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## RAIL-INDUCED TRAFFIC IN CHINA

### ABSTRACT

*The rapid development of China's railway has exerted an enormous influence on the intercity passenger transport structure in recent years. However, it has not satisfied the passengers' travel demand due to induced traffic. This paper is committed to solving such issue, with the aim of satisfying the current travel demand, and of anticipating the demand of the predicted traffic growth over the next 20 to 30 years. The paper has considered the increase in rail passenger kilometres caused by the growth of rail kilometres as rail-induced traffic. Based on the concept and former research of induced traffic, the panel data of 26 provinces and 3 municipalities of China between the year 2000 and 2014 were collected, and the elasticity models (including elasticity-based model, distributed lag model, high-speed rail (HSR) elasticity model and rail efficiency model) have been constructed. The results show the importance of model formation incorporation of rail-induced traffic. It is better to get the correct value in divided zones with different train frequencies or incorporation rail efficiency in cities or provinces. The lag time and rail types also need to be considered. In summary, the results analysis not only confirms the existence of rail-induced traffic, but also provides substantial recommendations to train operation planning.*

### KEY WORDS

*train operation planning; rail-induced traffic; elasticity model; rail kilometres; rail passenger kilometres;*

### 1. INTRODUCTION

Accurate traffic forecasts are central to proper appraisal of rail schemes, considering whether there are new railway constructions. The evaluation of the economic costs and benefits, and the appraisal of the safety and environmental impacts of the scheme are dependent on predictions of the amount and pattern of traffic using the new network compared with the one on the existing network. The scheme design is also determined by these forecasts. Under China's high-speed rail fast development, one question is: does improving the rail system introduce extra traffic, which would not otherwise be there without the improvements? Extra

traffic may be caused, for example, by people, in response to improved rail conditions, making more or longer trips. Therefore, rail-induced traffic is necessary to the accurate prediction, which means the generation of new rail traffic that would not have occurred at all without the capacity improvement.

The traditional four-step model has been used both in road and rail transportation planning. Due to the travel demand difference between road and rail, road-induced traffic models have not been applied in rail transport. There are merely few studies on rail-induced traffic, owing to the frequency-based approach. People would make a choice following the schedule time rather than vehicles' free chosen at any time. Therefore, the relationship between rail kilometres and rail passenger kilometres is the necessary reason to make train timetable based on the traffic forecasting, especially induced traffic has effect on travel demand. Until now, rail demand forecasting models could be distinguished as aggregate and disaggregate. Aggregate models are used to forecast railway demand based on aggregate demand elasticity values to GRP variations, railway travel times, fuel costs, population and so on. These models have not incorporated the rail kilometres' influencing [1, 2]. Disaggregate models focus on the competition among multi-modes, showing the effect of mode changes [3-6]. These models have not considered the cooperated relationship among road, rail and air transport, underestimating rail kilometres influencing. Therefore, present model formations have neglected induced traffic, which should be further researched.

The aim of this paper is to find out rail-induced traffic, and then construct the elasticity models for quantification and analysis. Elasticity models come from aggregate model following the research ideology of road-induced traffic, on the assumption that rail frequency-based approach has not constrained passengers' free chosen at any time. The rest of this paper is structured as follows. Section 2 describes the concept definition of rail-induced traffic. Section 3 shows

the data collection and analysis according to the influencing factors on people travel choices, based on the evidence of researches. Section 4 proposes some elasticity models and gets the elastic coefficients between rail kilometres and rail passenger kilometres, considering the population and GRP. Then these results are analysed in detail. The final section provides a summary of the research.

**2. RAIL-INDUCED TRAFFIC CONCEPT**

Rail-induced traffic means the additional demand due to the improvement of rail level of services. Rail improvement will have impact on peoples decision, such as trip generation (Whether or not to travel at all), trip distribution (Which destination is best for the purpose), trip scheduling (When is the best time to set out on the journey), mode choices (Which is the best mode of transport to use) and trip frequency (How often to repeat the journey within a given period). According to road-induced traffic studies, diverted demand and induced traffic are not separated in consideration. This means induced traffic is the generation of new vehicle traffic that would not have occurred at all without the capacity improvement, including time influencing. If after rail operation, you change other travel modes to rail, this is also induced traffic rather than diverted traffic. Following the ideology of road-induced traffic [7-12], the study on rail-induced traffic is mainly about the relationship between rail kilometres and rail passenger kilometres. The detail rail-induced traffic concept is in *Figure 1*, routinely used in this paper.

*Figure 1* shows the generated process of rail-induced traffic. Railway construction will increase rail accessibility, which directly affects people’s generalized travel cost. People would change travel choices such as trip frequency, destination or activity pattern, departure time etc. Considering over the long run, rail

travel mode chosen will become one habit, indirectly due to modifications of travellers’ lifestyle choices and land use. Therefore, rail construction will affect passengers’ travel habit, such as change of route, change in time, change in origins or destination, switching modes, and increase in trip frequency. Both switching from other modes to rail and the increase in trip frequency are apparently rail-induced traffic. Only the increase of rail passenger kilometres is regarded as induced traffic, among changing of routes, changing in timing and changing origins or destinations.

**3. DATA COLLECTION AND ANALYSIS**

**3.1 Data collection**

According to the economic theory of supply and demand, value is the determinant of people choosing travel or not. The growth of rail kilometres will increase rail accessibility, which means the generalized travel costs will be reduced. GRP (Gross Regional Product) is the influencing factor that causes people get rich and reduces the relative costs. Population is also the influencing factor, whose growth would inevitably lead to increased traffic. Therefore, the factors that affect rail passenger kilometres include population, rail kilometres, and GRP.

Based on the influencing factors, the data are collected through the national statistical databases [13], including 26 provinces and 3 municipalities of China between 2000 and 2014. The main reason for excluding the Xizang Autonomous Region was no rail construction before 2007, and in the Hainan province it was the lack of data from 2004 to 2007. For each province and city, the data collection includes population, GRP, rail kilometres and rail passenger kilometres. Basic characteristics of the provinces and cities are shown in *Table 1*.

	Given destinations					Change to more remote destinations (All else given)
	Given route, timing, vehicle-occupancy, mode and frequency	Change of route (All else given)	Change in timing (All else given)	Switch from other modes (All else given)	Increase in trip frequency (All else given)	
Given origins  (As now)		Existing traffic  Induced traffic  Re-assigned	Re-scheduled	Transferred	Induced traffic	Induced traffic (extra passenger-kilometres of railway)
Change to more remote origins		Induced traffic (extra passenger-kilometres of railway)			Induced traffic	Induced traffic

*Figure 1 – Definitions of rail-induced traffic*

Table 1 – Average data in China

Cities and provinces	Average GRP (Billion Yuan)	Average population (Million people)	Average rail kilometres [Km]	Average rail passenger kilometres [Billion passenger Km]
Beijing city	1,065.358	17.256	1,173.333	9.034
Tianjin city	686.115	11.827	773.333	11.254
Hebei province	1,531.077	69.894	4,973.333	61.395
Shanxi province	669.413	34.319	3,420.000	13.379
Inner Mongolia Autonomous Region	804.876	24.341	7,460.000	13.497
Liaoning province	1,377.348	42.921	4,293.333	44.330
Jilin province	647.431	27.251	3,846.667	18.062
Heilongjiang province	805.694	38.233	5,706.667	21.175
Shanghai city	1,292.326	20.487	360.000	5.362
Jiangsu province	3,048.653	76.799	1,746.667	31.420
Zhejiang province	2,049.172	51.377	1,486.667	28.561
Anhui province	940.261	60.931	2,673.333	36.982
Fujian province	1,116.146	36.108	1,813.333	12.444
Jiangxi province	709.499	43.642	2,640.000	45.652
Shandong province	2,899.892	93.779	3,566.667	36.647
Henan province	1,695.046	94.757	4,066.667	63.791
Hubei province	1,199.213	57.181	2,893.333	38.483
Hunan province	1,197.978	65.460	3,253.333	60.614
Guangdong province	3,431.797	97.017	2,406.667	39.992
Guangxi Zhuang Autonomous Region	712.801	47.557	3,000.000	14.893
Chongqing city	615.721	28.612	1,173.333	7.700
Sichuan province	1,300.422	81.398	3,133.333	22.078
Guizhou province	371.486	36.529	1,973.333	16.090
Yunnan province	581.728	45.004	2,373.333	6.826
Shaanxi province	751.568	37.083	3,420.000	31.283
Gansu province	319.514	25.512	2,473.333	26.015
Qinghai province	101.264	5.507	1,553.333	3.251
Ningxia Hui Autonomous Region	121.798	6.097	960.000	2.911
Xinjiang Uygur Auto	423.108	20.774	3,453.333	13.737
All	32,466.705	1,297.653	82,066.664	736.858

Table 1 shows that the growth of average population and GRP will increase rail passenger kilometres in most cities or provinces. Rail kilometres present one special quality. The growth of rail kilometres will increase rail passenger kilometres in the same city or province. Meanwhile, more rail kilometres will not generate more rail passenger kilometres in different cities or provinces.

### 3.2 Granger causality

Granger causality could define the causality relationship between dependent variable and

independent variable. According to the Granger test, both a backward and a forward lag exist in the regression. If the backward lag is statistically significant while the forward lag is not, then this indicates that the independent variable temporally precedes the dependent variable. If the significance is reversed, then the dependent variable precedes the independent variable. The relationship between rail kilometres and rail passenger kilometres is vital to express induced traffic. The results for the Granger test are presented in Table 2. The backward lag one year is statistically significant above the 95% level. The forward lag is not statistically significant. So this result suggests that rail

Table 2 – Results of the Granger test in China

Independent variables	log(rail-kilometres) backward lag one year	log(rail-kilometres) forward lag one year	log(GRP)	log(population)	constant	R <sup>2</sup>
Value	0.368	-0.020	0.325	0.419	2.089	0.895
t-statistic	13.629	-0.781	18.765	4.835	3.440	

kilometre growth precedes the growth in rail passenger kilometres.

### 3.3 Serial correlation and heteroscedasticity

Serial correlation means the relative relationship among values of the same random variable at different time or space. Time series data often exhibit serial correlation at different periods. Heteroscedasticity means that regression interference variance does

not remain constant in different observed data. In the amount of applied studies, the cross-section data and time-series data always appear heteroscedasticity. Based on the data collection, correlograms in Eviews show that some individual province and city residuals existing serial correlation and the White heteroscedasticity test implies the yearly heteroscedasticity (shown in Table 3) [14]. The method of period seemingly unrelated regressions (SUR) of generalized least squares

Table 3 – Serial correlation and heteroskedasticity test in cities and provinces

Cities and provinces	Breusch-Godfrey Lagrange Multiplier test (Prob Chi-square serial correlation)	White test (Prob Chi-square heteroskedasticity)
Beijing city	0.413	0.900
Tianjin city	0.093**	0.162*
Hebei province	0.491	0.659
Shanxi province	0.388	0.692
Inner Mongolia Autonomous Region	0.322	0.481
Liaoning province	0.171*	0.038**
Jilin province	0.223	0.169
Heilongjiang province	0.275	0.838
Shanghai city	0.178*	0.406
Jiangsu province	0.776	0.697
Zhejiang province	0.759	0.080**
Anhui province	0.832	0.868
Fujian province	0.145*	0.216
Jiangxi province	0.466	0.899
Shandong province	0.783	0.161*
Henan province	0.843	0.806
Hubei province	0.148*	0.427
Hunan province	0.589	0.641
Guangdong province	0.140*	0.203
Guangxi Zhuang Autonomous Region	0.036*	0.345
Chongqing city	0.014**	0.157*
Sichuan province	0.589	0.537
Guizhou province	0.082**	0.767
Yunnan province	0.874	0.277
Shaanxi province	0.099**	0.386
Gansu province	0.077**	0.465
Qinghai province	0.772	0.405
Ningxia Hui Autonomous Region	0.729	0.314
Xinjiang Uygur Auto	0.388	0.889

Note: \*\* means rejection region is 10%, \* means rejection region is 20%.

and period SUR of coefficient covariance can eliminate those problems efficiently [15]. The above dummy models all use these methods to reach the results.

#### 4. ELASTICITY MODEL CONSTRUCTION AND RESULTS ANALYSIS

Based on the collected influencing factors, elasticity model should be constructed. Induced traffic elasticity means the rate of change of rail passenger kilometres with respect to rail kilometres (Michael D. Meyer Eric J. Miller. 2001). Elasticity is thus a measure of the sensitivity to change in system conditions. From the economic view, the use of elasticity model has two advantages. First, the change of the unit measure will not affect the slope coefficient. So the units need not to be converted. Second, the log form of every variable can eliminate heteroscedasticity under normal circumstances. Above all, the elasticity model is the essential method to investigate in induced traffic [7-12]. A variety of statistical methods, discussed below, were estimated.

##### 4.1 Elasticity-based model construction and results analysis

###### 4.1.1 Elasticity-based model

Considering the impact factors of rail passenger kilometres, the basic model is set as:

$$\log(RPT_{it}) = c + \alpha_i + \tau_t + \sum_k \beta^k \log(X_{it}^k) + \lambda \log(RK_{it}) + \varepsilon_{it} \quad (1)$$

The parameters are defined as:

- $RPT_{it}$  - rail passenger kilometres in region  $i$ , for year  $t$ ;
- $c$  - constant term;
- $\alpha_i$  - fixed effect for region  $i$ , to be estimated;
- $\tau_t$  - fixed effect for year  $t$ , to be estimated;
- $\beta^k$  - coefficients to be estimated for demographic and other parameters;
- $X_{it}^k$  - value of demographic and other variables in region  $i$  for year  $t$ ;
- $\lambda$  - coefficient to be estimated for rail kilometres parameter;
- $RK_{it}$  - proxy for cost of travel time (rail kilometres) in region  $i$  for year  $t$ ;
- $\varepsilon_{it}$  - random error term.

The elasticity coefficient between rail kilometres and rail passenger kilometres is valued  $\lambda$ . This means

that rail-kilometres increased by 1%, rail passenger kilometres will grow  $\lambda\%$ . This model assumes that the elasticity coefficient of different regions at different time is the same. Similarly, the elasticity coefficient between other influencing factors and rail passenger kilometres is valued  $\beta^k$ .

###### 4.1.2 Results analysis

Based on the model structure and data collection, Table 4 presents the results of estimating the elasticity-based model using software Eviews 6.0. Almost all the coefficients were estimated with a high degree of precision, obtaining plausible signs and magnitudes. These prove that the usefulness of the elasticity-based model can show the relationships among influencing factors in an accurate way. The high  $R^2$  and  $F$  value mean the accurate model formation. The Durbin-Watson statistic means residual serial correlation does not exist in the model.

Table 4 shows the results of the estimation using the elasticity-based model. All coefficient signs have the expected direction, suggesting that the hypothesis of rail-induced traffic cannot be rejected. The rail kilometres elasticity of rail passenger kilometres is 0.301, meaning a 1% growth of rail kilometres will increase 0.301% rail passenger kilometres. Both population and GRP have significant impact on rail passenger kilometres. These show that when the population increases by 1%, rail passenger kilometres will grow by 0.434%; and a 1% growth of GRP will increase the rail passenger kilometres by 0.340%. Comparing the population elasticity and GRP elasticity of rail-induced traffic with road-induced traffic in Zhao and He, the parameters value are similar. These reflect that rail transport is an essential part in China when people choose travel modes. The elasticities of rail kilometres, population and GRP have a small difference, which supports the importance of induced traffic consideration.

Due to various city and province characteristics, rail kilometre influences on rail passenger kilometres should be different. Take Inner Mongolia Autonomous Region for example, owning a large amount of railways will generate few rail passenger kilometres. In order to distinguish different relationship types between rail kilometres and rail passenger kilometres, China will be divided into four regions according to train frequency. The first zone is the region where train frequency is more than 300 times a day, including Beijing city, Shanghai city, Jiangsu province, Hubei province, and

Table 4 – Results of the elasticity-based model in China

Independent variables	$\log(\text{rail-kilometres})$	$\log(\text{GRP})$	$\log(\text{population})$	constant	$R^2$	F-statistic	DW-statistic
Value	0.301	0.340	0.434	1.947	0.812	619.650	1.848
t-statistic	12.502	24.437	5.618	3.569			



Guangdong province. The second zone is the region where train frequency is more than 200 times a day, including Tianjin city, Hebei province, Liaoning province, Zhejiang province, Shandong province, Henan province, and Hunan province. These two zones are with high economic development or large population density. The third zone is the region where train frequency is more than 100 times a day, including Jilin province, Heilongjiang province, Anhui province, Fujian province, Jiangxi province, Sichuan province, and Shanxi province. The fourth zone is the region where train frequency is less than 100 times a day, including Shaanxi province, Inner Mongolia Autonomous Region, Guangxi Zhuang Autonomous Region, Chongqing city, Guizhou province, Yunnan province, Gansu province, Qinghai province, Ningxia Hui Autonomous Region, and Xinjiang Uygur Auto. These two zones are with low economic development or small population density. Based on elasticity-based model formation and data collection, the results in the divided zones are shown in Table 5.

Table 5 shows that various divided zones can be efficiently described by elasticity-based model, using high  $R^2$  and F-statistics. The rail kilometres elasticity of rail passenger kilometres in different divided zones is larger than that in China. Meanwhile, the GRP elasticity of rail passenger kilometres in different divided zones is smaller than that in China. These reflect that the influencing of rail kilometres has been underestimated in China, and the effect of GRP has been overestimated due to various social economy, population, and environment in cities or provinces. Huge differences among the divided zones are the arrival or departure frequency of train. The detail results will be analysed from the following three points.

In the first zone, the rail kilometres elasticity of rail passenger kilometres is 0.609, meaning a 1% growth of rail kilometres will increase rail passenger kilometres by 0.609%. These show that in case of rail construction, people will be attracted to rail transport, reflecting the importance of induced traffic. The GRP elasticity of rail passenger kilometres is 0.155,

reflecting that people can totally afford ticket price at present. The population elasticity of rail passenger kilometres is 0.531; larger than in other divided zones and China. This means that more than half of people would like to choose rail transport for long-distance travel. Therefore, the highest arrival or departure frequency of train aims to meet passengers' travel demand. We suggest railway station reconstruction in the first zone to afford the increasing train frequency.

In the second zone, the rail kilometres elasticity of rail passenger kilometres is 0.678, the largest in other divided zones. Both GRP (0.166) and population (0.140) elasticities of rail passenger kilometres are significantly positive; the value is small. These reflect that passengers' travel demand in rail transport may have been restricted due to low train frequency. Meanwhile, GRP elasticity of rail passenger kilometres shows passengers have weak reaction to ticket prices. Railway construction will increase train frequency to meet the passengers' travel demand. However, the increased ticket prices will not cut down the passengers' travel demand. Therefore, the growth of arrival or departure frequency of train in the second zone is suggested.

The results in both the third and the fourth zone have similar values. The GRP elasticity of rail passenger kilometres is 0.225 in the third zone, 0.273 in the fourth zone, showing the economic development may have effect on passengers' travel demand, compared with the first and the second zone. The rail kilometres elasticity of rail passenger kilometres is 0.390 in the third zone, and 0.409 in the fourth zone. And the population elasticity of rail passenger kilometres is 0.361 in the third zone, and 0.330 in the fourth zone, showing that passengers travel modes are chosen at free condition compared with the first and the second zone. Therefore, whether railway improvement and construction should be undertaken or not should be decided on the basis of a detailed analysis of individual city or province. Take Jilin province and Inner Mongolia Autonomous Region for example, the current railway construction is available to Jilin province due to

Table 5 – Results of the elasticity-based model in divided zones

Independent variables	First zone	Second zone	Third zone	Fourth zone
$\log(\text{rail-kilometres})$	0.609 (33.011)	0.678 (49.129)	0.390 (19.303)	0.409 (38.953)
$\log(\text{GRP})$	0.155 (6.286)	0.166 (10.820)	0.225 (12.978)	0.273 (27.313)
$\log(\text{population})$	0.531 (20.107)	0.140 (9.899)	0.361 (24.676)	0.330 (34.310)
constant	2.404 (11.917)	5.158 (38.145)	3.596 (24.029)	3.023 (48.682)
$R^2$	0.982	0.996	0.962	0.996
F-statistic	1,265.843	8,576.705	845.890	12,024.860

population and economy, and new railway construction is necessary for Inner Mongolia Autonomous Region due to geography.

## 4.2 Distributed lag model construction and results analysis

### 4.2.1 Distributed lag model

The growth of rail kilometres will increase rail passenger kilometres, which is called induced traffic in this paper. All induced traffic should not be generated in the first year. Rail development can also have a profound and long-term effect not only on the fabric of the nation, but also on the regional and local land-use patterns, the environment and the way in which people conduct their business and personal lives. Therefore, rail kilometres influencing rail passenger kilometres is consistent with the growth curve model. This means that the increase of rail passenger kilometres is not a transient response, but a long response after new rail. In summary, the lag model is important. It considers the time influence based on the basic model. The model is set as:

$$\log(RPT_{it}) = c + \sum_k \beta^k \log(X_{it}^k) + \sum_l \lambda^l \log(RK_{i(t-l)}) + \varepsilon_{it} \tag{2}$$

The parameters are defined as:

$\lambda^l$  - undetermined coefficient;

$RK_{i(t-l)}$ - rail kilometres in region  $i$  for year  $t-l$ .

The lag model considers not only the demographic and economic factors, but also the time lag effect. This reflects the response of new or improved road, so as rail kilometres in region  $i$  of year  $t$  are related with rail passenger kilometres of year  $t-l$ . Elasticities of rail kilometres with respect to rail passenger kilometres correspond to the coefficient on the rail-kilometres variable  $\sum_{l=0}^L \lambda^l$ . This model assumes that the elasticity coefficient of different regions at the same time period is the same.

Table 6 – Results of the lag model in China

Independent variables	$\log(RK_{it})$	$\log(RK_{i(t-1)})$	$\log(RK_{i(t-2)})$	$\log(RK_{i(t-3)})$	$\log(RK_{i(t-4)})$
Value	0.056	0.061	0.066	0.070	0.075
t-statistic	2.377	3.377	5.074	6.503	5.660
Variables	$\log(RK_{i(t-5)})$	$\log(RK_{i(t-6)})$	$\log(GRP)$	$\log(population)$	constant
Value	0.079	0.084	0.259	0.450	2.180
t-statistic	4.297	3.381	10.674	4.734	3.340
$R^2: 0.675$		$F$ -statistic: 133.114		$DW$ -statistic: 2.100	

Note: RK means rail kilometres

### 4.2.2 Results analysis

Based on the model structure and data collection, Table 6 presents the results of estimating the lag model using software Eviews 6.0. Using cross correlogram could get the 6-lag year. These results in Table 6 show that almost all the coefficients were estimated with a high degree of precision, obtaining plausible signs and magnitudes. These prove that the usefulness of lag model can show the time effect in an accurate way. High  $R^2$  and  $F$  value means the accurate model formation. Durbin–Watson statistics means that the residual serial correlation does not exist in the model.

These results in Table 6 suggest that the time effect needs to be considered. The lag rail kilometres elasticity with respect to rail passenger kilometres is significantly positive, increasing with time. These elasticity values reflect people’s reaction to rail improvement and cultivated travel mode choices habit. The rail kilometres elasticity of rail passenger kilometres is 0.056 in the short term and 0.435 in the long term. These mean that the new or improved railway will increase rail passenger kilometres less in the first year, whereas big growth is expected in the later years. The rail kilometres’ time effect on rail passenger kilometres reflect cumulated increase. Both GRP and population are also significant to rail passenger kilometres, whose value is similar to elasticity-based model.

## 4.3 HSR elasticity model construction and results analysis

### 4.3.1 HSR elasticity model

The first HSR in China is the Qinhuangdao-Shenyang HSR, which has been in operation since 2003. After that, different provinces or cities started to build HSRs. In 2015, China’s HSR operating mileage of 19,000 km was the highest in the world. The fast development of HSR has affected the passengers travel pattern, travel frequency, and travel distance, etc. Therefore, HSR should be considered in the separated way from the entyre rail network. The conventional rail kilometres and HSR kilometres are included in the HSR

elasticity model to show individual influences of different rail types. However, some provinces have not constructed HSR until 2014, such as Inner Mongolia Autonomous Region, Guizhou province, Yunnan province, Xizang Autonomous Region, Shaanxi province, Gansu province, Qinghai province, Ningxia Hui Autonomous Region, Xinjiang Uygur Auto and Hainan province. In summary, the HSR elasticity model is constructed to consider rail type influences. The model is set as:

$$\log(RPT_{it}) = c + \alpha_i + \tau_t + \sum_k \beta^k \log(X_{it}^k) + \delta \log(NK_{it}) + \gamma \log(HK_{it}) + \varepsilon_{it} \quad (3)$$

The parameters are defined as:

- $NK_{it}$ - conventional rail kilometres in region  $i$  for year  $t$ ;
- $HK_{it}$ - HSR kilometres in region  $i$  for year  $t$ ;
- $\delta$  - coefficient to be estimated for conventional rail parameter;
- $\gamma$  - coefficient to be estimated for HSR parameter.

The HSR elasticity model shows the interrelationships between rail passenger kilometres on various rail types to improve model estimation using contemporaneous correlation between error terms. This reflects various responses of the new or improved rail. Elasticity of conventional rail kilometres with respect to rail passenger kilometres is  $\delta$ . And the elasticity of HSR kilometres with respect to rail passenger kilometres is  $\gamma$ . This model assumes that a given amount of rail passenger kilometres on conventional rail will not affect the amount of rail passenger kilometres on HSR. The reverse is also reasonable.

#### 4.3.2 Results analysis

Based on the model structure and data collection, Table 7 presents the results of estimating the HSR elasticity model using software Eviews 6.0. These results in Table 7 show that all the coefficients were estimated with a high degree of precision, obtaining plausible signs and magnitudes. These prove that the usefulness of HSR elasticity model can show the influences of rail types. High  $R^2$  and  $F$  value means the accurate model formation. Durbin-Watson statistics means residual serial correlation does not exist in the model.

These results shown in Table 7 mean that the conventional railway elasticity to rail passenger kilometres (0.255) is nearly ten times larger than HSR elasticity to rail passenger kilometres (0.026). The huge elasticity gap is opposite to our basic thinking. This is due to

three reasons. In the first place, HSR kilometres grow from null to 13,357 kilometres. The basic conventional rail is nearly 100,000 kilometres and the unit of rail passenger kilometres is billion. So, travel distance of HSR is shorter than the normal speed rail. It is easy to make HSR kilometres grow 1%, but hard to increase the conventional rail by 0.1%. In the second place, HSR construction has not formed the national network. Many provinces are constructing or planning to construct HSR. So, many zeroes in the model calculation will cause small coefficient using least squares method. In the third place, people should have response time to travel mode changes, due to less travel time and higher ticket prices with HSR. Therefore, HSR will cause huge effect on rail passenger kilometres, which should be considered. Both GRP and population are significant to rail passenger kilometres. The elasticity value of GRP and population in HSR elasticity model is similar with that in the elasticity-based model, which shows stable influencing.

#### 4.4 Rail efficiency model construction and results analysis

##### 4.4.1 Rail efficiency model

Since 2006, all cities and provinces have constructed railways. Due to rail transportation characteristic, only two directed ways between two cities should meet the peoples' travel demand. People should choose rail modes based on the train timetable. In order to satisfy the peoples' travel demand, railways should also be constructed in the rural region, in spite of fewer passengers. Therefore, the length of railway is decided by geographical conditions. Some cities or provinces own a large amount of railways, such as Inner Mongolia Autonomous Region, Hebei province, Shandong province, Xinjiang Uygur Auto and so on. On the other hand, some cities or provinces own a little amount of railways, such as, Shanghai city, Beijing city, and Tianjin city. These lead to low rail passenger kilometres in some cities that have long railways. Meanwhile, some cities that have short railways will generate high rail passenger kilometres. Therefore, the rail efficiency should reflect the real rail kilometres' influences on rail passenger kilometres in various regions. The specification for the rail efficiency model is set as:

Table 7 – Results of the HSR elasticity model in China

Independent variables	log(conventional railway)	log(HSR)	log(GRP)	log(population)	constant
Value	0.255	0.026	0.332	0.485	1.795
t-statistic	9.216	8.217	17.744	5.590	2.873
$R^2: 0.717$		$F$ -statistic: 271.778		$DW$ -statistic: 1.864	



Table 8 – Results of the efficiency model in China

Independent variables	log(rail-kilometres)	log(GRP)	log(population)	constant	R <sup>2</sup>	F-statistic	DW-statistic
Value	0.399	-0.279	0.756	6.879	0.763	57.977	1.932
t-statistic	5.369	-2.695	5.972	6.444			

$$\log(RPT_{it}) = c + \alpha_i + \tau_t + \sum_k \beta^k \log(X_{it}^k) + \lambda \log(\mu RK_{it}) + \varepsilon_{it} \quad (4)$$

The parameter is defined as:

$\mu$  - the railway efficiency ratio.

Railway efficiency ratio  $\mu$  is defined as individual city or province rail passenger kilometres per rail kilometres as a percentage of Beijing city rail passenger kilometres per rail kilometres. The elasticity coefficient between efficient rail kilometres and rail passenger kilometres is valued  $\lambda$ . This means that efficient rail kilometres increased by 1%, and rail passenger kilometres will grow  $\lambda\%$ . This model assumes that the elasticity coefficient of different regions at different time is the same.

#### 4.4.2 Results analysis

Based on the model structure and data collection, Table 8 presents the results of estimating the rail efficiency model using software Eviews 6.0. These results in Table 8 show that all the coefficients were estimated with a high degree of precision, obtaining plausible signs and magnitudes. High R<sup>2</sup> and F value mean accurate model formation. Durbin-Watson statistics means residual serial correlation does not exist in the model. Due to little data collection in train timetable, only using 28 provinces and 3 municipalities of China in the year 2011 and 2012 the simulation results were obtained. The railway efficiency ratio is the percentage of passenger trains in other cities taking Beijing city in 2011.

Table 8 shows the results of the estimation using the rail efficiency model, suggesting that the 1% growth of rail kilometres will increase rail passenger kilometres by 0.399%, larger than elasticity-based model. These show the necessity of efficiency ratio. Compared with elasticity-based model in Table 4, one special difference is that GRP elasticity of rail passenger kilometres is significantly negative, which is contradictory to people's basic thinking. We think it is because GRP development also makes people choose air transport. Due to HSR construction, air transport has to decrease air ticket price to compete with HSR. Therefore, passengers tend to choose HSR for short distances and air transport for long distances. Population has significant impact on rail passenger kilometres, showing the population increased by 1%, rail passenger kilometres will grow by 0.756%. The population elasticity is nearly

Table 9 – Errors between actual and predicted values in China

City or province	Error
Beijing city	0.014
Tianjin city	-0.015
Hebei province	-0.017
Inner Mongolia Autonomous Region	0.021
Shanxi province	0.017
Liaoning province	-0.015
Jilin province	0.0001
Heilongjiang province	0.009
Shanghai city	0.028
Jiangsu province	0.009
Zhejiang province	-0.001
Anhui province	-0.013
Fujian province	0.023
Jiangxi province	-0.032
Shandong province	0.014
Henan province	0.015
Hubei province	-0.011
Hunan province	-0.027
Guangdong province	0.008
Guangxi Zhuang Autonomous Region	0.017
Chongqing city	0.026
Sichuan province	0.020
Guizhou province	-0.007
Yunnan province	0.048
Shanxi province	-0.017
Gansu province	-0.030
Qinghai province	0.010
Ningxia Hui Autonomous Region	0.009
Xinjiang Uygur Auto	0.0005

1.75 times as elasticity-based, reflecting passengers would like to travel by train after 2010.

#### 4.5 Errors analysis

In order to show whether the model could predict rail demand, errors between actual and predicted values are shown in Table 9 in China on the basis of elasticity-based model. The results show that high precision (above 95%) for prediction could guarantee travel demand model construction incorporation induced traffic. The error values appear both positive and negative, meaning the forecasting model could better predict travel demand. The differences in error

values could show cities or provinces have different qualities, meaning that divided zones consideration are valuable to research.

## 5. CONCLUSION

Elasticity-based model, distributed lag model, HSR elasticity model and rail efficiency model are constructed to confirm the existence of induced traffic. So, it is necessary to consider the rail-induced traffic in China in the future. Time effect, divided zones, rail efficiency and HSR should be paid more attention to research. Based on the data collection of 26 provinces and 3 municipalities of China between the year 2000 and 2014, the rail kilometres' elastic coefficients to rail passenger kilometres turn out to be 0.026-0.678. And the population also increases rail passenger kilometres. HSR elasticity to rail passenger kilometres is 0.026, showing HSR kilometres growth of 1%, and passenger-kilometres of railway increase 0.026%. HSR increasing construction would generate considerable induced traffic under fast development of rail. In summary, different elasticity models can be suitable to various research aims. The forecasting will support the reasonable rail operational planning, which is suitable to passenger transportation planning.

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### 中国铁路诱增交通量

#### 摘要

近年来, 中国铁路的快速发展对城际客运运输结构产生了巨大影响。然而由于诱增交通量的存在, 迅猛增长的铁路里程并没有满足人们日益增长的需求。铁路诱增交通量是铁路里程增长所导致铁路客运周转量的增加。为了解决上述问题, 本文致力于构建需求预测模型, 以实现当前交通需求的准确测算, 并可以有效预测考虑潜在需求的未来20年或30年的交通量。基于诱增交通量的定义和相关研究情况, 应用中国26个省市和3个自治区2000年-2014年面板数据收集, 构建弹性系数模型, 其中包括基本模型、分布滞后模型、高速铁路弹性系数模型和铁路效用模型。结果表明了考虑铁路诱增交通量模型

构建的重要性。在省市中, 依据列车频率确定分区或者考虑铁路效用将获得准确预测值。延迟时间和铁路类型也需要考虑。总之, 结果分析不仅证明了铁路诱增交通量的存在, 更为今后的铁路列车运行计划提供实质建议。

#### 关键词

列车运行计划; 铁路诱增交通量; 弹性系数模型; 铁路营业里程; 铁路客运周转量;

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