Does China’s High-Speed Rail Development Lead to Regional Disparities?  
A Network Perspective

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Abstract: This research examines whether cities are getting more equally accessible and connected via high-speed rail (HSR) in China over the period from 2010 to 2015. Existing studies mainly use network centralities to describe the spatial pattern of HSR network without measuring the spatial disparity of these centralities. Most of them rely on the infrastructure network and thus fail to incorporate HSR service quality in the centrality measures. Using HSR timetable data, we incorporate both scheduled travel time and daily frequency of each origin-destination city pair into three centrality measures and further quantify their inequalities using Gini index and Theil index. 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 dimensions of comparison. In general, although the difference between economic regions or between megalopolises has reduced, small/medium-sized cities not belonging to any major city cluster are further lagged behind in HSR development. 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 other regions.

Keywords: High-speed rail; network centralities; regional disparity; China

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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 HSR development (Fujita and Thisse, 1996). This is because reduced transportation cost may reinforce the “siphon 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). 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).¹ For instance, in the context of China, Zheng and Khan (2013) find that HSR 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. Martinez 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.

¹ For a recent survey of the literature, see Zhang et al. (2019).
(Qin, 2017). As suggested by Qin (2017), such by-passing behavior of HSR services may weaken the relative economic position of small cities, as small cites are further marginalized comparing with the enhanced linkages among large cities. To better understand the impact of HSR on regional economy, therefore, we need first to investigate the important question of whether cities in a HSR network are getting more equally accessible and connected as the network expands.

This study focuses on the spatial disparity of Chinese cities’ HSR development 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 its 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 view point of provision of HSR services and pave the way for a better understanding of the HSR impact on regional economy.

To address our research question, we use HSR timetable data over the 2010-2015 period to evaluate a city’s status of HSR development from a network perspective. In particular, we employ the weighted degree, betweenness and harmonic centralities to measure a city’s connectivity, transitivity and accessibility, respectively. 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 schedule delays. Then, by calculating Gini index and Theil index of these centrality measures across HSR cities, we explore whether inequalities among cities increased or decreased over the study period. Theil 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 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. Our results may further provide indirect evidence on the changing patterns of the distribution of economic activities among Chinese cities, as timetable data is affected by both the supply and demand for HSR services.
Our study is most relevant to the stream of studies that apply complex network theories to measure centralities of cities in the 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), and analysis 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) and Jiao et al. (2017) are two exceptions here, but they fail to fully utilize the timetable data. 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. Moreover, all of the studies use the closeness centrality to measure accessibility. 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. The most crucial difference with our paper is that none of the above studies quantifies the changes in disparities in terms of the provision of HSR services as the HSR network expands.

Another highly relevant paper is conducted by Jiao et al. (2014). They predict the changes in disparity of Chinese cities’ accessibility based on future HSR expansion plans. Although they also measure disparity, their main focus is on accessibility which is defined by average travel time, daily accessibility and potential values, and is measured across all transportation modes. Thus, their study ignores such features as connectivity and transitivity, but some studies suggest connectivity is more important in determining regional economic development (e.g.

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

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.
Jiao et al., 2017). Furthermore, as their study is based on planned future HSR infrastructure, their measures of accessibility may not reflect the actual provision of HSR services. As a result, even in terms of the accessibility measure alone, our results are, as discussed below, somewhat different from theirs.

The rest of the paper is organized as follows. Section 2 presents the methodology and describes the data. Section 3 compares HSR infrastructure network and service network, and explains why the latter is chosen for further analysis. Section 4 displays the disparity analysis on three dimensions, namely, economic regions, tiers of cities, and megalopolises. Section 5 contains concluding remarks.

2. Methodology

2.1 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 change is also called P-space.

In this study, we use L-space to represent HSR infrastructure network and P-space to represent HSR service network.⁴ Fig. 1 distinguishes these two representations of an example

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⁴ 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.
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.

![Fig. 1 Representations of HSR infrastructure network versus service network](image)

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 by 2015 the network has reached a total length of 19,730 km, covered 28 out of 31 provinces and formed a grid network consisting of four north-south corridors and four east-west corridors. This makes China’s HSR network the largest in the world in terms of both total length and traffic volume. 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 are all included in our study, resulting in 341 cities being assessed. The HSR infrastructure data is obtained from international union of railways (UIC). Train timetable data is retrieved from China Train Timetable (2010-2015, July editions), and all kinds of bullet trains (G, C and D) are considered. 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.
2.2 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.\(^5\) 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 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.\(^6\)

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:

\[
C_D^i = \sum_{i \neq j \in N} a_{ij}w_{ij}
\]

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 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.

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\(^5\) This is also done in, e.g., Liu et al. (2019).

\(^6\) In transportation systems, the weights can be ridership, travel cost, geodesic distance and so on.
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:

\[
C_D(i) = \sum_{i \neq j \in N} a_{ij}w_{ij} + \sum_{i \neq j \in N} a_{ji}w_{ji}
\]  

(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.

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. The betweenness of city \( i \) is written as:

\[
C_B(i) = \sum_{j \neq i \neq k \in N} \frac{\delta_{jk}(i)}{\delta_{jk}}
\]  

(3)

where \( \delta_{jk} \) 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 \( i \). Whilst, equation (3) applies to both infrastructure and service networks, these two networks generate different values of betweenness, since shortest paths are defined differently. The identification of shortest path between nodes in the network is discussed below when defining harmonic centrality.

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:

\[
C_H^I(i) = \sum_{i \neq j \in N} \frac{1}{d(i,j)}
\]  

(4)
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 series 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). In the directed service network, the formula is rewritten as:

\[
C^S_H(i) = \sum_{i \neq j \in N} \frac{1}{d(i, j)} + \sum_{i \neq j \in N} \frac{1}{d(j, i)} \tag{5}
\]

where

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

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 average schedule delay of 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 schedule delay, 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.

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:
\[ A(i) = \omega_1 \frac{C_D(i) - \mu_{C_D}}{\sigma_{C_D}} + \omega_2 \frac{C_B(i) - \mu_{C_B}}{\sigma_{C_B}} + \omega_3 \frac{C_H(i) - \mu_{C_H}}{\sigma_{C_H}} \]  

(6)

where \( \mu \) and \( \sigma \) indicate the mean and standard deviation of the corresponding centrality measure. \( \omega_1, \omega_2 \) and \( \omega_3 \) 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 Disparity measures

We apply Gini index and Theil’s T index to measure regional inequality.\(^7\) Gini coefficient is a popular indicator based on Lorenz curve. According to Allison (1978), the performance of Gini index depends on the shape of the distribution and it is more sensitive to an increase in inequality which affects a larger number of cities. Theil’s T index is more sensitive to an increase in inequality among cities with higher proportional difference in centrality values. Unlike Gini index, Theil’s T index can be decomposed into between-group inequality and within-group inequality. 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 sizes.\(^8\)

The Gini index (Sen, 1973) is calculated as:

\[ G = \frac{1}{n} \left[ n + 1 - 2 \left( \frac{\sum_{i=1}^{n} (n + 1 - i) y_i}{\sum_{i=1}^{n} y_i} \right) \right] \]  

(7)

where \( n \) is the number of cities included in measuring the inequality, and \( y_i \) is the centrality value of the \( i \)th city sorted in ascending order. Theoretically, Gini index ranges from 0 (complete equality) to 1 (complete inequality). In our case, the smaller the Gini index of the centrality measures, the more equal the cities are served by HSR.

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

\[ T = \frac{1}{n} \sum_{i=1}^{n} \frac{x_i}{\mu} \ln \left( \frac{x_i}{\mu} \right) \]  

(8)

\(^7\) Our results are consistent with those obtained from using other inequality measures, such as coefficient of variation and Theil’s L index.

\(^8\) One weakness of Theil 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.

Electronic copy available at: https://ssrn.com/abstract=3472993
where \( n \) is the number of cities included in measuring the inequality, \( x_i \) is the centrality measure for city \( i \), and \( \mu \) is the average centrality measure of all the \( n \) cities. Equation (8) can be decomposed into between-group inequality (\( T_B \)) and within-group inequality (\( T_W \)):

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

(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 index of group \( j \), and \( \bar{x}_j \) is the average centrality measure of group \( j \).

3. Infrastructure network versus service network

To better differentiate our study with those similar ones in the literature, we compare our centrality rankings with similar analysis available in the literature. In the context of infrastructure network, we compare our results with those of Chen et al. (2018). Chen et al. (2018) use average betweenness and average closeness across cities within each geographic region of China to rank various regions’ HSR development. The construction of their centralities is closer to our definition in the infrastructure network and they also use estimated travel time to weight the edges. In the context of service network, we compare our results with Jiao et al. (2017) who provide rankings of top-20 Chinese cities in degree, betweenness and closeness centralities based on HSR schedules.

Tables 1 and 2 compare our findings with Chen et al. (2018) in region-level rankings of betweenness and accessibility (closeness or harmonic centralities). The regions are defined in the same way as Chen et al. (2018). Although in both studies Central China and East China have stronger positions and Southwest China has weaker position, there also exist some difference between our rankings and Chen et al. (2018)’s. In particular, Chen et al. (2018) give much higher rankings to North China and Northeast China and much lower rankings to South China than our rankings. The main cause of this difference lies in the choice of cities. In our study, we include all the cities with a total population over one million and urban population over 0.5 million, regardless of having HSR stations or not. Chen et al. (2018) only count cities connected on HSR network. Chen et al. (2018)’s approach does not really reflect HSR development of an average city in a region, since many cities are not accessible by HSR. For

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9 Although the usage of harmonic centrality also contributes to the difference in the rankings, we believe the driving force is the choice of cities, since similar difference occurs with betweenness.
example, Chen et al. (2018) overstate the ranking of North China, because a few megacities in that region, i.e. Beijing, have very strong HSR connections while majority of the other cities in the same region are not connected by HSR. Taking average only among cities with HSR services does not tell the true overall HSR development of that region.

Table 1 Comparison of region-level rankings based on average betweenness

| Rank | Chen et al. (2018) | Our analysis |
|------|-------------------|--------------|
|      | 2010  | 2011  | 2012  | 2013  | 2014  | 2010  | 2011  | 2012  | 2013  | 2014  |
| 1    | D     | A     | A     | D     | D     | D     | C     | C     | D     | D     |
| 2    | C     | C     | D     | C     | C     | C     | D     | C     | C     | C     |
| 3    | A     | D     | B     | A     | B     | E     | E     | E     | A     | A     |
| 4    | B     | B     | C     | B     | A     | B     | A     | A     | E     | E     |
| 5    | F     | F     | E     | E     | E     | A     | B     | B     | B     | B     |
| 6    | E     | E     | F     | F     | F     | F     | F     | F     | F     | F     |

Note: A: North China, B: Northeast China, C: East China, D: Central China, E: South China, F: Southwest China.

Table 2 Comparison of region-level rankings based on average accessibility

| Rank | Chen et al. (2018) – closeness | Our analysis – harmonic |
|------|--------------------------------|------------------------|
|      | 2010  | 2011  | 2012  | 2013  | 2014  | 2010  | 2011  | 2012  | 2013  | 2014  |
| 1    | B     | A     | A     | C     | C     | C     | C     | C     | C     | D     |
| 2    | C     | C     | D     | A     | D     | D     | E     | E     | D     | E     |
| 3    | A     | B     | B     | D     | A     | B     | D     | D     | A     | C     |
| 4    | D     | D     | C     | B     | E     | A     | A     | A     | E     | A     |
| 5    | F     | F     | E     | E     | B     | E     | B     | B     | B     | B     |
| 6    | E     | E     | F     | F     | F     | F     | F     | F     | F     | F     |

Note: A: North China, B: Northeast China, C: East China, D: Central China, E: South China, F: Southwest China.

Table 3 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 is contributed by three major differences with Jiao et al. (2017). First, when calculating degree centrality, Jiao et al. (2017)’s approach is equivalent to taking the geometric mean of unweighted degree and strength, while our degree centrality is equivalent to strength. Our approach is more likely to upgrade cities with fewer connections but higher HSR service frequencies. Second, when generating the other two centralities, we weight each edge by both in-vehicle travel time and schedule delay while Jiao et al. (2017) only take into account schedule delay. As the in-vehicle time vary significantly across edges depending on geographical locations and types of HSR services.

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The formula of Jiao et al. (2017)’s degree centrality can be rewritten into \( C_D(i) = \sqrt{\left(\sum_{j \neq i} a_{ij}\right)\left(\sum_{j \neq i} w_{ij}\right)} \).
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.

Table 3 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 | Qinghuangdao |
| 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 | Baodi | Xiamen | Tianjin | Sannings |
| 19   | Zhuzhou | Xi’an | Shenzhen | Hefei | Huanggang | Changsha |
| 20   | Xi’an | Bengbu | Lanzhou | Xuzhou | Shaoying | Shijiazhuang |

Similarity 60% 65% 65%

We then 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. Fig. 2(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. This is consistent to the preference of flow approach (service network) over node approach (infrastructure network) in characterizing urban networks (Yang, et al., 2019). 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 (Fig. 2(d)). This is mainly because harmonic centralities of these two networks
both increase overtime as more cities are linked by HSR. This inter-temporal correlations are weaker when degree and betweenness centralities are in concern.

(a) Pearson correlation  
(b) Spearman correlation  
(c) Kendall correlation  
(d) All periods pooled

Fig. 2 Correlations between centralities obtained from infrastructure network and service network

Fig. 3 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.

Table 4 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. Thus, discussions in the next section are based on the centralities generated from service networks.

Table 4 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 |

4. Disparity analysis

Fig. 4 compares overall disparities among all the selected cities by using Gini index and Theil’s T index. Both Gini and Theil indexes 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.\textsuperscript{11} As a result, the inequality in aggregate measure (Agg) remains almost unchanged with a slight increase in Theil. There exists a difference between Gini and Theil indexes with respect to degree (Dgr). The former shows a decreasing trend, while the latter is quite stable. The rest of Section 4 focuses on the inequalities within and between different economic regions, tiers of cities, and megalopolises. Since Gini index cannot be easily decomposed, the analysis in the following subsections is based on Theil index.

\textsuperscript{11} As Gini index ranges between 0 and 1 and the inequality of betweenness centrality is very close to the upper bound, there is a slight increase in the inequality of betweenness, which is not as obvious as the case of Theil index.
Fig. 4 Overall disparity: Gini index vs. Theil’s T index

4.1 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. Fig. 5 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.

Table 5 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 5 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                       | 0.0136| 0.0120| 0.0124| 0.0135| 0.0127| 0.0089 |
| 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                       | 0.0070| 0.0071| 0.0066| 0.0074| 0.0087| 0.0100 |
| 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                       | 0.0012| 0.0020| 0.0016| 0.0050| 0.0028| 0.0022 |
| 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                       | 0.0004| 0.0010| 0.0003| 0.0004| 0.0023| 0.0041 |
| 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 within-region inequality (Fig. 6). 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.
Fig. 6 Between-region and within-region disparity: Theil index 2010-2015

The within-region disparity shown in Fig. 6 is the average disparity across all the four regions. However, the inter-temporal variations of individual regions may differ (Fig. 7). 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.

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.

4.2 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.\(^\text{12}\) 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 6 presents the average centrality values of each tier of cities. Although tier 1 cities are undoubtfully much better-developed in HSR than the other two tiers, which is consistent with Xu et al. (2018), medium and small cities have experienced faster growth since 2013. For

\(^{12}\) 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.
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 6 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                    | 1068.7  | 1502.9  | 1480.6  | 2183.6  | 3191.7  | 4829.0  |
| 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                    | 63.71   | 54.92   | 51.40   | 142.49  | 183.70  | 268.37  |
| 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                    | 0.029   | 0.703   | 0.275   | 1.174   | 17.122  | 31.319  |
| 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  |

Fig. 8 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.
Fig. 8 Between-tier and within-tier disparities: Theil index 2010-2015

Fig. 9 reports the changes in within-tier inequalities of tier 1, tier 2 and tier 3 cities respectively. In general, HSR development among tier 1 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 (Fig. 9). 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 (Fig. 8(b)) and little change in the within-tier inequality of aggregated indicator of all the three tiers.

![Fig. 9 Within-tier disparities by tiers of cities](image)

### 4.3 Disparities by megalopolises

Megalopolis, officially be termed as 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 develop five world-class city clusters among others, 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 7) and play a key role in China’s economy as they account for 55% of China’s GDP. According to the new urbanization plan, these megalopolises have the highest priority over the other cities to be developed 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 7 Economic and population sizes of the five megalopolises (Source: China index academy) |
|-------------------------------------------------|--------|-----------------|-----------------|-----------------|-----------------|
| Megalopolis                        | Land area (km²) | 2016 GDP (1000 billion CNY) | 2015 population (10 million) | GDP per capita (1000 CNY) | GDP Density (10,000 CNY / km²) |
|-----------------------------------|-----------------|-----------------------------|-------------------------------|----------------------------|-------------------------------|
| 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                          |

Electronic copy available at: https://ssrn.com/abstract=3472993
| Cheng-Yu Region | 24.0 | 4.8 | 98.19 | 49.1 | 2007 |
|-----------------|------|-----|-------|------|------|
| China total     | 963.4| 74.4| 1370  | 54.0 | 772  |

Fig. 10 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. Non-megalopolises’ share of HSR services has increased by about 10%, but in terms of connectivity and transitivity, the gap between megalopolises and non-megalopolises has been widened during the study period. In terms of accessibility, the gap was narrowed till 2014 and further enlarged in 2015. This finding is somewhat consistent to the new urbanization plan.

Table 8 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 8 Mean centrality values by megalopolises

| Megalopolis (number of cites) | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|-------------------------------|------|------|------|------|------|------|
| Yangtze River Delta (26)      |      |      |      |      |      |      |
| Dgr 391                       | 941  | 879  | 1276 | 1555 | 2087 |
| Btw 516.85                    | 653.25 | 592.21 | 1163.6 | 971.75 | 1016.2 |
| 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 |
| 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 34.59                     | 162.16 | 162.94 | 160.53 | 634.69 | 967.61 |
| 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 |
| 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 775.51                    | 557.91 | 492.66 | 1043.1 | 2129.7 | 2672.8 |
| 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 |
| 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 218.31                    | 298.88 | 294.68 | 486.75 | 667.12 | 1189.9 |
| 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 |
| 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 1.014                     | 69.46 | 0.767 | 0.776 | 242.79 | 789.80 |
| 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 (Fig. 11), especially in terms of connectivity and accessibility. Another interesting observation from Fig. 11(d) is that the aggregated indicator has very low Theil 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 (Fig. 12). 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.
Fig. 11 Between-megalopolis and within-megalopolis disparities: Theil index 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 indexes of each megalopolis are shown in Table 9. The Theil indexes 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 indexes 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 9 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 | Intra-region | Out-region | Intra-region | Out-region |
| JJJ         | 2010 0.367 0.184 | 2015 0.241 0.185 | 2010 0.845 0.065 | 2015 0.498 0.737 | 2010 0.203 0.084 | 2015 0.148 0.084 | 2010 0.467 0.395 | 2015 0.446 0.431 |
| YRD         | 2010 0.230 0.191 | 2015 0.153 0.128 | 2010 0.287 0.232 | 2015 0.730 0.794 | 2010 0.161 0.096 | 2015 0.115 0.045 | 2010 0.389 0.304 | 2015 0.413 0.582 |
| PRD         | 2010 0.298 0.263 | 2015 0.267 0.302 | 2010 0.698 0.365 | 2015 0.517 0.699 | 2010 0.140 0.138 | 2015 0.055 0.045 | 2010 0.434 0.256 | 2015 0.458 0.479 |
| MYR         | 2010 0.513 0.264 | 2015 0.377 0.504 | 2010 0.495 0.329 | 2015 0.992 1.475 | 2010 0.355 0.105 | 2015 0.198 0.297 | 2010 0.687 0.424 | 2015 0.506 0.559 |
| CY          | 2010 0.786 0.330 | 2015 0.012* 1.210 | 2010 0.562 0.316 | 2015 0.038 0.250 | 2010 0.416 0.188 | 2015 0.010 0.510 | 2010 0.754 0.568 | 2015 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.

5. Concluding remarks

In this paper, we examine whether cities in China are getting more equally served by HSR as the HSR network expands. Using HSR timetable data, our research explores Chinese cities’ spatial disparities in connectivity, transitivity and accessibility in the HSR network and emphasizes 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. The literature mainly focuses on the impact of HSR on regional economy and debates whether HSR reduces or increases spatial disparity in economic development, but our focus is HSR development per se instead of its economic impact. However, a better understanding on how cities are served by HSR may shed light on their economic development.

The answer to our research question is complex and depends on the dimensions in concern. There are three major insights as summarized in Table 10. First, the difference between economic regions has 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 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 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 find the reduced disparity mainly applies to HSR services within each megalopolis. Nevertheless, non-core cities have become further falling behind in connecting to cities outside of their own megalopolises. The only exceptions are Jing-Jin-Ji and Yangtze River Delta in “out-region” electric copy available at: https://ssrn.com/abstract=3472993
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 are most likely to lose and further lagged behind in HSR development.

Table 10 Summary of inter-temporal changes in disparities

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

Our study reveals 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.

Our study has two major limitations. First, cautions should be taken when interpreting our results, since we only include HSR in the picture. In fact, addition of HSR services may be accompanied with reduction in other services, such as inter-city coaches, conventional trains and short/medium haul flights. Note that 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 transport. Second, it would be useful to investigate the economic drivers underlying these disparity impacts by HSR, similar in spirit to the recent work on connectivity at Chinese airports (for example, 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 by 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.
Appendix: Difference of closeness and harmonic centralities in a disconnected network

Suppose every edge in Figure A1 has a length equal to 1. Then, nodes f and g achieve the highest closeness despite that their accessibility to other nodes are much weaker, since they are isolated from all the other six nodes. Harmonic centrality on the other hand reflects that nodes linked to the main subgraph (the left-hand side subgraph) have stronger accessibility.

|       | Closeness | Harmonic |
|-------|-----------|----------|
| a     | 1/9       | 3        |
| b     | 1/9       | 3        |
| c     | 1/9       | 3        |
| d     | 1/9       | 3        |
| e     | 1/9       | 3        |
| o     | 1/5       | 5        |
| f     | 1/1       | 1        |
| g     | 1/1       | 1        |

Figure A1. An example of a disconnected network
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