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Does High-speed Rail Development Affect Airport Productivity? Evidence from China and Japan

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Abstract: This paper examines the effects of HSR development on airport technical efficiency and the labor productivity at airports. Existing literature mainly focuses on the impacts of HSR on passenger traffic. In addition to passengers, HSR development may influence airports' other outputs such as cargo and flight movements together with various inputs. These inputs and outputs collectively determine airports' technical efficiency. With access to a dataset consisting of 46 Chinese airports and 16 Japanese airports from 2007 to 2015, the paper firstly adopts both the standard two-stage Data Envelopment Analysis (DEA) and double bootstrap methods to evaluate the impacts of HSR development on airports' technical efficiency. We then evaluate the effects of HSR on airport labor productivity which is measured by both work-load units per employee and aircraft movements per employee. Our main findings indicate that HSR development relates to a decline in airport efficiency. Airports located in cities that have better connectivity or accessibility in the HSR network suffer more efficiency loss than the others. It is also observed that the locational advantage of HSR stations relative to airports is negatively associated with airport efficiency. By contrast, good intermodal linkage between the airport and its nearest HSR station is positively correlated with airport efficiency. Furthermore, the study reports different results between China and Japan with respect to the effects of HSR on labor productivity.

Keywords: High-speed rail; Airport efficiency; DEA; Double bootstrap; Labor productivity

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1. Introduction

The rapid development of high-speed rail (HSR) around the world, especially in Northeast Asia, has attracted many researchers to study the interaction between air transport and HSR. Many studies examine the impacts of HSR on airports' passenger traffic (e.g. Yang and Zhang, 2012; Clewlow et al., 2014; Jiang and Zhang, 2014; Zhang et al., 2018; Liu et al., 2019). Overall, the development of HSR tends to reduce air traffic in many markets, but improved air-HSR integration and hence a better air-HSR intermodal service may increase air traffic in many cases (refer to Zhang et al. (2019) for a comprehensive literature review on this topic). However, few studies have investigated the effects of HSR on airport productivity.

The possible impact of HSR on airport productivity can be more complicated than its impact on airports' passenger volume, as airport productivity is affected by various output dimensions, such as passenger numbers, aircraft movement, and cargo throughput. Dobruszkes (2011) and Dobruszkes et al. (2014) reveal that a decline in the number of passengers does not necessarily result in a decrease in the number of flights for some given routes. On those routes, airlines may arrange more flights per day using smaller airplanes to compete with HSR. A real-world case is *Guiyang-Guangzhou Air Express*, a service promoted by Guiyang airport in 2014, which provides cheaper and more flights per day to confront the competition from HSR. Such express services are very popular on the HSR-affected routes. As a result, the output of an airport captured by its total aircraft movements may not be negatively influenced as the passenger number would be. Additionally, HSR development may also affect airports' other outputs such as cargo throughput and inputs such as employees. For example, Chen and Jiang (2020) investigate the impacts of HSR entry on air cargo in China and conclude that the entry of HSR services reduces air cargo throughput in the domestic market. These situations make the impacts of HSR on airport productivity more complicated and worthy of further investigation.

Aiming at filling the research gap, this study explores the effects of HSR on the productivity of airports in the context of two Northeast Asian countries, China and Japan, where HSR traffic accounts for over 80% of the world.[1] In particular, we examine (1) how the level of HSR development (not just the presence of HSR service) associates with airport technical efficiency, (2) whether improving air-HSR intermodal linkage could increase airport productivity, and (3) how the locational advantage of the HSR station relative to the airport affects airport productivity. After answering the above questions, we can contribute to the literature by providing a more comprehensive understanding on the impact of HSR-related factors on airport technical efficiency, an aspect that has received scant attention in the literature. Moreover, to our knowledge, this is the first empirical study to explore the impact of HSR on airports' labor productivity. Research findings from this study may be of interest to policy makers on decisions related to airport capacity expansion, HSR development and promotion of air-HSR intermodal services.

With access to a dataset from 2007 to 2015, we first employ data envelopment analysis (DEA) approach to assess the technical efficiency of 62 airports in China and Japan. The obtained efficiency scores are then used as dependent variables in the second-stage regression analysis to examine the effects of HSR on airport efficiency. In terms of the main variables of interest, we use two measures, HSR connectivity and HSR accessibility, to capture the level of HSR development. The quality of air-HSR intermodal service is captured by the distance between an airport and its nearest HSR station. The locational advantage of the HSR station compared to the airport is measured by ratio of the distance from an airport to its city center and the distance from the airport's competing HSR station to the city center. Moreover, we estimate our results by adopting the double bootstrap method.[2] Given that the inputs of most sample airports have changed marginally except the number

[1] More information about the development of HSR network in China and Japan can be found in Wan et al. (2016) and Liu et al. (2019).

[2] This is to respond to the criticism that the traditional two-stage DEA approach lacks a well-defined data generation process and there exists unknown serial correlation of the efficiency scores in the first stage (Simar and Wilson, 2007).

of employees during our study period, we also examine the effect of HSR on airports' labor productivity, which is measured by the work-load units per employee and the aircraft movements per employee.

We find that HSR development relates to a decline in the technical efficiency of airports. Airports located in cities that have better positions in the HSR network suffer more efficiency loss than the others. We also find that the locational advantage of HSR stations is negatively associated with airport performance. By contrast, good access to an airport from its nearest HSR station is positively correlated with airport efficiency, especially for the airports in China. Furthermore, HSR development is likely to decrease the labor productivity at Chinese airports, but the development of HSR in Japan is found to increase the aircraft movements per employee.

The paper is organized as follows. Section 2 presents the literature review. Section 3 discusses our methodology and Section 4 describes data construction. Section 5 reports the empirical findings and Section 6 contains concluding remarks.

2. Literature review

This study is related to the literature using DEA approach to evaluate airport efficiency. The application of DEA has a long history, and has gained vast popularity in the transportation field in recent years. Libert and Niemeier (2013) already thoroughly reviewed the application of DEA in airport benchmarking by comparing the selection of DEA models, the choice of inputs and outputs, and the context of investigation. As almost all the articles reviewed by Libert and Niemeier (2013) were published before 2010, studies published after 2010 on adopting two-stage DEA approach and double bootstrap DEA methods are listed in Table 1.

Table 1 Studies adopting two-stage DEA or bootstrap techniques to identify factors affecting airport efficiency (2010-2020)

Research	Sample	Influencing Factors	Methodology: Model	Methodology: Account for observed heterogeneity	Variables for productivity measures: Inputs	Variables for productivity measures: Outputs
Chaouk et al. (2020)	59 European and Asia-Pacific airports (2009, 2015)	Safety and security; Human development; Macro-economic development; Institutions composition.	Output-oriented CRS; Output-oriented VRS.	Two-stage approach with Tobit regression; Bootstrap with truncated regression.	Number of employees; Number of runways; Terminal size; Number of gates.	Passenger traffic; Cargo throughput; Aircraft movements; Non-aeronautical revenues.
Karanki & Lim (2020)	59 US airports (2009-2016)	Hub status; Agreement types.	Output-oriented CRS; Output-oriented VRS.	Bootstrap with truncated regression.	Number of employees; Number of gates; Terminal size; Operational costs.	Work unit load; Non-aeronautical revenues.
Ngo & Tsui (2020)	11 New Zealand airports (2006-2017)	Privatisation; Low-cost carrier; Disaster (earthquake); Global financial crisis; GDP per capita; Number of domestic destinations; Number of international destinations; Number of establishments; Number of regional guest arrivals.	Slack-Based Measure DEA-Window Analysis.	Two-stage approach with Tobit regression.	Runway lengths; Operational costs; Labor costs.	Aircraft movements; Aeronautical revenues; Non-aeronautical revenues.
Galli et al. (2020)	31 Italian airports (2003-2014)	HSR development; GDP per capita; Population; Stock exchange; Public share; Hub status; Airport market share.	Output-oriented CRS.	Bootstrap with truncated regression.	Number of employees; Number of runways.	Passenger traffic; Cargo throughput; Aircraft movements.

Fragoudaki & Giokas (2016)	38 Greek airports. (2011)	Number of destinations; Geographical location; Accommodation infrastructure; Mixture of operations; International airports.	Output-oriented VRS.	Two-stage approach with Tobit regression.	Runway lengths; Terminal size; Apron size.	Passenger traffic; Cargo throughput; Aircraft movements.
Orkcu et al. (2016)	21 Turkish airports (2009-2014)	Population; Hub status; Operating hours; Mixture of operations; International passenger traffic.	Output-oriented VRS; Malmquist-DEA.	Bootstrap with truncated regression.	Number of runway; Runway lengths; Terminal size.	Passenger traffic; Cargo throughput; Aircraft movements.
Merkert & Assaf (2015)	30 International airports (2013)	Non-aeronautical revenues; Ownership; Low-cost carrier; Geographical location.	Output-oriented VRS Bootstrap.	Two-stage approach with Tobit regression; Bootstrap with truncated regression.	Runway lengths; Terminal size; Full time equivalent.	Passenger traffic; Cargo throughput; Aircraft movements.
D'Alfonso et al. (2015)	34 Italian airports (2010)	Competition.	Output-oriented VRS.	Two-stage approach with location scale non-parametric regression.	Number of employees; Number of runways; Number of gates; Number of terminals; Number of check-in desks; Airport size.	Passenger traffic; Cargo throughput; Aircraft movements.
Adler & Liebert (2014)	48 European airports and 3 Australian airports (1998-2007)	Non-aeronautical revenues; Heavy delays; Runway capacity utilization rate; Ownership; Competition; Regulation.	Input-oriented VRS.	Robust cluster regression.	Labor costs; Operational costs; Runway capacity.	Passenger traffic; Cargo throughput; Aircraft movements; Non-aeronautical revenues.
Coto-Millan, et al. (2014)	35 Spanish airports (2009-2011)	Airport size; Low-cost carrier.	Input-oriented VRS; Input-oriented CRS; Malmquist-DEA.	Two-stage approach with Tobit regression.	Labor costs; Operational costs; Value of fixed assets.	Passenger traffic; Cargo throughput; Aircraft movements.

Merkert & Mangia (2014)	35 Italian and 46 Norwegian airports (2007–2009)	Airport size; Population; Mixture of operations; Competition; Profitability.	Input-oriented VRS; Input-oriented CRS; Input-oriented NIRS.	Bootstrap with truncated regression.	Number of employees; Number of runways; Runway lengths Terminal size; Runway size; Apron size; Airport size.	Passenger traffic; Cargo throughput; Aircraft movements.
Scotti et al. (2014)	44 US airports (2005-2009)	Airport size; Average fleet size; Percentage of night flights; Multiple airport system; Percentage of international passenger.	Output-oriented CRS; Directional distance function approach.	Two-stage approach with Tobit regression.	Number of gates; Runway lengths; Terminal size; Airport size; Operational costs.	Passenger traffic; Cargo throughput; Aircraft movements.
Tsui et al. (2014a)	21 Asia-Pacific airports (2002-2011)	Population; GDP per capita; Percentage of international passenger; Hub status; Operating hours; Alliance membership of dominant airline; Ownership.	Output-oriented VRS.	Two-stage approach with Tobit regression.	Number of employees; Number of runways; Terminal size; Runway lengths.	Passenger traffic; Cargo throughput; Aircraft movements.
Tsui et al. (2014b)	11 New Zealand airports (2009-2011)	Population; Hub status; Operating hours; Ownership; Disaster; Sport tournament.	Input-oriented VRS; Slack-based DEA; Malmquist-DEA.	Bootstrap with truncated regression.	Number of runways; Operating costs.	Passenger traffic; Aircraft movements; Total revenues.
Chang et al. (2013)	41 Chinese airports (2008)	Distance to city centre; Flight area grade; Number of airlines; City level.	Output-oriented VRS; Output-oriented CRS; Output-oriented NIRS.	Bootstrap with truncated regression.	Terminal size; Runway size; Operating hours.	Passenger traffic; Cargo throughput; Aircraft movements.

Ha et al. (2013)	12 Northeast Asian airports (1994-2011)	Ownership; Corporatization; Localization; State shares; Competition; HSR; Airline concentration; Dominant airline market share; Customer power.	Output-oriented VRS; Output-oriented CRS.	Two-stage approach with Tobit regression.	Number of employees; Terminal size; Runway lengths.	Work load unit.
Martini et al. (2013)	33 Italian airports (2005-2008)	Fleet mix; Ownership; Airport size; Low-cost carriers.	Output-oriented VRS; Directional distance function approach.	Bootstrap with truncated regression.	Number of parking spaces; Number of baggage claims; Runway lengths; Terminal size.	Work load unit; Aircraft movements; Local air pollution; Noise levels.
Assaf & Gillen (2012)	73 International airports (2003-2008)	Non-aeronautical revenues; Regulation; Ownership.	Output-oriented VRS; Semiparametric Bayesian stochastic frontier model.	Two-stage approach with Truncated regression; Bootstrap with truncated regression.	Number of employees; Number of runways; Terminal size; Operational costs.	Passenger traffic; Aircraft movements. Non-aeronautical revenues;
Barros et al. (2012)	27 French airports (2000-2008)	Airport size; Low-cost carriers; Hub status.	Output-oriented CRS.	Bootstrap with truncated regression.	Number of employees; Passenger terminal size; Runway size.	Passenger traffic; Total freight volume; Total mail volume; Aircraft movements.
Gitto & Mancuso (2012)	28 Italian airports (2000-2006)	Hub status; Seasonality; Capital composition; Liberalization.	Output-oriented CRS; Bootstrap.	Bootstrap with truncated regression.	Number of employees; Terminal size; Runway size.	Passenger traffic; Cargo throughput; Aircraft movements.
Merkert & Mangia (2012)	46 Norwegian airports (2007–2009)	Geographical location; Population.	Input-oriented VRS; Input-oriented CRS; Input-oriented NIRS.	Bootstrap with truncated regression.	Number of employees; Number of runways; Runway lengths Terminal size; Runway size; Apron size; Airport size.	Passenger traffic; Cargo throughput; Aircraft movements.

Note: VRS = Variable returns to scale; CRS = Constant returns to scale; NIRS = Non-increasing returns to scale. The articles are presented in reverse chronological order.

As depicted in Table 1, majority of the recent studies concentrates on countries in Europe and the Asia-Pacific region. A common practice in the literature is to use the output-oriented DEA model which is based on the assumption that the primary goal of airports is to maximize their outputs with a given set of inputs. The “variable returns to scale” (VRS) model appears to be more popular than the constant returns to scale (CRS) model. The major rationale behind this is that sampled airports in most studies are of different sizes (e.g. Adler and Liebert, 2014; D’Alfonso et al., 2015). VRS models are used to adjust the potential scale effect on airport efficiency, so that small airports can be compared with large airports in their efficiency scores. In this study, we follow the majority of existing studies and adopt output-oriented VRS model. For the assessment of airport efficiency, passenger volume, cargo throughput, and aircraft movements are the most preferred output variables, whereas the selection of input variables largely depends on the availability of data. Nonetheless, the number of employees, runway lengths, and terminal size are among the most frequently used input variables.

Our research is also relevant to the studies exploring the determinants of airport technical efficiency. According to Table 1, we find that GDP per capita, population of the airport’s catchment area, hub status, airport size, ownership, competition, and low-cost carriers are the most frequently identified factors in the DEA-related literature. In addition, there are a number of previous studies using other methods, such as stochastic frontier analysis and total factor productivity, to examine the association between airport efficiency and exogeneous factors. For example, Oum et al. (2004) and Oum et al. (2008) use stochastic frontier analysis to investigate the effect of ownership forms on airport efficiency; Yan and Oum (2014) adopt stochastic frontier analysis to identify the influence of government corruption on the efficiency of commercial airports in the context of the US; Randrianarisoa et al. (2015) apply residual variable factor productivity to examine the correlation between government corruption and airport productivity in European countries. Note that most literature includes competition pressure from neighbouring airports as one of the determining factors, while ignoring competition from other modes of transport such as HSR.

HSR could affect airports in two ways. First, HSR can have a traffic redistribution effect on airports. That is, some primary hub airports with good air connectivity may win traffic from smaller airports that have limited air routes after the introduction of HSR, which in some cases could intensify the competition between large and small airports (Liu et al., 2019; Zhang et al., 2019). Second, HSR itself may be a strong rival to air travel through attracting passengers who used to travel by airplanes. As a result, all these aspects will influence airport technical efficiency.

We find only one study investigating the impact of HSR on airport efficiency. Galli et al. (2020) use double bootstrap procedure to examine the association between HSR and airport technical efficiency in the context of Italy. The authors develop three variables, i.e., the distance between an airport and its nearest HSR station, the travel time between an airport and its nearest HSR station, and the presence of HSR links in the region of the airport, to measure the development of HSR. They find that the proximity between airport and its nearest HSR station is positively correlated with airport efficiency. Our study is different from Galli et al. (2020) in the following ways. First, we not only take into account the intermodal linkage between HSR and air travel, which is measured by the distance between an airport and its nearest HSR station, but also consider the relative location advantage of a city's HSR stations by developing a variable that compares the ease of access to the city center from the airport and the airport's corresponding HSR stations. Second, we consider the heterogeneity of HSR services among different airports by using train timetable information and calculate the HSR connectivity and accessibility for each airport's city. Third, we explore the impact of HSR on the labor productivity at airports, which has received scarce attention.

3. Research methodology

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

3.1 Two-stage DEA

Two-stage procedure is a method wherein efficiency is assessed in the first stage and then the resulting efficiency scores are regressed on some exogenous variables in the second stage. In this study, we calculate the efficiency of airports by DEA which is a non-parametric approach for the identification of efficiency frontiers.[3] In this paper, we employ an output-oriented DEA model. There are two main reasons. First, it is infeasible to cut the costly airport infrastructures without years of rigorous planning even though an airport can lay off its employees in the short run. Second, this study aims to provide decision makers at an airport with a view that enables them to verify how far the airport's outputs can be increased with the current level of inputs. We also assume that, in the case of airport operations, an increase or decrease in inputs does not result in a proportionate change in outputs. Therefore, we use an output-oriented VRS DEA model to evaluate the efficiency scores of airports in the first stage.

Supposing that we have n decision-making units (DMUs) and each DMU consumes m different inputs to produce s different outputs, we can obtain the efficiency score of each DMU by solving the following linear programming problem:

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[3] Compared to parametric efficiency measures such as stochastic frontier analysis (SFA), DEA allows the use of multiple inputs and outputs without imposing assumptions about the specification of a functional form for the frontier and the probability distribution of the error terms (Cummins and Xie, 2016). On top of that, the DEA efficiency score can be easily obtained by solving a number of linear programming problems while SFA relies on maximum likelihood estimation, which means that ill-structured data can lead to numerical problems when estimating the coefficients with the SFA model (Chen et al., 2015). We tried the one-step SFA model in this study, however, there exists convergence problems due to the structure of our data. A possible reason might be that we involve too many dummy variables in the model.

$$\text{Max } \theta$$

subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}, \qquad i = 1,2, \dots, m$$

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

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

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

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

The first-stage DEA only calculates efficiency scores without associating the efficiency with other environmental variables. To quantify the effects of HSR on airport efficiency, in the second stage, the obtained scores are then carried over to the Tobit regression analysis using the following models[4]:

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

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

[4] A fundamental difference between truncated regression and Tobit is how data is observed. In the former case, the sample is truncated and hence both dependent and independent variables are missing for certain observations, and hence these observations are dropped from regression. In the latter case, only the dependent variable cannot be well observed and hence censored for certain observations, but the independent variables can be well observed, and therefore the regression does not drop those problematic observations.

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

After involving the possible substitute and complement effects of HSR on air transport, Equation (2) can be extended as follows:

$$\theta_{it}{}^{*} = \beta_0 + \beta_1 HSR_{it} + \beta_2 HSR_{SE_{it}} + \beta_3 HSR_{CE_{it}} + \mathbf{X}_{it}\boldsymbol{\gamma} + \delta_i + \epsilon_{it} \qquad (3)$$

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

where $HSR_{SE_{it}}$ and $HSR_{CE_{it}}$ measure the HSR station's relative location advantage over airport and the possible cooperation between HSR and air transport, respectively.

3.2 Bootstrap DEA

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

However, the assumption about DGP in Simar and Wilson (2007) is restrictive because it does not include a two-sided noise term. As a result, the preference for truncated regression over Tobit in the second stage is less appropriate (Banker and Natarajan, 2008). In addition, the approach proposed by Simar and Wilson (2007) assumes that the exogenous factors only affect the inefficient processes but not the frontier, which should be tested further (Simar and Wilson, 2011). Thus, in this paper, we apply both standard two-stage procedure and Simar and Wilson (2007) method to check the robustness of our estimations. Note that the independent variables used in the double bootstrap procedure are the same as those used in the standard two-stage approach (Equations (2) and (3)).

3.3 HSR effect on airport's labor productivity

Labor and capital are two most important inputs at airports. However, an airport's physical infrastructures, such as terminal buildings and runways, cannot be frequently adjusted. This is because capacity expansion projects associated with terminal buildings and runways are lumpy and indivisible (Oum and Zhang, 1990) and usually requires years of planning and construction. According to our data, only a few airports expanded their terminals or built new runways during our study period. By contrast, most airports adjusted their numbers of employees annually to cope with market dynamics, meaning that airport productivity reflected by labor productivity may be various, which largely depends on the development of HSR in the city. Thus, we also look into the impact on partial productivity of labor. In this study, we use two common measures of labor productivity. One is based on work-load unit (WLU) per employee, which calculates the amount of passengers and cargos handled by an average worker. The calculation of WLU follows Ha et al. (2013).[5] The other one is the aircraft movements per employee. Similar to Equations (2) and (3), Equation (4) is the baseline model and Equation (5) extends

[5] We convert one passenger into 100 kg, and one WLU equals to one passenger or 100kg cargo.

the model by including the relative location advantage of HSR station and the accessibility between HSR station and airport. The specifications are:

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

$$\ln(L_{it}) = \beta_0 + \beta_1 \ln(HSR_{it}) + \beta_2 \ln\left(HSR_{SE\,it}\right) + \beta_3 \ln\left(HSR_{CE\,it}\right) + \mathbf{X}_{it}\boldsymbol{\gamma} + \delta_i + \epsilon_{it} \tag{5}$$

where L_{it} is the labor productivity, measured by WLU per employee or aircraft movements per employee, at airport *i* in year *t*.

4. Data and variable construction

By the end of 2015, there are more than 200 civil airports[6] in mainland China serving in total 914.8 million passengers (CAAC, 2015) and 87 airports in Japan serving 277.7 million passengers. Considering the availability of data, this paper only includes airports that have over two million passengers in 2015, resulting in a panel of annual data for 48 Chinese airports and 18 Japanese airports over the time period from 2007 to 2015. Among the 48 Chinese airports, Shanghai Hongqiao Airport (SHA) and Shanghai Pudong Airport (PVG) are merged into one airport entity (SHPV) because they are operated by the same airport authority and hence the employee data available to the public is aggregated across these two airports. Beijing Nanyuan Airport (NAY) is excluded due to the lack of employee data. In the case of Japan, Naha Airport (OKA) and Ishigaki Airport (ISG) are removed since they are located on Ishigaki Island which cannot be accessed by HSR. As a result, our estimation is based on 46 Chinese airports and 16 Japanese airports, covering majority of large cities in China and Japan. The sampled Chinese airports account for 92.2% of China's air passenger traffic, 97.7% of freight throughput and

[6] 206 out of the 210 commercial airports have regular service.

77% of aircraft movements. The sampled Japanese airports account for 81.7% of Japan's air passenger traffic, 90.3% of freight throughput and 74.8% of aircraft movements.

As discussed in Section 2, this paper includes three input variables, i.e., runway length which is defined by the total length of all the runways of the airport, terminal size which is the sum of passenger and cargo terminal areas, and the number of full-time employees. As for output variables, we consider passenger throughput, cargo throughput and aircraft movements. The data for input and output variables are collected from various sources, including *Statistical Data on Civil Aviation of China* (2008-2016) published by the Civil Aviation Administration of China, Japanese Ministry of Land, Infrastructure, Transport and Tourism (MILT, 2007-2015), airports' annual reports, airports' official websites, and the authors' direct contact with airports managers. Tables 2 and 3 present the descriptive statistics of the input and output variables.

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

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

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

Variable	Observation	Mean	Std.	Min	Max
Outputs (000)					
Passengers	144	12563.88	16432.51	1717.10	75254.95

Cargo	144	295.41	532.58	0	2254.42
Flight Movements	144	94.88	91.91	14.37	438.54
Inputs					
Runway length (m)	144	4228.69	2183.73	2500	11000
Terminal Size (m^2)	144	201660.2	288871.1	17052	1177700
Employee	144	160.65	185.78	4	773

Control variables used in the regression analysis are listed and explained in Table 4. We control the population size and real GDP per capita of the airport's hinterland. Following Liu et al. (2019), we define the hinterland of an airport as the municipality or prefecture-level city where the airport locates for the case of China and the prefecture in which the airport is situated for the case of Japan. The population size is measured by the number of permanent residents in the hinterland. The real GDP per capita is the ratio of hinterland's real GDP, using 2007 as the base year, and the hinterland's population size. We also control for airport's characteristics which are known to influence airport performance, such as privatization and hub status. Ha et al. (2013) reported that intersecting runway structure was negatively associated with airport efficiency. Thus, we follow the literature and use runway structure (*RwyStructure*) to indicate the situation of runway intersection or closely (less than 460 meters) located parallel runways. In addition, we include jet fuel price (*Fuel*) and airport competition (*Compete*) to capture external factors that may affect airports' outputs. Data for *Fuel* is obtained from IATA Fact Sheet. Scotti et al. (2012) found that the intensity of airport competition had a negative impact on airport efficiency. Thus, c*ompete* reflects the intensity of airport competition measured by the number of airports within a catchment area of 100 km around the airport, which definition is in line with Bel and Fageda (2010). Further, we control for exogenous demand shocks, such as the Winter Storm and Wenchuan earthquake occurred in China in 2008, global financial crisis in 2009,[7] and Tohoku earthquake and tsunami occurred in Japan in 2011. The descriptive statistics of independent variables are provided in Appendix 1.

Table 4. Description of control variables

Variable	Label	Definition
Population	POP	The total population of an airport's hinterland as a proxy for the market size of the airport.
GDP per capita	GDP_POP	The real GDP per capita of an airport's hinterland as a proxy for the market size of the
Privatization	Private	Dummy variable. It equals to 1 if an airport is fully or partially private.
Hub status	Hub	Dummy variable. It equals to 1 if an airport is an international hub (Beijing, Shanghai, Guangzhou, Haneda, Narita, Kansai).
Runway structure	RwyStructure	Dummy variable. It equals to 1 if two runways are too close to each other (< 460m) or have intersections (Guangzhou, Haneda, Shanghai
Jet Fuel Price	Fuel	Aviation jet fuel price which is measured by US 100 dollar/bbl (Base = 2000).
Competition	Compete	Number of airports within a 100km radius of the airport.
Winter storm and Wenchuan earthquake	Disaster (China)	Dummy variable. Year 2008 = 1
Global financial crisis	GFC	Dummy variable. Year 2009 = 1
Tokoku earthquake and tsunami	Disaster (Japan)	Dummy variable. Year 2011 = 1

The HSR-related variables of interest, i.e. HSR_{it}, ${HSR_{SE}}_{it}$, and ${HSR_{CE}}_{it}$ are constructed in the following way. To capture the development of HSR, HSR_{it} is measured by either HSR connectivity or HSR accessibility in the city where airport *i* locates in year *t*. HSR connectivity captures the number of cities that are directly connected to a particular city by HSR, whereas HSR accessibility measures the convenience of travelling by HSR from a city to all other cities in the network. This approach enables us to take into account the heterogeneity

[7] In 2008, the Beijing Olympic Games may also affect the airport efficiency in China which is also captured by this dummy variable. While the global financial crisis started in 2008, its impact on air traffic was the most prominent in 2009.

in individual cities' HSR development. The calculation of HSR connectivity and accessibility follows Liu et al. (2019) and Liu et al. (2020). The value of HSR_{it} equals zero when there is no HSR station in the city. The calculation is based on China Train Timetable (2007-2015) and Japan Railway Timetable (2007-2015). HSR_SE_{it} and HSR_CE_{it} capture HSR's ability to substitute and complement air transport, respectively, from the perspective of ground access. HSR_SE_{it} is measured by the locational advantage of HSR station relative to airport when being accessed from the city center. It is calculated based on Equation (6):

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

where $AirtoCity_{it}$ is the road distance between airport i and its city center and $HSRtoCity_{it}$ denotes the road distance between the HSR station and the city center. It is worth noting that passengers may travel to a neighboring city to take HSR when there is no HSR station in the city. Thus, if there is no HSR station in the city, we choose the nearest HSR station to the airport instead. On the other hand, if there are more than one HSR stations in the city, we take the average distance from these HSR stations to the city center to calculate $HSRtoCity_{it}$. As shown in (7), HSR_CE_{it} reflects the convenience of transferring between air and HSR and hence the easiness of conducing intermodal feeding between these two modes. It is measured by the reciprocal of the road distance between airport i and its nearest HSR station, as shown in Equation (6). Again, we calculate the mean value of the distance when there are multiple HSR stations in airport i's city. It is expressed as:

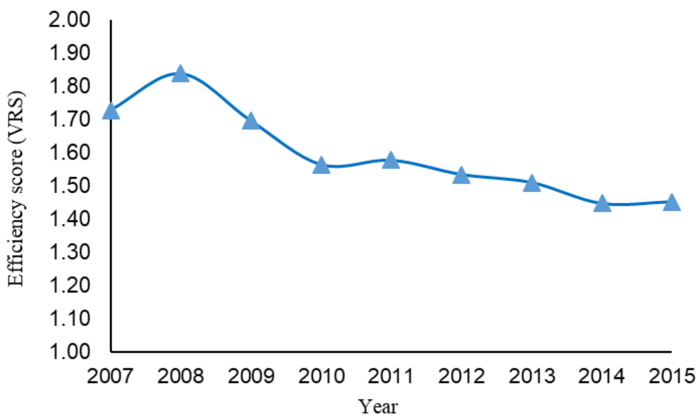
$$HSR\_CE_{it} = \frac{1}{AirtoHSR_{it}} \tag{7}$$

5. Empirical results

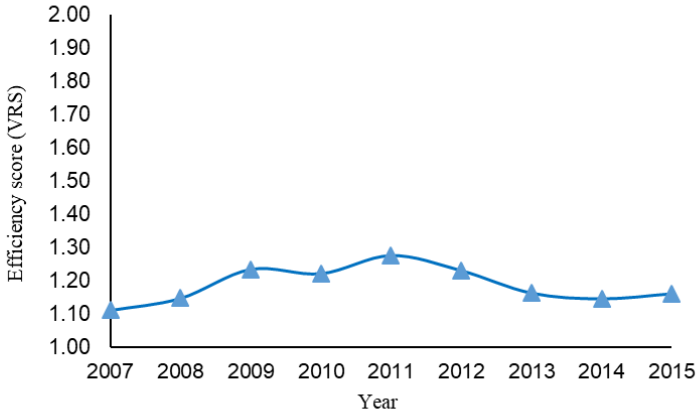
5.1 Airport Efficiency

We pool all years from 2007 to 2015 together and calculate the efficiency scores of airports in China and Japan separately. The average standard DEA scores of Chinese airports and Japanese airports over the 2007-2015 period are 1.781 and 1.248 respectively, indicating that airports in China, on average, can improve their outputs by 43.8% and Japanese airport, on average, can increase their outputs by 19.8% to reach the efficient frontiers with their current levels of inputs.

Figure 1 shows the overall trend of airport efficiency in China and Japan. Chinese airports appear to become more technically efficient during our observation period. However, there was a loss in efficiency in 2008 among airports in China. This might be attributed to a series of natural disasters such as Chinese winter storm and Wenchuan earthquake occurred in the first half of 2008 and the tightened security measures prior to and during the Beijing Olympic Games. By contrast, Japanese airports seem to be more stable than their counterparts in China. The technical efficiency of Japanese airports fell to its lowest level in 2011 because of the Tohoku earthquake and tsunami.



(a) Chinese airports



(b) Japanese airports

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

Figure 2 shows the distribution of efficiency scores across the 46 airports in China in ascending order of the airports' latitudes. We observe that airports in the southern part of China where HSR networks are more developed, on average, are more technically efficient than those in the north. We also find that the international hub airports located in metropolises such as Shanghai (SHPV), Beijing (PEK), and Guangzhou (CAN) have lower median values and little inter-quartile ranges of efficiency scores, indicating that these airports are the most efficient and stable ones during our study period. On the other hand, the airports close to these hub airports are far from efficient, for example, Wuxi (WUX) which is about 160 km away from SHPV, Tianjin (TSN) which is about 150 km away from PEK, Zhuhai (ZUH) which is about 200 km away from CAN, and Chaoshan (SWA) which is about 250 km away from XMN. This is consistent with the widely noted traffic leakage from regional airports to "nearby" primary airports as passengers in the catchment of the regional airports are willing to spend several hours of extra ground travel time to take the advantage of lower fares and more airline services at primary airports (Leon, 2011; Lian and Ronnevik, 2011). As a result, these regional airports are less capable of exploiting their inputs and tend to have lower capacity utilization than their nearby primary airports, despite that they serve overlapping geographical markets.

Similarly, we plot the distribution of efficiency scores for the 16 Japanese airports in Figure 3. The airports are sorted based on the ascending order of their longitudes. Most airports with low efficiency are situated along the Tokaido Shinkansen which is the busiest HSR line in Japan. It also reveals that airports in the west, on average, performs better than those in the east where the HSR lines are more densely distributed.

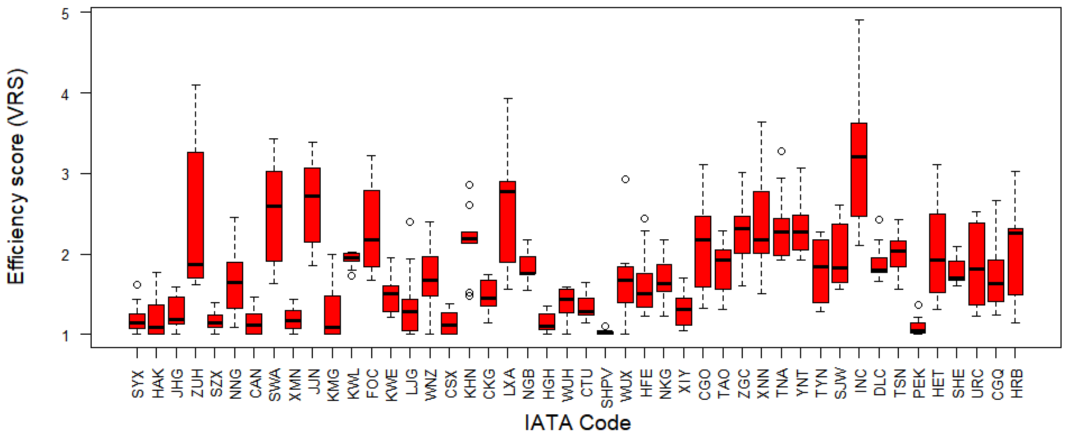


Figure 2. Boxplot distribution of Chinese airports' efficiency scores between 2007 and 2015

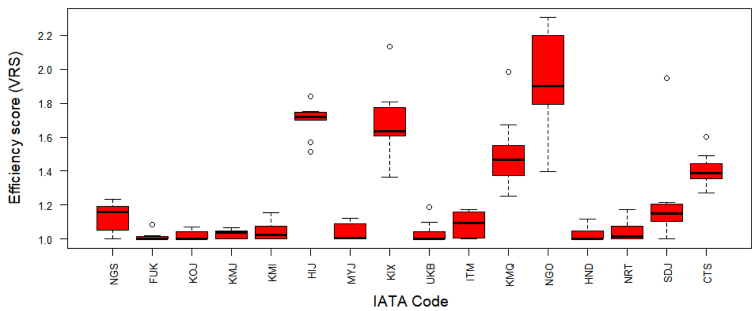


Figure 3. Boxplot distribution of Japanese airports' efficiency scores between 2007 and 2015

As shown in Table 5, the average annual efficiency scores of Chinese airports range from 1.034 (Shanghai airport group, SHPV) to 3.204 (Yinchuan airport, INC). According to the average annual efficiency change rate, airports with the most significant improvement in efficiency include Zhuhai (ZUH), Harbin (HRB), Hohhot (HET), Changchun (CGQ) and

Chaoshan (SWA) airports. The scores of these airports drop by over 10% every year on average, which reflects an increase in airport technical efficiency, meaning that the resources at these airports are increasingly well-utilized. For example, the efficiency score of Harbin airport decreased from 3.021 in 2007 to 1.142 in 2015, achieving an above-average efficiency gain. On the contrary, the DEA scores of Wuxi (WUX) and Wenzhou (WNZ) airports experienced a notable increase, as they have grown by more than 5% on average every year. Given that Wuxi and Wenzhou are well-connected in the HSR network, this drop might be partially attributed to the decline in airport throughputs resulting from the development of HSR.

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

IATA Code	Airport name	Mean	Std.	Average Year-over-Year Change (%)
SHPV	Shanghai Pudong Airport Shanghai Hongqiao Airport	1.034	0.073	-0.14
PEK	Beijing Capital Airport	1.101	0.264	-0.72
HGH	Hangzhou Xiaoshan Airport	1.147	0.004	-4.11
CSX	Changsha Huanghua Airport	1.150	0.070	-3.62
CAN	Guangzhou Baiyun Airport	1.165	0.055	-4.95
SZX	Shenzhen Baoan Airport	1.172	0.007	0.88
XMN	Xiamen Gaoqi Airport	1.194	0.260	-0.19
SYX	Sanya Fenghuang Airport	1.214	0.123	-6.59
HAK	Haikou Meilan Airport	1.23	0.172	-7.86
JHG	Xishuangbanna Gasa Airport	1.276	0.135	3.63
KMG	Kunming Changshui Airport	1.282	0.021	-0.08
XIY	Xian Xianyang Airport	1.319	0.056	-0.11
CTU	Chengdu Shuangliu Airport	1.348	0.061	0.30
WUH	Wuhan Tianhe Airport	1.381	0.415	1.48
LJG	Lijiang Sanyi Airport	1.386	0.035	-1.15
CKG	Chongqing Jiangbei Airport	1.458	0.049	-5.97
KWE	Guilin Liangjiang Airport	1.510	0.052	-5.91
HFE	Hefei Xinqiao Airport	1.638	0.030	2.28
WNZ	Wenzhou Longwan Airport	1.676	0.000	5.27
NNG	Nanning Wuxu Airport	1.682	0.119	-5.82
WUX	Sunan Shuofang Airport	1.691	0.593	8.84

NKG	Nanjing Lukou Airport	1.704	0.039	-5.14
CGQ	Changchun Longjia Airport	1.752	0.233	-10.28
TYN	Taiyuan Wusu Airport	1.782	0.090	-5.22
SHE	Shenyang Taoxian Airport	1.798	0.071	-3.01
TAO	Qingdao Liuting Airport	1.815	0.168	-5.99
NGB	Ningbo Lishe Airport	1.830	0.039	-4.50
URC	Urumqi Diwopu Airport	1.846	0.086	-8.98
DLC	Dalian Zhoushuizi Airport	1.914	0.183	-4.40
KWL	Guiyang Longdongpu Airport	1.931	0.068	-0.13
SJW	Shijiazhuang Zhengding Airport	1.976	0.452	0.36
TSN	Tianjin Binhai Airport	1.987	0.166	-5.91
HRB	Harbin Taiping Airport	2.015	0.204	-13.45
HET	Hohhot Baita Airport	2.075	0.034	-11.63
CGO	Zhengzhou Xinzheng Airport	2.098	0.450	-8.83
KHN	Nanchang Changbei Airport	2.155	0.033	-3.36
ZGC	Lanzhou Zhongchuan Airport	2.244	0.384	-3.64
FOC	Fuzhou Changle Airport	2.341	0.057	-8.68
TNA	Jinan Yaoqiang Airport	2.355	0.239	-7.34
YNT	Yantai Penglai Airport	2.389	0.410	-1.90
XNN	Xining Caojiapu Airport	2.436	0.166	-8.74
ZUH	Zhuhai Jinwan Airport	2.489	0.587	-14.9
SWA	Jieyang Chaoshan Airport	2.537	0.162	-10.17
LXA	Lhasa Gongga Airport	2.550	0.825	-8.86
JJN	Quanzhou Jinjiang Airport	2.651	0.228	-5.18
INC	Yinchuan Hedong Airport	3.204	1.019	-7.68
Overall		1.781	0.195	-4.18

According to Table 6, the average efficiency scores of Japanese airports vary from 1.015 (Fukuoka airport, FUK) to 1.946 (Chubu airport, NGO). Most primary airports, such as Haneda, Narita and Osaka, operate at high level of efficiency, whereas Kansai Airport with an average score of 1.669 is among the least efficient airports in our Japanese sample. In addition, we observe that the efficiency of Japanese airports has stagnated over time. The loss in efficiency is particularly severe at Komatsu (KMQ), Kansai (KIX), Chubu (NGO) and Sendai (SDJ) airports. Each of them has lost efficiency by more than 2% per year on average.

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

IATA Code	Airport name	Mean	Std.	Average Year-over-Year Change (%)
FUK	Fukuoka Airport	1.015	0.027	0.06
KOJ	Kagoshima Airport	1.026	0.030	0.09
HND	Haneda Airport	1.030	0.046	0.10
KMJ	Kumamoto Airport	1.032	0.025	0.03
UKB	Kobe Airport	1.039	0.065	0.22
MYJ	Matsuyama Airport	1.040	0.052	0.11
KMI	Miyazaki Airport	1.050	0.056	0.11
NRT	Narita Airport	1.051	0.066	0.39
ITM	Osaka Airport	1.095	0.075	-1.06
NGS	Nagasaki Airport	1.137	0.083	1.82
SDJ	Sendai Airport	1.213	0.286	2.68
CTS	New Chitose Airport	1.409	0.099	-0.63
KMQ	Komatsu Airport	1.518	0.212	6.81
KIX	Kansai Airport	1.669	0.234	4.76
HIJ	Hiroshima Airport	1.700	0.099	1.69
NGO	Chubu Airport	1.946	0.305	4.15
Overall		1.248	0.072	1.20

In both China and Japan, we find that large airports, in general, are more technically efficient. This observation is consistent with the literature focusing on other countries, for example, Italy (Curi et al., 2011; D'Alfonso et al., 2015), UK (Assaf, 2009), and New Zealand (Abbott, 2015; Ngo and Tsui, 2020). The finding suggests that small airports in China and Japan have more spare capacity and could improve their throughput with their current levels of inputs. On top of this, we find that airports' technical efficiency is less balanced in China than in Japan.

5.2 The impact of HSR on DEA Score

In this section, we discuss and compare the results obtained from the two-stage DEA approach and the double bootstrap procedure. Tables 7 and 8 report the parameter estimation for Chinese airports and Japanese airports, respectively. In both tables, the first four columns present the results using standard two-stage DEA approach and columns (5)-(8) show the regression results with Simar and Wilson (2007) double bootstrap procedure. Columns (1), (2), (5), and (6) report estimates for Equation (2) and columns (3), (4), (7), and (8) report estimates for Equation (3).

In the case of Chinese airports, variable HSR is positive and statistically significant in all specifications, suggesting that HSR development is negatively related to airport efficiency. More specifically, increasing the connectivity and accessibility of a city in the HSR network implies a loss in the technical efficiency of the city's airports. The loss in technical efficiency can be explained by the reduction in the airport's outputs due to HSR development. Liu et al. (2019) find that HSR development is negatively associated with the passenger traffic at Chinese airports. Chen and Jiang (2020) report that air cargo traffic and flight frequencies in Chinese domestic market decrease after the entry of HSR. The coefficient of HSR_CE is negative and statistically significant, meaning that improving the linkage between airport and HSR station may help increase the technical efficiency of the airport. This is because an easy access to the airport from HSR stations may promote HSR to feed traffic to the airport, which accordingly brings more traffic to the airport (Zhang et al., 2018; Liu et al., 2019). This finding is consistent with Galli et al. (2020) and Fernandez et al. (2021). The latter studied 21 European airports and documented that airports with the presence of HSR station in the airport are, on average, 23% more technically efficient. On the contrary, the coefficient of HSR_SE is positive and statistically significant at $p = 0.05$ level (column (3)) and $p = 0.1$ level (column (7)). This indicates that airport productivity is more likely to decrease when the airport is less convenient to be accessed (due to longer ground travel time) from the city center than the competing HSR station. The convenience of airport access/egress or HSR station access/egress can affect the competitiveness of the respective modes of transport (Talebian and Zou, 2016), as passengers' valuations on airport's and HSR station's access/egress times are the highest among all the time components of a journey except delays (Roman et al., 2007). Givoni and Banister (2012) also argue that HSR would be less attractive if its stations are located outside of the city downtown. Thus, the locational disadvantage of airport relative to HSR station (in terms of the relative closeness to the city center) can shift airport's demand to HSR, leading to reduced air passenger volume and aircraft movement and hence productivity.

Most estimates for control variables satisfy our expectation. GDP per capita of an airport's catchment area is reported to have a positive and statistically significant impact on the airport efficiency, indicating that the improvement in people's living standards is associated with the increase in airport efficiency. Hub airports appear to be more efficient, which is consistent with the literature (e.g. Tsui et al., 2014). Runway structure is statistically significant and negatively related to airport efficiency. This implies that airports with closely located parallel runways or intersecting runways are less technically efficient. Ha et al. (2013) also reported similar finding. Airports facing fierce competition, measured by the number of airports within the airport's catchment area, are less efficient, which is consistent with Scotti et al.'s (2012) finding with Italian airports. It can be explained by the fact that higher number of nearby airports implies lower market power of the airport due to possible competition among airports seeking to attract common traffic (Bel and Fageda, 2010; Bilotkach et al., 2012). Global financial crisis is positive and statistically significant, indicating that airports tend to be less efficient during the period of economic downturn. In addition, the coefficients of Disaster are statistically positive. As we mentioned earlier, a series of natural disasters such as Chinese winter storms and Wenchuan earthquake occurred in the first half of 2008 had substantially affected air traffic.

In the case of Japanese airports, without controlling for HSR_SE and HSR_CE (columns (1), (2), (5), and (6) in Table 8), the coefficients of variable HSR are positive and statistically significant, indicating that HSR development is negatively associated with airport efficiency. Specifically, adding one more HSR connection to the city implies an increase of 0.007 in the airport's efficiency score, resulting in a maximum of 0.69% drop in airport efficiency. Likewise, the coefficient on HSR accessibility is equal to 0.630, which means a 0.01 unit increase in the HSR accessibility may decrease airport efficiency by up to 0.39%.[8] This arises partly because of the shift in passengers from airplanes to bullet trains in Japanese domestic markets. During our study period, three new lines were opened, namely, Hachinohe-Shin Aomori (part of Tohoku line), Hakata-Shin Yatsushiro (part of Kyushu line), and Nagano–Kanazawa (part of Hokuriku line). The opening of these branch lines enables people living in the remote areas to travel to megalopolises such as Tokyo and Osaka by HSR. Coefficients of variable HSR_SE are all statistically significant while those of HSR_CE are not always statistically significant, implying that the locational advantage of HSR station plays a key role while the HSR-air complementary effect is much milder in Japan. This finding is slightly different from that of China, probably because the average domestic travel distance in Japan is much shorter than in China. Li and Sheng (2016) document that air-HSR intermodal service is not competitive in relatively short routes and the competitive distance for air-HSR intermodal service is between 1200 km and 1600 km. In fact, almost all domestic air routes in Japan is less than 1200 km and in these markets air transport and HSR compete fiercely, while many major domestic air routes in China are above 1200 km, such as Beijing - Guangzhou, Shanghai - Chengdu, which is ideal for intermodal cooperation between air and HSR when there is a convenient linkage between the airport and HSR station. We also observe that the characteristics of an airport's hinterland, such as the population and GDP per capita of the airport's hinterland, have positive impacts on

[8] DEA is a linear programming technique for determining how DMUs perform in relation to the frontier. DMUs on the frontier itself are assigned an "efficiency rating" of 100 percent, whereas units falling behind the frontier are assigned a rating of less than 100 percent. Since we adopted output-oriented DEA model, the efficiency scores range between 1 and infinity. Here, we first transform the efficiency scores into efficiency ratings by taking the reciprocal of the efficiency score, and then carry out the analysis. For example, supposing the initial efficiency score of an airport is x, increasing one more HSR connection in the city where the airport locates implies the efficiency score of the airport will be increased to x+0.009. In other words, the efficiency rating of the airport decrease from 1/x to 1/(x+0.009), indicating a maximum of 0.69% (when x =1, the difference can reach its maximum) decline.

airport efficiency and the earthquake and tsunami occurred in 2011 severely affected airport performance.

As shown in Tables 7 and 8, the estimates for our key variables are consistent when using standard two-stage DEA and double bootstrap procedure, in particular, the regression results of HSR measured by connectivity and accessibility. However, there are marginal differences between these two approaches. First, the coefficients of variable HSR have larger values when using double bootstrap procedure. Second, in the case of China, HSR_CE becomes more statistically significant while HSR_SE becomes less statistically significant. Third, in the case of Japan, the estimates for both HSR_SE and HSR_CE become statistically significant.

Table 7. Impact of HSR on airport technical efficiency (China)

China	Two-Stage DEA				Double bootstrap procedure			
	(1) HSR = Connectivity	(2) HSR = Accessibility	(3) HSR = Connectivity	(4) HSR = Accessibility	(5) HSR= Connectivity	(6) HSR= Accessibility	(7) HSR= Connectivity	(8) HSR Accessibility
POP	-0.012	0.037	-0.014	0.035	-0.039	0.010	-0.039	0.008
	(0.051)	(0.051)	(0.050)	(0.051)	(0.076)	(0.075)	(0.074)	(0.076)
GDP_POP	-0.354***	-0.306***	-0.357***	-0.309***	-0.495***	-0.453***	-0.498***	-0.473***
	(0.035)	(0.036)	(0.035)	(0.036)	(0.045)	(0.045)	(0.043)	(0.047)
Privatize	0.087	0.058	0.128	0.099	-0.063	-0.065	0.018	0.016
	(0.191)	(0.193)	(0.191)	(0.194)	(0.354)	(0.373)	(0.373)	(0.390)
Hub	-1.330**	-1.732***	-1.390**	-1.750***	-2.163**	-2.607**	-2.274**	-2.678**
	(0.622)	(0.636)	(0.615)	(0.633)	(0.994)	(1.006)	(0.973)	(1.057)
Fuel	0.241**	0.058	0.289**	0.092	0.178	-0.001	0.234	0.050
	(0.112)	(0.106)	(0.112)	(0.106)	(0.148)	(0.138)	(0.143)	(0.134)
Compete	0.437**	0.493**	0.362*	0.430**	0.550*	0.525*	0.393	0.349
	(0.195)	(0.200)	(0.196)	(0.200)	(0.312)	(0.312)	(0.303)	(0.317)
RwyStructure	0.135***	0.143***	0.132***	0.141***	0.266***	0.278***	0.262***	0.281***
	(0.025)	(0.025)	(0.024)	(0.025)	(0.039)	(0.039)	(0.038)	(0.040)
Disaster	0.186***	0.253***	0.152**	0.226***	0.287***	0.350***	0.243***	0.307***
	(0.069)	(0.068)	(0.069)	(0.069)	(0.084)	(0.083)	(0.082)	(0.086)
GFS	0.168**	0.137*	0.160**	0.129*	0.173**	0.143	0.164*	0.133
	(0.069)	(0.071)	(0.069)	(0.070)	(0.087)	(0.089)	(0.086)	(0.088)
HSR	0.009***	1.549**	0.010***	1.972***	0.011***	2.104***	0.013***	3.245***
	(0.001)	(0.615)	(0.001)	(0.648)	(0.002)	(0.772)	(0.002)	(0.887)

HSR_SE			0.020**	0.011			0.020*	0.010
			(0.009)	(0.009)			(0.011)	(0.010)
HSR_CE			-3.232**	-3.209**			-5.302***	-6.708***
			(1.372)	(1.454)			(1.906)	(2.158)
Constant			2.984***	2.428***	3.480***	3.156***	3.854***	3.635***
			(0.623)	(0.626)	(1.003)	(1.018)	(0.994)	(1.012)
Airport Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	414	414	414	414	414	414	414	414
LR chi2	529.11	512.55	536.48	517.66				
Log likelihood	-172.92	-181.20	-169.24	-178.64				
Wald chi2					795.14	737.10	833.53	803.24

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

Table 8. Impact of HSR on airport technical efficiency (Japan)

Japan	Two-stage DEA				Double bootstrap procedure			
	(1) HSR = Connectivity	(2) HSR = Accessibility	(3) HSR = Connectivity	(4) HSR = Accessibility	(5) HSR = Connectivity	(6) HSR = Accessibility	(7) HSR = Connectivity	(8) HSR = Accessibility
POP	-0.507**	-0.491*	-0.455*	-0.454*	-0.688	-0.750	-0.473	-0.531
	(0.246)	(0.249)	(0.238)	(0.238)	(0.463)	(0.500)	(0.431)	(0.423)
GDP_POP	-0.454***	-0.460***	-0.457***	-0.457***	-0.597***	-0.629***	-0.588***	-0.618***
	(0.109)	(0.109)	(0.101)	(0.101)	(0.160)	(0.162)	(0.142)	(0.153)
Privatize	-0.114	-0.111	-0.105	-0.105	-0.590	-0.577	-0.464	-0.484
	(0.093)	(0.093)	(0.086)	(0.087)	(0.482)	(0.519)	(0.420)	(0.411)
Fuel	0.079	0.082	0.140**	0.140**	0.157	0.173	0.215**	0.216**
	(0.066)	(0.066)	(0.064)	(0.064)	(0.103)	(0.103)	(0.100)	(0.096)
Compete	0.866	0.869	0.769	0.769	-0.221	-0.183	0.309	1.150**
	(48.32)	(48.248)	(22.71)	(22.72)	(0.262)	(0.221)	(0.333)	(0.522)
GFS	0.080	0.079	0.089*	0.089*	0.107	0.110	0.126*	0.127*
	(0.051)	(0.051)	(0.047)	(0.047)	(0.077)	(0.078)	(0.068)	(0.068)
Disaster	0.123***	0.123***	0.123***	0.124***	0.166***	0.164***	0.170***	0.163***
	(0.039)	(0.039)	(0.036)	(0.036)	(0.059)	(0.059)	(0.053)	(0.052)
HSR	0.007**	0.630**	0.0004	0.012	0.028***	2.416***	0.007	1.492
	(0.003)	(0.277)	(0.004)	(0.508)	(0.007)	(0.661)	(0.012)	(1.154)
HSR_SE			0.074***	0.074***			0.085***	0.085***
			(0.017)	(0.017)			(0.023)	(0.024)
HSR_CE			-2.752	-2.650			-10.57*	-17.17**
			(3.538)	(4.514)			(5.611)	(7.659)**

Constant	4.788	4.716	4.552	4.543	7.316***	7.699***	5.524**	5.118**
	(48.34)	(48.27)	(22.75)	(22.76)	(2.724)	(2.927)	(2.471)	(2.462)
Airport Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	144	144	414	414	144	144	144	144
LR chi2	267.63	267.78	286.66	286.65				
Log likelihood	50.25	50.32	59.76	59.76				
Wald chi2					327.87	324.81	341.28	343.67

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

Hub and *RwyStructure* are omitted due to multi-collinearity.

5.3 The impact of HSR on airport's labor productivity

Table 9 presents the impact of HSR on the labor productivity at Chinese airports. Columns (1)-(4) report the estimates using WLU as dependent variable and columns (5)-(8) show regression results using aircraft movements per employee as dependent variable. We find that variable HSR has a negative and statistically significant impact on airport labour productivity. Specifically, a 1% increase in HSR connectivity or accessibility reduces labour productivity by approximate 0.1%, which is in line with the findings in Section 5.2. It can be explained by the reduction of passenger and cargo traffic in Chinese domestic market due to HSR development, as Liu et al. (2019) find HSR connectivity and accessibility in general reduce domestic airport passenger traffic.

Columns (3), (4), (7), and (8) take into account the relative location advantage of HSR station (HSR_SE) and the possible complementary effect of HSR on aviation (HSR_CE). We observe that a reduction in the distance between an airport and its nearest HSR station implies an increase in WLU per employee. However, the effect is not statistically significant on aircraft movements per employee (columns (7) and (8)). A possible explanation is that the intermodal integration of HSR and air transport in China is still at the preliminary stage. Although the improvement in the linkage between airport and HSR station may bring additional traffic, in particular passenger traffic, to the airport, it is not significant enough to contribute to more flights. In fact, only a few sampled airports were directly connected to the HSR network between 2007 and 2015. Further, our results show that variable HSR_SE is statistically significant in all specifications, indicating that the locational advantage of HSR station relative to airport has a negative impact on the airport's labour productivity, which is consistent to our findings in Section 5.2.

Table 10 shows the regression results for Japanese airports. We observe that there is in general no statistical evidence that the three HSR-related variables are strongly associated with airport's labour productivity. This is possibly because Japanese airports have experienced with HSR for quite a long time since the 1970s and the competition between HSR and air transport has reached a certain equilibrium years ago (Liu et al., 2019). The recent changes in Japanese HSR system during our study period are relatively minor and not enough to break this equilibrium. The only exception is that variable HSR has a positive and statistically significant coefficient when the dependent variable is aircraft movements per employee, and the elasticities of HSR connectivity and accessibility are 0.041 and 0.68, respectively. This result may be explained by the fast growth of business jet travellers in Japan as scheduled airline services gradually deteriorate due to the competition of HSR. According to the Ministry of Land, Infrastructure, Transport and Tourism (MILT), business aviation traffic in Japan has grown an average of 10.2 percent per year during the past five years, resulting in a significant increase in business jet movements.[9] In addition, airlines may reduce aircraft size when competing with HSR. As more ground staff are needed to serve a larger aircraft than a smaller aircraft, an increase in aircraft movement per employee can be an outcome of airlines' adjustment on aircraft size. Due to data limitation, we are not able to test these possible channels of influence in this study, which can be done in the future when relevant data become available.

[9] The information is retrieved from https://www.ainonline.com/aviation-news/business-aviation/2019-04-16/japan-business-aviation-grows-amid-welcoming-atmosphere

Table 9. Impact of HSR on labor productivity at airports (China)

China	DV = WLU per employee				DV = aircraft movements per employee			
	(1) HSR = Connectivity	(2) HSR = Accessibility	(3) HSR = Connectivity	(4) HSR = Accessibility	(5) HSR = Connectivity	(6) HSR = Accessibility	(7) HSR = Connectivity	(8) HSR = Accessibility
Ln(HSR)	-0.098	-0.117	-0.094	-0.108	-0.079	-0.101	-0.074	-0.096
	(0.036)**	(0.039)***	(0.034)**	(0.040)**	(0.033)**	(0.035)***	(0.031)**	(0.036)**
Ln(HSR_SE)			-0.124	-0.123			-0.090	-0.088
			(0.047)**	(0.050)**			(0.047)*	(0.050)*
Ln(HSR_CE)			0.188	0.167			0.113	0.094
			(0.091)**	(0.095)*			(0.089)	(0.093)
Constant	3.783	3.539	4.726	4.452	2.721	2.473	3.348	3.052
	(0.693)***	(0.643)***	(0.789)	(0.744)***	(0.717)***	(0.648)***	(0.630)***	(0.664)***
Airport Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	261	261	261	261	261	261	261	261
R-square	0.513	0.507	0.531	0.525	0.303	0.301	0.321	0.320

Note: Standard errors are in parentheses. Robust standard errors clustered by airport are reported in brackets. **p <0.1; **p<0.05; ***p<0.01.*
Columns (1), (2), (5), and (6) report the estimates for Equation (4). Columns (3), (4), (7), and (8) report the estimates for Equation (5).
We control for population GDP per capita, privatization, jet fuel price, competition, disaster, and global financial crisis. All estimates for these control variables satisfy our expectation. Regression results of these variables are not presented to save space.

Table 10. Impact of HSR on labor productivity at airports (Japan)

Japan	DV = WLU per employee			DV = aircraft movements per employee		
	(1) HSR = Connectivity	(2) HSR = Accessibility	(3)	(4) HSR = Connectivity	(5) HSR = Accessibility	(6)
Ln(HSR)	-0.018	-0.108		0.046	0.680	
	(0.037)	(0.383)		(0.020)**	(0.203)***	
Ln(HSR_SE)			-0.114			-0.002
			(0.195)			(0.277)
Ln(HSR_CE)			0.210			0.112
			(0.381)			(0.546)
Constant	4.874	4.672	5.483	-1.640	-1.363	-0.831
	(2.623)*	(2.676)	(3.001)*	(2.919)	(2.830)	(3.800)
Airport Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes
N	144	144	144	144	144	144
R-square	0.230	0.227	0.231	0.355	0.370	0.365

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

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

Columns (1), (2), (5), and (6) report the estimates for Equation (4). Columns (3), (4), (7), and (8) report the estimates for Equation (5).

We control for population GDP per capita, privatization, jet fuel price, competition, disaster, and global financial crisis. All estimates for these control variables satisfy our expectation. Regression results of these variables are not presented to save space.

6. Conclusion

This paper examines the impact of HSR development on airport productivity in the context of China and Japan. We consider 46 Chinese airports and 18 Japanese airports and conduct the analysis over the period of 2007-2015. To capture the heterogeneity of HSR development among different cities, we employ HSR connectivity and accessibility developed by Liu et al. (2019). Besides, the potential complementarity between HSR and air transport is captured by the distance between an airport and its nearest HSR station. The locational advantage of the HSR station relative to the airport is also considered in the model to capture the infrastructure access/egress-related competition effect of HSR after controlling for the level of HSR development. We first examine the impact of HSR on airport technical efficiency with both standard two-stage DEA and double bootstrap procedure. Then, we investigate the association between HSR and airport labor productivity which is measured by WLU per employee and aircraft movements per employee.

We draw three major conclusions from this study. First, in both China and Japan, the level of HSR development appears to be negatively associated with airport efficiency. Second, Chinese airports' technical efficiency is positively and statistically significantly associated with the potential of air-HSR intermodal service but its association with the relative locational advantage of the HSR station is weak. However, Japanese airports' technical efficiency is strongly and negatively correlated with the locational advantage of the HSR station but has a weak relationship with the air-HSR intermodal linkage. Third, HSR development is associated with the decrease of labor productivity at Chinese airports, but it is associated with an increase in aircraft movement per employee at Japanese airports.

Our main findings have the following policy implications. First, apart from many other concerns, policy makers need to take into account the impact of HSR on airports when deciding on airports' capacity expansion. Instead of constructing new infrastructures, improving the current facilities at airports with advanced technologies, and reducing the ground access time may be a better alternative in the context of HSR development. Second, HSR development may negatively affect airports' productivity if it is not well planned. This reduction in technical efficiency is likely to be contributed by air traffic loss due to air-HSR competition and hence reduced utilization of airport capacity. According to the findings with Japanese airports, airports may gradually adjust their labor inputs to cope with the competition of HSR and retain high labor productivity in the long term, but the negative impact of HSR on airport's technical efficiency (measured by both labor and capital inputs) can remain for a long time. That is, HSR may cause welfare loss via airports' loss of efficiency if it is not coordinated with airport infrastructure development. Thus, policy makers should be more cautious in airport expansion projects as well as HSR expansion projects as difficulty in investment cost recovery may persist if the airports, especially those small ones, are not able to retain traffic as the HSR network expands. Third, in the case of China, given that reducing the access time between HSR stations and airport terminals may help the airport gain productivity, it would be a good idea to promote air-HSR intermodal linkage. This finding is in line with Xia and Zhang (2017).

Although the paper has revealed many new insights into the association between HSR and airports, some important extensions could be made for further investigation. First, the study can be extended by including more relevant variables, for example, the number of airlines in service in an airport, to test the robustness of our estimates. Second, further studies should be conducted to investigate the differentiated impacts of HSR on WLU per employee and aircraft movement per employee as revealed by this study. This different result may indicate a more complicated channel of reactions by airlines and passengers, such as the change of aircraft size and the possible diversion of demand from scheduled flights to business jets. Third, as a complement to this research, it would be interesting to explore the effect of HSR on the cost efficiency of airports.

Appendix 1 Descriptive statistics for independent variables

Table A1. Descriptive statistics of influential factors for Chinese airports

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

Table A2. Descriptive statistics of influential factors for Japanese airports

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

Appendix 2 Simar and Wilson (2007) double bootstrap procedure

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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