measured the number of links from a given node (i.e., degree of a node). However, the connectivity index has rarely been used to evaluate a planned (or future) transport network partially because the connectivity index is often based on the real travel time or cost between two locations on the network.

2.2 Effects of HSR

HSR has become an important transport mode in recent decades and constructed in many countries (Levinson, 2012). Given the development in HSR construction, numerous papers that analyze the effects of HSR have been published (Cartenì et al., 2017). Many scholars have likewise evaluated the benefits of HSR. First, the introduction of HSR could improve the efficiency of regional transport networks, specifically by enhancing the accessibility and carrying capacity of railway networks (Marr and Sutton, 2007; Martínez and Givoni, 2012; Cao et al., 2013; Shaw et al., 2014; Wang et al., 2016). Second, HSR could optimize the speed and cost of long-haul trips between cities (Yang and Zhang, 2012; Abrate et al., 2016; Wang et al., 2016). Third, HSR could generate large energy savings for railway networks (Krishnan et al., 2015; Lu, 2016). Fourth, HSR could stimulate incremental consumption growth and promote economic development (Jia et al., 2017), particularly in the service sector (Cheng et al., 2015; Circella, 2015; Chen et al., 2016). In addition, HSR could facilitate the reshaping of a region by enhancing the accessibility of different markets, thereby contributing to regional development (Zheng and Kahn, 2013). Moreover, HSR could affect urban development, as elucidated in an increasing number of studies (Guerra, 2014; Shen et al., 2014; Chen and Haynes, 2015a; Yin et al., 2015). Most notably, HSR could increase property price in urban areas (Andersson et al., 2012; Chen and Haynes, 2015a). Lastly, HSR could accelerate the development of different sectors besides housing, including tourism (Coronado et al., 2013; Chen and Haynes, 2015b; Albalate and Fageda, 2016; Moyano et al., 2016; Pagliara et al., 2017), machinery manufacturing (Morgan Stanley Research Global, 2015), and logistics (Boloukian and Siegmann, 2016).

HSR has been continuously subject to questions and criticisms despite its benefits. A few scholars explained that the large-scale construction of HSR may induce irreversible environmental damage (He et al., 2015). Others insisted that HSR would cause unbalanced and inappropriate economic development as the major share of the budget would be spent on infrastructure rather than on the advancement of the living standard of the locals (Zhao et al., 2015). In a few cases, the introduction of HSR did not solve the insufficient carrying capacity of the existing railway networks (Wu et al., 2014). Even worse, the introduction of HSR could adversely affect the air transport sector of a region because of intense competition (Börjesson, 2014; Dobruszkes et al., 2014; Fu et al., 2012; Takebayashi, 2016), particularly for short- and medium-distance journeys (Chai et al., 2018) and in thin markets (Zhang et al., 2017) Consequently, the future advancement of the aviation market is hindered (Wang et al., 2017).

2.3 Thrust of this study

Very limited studies have integrated connectivity and accessibility into the measurement and reflected the spatiotemporal LOS evolution of an HSR network. Even less are the studies that analyze how to allocate the HSR resources across cities based on the differences in accessibility and connectivity indices. This study fills such gaps in existing studies. First, it introduces a new connectivity–accessibility index. Subsequently, it uses CHSRN, the largest of its kind in the world, as an example to show how HSR past or planned constructions would influence the levels of connectivity and accessibility of the different cities on the network in four time periods between 2007 and 2030. Finally, a performance persistence analysis is conducted to reflect the evolution of winners and losers.

3. Methods

3.1 Background

The first segment of China's HSR network emerged in 2007[2] against the backdrop of the country's perception of or concerns about the insufficient carrying capacity of the railway network. The "Mid-to-Long-Term Railway Network Plan (Version 2004)" ("PLAN-2004" hereinafter), which was the first national HSR planning proposal issued in 2004, indicated that China had increased the maximal speed of its passenger rail lines to 160 km/h as of 2007. After realizing the made-in-China goal for the core HSR technologies, China formulated an

[2] A few studies (e.g., Jiao et al., 2014) consider the Shenyang–Qinhuangdao Railway, which has a speed of 200 km/h (which was opened in 2003), as the first HSR route in China. However, considering it as the first HSR route in China may be inaccurate because HSR is often defined as a passenger-dedicated railway designed for speed of over 250 km/h.

ambitious plan for HSR construction, which is to build an HSR network comprising four vertical (north–south) corridor lines and four horizontal (west–east) corridor lines; this HSR network was completed in 2015 (Xu et al., 2017). The total track mileage of the HSR network would reach 19,000 km by 2020 based on PLAN-2004. China followed this plan and implemented numerous HSR constructions from 2007 to 2015. In 2015, China had an HSR network equipped with complete system technologies. This HSR network had the longest operating mileage and highest-speed tracks all over the world. The total mileage of the HSR tracks in China reached 20,000 km by July 2016, thereby achieving the goal specified in PLAN-2004 five years ahead of schedule.

On July 20, 2016, China issued a new national railway network plan, the "Mid-to-Long-Term Railway Network Plan (Revised in 2016)" ("PLAN-2016" hereinafter). PLAN-2016 indicates that the total mileage of HSR tracks would be expanded to 30,000 km by 2020, which is equivalent to a 58% increase from the PLAN-2004 target. Furthermore, the total mileage of HSR tracks would reach 38,000 km by 2025, serving nearly all capital cities and cities with a population of 0.5 million. Accordingly, the total mileage of the HSR tracks will double by the next decade. The HSR network specified in PLAN-2016 is shown in Fig. 1.

(Insert Fig. 1 here)

After the realization of PLAN-2004, HSR has already transformed the connections among and the relative locations of Chinese cities in approximately 10 years. PLAN-2016 can be expected to continue effecting the same changes. That is, the HSR network has already reshaped and will continuously shape the spatial accessibility of cities in the world's most populous country. Analyzing the new connectivity and accessibility levels of Chinese cities because of the HSR network growth or planned growth is a stimulating task for scholars based in China and overseas. Such an analysis can demonstrate how rapidly an HSR network can be built and how significantly it can influence cities with millions of residents.

In this light, this study proposes a connectivity–accessibility measure for the different cities on the HSR network in different time periods between 2007 and 2030. The four time periods of concern are **2007–2010**, **2011–2015**, **2016–2020**, and **2021–2030**. The first three time periods are divided based on China's national economic and social development plans (i.e., the Five-year Plan released by the National Development and Reform Commission). In addition, PLAN-2016 uses 10 years as the unit of analysis because predicting development after 2020 is difficult if not impossible. Thus, the fourth time period in this study comprises 10 years to better reflect the planned HSR growth from 2021 to 2030. Evidently, the fourth time period is notably different from the first three.

3.2 Indices

3.2.1 Connectivity index

Taaffe et al. (1996) and Rodrigue (2013) explained that the beta index is a common measure to evaluate the level of connectivity in a graph. This index is expressed as the number of links over the number of nodes. The beta index β is represented mathematically as follows:

$$\beta = \frac{e}{v}, \quad (1)$$

where e and v denote the number of links and nodes, respectively, on the graph.

The objective of this study is to evaluate the connectivity level of the HSR network within a city's domain for each time period. Thus, we extend the traditional beta construction method by incorporating the time dimension and consequently modified Equation (1) to define the new (time-varying) beta index as follows:

$$Beta_i^t = \frac{S_i^t}{N_i^t}, \quad (2)$$

where $Beta_i^t$ is the beta index of city *i* during the *t*th time period, S_i^t is the number of HSR lines passing through the boundary of city *i* during the *t*th time period, and N_i^t is the number of HSR stations within the boundary of city *i* during the *t*th time period.

The number of HSR stations in a city is fixed within its domain during a given time period. Accordingly, the higher the number of HSR segments within a city, the higher number of HSR routes passing through the city and the higher the level of the HSR network connectivity of the city.

3.2.2 Accessibility indices

The LBA and PBA of a city on the HSR network should simultaneously investigated.

(1) LBA

For LBA, the cumulative opportunity measure of accessibility, which emphasizes the number of potential activities within a predefined region instead of the distances (Yang et al., 2016; 2018), is used. All available opportunities within the predefined region are weighted equally, whereas all unavailable ones are ignored. LBA is calculated as the number of places the subject city could be reached by HSR within a given distance threshold divided by 100 and expressed as follows:

$$LBA_i^t = \sum_{p\in\Omega_i^d} \delta_p^t / 100 \quad (3)$$

where p is the index of place; Ω_d denotes the set of places within the buffer domain, which treats city i as the central point and uses the distance threshold d; δ_p^t is a 0–1 variable, which equals to 1 if at least one HSR station is located within the boundary of place p and 0 otherwise.

Equation (3) expresses the number of places that can be reached from the center of city i by HSR within the domain of the distance threshold. Morgan Stanley Research Global (2015) and Moyano (2018) indicated that the suitable influencing distance for HSR is between 400 km and 600 km. The radius of the buffer domain of the city is set at 500 km herein. Moreover, a county is the smallest administrative district unit planned to locate an HSR station in China. Thus, the "place" in Equation (3) is a county. Equation (3) calculates the number of counties that can be directly reached by HSR within the 500 km domain of a city during a given time period.

(2) PBA

HSR is nearly dedicated to passenger transport instead of freight transport or both; thus, Hansen's extensively used classical PBA model (Hansen, 1959) is used to calculate a city's PBA with respect to the HSR network as follows:

$$PBA_i^t = \sum_{j\in\Omega_i'^d} Pop_j^t \exp\left(-\gamma d_{ij}\right), \quad (4)$$

where Ω_d' denotes the set of cities within the d domain of city i, Pop_j^t denotes the residential population of city j during time period t, d_{ij} is the physical distance between administrative centers of city i and city j on the HSR network, and γ is the distance decay parameter.

3.2.3 Overall connectivity–accessibility index

To evaluate the connectivity and accessibility of a city on the HSR network during a specific time period, we design an overall index (I_i^t) ("connectively–accessibility index" hereinafter), which is a linear combination of the three indices. The connectively–accessibility index is expressed as follows:

$$I_i^t = \theta_1 Beta_i^t + \theta_2 LBA_i^t + \theta_3 PBA_i^t. \quad (5)$$

The overall index for the accessibility and connectivity levels of a city on the HSR network consists of three independent indices: beta, LBA, and PBA indices. The respective definitions of the three indices reflect the role of a city on the HSR network on widely different aspects. First, the beta index reflects the connectivity degree of the HSR network within the domain of a city. Second, the LBA index reflects the number of counties covered within the 500 km threshold. Lastly, PBA reflects the potential population that will take HSR to get to the subject city. These three indices are independent of one another but subject to the structure of the HSR network and distribution of the residential population.

The three indices are illustrated in Fig. 2. City A in Fig. 2 is the city subject for the index computation during time period t. Moreover, 3 HSR lines and 4 HSR stations are located within its boundaries. Consequently, $Beta_A^t = 0.75$. A total of 13 counties own an HSR station within the 500 km buffer area. Therefore, $LBA_A^t = 0.13$. The 13 counties are directly "reachable" from City A by HSR without any transfer to another long-haul transport means. If these counties have a total population of 1 million and the distance decay parameter γ equals 0.01, then the PBA value can be calculated using Equation (4). Accordingly, $PBA_A^t = 0.59$.

The entropy method based on information theory is a well-known objective weight determination method and it assigns additional weights to attributes; thus, this method allows for an improved differentiation of alternatives (Xu, 2004). This method is initially used to assign the weights of the three indicators by using the data we have obtained for all the cities. The results show that the weights of the beta, LBA, and PBA indicators are 33.28%, 32.45%, and 34.27%, respectively. All the indices carry nearly identical weights. Thus, we set $\theta_1 = 1$, $\theta_2 = 1$, and $\theta_3 = 1$. An inherent assumption is that all the three attributes corresponding to the indices are equally important for a city to enjoy the benefits of HSR. Therefore, the overall connectivity–accessibility index of City A is 1.47 as calculated using Equation (5).

(Insert Fig. 2 here)

3.2.4 Determination of the winners and losers using the connectivity–accessibility index

At present, China's administrative hierarchy (from top to bottom) includes province, prefecture, and county. Moreover, there are four (province-level) direct-controlled municipalities (Beijing, Shanghai, Tianjin, and Chongqing) and two (province-level) special administrative regions (Hong Kong and Macau). Each province owns a capital city, which is often the most populous and economically developed city in that province. As of February

2016, China has 34 capital cities (“Level 1 cities” hereinafter) and 334 prefectures. This study initially calculates the indices of the 34 capital cities. However, if only Level 1 cities are analyzed, then a biased picture of CHSRN and its impact on the cities may be generated. Other cities, such as Shenzhen and Suzhou, have received HSR investment from the national government in each time period. To obtain a complete picture of CHSRN and its impact on cities, we have randomly selected 50 noncapital cities (“other cities” hereinafter), the indices of which are calculated using the same method used for the Level 1 cities. The other cities are further categorized into two groups. Group 1 comprises the subprovincial cities (SPCs), such as Shenzhen and Dalian. Unlike regular prefectures, SPCs enjoy more autonomy because they can implement their own legislation without soliciting approval from the home provincial government. Group 2 comprises regular prefectures that have to report to their respective home provincial governments on various affairs (“Level 3 cities” hereinafter). In addition, we have developed a separate database for completed or planned constructions of the HSR lines. Thus, we can differentiate which HSR lines were or will be built and when. For the planned constructions, the database relies on the statistics in PLAN-2016.

To analyze the benefits of constructing the HSR network to different tiers of cities, we define “winner” or “loser” based on the normalized differences in the I value in different time periods:

$$DI_i^{t1-t2} = I_i^{t2} / \overline{I}_i^{t2} - I_i^{t1} / \overline{I}_i^{t1}, \tag{6}$$

where DI_i^{t1-t2} denotes the normalized differences in the I value of city i between time period $t1$ and time period $t2$; I_i^{t1} and I_i^{t2} denote the I values of city i in time periods $t1$ and $t2$, respectively; and $\overline{I}_i^{t1}$ and $\overline{I}_i^{t2}$ denote the normalized I values of city i in time periods $t1$ and $t2$, respectively.

For easy comparison, DI_i^{t1-t2} is normalized with the average value as follows:

$$DI_i'^{t1-t2} = \frac{DI_i^{t1-t2}}{\overline{DI}^{t1-t2}}, \tag{7}$$

where $DI_i'^{t1-t2}$ is the normalized value of DI_i^{t1-t2} and $\overline{DI}^{t1-t2}$ represents the average value of DI_i^{t1-t2} of all the cities.

We set the following rules for defining the “winner” and “loser” because of the changes in the normalized connectivity–accessibility index of a city on the HSR network:

$$W^{t2} = \left\{ i \middle| DI_i'^{t1-t2} \geq 0 \right\}, \tag{8}$$

$$L^{t2} = \left\{ i \middle| DI_i'^{t1-t2} < 0 \right\}, \quad (9)$$

where W^{t2} and L^{t2} denote the sets of "winners" and "losers," respectively, in time period $t2$. Thus, a city will be categorized as a winner of a given time period if the "relative" connectivity–accessibility level of that city in a given time period is not lower than that in the previous time period. Otherwise, that city is regarded as a loser.

Equation (6) reveals the mathematical difference in the comparative *I* value of a city, which is computed as the ratio of the *I* value of a city to the average *I* value of all the cities. In reality, "winning" based on the connectivity and accessibility indices means an increase in the comparative connectivity–accessibility level (calculated by the ratio of the overall index to the average overall index) of a city on the HSR network in two consecutive time periods. By contrast, "losing" is reflected by a decrease in the comparative connectivity–accessibility level of a city on the HSR network in two consecutive time periods.

3.2.5 Performance persistence analysis based on the winner and loser statuses

The evolution of the winner and loser statuses is tracked using a nonparametric method based on a two-way contingency table, which has been applied in a few previous studies (e.g., Brown et al., 1992; Brown and Goetzmann, 1995). The table depicts the number of win–win, win–lose, lose–win, and lose–lose cities in two consecutive time periods. The cross-product ratio, which is the odds ratio of the number of repeat performers (i.e., win–win and lose–lose) to the number of others (i.e., win–lose and lose–win), can be expressed as follows:

$$C^{t1-t2} = WW^{t1t2} \times LL^{t1t2} / (WL^{t1t2} \times LW^{t1t2}), \quad (10)$$

where C^{t1-t2} is the cross-product ratio for $t1$ and $t2$, WW^{t1t2} is the number of cities categorized as winners for two consecutive time periods ($t1$ and $t2$), LL^{t1t2} is the number of cities categorized as losers for two consecutive time periods ($t1$ and $t2$), WL^{t1t2} is the number of cities categorized as winners in $t1$ and losers in $t2$, and LW^{t1t2} is the number of cities categorized as losers in $t1$ and winners in $t2$.

A chi-square analysis can be conducted to confirm whether a ratio is statistically different from 1 (Carpenter and Lynch, 1999). A ratio significantly above 1 indicates performance persistence. By contrast, a ratio value significantly below 1 indicates a negative relationship between the performances in two time periods. Furthermore, if the evidence supporting that the ratio is different from 1 is insufficient, then no relationship exists between the performances in the first and second time periods.

4. Results

4.1 Time-dependent indices of different types of cities of China

4.1.1 Level 1 cities

Table 1 presents the time-dependent index values of the Level 1 cities of China. Hangzhou (capital city of Zhejiang Province) had the highest comprehensive evaluation index (I = 4.88) in 2007–2010. During this time period, only one HSR line was constructed to connect Hangzhou. By contrast, three HSR lines passing through Chongqing and Chengdu (capital of Sichuan Province) were opened in the same time period. However, the accessibility index values (LBA and PBA) of both cities were lower than those of other Level 1 cities, such as Hangzhou and Nanjing (capital of Jiangsu Province). Table 1 shows that 15 Level 1 cities lacked any HSR lines in 2007–2010. Consequently, the I values of these cities are equal to 0.

(Insert Table 1 here)

The situation changed in 2011–2015. In this time period, Wuhan (capital of Hubei Province) had the highest I value because four HSR lines to or through Wuhan were constructed. In the same time period, the city with the most HSR lines and stations was Chengdu. In addition, nearly all Level 1 cities were connected by HSR lines in this time period, except Hong Kong, Macao, Hohhot (capital of Inner Mongolia), Yinchuan (capital of Ningxia), and Lhasa (capital of Tibet).

In 2016–2020, all Level 1 cities, except Macao and Lhasa, had at least one HSR line based on PLAN-2016. Table 1 shows that Wuhan would still top the I ranking. Following Wuhan, Chongqing, Changsha (capital of Hunan Province), and Chengdu have relatively high I values.

The tremendous HSR growth was drawn from PLAN-2016. Thus, the indices in 2021–2030 could reflect China's ambitious vision of the HSR network construction. Table 1 shows that Chongqing would have the highest I value in that time period. That is, Chongqing would become the most important hub in China's HSR network based on PLAN-2016. In 2021–2030, 16 HSR lines and 45 HSR stations would serve Chongqing (see Fig. 1). However, the LBA result indicates that the hub of the reachable counties within the 500 km radius would not be Chongqing but Hefei.

4.1.2 Other cities

(Insert Table 2 here)

Table 2 tabulates the time-dependent index values of the other cities of China. A comparison of Table 1 and Table 2 shows that a few other cities had higher I values than the Level 1 cities in 2007–2010. This result implies that in the initial development of CHSRN, a few other cities have benefited more in terms of connectivity and accessibility from the construction of the HSR network than Level 1 cities did. Wenzhou, Jiujiang, Liuan, Ningbo, and Suzhou had high I values in 2007–2010. Nearly all the cities are located in the Yangtze River Delta Region (YRDR), in which the central city is Shanghai. This result indicates that YRDR obtained the heaviest investment on HSR projects in the early days of CHSRN. This trend slightly changed in 2011–2015. In particular, a few Level 3 cities in Central China, such as Bengbu (a prefecture of Anhui Province) acquired a relatively high I value in this time period. This result indicates that the HSR constructions were intensified outside YRDR in 2011–2015. Table 2 shows that the differences in the I value between SPCs and Level 3 cities would decrease further. In 2021–2030, nearly all other cities would have comparable I values.

Table 1 and 2 show that not all cities experience similar growths in their I value, thereby reflecting a city's overall connectivity–accessibility level across the time periods. The I value of a city can change over time because of the HSR constructions. Once other cities have numerous HSR lines or stations, a city that lacks one should expect a decreased I value. In reality, Wenzhou serves as a case in point (see Table 2). The I value of Wenzhou in 2007–2010 was relatively high compared with all Level 3 cities. However, the relative magnitude of I decreases gradually in the ensuing time periods. The case of Wenzhou relatively shows how China allocates its resources to HSR construction over time and implies which cities are substantially favored or ignored in the process. That is, a few winners or losers in the HSR constructions constantly emerge in terms of connectivity and accessibility. Our indices enable us to immediately differentiate the winners and losers and are replicable across time periods.

4.2 Change in connectivity–accessibility in the spatiotemporal dimension

Stacked bar graphs and spatiotemporal contour maps of I values (see Figs. 3 and 4, respectively) are created to visualize the change in the comprehensive connectivity–accessibility value of all the cities on CHSRN in different time periods. Other findings on CHSRN can be drawn from these figures and the most notable ones are summarized as follows.

(Insert Fig.3-a, Fig.3-b here)

(Insert Fig.4-a, Fig.4-b. Fig.4-c, Fig.4-d here)

(1) The maximal I value in different time periods has been marked with red color in Figs. 3-a and 3-b. A comparison of Figs. 3-a and 3-b shows that Level 1 cities do not constantly have high I values than other cities. Hangzhou initially leads in the I ranking and Chongqing would assume the position in 2030 (see Fig. 3-a). This result indicates that China would add more HSR projects in its areas rather than in YRDR in approximately 15 years based on PLAN-2016. Notable differences exist in the I values of different Level 1 cities across the four time periods. This result implies that China’s HSR investment will be unevenly distributed among provinces.

(2) The deviation in the I values between SPCs and Level 3 cities would decline gradually (see Fig. 3-b). For those cities on CHSRN, they could be equally connected or accessible.

(3) As expected, the overall service area of CHSRN consistently expands over time. The contour lines of index I in Fig. 4-a have two concenters in 2007–2010: the Jing–Jin–Ji (Beijing, Tianjin and Hebei Provinces) Region and YRDR. However, the concenters of the contour lines of index I in Figs. 4-b, 4-c, and 4-d spread to the inland areas of China. Wuhan and Chongqing have and would have the densest contour lines in 2016–2020 and 2021–2030 (see Figs. 4-c and 4-d, respectively).

(4) The gap in the connectivity–accessibility levels between the eastern and western regions of China would gradually reduce. However, the gap would not be completely eliminated by 2030 based on PLAN-2016. In 2007–2010, a large gap existed between the eastern and western regions of China in the I values. After the intense HSR infrastructure investment in 2011–2015, the connectivity–accessibility levels of different cities would be improved in Southern and Northern China and in Western and Eastern China. In 2030, all provinces in Mainland China (except Tibet) would own HSR services.

(5) The Jing–Jin–Ji Region and YRDR are the two most important regions with the

highest connectivity–accessibility levels across all time periods (see Fig. 4). Nearly all existing HSR routes in China are to or from these two regions. Consequently, improvements in the connectivity and accessibility of the HSR network in the other regions would substantially benefit from adding connections with both regions.

(6) How to and whether we need to improve the connectivity and accessibility of the HSR network in Tibet are important questions because Tibet is on a plateau and new technologies are needed to construct HSR lines. Accordingly, Figs. 4-c and 4-d show that if contour lines are located in Tibet, then the spatiotemporal map of the I values within Western China could change considerably.

4.3 City profiles: Winners and losers

The differences in the I values between the current time period (2011–2015) and the forthcoming time period (2016–2020) and the future 10 years (2021–2030) are computed for Levels 1 and other cities to differentiate which cities have benefited the most from China's completed and planned HSR constructions. The results are presented in Fig. 5.

(Insert Fig. 5-a and Fig. 5-b Here)

In Fig. 5, winners are depicted as red points and losers as blue points. Moreover, Fig. 5-a presents the differences in the I values of the cities between the current time period (2011–2015) and the forthcoming time period (2016–2021) for all the cities above the prefecture level in China. That is, the $DI_i'^{t1-t2}$ values in $t2 = 2016-2020$ and $t1 = 2011-2015$. In addition, Fig. 5-a details the spatial distributions of the winners and losers. The majority of the winners in 2016–2020 are located in the inland areas of China. In particular, Shenyang, Taiyuan, Yinchuan, Lanzhou, Xi'an, Chongqing, Chengdu, Guiyang, and Kunming would be the most significant winners in 2016–2020. Eastern China would have a few losers in this time period. Evidently, these results do not mean that Eastern China would not see any new HSR lines. Instead, relatively numerous HSR lines would be constructed outside this region in 2016–2020. That is, inland cities can expect additional HSR infrastructure and investment in these five years. Moreover, the construction of HSR routes in the inland areas of China would result in convenience because of the rapid connection between the eastern and midwestern regions of China. Consequently, many eastern cities would also be included in the family of "winners" in 2016–2020 (see Fig. 5-a).

The differences in the I value of the cities between the current time period (2011–2015) and the forthcoming time period (2016–2021) are shown in Fig. 5-b. Accordingly, the winners and losers are predicted in terms of the connectivity and accessibility of the HSR infrastructure included in the HSR network specified in PLAN-2016. Similarly, winners are likely to emerge from the inland areas of China than in Eastern China. Additional winners would also come from the northeastern region of China. A few losers shown in Fig. 5-a would become winners in Fig. 5-b, including Guangzhou, Shenzhen, Wuhan, and Hefei. This change implies that PLAN-2016 would compensate at least a few losers over time. The cities in YRDR would lose more in 2021–2030 (Fig. 5-b) than in 2016–2020 (Fig. 5-a). This result implies that by 2021, the region would already have an extremely mature HSR network and would only experience minor HSR growth.

In summary, Shenyang, Taiyuan, Yinchuan, Xi'an, Chengdu, Chongqing, and Nanning would become the biggest winners in 2016–2020. By contrast, Nanjing, Hefei, Fuzhou, Shenzhen, Hangzhou, Changsha, and Nanchang would be the biggest losers. In addition, Dalian, Dandong, Chengde, Taiyuan, Xi'an, Chongqing, Chengdu, Guiyang, Nanning, and Shenzhen would be the winners in 2021–2030. By contrast, Shanghai, Hangzhou, Nanchang, and Fuzhou would be the losers.

4.4 Performance persistence analysis in different periods

Table 3 shows the results of the performance persistence analysis based on two-way contingency tables for a total of 84 cities (34 Level 1 cities and 50 other cities). The three cross-product ratios are significantly different from 1. In addition, the ratio in the second interval is 4.96, which is above 1. This result implies that a winner (or loser) in a time period would likely retain the winner status in the subsequent period. That is, if a city wins in 2011–2015, then the probability that city winning in 2016–2020 is above 50 percent. This result suggests that the HSR construction in 2016–2020 would aggravate regional inequality in terms of connectivity and accessibility. Moreover, the ratios for the first and third intervals are 0.01 and 0.65, respectively, which are above 1. This result implies that a winner (or loser) in a given time period will likely be a loser (or winner) in the subsequent period. That is, if a city wins in 2007–2010 (or 2016-2020), then the probability that the city will lose in 2011–2015 (or 2021–2030) is above 50 percent. Thus, the HSR constructions in 2011–2015 (or 2021–2030) have narrowed (or will narrow) the gap between the connectivity–accessibility levels of the cities in China. In 2030, the overall connectivity–accessibility levels between cities will relatively converge.

(Insert Table 3 here)

5. Discussion and conclusions

One can never over-exaggerate the importance of the HSR systems to a populous and sizable country, such as China. HSR planners and decision-makers constantly face critical questions, such as where to build an HSR line, when, and why. China has used a frequently updated national plan for HSR development to address the “where” and “when” questions. Given the efficient and rapid implementation of the plan, an increased number of Chinese cities have generally experienced immense changes in terms of HSR connectivity and accessibility in the past decade. However, new challenging questions arise: Which cities have experienced more negative or positive changes than others did? Do the most populous cities or developed, dense, coastal regions always benefit more from the new HSR lines/stations? What governs the sequence of HSR line constructions? What will be the answers to the preceding questions when new plans (e.g., PLAN-2016) are implemented? To the best of our knowledge, these questions have yet to be systematically answered in existing studies. Thus, the current study proposes several indices to obtain the answers to a few of these challenging and important questions. Given the separate database that records all completed and planned HSR constructions in four different time periods, we were able to answer a few questions and present how the answers vary across the time periods.

In particular, our study reconfirms that China initially allocated the highest HSR investment on the densely populated and economically better-developed coastal region (i.e., YRDR). Evidently, such an allocation is an economically wise decision. As expected, the results show that the HSR connectivity and accessibility of the cities in YRDR had experienced more substantial growth, as well as possibly more HSR-triggered transformations, than other cities in the country did. Our indices can efficiently inform us which city benefited (or lost) the most from the HSR investment in terms of connectivity and accessibility. Our analysis shows a counterintuitive result. That is, not the most populous cities, such as Shanghai and Beijing, benefited the most. Without the indices, we could still erroneously believe that the widely accepted assumption is constantly the case because, on the surface, the more populous cities have been connected to more HSR lines. Without the indices, most, if not all, planners and decision makers may not realize that a few cities (e.g., Hefei) have benefited immensely from the completed HSR constructions. In 5–15 years, inland cities in China would be the future winners because of the HSR investment/constructions in terms of connectivity and accessibility. That is, a high degree of regional inequality in connectivity–accessibility prevailed in the early HSR development stage, but the map of connectivity–accessibility would become spatially balanced in 2030. The proposed indices can immediately provide information on which cities would benefit or lose more than others do. Moreover, the subsequent performance persistence analysis based on the indices enables us to track the evolution of the winner and loser status.

Our study has provided new tools to those who would like to evaluate the impact of expensive HSR investment on different cities or regions and monitor winners and losers over time. We are unaware as to whether similar evaluations or monitoring have been undertaken when the planners and decision makers in China developed and updated the HSR plans, namely, PLAN-2004 and PLAN-2016. These evaluation or monitoring results presented in this study could help in answering the aforementioned "why" questions about the completed or planned HSR constructions/projects. For example, the ability to justify the question why an additional HSR line was built even if doing so does not have a huge impact on the overall connectivity and accessibility of the HSR network can enable planners and decision makers to make sound decisions on future HSR investment and projects. Apart from connectivity and accessibility, a few factors (e.g., economic development, socially equity, environmental impact, financial sustainability, and administrative feasibility) are worth considering in the decision-making process.

Despite the contributions of this study in HSR research, our research can still be enhanced and improved in the future in at least three aspects. First, the actual usage of the completed HSR lines could be studied. Second, indices with extensive sociodemographic data may be combined to evaluate the wide impact of HSR on different cities. Our indices currently do not account for the actual usage of different HSR lines. Consequently, we are prevented from drawing definite conclusions as to whether and how well different cities have reached their new or improved levels of HSR connectivity and accessibility. Furthermore, we cannot forecast how future improvements in HSR connectivity and accessibility may influence different cities. In particular, our indices only incorporate limited sociodemographic information, such as the population of a prefecture or a county. Accordingly, we cannot accurately quantify the extent to which HSR has transformed different cities in the aspects spillover or agglomeration of economic activities and redistribution of the population with the connectivity–accessibility index proposed in this study. These aspects, based on our personal experience, are actually occurring and will continue to occur at an unprecedented scale and pace. However, these aspects have rarely been investigated. Lastly, choosing an appropriate normalization method is a problem that deserves attention. That is, taking the value by experience or by the ordinary least squared regression method can be applied. However, studying the effects of HSR in China is unique because the considerable size of the country and serviced cities do not allow for an example to be obtained for the parameter selection. These limitations can be substantially addressed in future research.

Appendix:

Acronyms:

HSR	high-speed rail
CHSRN	China's HSR network
LBA	Location-based accessibility
PBA	Potential-based accessibility
TCA	Transport capacity-based accessibility
LOS	Level of service
CTN	Connectivity of transport network

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