Xi'an Jiaotong-Liverpool University

Research Institute for Economic Integration

Working Papers Series

(RIEI WP series)

Heterogeneous Economic Impacts of Transportation Features on Prefecture-level Chinese Cities

by

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Working paper number: 2015-02

Notes:
Original version: 3 Aug 2015

Heterogeneous Economic Impacts of Transportation Features on Prefecture-Level Chinese Cities

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Abstract

The present paper examines the heterogeneous economic impacts of transportation characteristics, with a consideration of spatial heterogeneity, across Chinese prefecture-level cities. Using data from 237 Chines cities from 2000 to 2012, a random-parameters model was applied to account for the heterogeneity across these cities.

The estimation results revealed significant variability across cities, with the computed impacts (elasticity values) of transportation-related features (highway and railway freight volumes, highway passenger volume, urbanization rate, public transit, paved roads, and highway congestion rate) varying significantly across cities.

The impacts were mostly positive, except for highway congestion rate. A 1% increase in a city's highway and railway freight volumes would increase the city's gross product per capita from 0.0001% to 0.0972% and 0.0001% to 0.0254% across cities in China, respectively. While a 1% increase in highway congestion rate would decrease the city's gross product per capita by an average of 0.031%.

Keywords: Chinese cities, economic growth, heterogeneity, highway, railway, freight, random-parameters model

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1. Introduction

Transportation infrastructure has been prioritized by both central and local Chinese governments since the eighth five-year plan (1991-1995) with the realization of significant role played in promoting economic development, and since then, transportation infrastructure continues to be an essential part of China's regional development policy. The total length of railway in operation has been increased from 57.8 thousand kilometers to 103.1 thousand kilometers since 1991 until 2013, while the length of highway has increased significantly from 1041.1 thousand kilometers (in 1991) to 4356.2 (in 2013) thousand kilometers (National Bureau of Statistics of China, 2013). At the end of the first five-year plan, the length of highway was 137.1 thousand kilometers, thus, it can be inferred that China has made significant investment in transportation infrastructure development over the recent three decades, and the average growth rate was over 10% per year, since 1978. During the 2008-2009, China stimulated the economy by using 40% of the US$586 billion economic stimulus package devoted to infrastructure development.

From the significant investments made to develop infrastructure, especially transportation infrastructure, China can be observed to see a substantial growth in her economic output, and the question that ought to be answered is whether the infrastructure investment strategies contributed to the economic growth of the Chinese economy (Barro and Sala I Martin, 2004).

There is an abundant of international empirical evidence showing an affirmative answer to the first question with a wide range of elasticity estimates (see survey papers by Romp and De Haan, 2005; Melo, P. C., et.al, 2013 and Deng, T., 2013). The variety could be attributed to varied econometric specifications with or without accounting for the time and spatial effects, the definitions and measures of public infrastructure, the estimation methodology as well as research contexts in terms of study period and geographical scales. The strand of literature (see Table 1) analyzed the effects of public infrastructure on private output, and was brought to the limelight by the seminal paper of Aschauer (1989). The elasticity results in his paper ranges from 0.25 to 0.56, and the different types of public inputs are termed as the ‘core’ infrastructure such as streets, highways, mass transits, and airports. These results were found to be consistent with other studies (Munnell, 1990 and 1992; Berndt and Hansson, 1992; Sanchez-Robles, 1998, Kavanagh, 1997; Carboni and Medda, 2011) which were carried out at both national and regional levels.

The different impact of transport investments in each city may be caused by the decentralized economic structure even through China is a politically centralized country (Xu Chenggang 2011). During the transition toward a market-based economy since the beginning of the reform period, this decentralization process has exerted contrasting influences on the infrastructure provision at regional levels. This becomes more evident after the 1994 tax reform when more than 60% of local tax revenues went to the central government while the local expenditure needs remain roughly the same. This leads to conflicting interests for local government with twin identities as both a public good and service provider and an entrepreneur. On one hand, a local official such as a provincial governor has been forced to meet the demand for varied types of public goods and services in different subordinate cities, and on the other hand, he has to focus on the most productive activities to promote the provincial economic growth. It is thus intriguing to see which group of the subordinate cities in this specific region contributes the most to its aggregate output leveraging on the infrastructure investment. Thus, this study generates two-fold policy implications with results providing heterogeneous elasticity estimation across Chinese cities, and with analysis of varied contribution from both intra-city and inter-city transport connections. These results would benefit both central and regional policy-makers.

Using Chinese provincial level data, a few papers have examined the contribution of the aggregate public infrastructure to the productive performance (Vijvereberg, Fu and Vijverberg, 2011), the spatial spillover effects of transport infrastructure (Zhang, 2008; Yu, Jong, Storm and Mi, 2013) as well as the poverty reduction effect (Fan and Zhang, 2004). Similarly, Demurger (2001) measures the transport endowment using the overall network density (incorporating road, railway and waterway) based on a panel data from 24 Chinese provinces (excluding municipalities) during 1985-1998, and shows that transport facilities are a key differentiating factor in explaining the growth gap. Hong, Chu and Wang (2011) constructs a provincial-level comprehensive index based on quantity and quality of railway, roadway, airport and seaport to show that the output elasticity of land transport (including roadway and railway) ranges from 0.554 to 2.757. The role of China's bullet trains to facilitate market integration and mitigate the cost of megacity growth is also confirmed by Zheng and Kahn (2013).

The present paper, with a regional focus on China, carried out a study using annual data from 2000-2012 at city level to gain a better understanding of the impact of transportation infrastructure on city economic performance. Compared with the existing studies discussed earlier, the present study can be considered as unique because it shows the first attempt to investigate the heterogeneous output effects across varied-sized Chinese cities of both inter-city and the intra-city transport network. In the present study, highways and railways are considered to represent inter-city infrastructure and the public road network to represent intra-city infrastructure. A random parameters model (Agbelie, 2014) is adopted to account for possible unobserved heterogeneity across cities to shed light on the effect of transportation-related characteristics (including transportation freight and passenger volumes, public transit transportation, paved road, and highway congestion) on a city's economy in China. We thus answer the question to what degree transport infrastructure and which type of transport infrastructure matters for which specific city in China.

The present paper is structured in five sections, with Section 1 discusses the existing literature, and the problem statement. Section 2 presents the data and empirical setting, and the methodology is discussed in Section 3. The estimated results and discussions on the estimated parameters and elastic values are found in Section 4. The summary and conclusions are presented in Section 5.

2. Data and empirical setting

China consists of 34 provincial administrative units including 23 provinces, 5 autonomous regions, 4 municipalities, and 2 special economic zones. Subordinate to provinces are prefectures (dijishi) and each prefecture has at least one core city (shixiaqu), some rural counties (xian), and several county-level cities (xianjishi). The current number of Chinese prefecture cities is 289, however, due to the unavailability of consistent data across all the cities, only 237 prefecture cities were considered in the present study. Thus, the analysis was carried out using data from prefecture-level city, which includes both the urban and rural administrative areas.

The city-level data (gross city product (GCP), price index for converting nominal variables into real variables, physical measures of transport infrastructure-related characteristics, passenger and freight volumes of different transport mode, and demographics) available for the present study were collected from a number of sources including the China City Statistical Yearbook (various years 2000-2013), CEIC, China Data Online and Wind Database. The period of data collected was from 2000 to 2012.

The fixed asset investment variable was used in the model to represent the total workload on construction and purchase for fixed assets during the analysis period (2000 -2012), and this data was collected from CEIC and used as a proxy for the private capital stock. The descriptive statistics of the significant variables used in the final model are presented in Table 2.

3. Methodological approach

To examine the economic impacts of highway and railway across the selected cities in China, a methodological procedure that accounts for unobserved heterogeneity across cities will be appropriate. In the past, a number of statistical methods have been used to carry out this type of investigation including ordinary least square regression models, and fixed-effects model (Aschauer, 1989; Munnell and Cook, 1990; Ozbay et al., 2007). However, in recent years, a new methodological approach, a random-parameters regression model (Agbelie, 2014), has been applied for the first time in economic impact analysis of transportation infrastructure expenditure to capture unobserved heterogeneity across observations and also heterogeneity across observations and time. This new method has been shown to be more statistically robust compared to the previous statistical methods (ordinary least squares regression, fixed- and random-effects models). Furthermore, the random-parameters regression model is able to account for unobserved heterogeneity across observations compared to the previous statistical methods. Thus in the present paper, we will follow the random-parameters regression model as derived and applied to investigate the economic impacts of transportation infrastructure expenditures by Agbelie (2014). Starting with the equation:

$$LnY_{k,t} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_{\mathrm{k}} Ln\boldsymbol{X}_{\mathrm{k},\,t} + \varepsilon_{\mathrm{k},\,t} \,, \qquad (1)$$

where $Y_{k,t}$ is the gross city's product (GCP) per capita (in 2010 USD) for city *k* at year *t*, $\boldsymbol{X}_{\mathrm{K},t}$ is a vector of the independent variables (highway freight volumes, railway freight volumes, paved roads, highway passenger volume, fixed asset investment urbanization rate, public transportation unit per ten thousand people, industrial sector's contribution to gross city product, highway congestion rate, and labor participation rate) for city *k* in time *t*, $\boldsymbol{\beta}_{\mathrm{k}}$ is a vector of estimable parameters, and $\varepsilon_{k,t}$ are normally distributed random disturbances.

The estimation of Equation (1) by the ordinary least square approach has two distinct issues. First, the possibility of highway and railway freight volumes being endogenous (simultaneous casualty bias), that is, it may be possible that higher GCP generates higher freight volumes in highway and railway, while it is expected also that higher freight volumes in highway and railway would generate higher gross product in a city. Thus, the gross product and freight volumes could be endogenous and violating the fundamental assumption underpinning the ordinary least squares estimation, resulting in biased coefficient estimates. This concern was resolved in the present study by adopting instrumental variable procedure whereby highway and railway freight volumes are regressed against exogenous variables and the predicted values were used as variables in the estimation of Equation (1). The second issue with the estimation was that each of the cities will produce 13 observations from 2000-2012, and these 13 observations are likely to share unobserved effects resulting in serially correlated data, thus, violating one of the OLS assumptions of no serial correlation . This issue can be resolved by allowing the constant term to vary across observations (see Washington et al, 2011). Therefore, the use of the random parameters model will allow all estimable parameters to be fixed for each individual city but to vary across cities.[2]

To include random-parameters in Equation (1), city-specific estimable parameters are written as,

$$\beta_k = \beta + \varphi_k \quad , \qquad (2)$$

where β_k is a parameter estimated for city k, β is a parameter estimate fixed across city, and φ_k is a randomly distributed term (for each city k) that can take on an extensive variety of distributions including the log-normal, beta, normal, and so on. Equation 1 can be estimated, with such random

[2] Simple fixed and random effects models were also estimated, in addition to a finite mixture model. However, likelihood ratio tests clearly indicate that a full random-parameters approach provides a superior statistical fit to the data.

parameters (since β_k varies across cities according to the random term φ_k as shown in Equation 2), with maximum likelihood techniques. Nonetheless, the maximum likelihood estimation of random-parameters regression model is computationally cumbersome, thus, simulation-based likelihood methods have been proven to be more appropriate, and an approach that uses Halton draws (Halton, 1960) has been shown to provide a more efficient distribution of draws than purely random draws (see Greene, 2012). Thus, for the present study's estimation of the random parameters model, Halton draws were used.

To interpret estimation findings, the elasticity of gross city product per capita (GCPPC) with respect to each independent variable was,

$$\boldsymbol{\beta_k} = \frac{\frac{\Delta Y_k}{Y_k}}{\frac{\Delta \boldsymbol{X_k}}{\boldsymbol{X_k}}}, \qquad (3)$$

where ΔY_k is the change in gross city product per capita for the k^{th} city, and Y_k is the k^{th} city's GCPPC, ΔX_k is the change in independent variable for the k^{th} city.

4. Estimation results

The estimated results are illustrated in Table 3[3] and the detailed estimation for each specific city[4] is reported in Table 4a-4d.[5] Turning to specific variables, it can be observed that highway freight volume was found to be statistically significant with a lognormal distribution and the expected positive sign, indicating that an increase in highway freight volume increases gross city product per capita (GCPPC). The average elasticity for highway freight volume across cities was

[3] Detailed estimated parameters for the 237 cities are available upon request.
[4] The cities in Table 4a-4b are labelled with the upper case letters denoting the province and the lower case letters denoting the city names.
[5] A full random-parameters model was estimated with each observation having its own parameters (each city would generate 13 observations, one for each year of data). However, likelihood ratio test results clearly show that the model with parameters varying across cities but fixed within each city provided the best statistical fit.

0.016 (as shown in Table 3), showing that a 1% increase in highway freight volume would increase a city's gross product per capita, on average, by 0.016% and the impact varies from 0.0001 to 0.0972 across the selected cities in China. Thus, it can be observed that the computed elasticity values vary significantly across different tier of cities[6] shown in Table 4a-4d. For example, highway freight volume generated the highest impact of 0.0972 in the city of Shenzhen (Table 4a) and the lowest impact value of 0.0001 in the cities of FJzhangzhou (Table 4c) and JXjian (Table 4d). The average elasticity for highway freight volume is 0.0304, 0.0142, 0.0148 and 0.0165 for the 1st, 2nd, 3rd and 4th tier cities in China. This indicates the unbalanced impacts of highway freight volume across Chinese cities.

The parameter for railway freight volume was found to be statistically significant with a positive impact on the GCPPC. The average elasticity was rather a modest 0.005 across all cities and was found to range from 0.0001 to 0.0254 across the selected cities. Thus, a 1% increase in railway freight volume would increase GCPPC by 0.0001% in the city of AHanqing (Table 4c), SDrizhao (Table 4c), HuNzhuzhou (Table 4c), SCmianyang (Table 4c), SDzibo (Table 4c) and GDchaozhou (Table 4d) to 0.0307% in the city of HBqinhuangdao (Table 4c) across mainland China. It appears that while railway freight volume positively impacted a city's gross product per capita, on average, it generated a lower economic impact compared to highway freight volume. This result is consistent in direction with previous studies (Sonstegaard, 1992; Agbelie, 2014) which found that in many countries, highways seem to be a more effective way to transport freight within short distances and flexible time periods; thus, the higher economic impact from highways compared to railways. In addition, the railway impact in the 1st tier of Chinese cities has been the lowest (0.0065) compared with the 2nd tier cities (0.0079). The contribution of railway freight

[6] The subdivisions of the 1st-, 2nd-, 3rd-, and 4th-tier cities are based on the definitions given by the Institute of Finance and Trade Economics, Chinese Academy of Social Sciences.

volume was found to be approximately the same in the 3rd (0.0072) and the 4th tier cities (0.0073).

The area of paved roads, which reflects the extent of quality highway network in a city, produced a positive and statistically significant effect, indicating that paved highway infrastructure can also be considered as an important factor in determining a city’s gross product, ostensibly by providing mobility and accessibility resulting in economic productivity. A 1% increase in paved road area in a city would increase GCPPC by an average of 0.007%, and this impact varies significantly from 0.00001% to 0.0233% across the selected 237 cities in China.

Highway passenger volume, which indicates the number of people commuting from one place to another along the highway network, was found to produce a statistically significant random parameter. The average elasticity was 0.017 (about 6 percent more than the average elasticity of highway freight volumes) with respect to GCPPC, with values ranging from 0.0001 to 0.1415 across cities. It can be observed that highway passenger volume significantly impacts a city’s gross product, and if this variable is ignored in the economic impacts analysis of transportation at the city’s level, the impacts from the other transportation variables would be exaggerated.

Total investment in fixed assets (including highway and railway infrastructures) was also examined, and observed to be statistically significant with a positive sign, indicating that an increase in total fixed asset expenditures increases gross city product. The elasticity for fixed asset investment was found to vary from 0.007 to 0.103 across cities, with an average elasticity value of 0.051. Thus, a 1% increase in total fixed asset investments would increase gross city product per capita, on average, by 0.051% across cities.

Urbanization rate, considered as the ratio of a city’s urban population to the city’s total population, was found to produce a statistically significant random parameter, and the average elasticity was 0.313, and varies from 0.002 to 1.042 across cities. The result indicates that a 1%

increase in the urbanization rate would increase a city's gross product per capita, on average, by 0.313%, and the economic impact across cities varies from 0.002 to 1.042. This result indicates that as a city's urban population increases, the higher the likelihood of increasing the city's gross income per capita.

Public transportation unit per person, which reflects the number of public transportation units per person in a city, was found to be statistically significant and the sign was positive. Therefore, a 1% increase in public transportation unit per person would increase gross city product per capita, on average, by 0.021%, and the impact varies from 0.012% to 0.034% across cities. From the computed impact value, the result indicates that an increase in public transportation units per person would facilitate mobility and would improve accessibility, thus enhancing economic activity in a city.

Highway congestion rate, considered as the ratio of a city's transportation units including buses and taxies divided by the city's area of paved roads at year-end, was also found to be statistically significant with a negative impact on a city's gross product. The average elasticity was -0.031 and was found to range from -0.118 to -0.001 across cities. The result indicates that as a city's number of transportation units per paved highway area increases, there is a negative impact on its economy activity due to relatively longer travel time for passengers and freights resulting in inefficiencies. Thus, a 1% increase in highway congestion rate would reduce GCPPC, on average, by 0.031%.

With regard to non-transportation related variables, estimation results presented in Table 3 show that an increase in the labor participation rate (percentage of employable people in a city) increases the gross city product per capita. Thus, a 1% increase in labor participation rate would increase, on average, the GCPPC by 3.110% and the impact varies from 2.547% to 3.622% across cities, suggesting that labor participation rate, on average, had an elastic relationship with economic output in a city.

Industrial sector's contribution to a city's gross product per capita resulted in statistically significant random parameter, and a 1% increase in industrial sector's contribution would increase, on average, a city's gross product by 0.127%, and the impact varies from 0.103% to 0.149% across cities. Finally, the service sector's contribution to the gross product of a city produced a statistically significant random parameter, and a 1% increase in this sector's contribution would increase a city's gross product by 0.362%, and the economic impact varies from 0.148% to 0.510% across cities. The result indicates that the service sector's elasticity was relatively higher than that of the industrial's sector – a finding that is consistent with the findings of previous studies (Tamura et al., 2005; Sheehan, 2006; Agbelie, 2014). The preceding studies concluded that although in the past the service sector had not been innovative and unproductive resulting in relatively lower wage jobs, recent trends show that the service sector continues to be more innovative and productive compared to the industrial sector in many countries.

5. Summary and Conclusions

The present paper takes a renewed look at the relationship between transport and its effect on a city's gross product. In the past, cross-city analyses of this topic, especially in China, did not receive adequate attention due to data limitations and the absence of a methodological framework that could account for unobserved heterogeneity across cities. This paper uses a multi-city data base to estimate a random-parameters model to account for unobserved heterogeneity across cities.

The results show that key transportation measures, which have not been considered in past economic impact studies, including highway and railway freight volumes, highway passenger volumes, congestion rate, public transportation, area of paved roads, fixed asset investment clearly influence a city's gross product. However, the magnitude of the influence and the resulting impact on a city's economic output with respect to transportation varies considerably across cities. Among highway and rail freight volumes, it was also found that highway freight volume has a much larger effect on a city's economic output compared to railway freight volume.

The findings of this paper generate significant policy implications in transportation infrastructure evaluations across Chinese cities. At the national level, the differences in elasticity values can be used to develop effective expenditure strategies for assigning weights to each mode in a multimodal objective analysis framework. At regional policy level, the elasticity values estimated for highways and railways can be adopted to influence the distribution of transportation investment between inter- and intra-city transport networks.

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Table 1: Empirical evidence on the estimates of output elasticity of public/transport infrastructure

Study	Aggregation Level	Data Type	Econometric method	Elasticity estimation
Aschauer (1989)	National	Time series	Cobb-Douglas production function	The elasticity of non-military capital stock: 0.25-0.56
Brun et al. (2002)	Sub-national	Panel data	Barro-type model	No impact of the length of roads on economic growth
Berndt and Hansson (1992)	Swedish National Level	Time series	Dual cost function	The Public infrastructure on the productivity growth: 0.058-0.149
Chiara Del Bo& Massimo Florio (2011)	Sub-national (EU regions)	Panel data	Cobb-Douglas production function with Spatial Durbin Model	The output elasticity of transport infrastructure: 0.05
Demurger (2001)	Sub-national (Provincial)	Panel data	Growth equation	Positive effect on per capital income over 1985-1998 for 24 provinces
Fleisher&Chen (1997)	Sub-national (Provincial)	Panel data	Production function	Minor impact on provincial total factor productivity growth from 1978-1993
Fan, Zhang&Zhang(2002)	Sub-national (Provincial)	Panel data	Simultaneous equation system	The contribution of roads expenditure to the rural area agricultural sector productivity: 0.085
Kavanagh (1997)	Ireland national level	Time series	Production function	The elasticity of public capital on output: 0.36
Ozbay et al. (2007)	Sub-national (County)	Panel data	multiple regression	The elasticity of highway investment ranges from 0.02 to 0.21
Vijverberg, Fu&Vijverberg (2011)	Sub-national (Provincial)	Panel data	Cost function with Maximum Likelihood estimation	The contribution of public infrastructure to the growth in labor productivity among industrial enterprises: 0.02-0.03
Zhang (2008)	Sub-national (Provincial)	Panel data	Production function	The output elasticity of transport infrastructure: 0.11

Table 2. Descriptive statistics of selected variables.

Variable Description	Mean	Std. dev.	Min	Max
Highway freight volumes (in ten thousands)	6,343.2	6,992.5	9.0	95,009.0
Railway freight volumes (in ten thousands)	1,166.9	1,950.3	4.9	30,009.0
Paved roads (in km^2)	1,204.6	1,756.3	6.0	21,490.0
Highway passenger volume (in ten thousands)	7,674.6	11,701.6	82.0	179,369.0
Fixed asset investment (in millions of 2010$USD)	8.63	13.2	0.08	150.1
Urbanization rate	0.54	0.52	0.08	0.90
Public transportation unit per ten thousand people	60.4	45.5	19.3	525.6
Industrial sector's contribution to gross city product (in millions of 2010$USD)	6.8	14.4	0.06	218.7
Service sector's contribution to gross city product (in millions of 2010$USD)	8.3	12.2	0.09	126.8
Highway congestion rate	4.24	5.95	0.27	37.12
Labor participation rate	0.71	0.02	0.68	0.74

Table 3. Random parameters model estimation results (All random parameters are normally distributed).

Variable Description[7]	**Parameter Estimate**	***t*-Statistic**
Constant	1.882 (0.153)	29.937 (6.100)
Log of highway freight volumes (in ten thousands)	0.016 (0.041)	6.298 (10.575)
Log of railway freight volumes (in ten thousands)	0.005 (0.019)	2.989 (4.087)
Log of paved roads (in km^2)	0.007 (0.006)	1.309 (13.774)
Log of highway passenger volume (in ten thousands)	0.017 (0.056)	4.673 (5.323)
Log of fixed asset investment (in millions of 2010$USD)	0.051 (0.029)	7.837 (5.015)
Log of urbanization rate	0.313 (0.307)	7.296 (6.516)
Log of public transportation unit per person	0.021 (0.007)	6.541 (22.617)
Log of highway congestion rate	-0.031 (0.300)	-5.870 (23.048)
Log of labor participation rate	3.110 (0.406)	18.883 (6.387)
Log of industrial sector's contribution to gross city product	0.127 (0.016)	17.143 (18.128)
Log of service sector's contribution to gross city product	0.362 (0.101)	9.545 (9.102)
Number of observations	3,081	
Log-likelihood at zero *LL*(0)	-4,067.839	
Log-likelihood at convergence *LL*(**β**)	-802.681	
ρ^2 [1 – *LL*(**β**)/ *LL*(0)]	0.803	

[7] Value in parenthesis is the standard deviation of parameter distribution for parameter estimate and t-statistic

Table 4a: Elasticities of highway and railway freight volumes in Tier 1 cities

City	Highway Freight Volume Output Elasticity (HFVOE)	Railway Freight Volume Output Elasticity (RFVOE)
Beijing	0.0069	0.0069
Tianjin	0.0110	0.0110
Shanghai	0.0172	0.0019
Guangzhou	0.0197	0.0062
Shenzhen	0.0972	0.0064

Table 4b: Elasticities of highway and railway freight volumes in Tier 2 cities

City	HFVOE	RFVOE	City	HFVOE	RFVOE	City	HFVOE	RFVOE
HBshijiazhuang	0.0039	0.0039	JSsuzhou	0.0172	0.0039	HNzhengzhou	0.0247	0.0092
HBtangshan	0.0005	0.0005	ZJhangzhou	0.0036	0.0099	HBwuhan	0.0080	0.0052
SXtaiyuan	0.0182	0.0182	ZJningbo	0.0129	0.0237	HuNchangsha	0.0089	0.0008
NMGhohhot	0.0622	0.0065	AHhefei	0.0018	0.0030	GXnanning	0.0152	0.0068
NMGbaotou	0.0252	0.0079	FJfuzhou	0.0016	0.0074	Chongqing	0.0157	0.0087
LNshenyang	0.0104	0.0037	FJxiamen	0.0206	0.0165	SCchengdu	0.0046	0.0071
LNdalian	0.0052	0.0064	FJquanzhou	0.0004	0.0116	GZguiyang	0.0048	0.0076
JLchangchun	0.0099	0.0096	JXnanchang	0.0134	0.0010	YNkunming	0.0417	0.0242
HLJharbin	0.0141	0.0021	SDjinan	0.0144	0.0042	ShXxian	0.0447	0.0009
JSnanjing	0.0007	0.0002	SDqingdao	0.0011	0.0124	GSlanzhou	0.0125	0.0035
JSwuxi	0.0257	0.0053	SDyantai	0.0065	0.0064	XJurumqi	0.0187	0.0221

Table 4c: Elasticities of highway and railway freight volumes in Tier 3 cities

City	HFVOE	RFVOE	City	HFVOE	RFVOE	City	HFVOE	RFVOE
HBqinhuangdao	0.0307	0.0307	ZJlishui	0.0065	0.0091	HByichang	0.0166	0.0100
HBhandan	0.0181	0.0181	AHwuhu	0.0292	0.0012	HBxiangfan	0.0094	0.0058
HBxingtai	0.0289	0.0289	AHbengbu	0.0046	0.0071	HuBjingzhou	0.0083	0.0037
HBbaoding	0.0081	0.0081	AHhuainan	0.0111	0.0039	HuNzhuzhou	0.0205	0.0001
HBchengde	0.0100	0.0100	AHmaanshan	0.0140	0.0174	HuNxiangtan	0.0284	0.0046
HBcangzhou	0.0125	0.0125	AHanqing	0.0203	0.0001	HuNhengyang	0.0009	0.0032
HBlangfang	0.0152	0.0152	FJzhangzhou	0.0001	0.0149	HuNyueyang	0.0051	0.0038
SXdatong	0.0033	0.0033	JXjingdezhen	0.0177	0.0020	HuNchangde	0.0159	0.0158
LNanshan	0.0181	0.0099	JXjiujiang	0.0055	0.0088	HuNchenzhou	0.0051	0.0043
LNfushun	0.0302	0.0069	JXxinyu	0.0334	0.0026	GDshantou	0.0141	0.0030
LNbenxi	0.0170	0.0021	JXganzhou	0.0091	0.0072	GDzhanjiang	0.0167	0.0078
LNdandong	0.0071	0.0013	SDzibo	0.0206	0.0001	GDmaoming	0.0047	0.0034
JLjilin	0.0140	0.0012	SDzaozhuang	0.0185	0.0018	GDzhaoqing	0.0076	0.0014
HLJqiqihar	0.0186	0.0011	SDdongying	0.0285	0.0170	GDhuizhou	0.0027	0.0064
HLJdaqing	0.0305	0.0089	SDweifang	0.0121	0.0084	GDmeizhou	0.0266	0.0004
HLJmudanjiang	0.0055	0.0042	SDjining	0.0032	0.0014	GDqingyuan	0.0212	0.0007
JSxuzhou	0.0007	0.0019	SDtaian	0.0040	0.0073	GXliuzhou	0.0505	0.0095
JSchangzhou	0.0239	0.0048	SDweihai	0.0158	0.0135	GXbeihai	0.0170	0.0028
JSnantong	0.0013	0.0182	SDrizhao	0.0217	0.0001	GXyulin	0.0236	0.0064
JSlianyungang	0.0131	0.0011	SDlinyi	0.0180	0.0048	HaNhaikou	0.0094	0.0211
JShuaian	0.0188	0.0048	SDdezhou	0.0155	0.0095	SCdeyang	0.0204	0.0061
JSyancheng	0.0086	0.0007	SDliaocheng	0.0095	0.0025	SCmianyang	0.0049	0.0001
JSyangzhou	0.0090	0.0035	SDbinzhou	0.0034	0.0135	SCyibin	0.0115	0.0019
JSzhenjiang	0.0245	0.0069	HNkaifeng	0.0044	0.0036	GZzunyi	0.0519	0.0133
JStaizhou	0.0050	0.0033	HNluoyang	0.0073	0.0066	ShXbaoji	0.0293	0.0169
ZJwenzhou	0.0122	0.0039	HNpingdingshan	0.0049	0.0101	ShXyanan	0.0103	0.0063
ZJjiaxing	0.0335	0.0063	HNanyang	0.0226	0.0063	GStianshui	0.0233	0.0137
ZJshaoxing	0.0078	0.0047	HNxinxiang	0.0124	0.0056	QHxining	0.0107	0.0058
ZJjinhua	0.0034	0.0046	HNjiangzuo	0.0115	0.0107	NXyinchuan	0.0152	0.0163
ZJquzhou	0.0090	0.0035	HNxuchang	0.0112	0.0190			

Table 4d: Elasticities of highway and railway freight volumes in Tier 4 cities

City	HFVOE	RFVOE	City	HFVOE	RFVOE	City	HFVOE	RFVOE
HBzhangjiakou	0.0078	0.0078	AHliuan	0.0157	0.0201	HuNhuaihua	0.0146	0.0083
HBhengshui	0.0057	0.0057	AHhaozhou	0.0085	0.0030	HuNloudi	0.0034	0.0020
SXyangquan	0.0172	0.0172	AHxuancheng	0.0053	0.0092	GDshaoguan	0.0123	0.0027
SXchangzhi	0.0031	0.0031	FJsanming	0.0105	0.0003	GDchaozhou	0.0164	0.0001
SXjincheng	0.0150	0.0150	FJnanping	0.0044	0.0051	GXguizhou	0.0097	0.0012
SXshuozhou	0.0251	0.0251	FJlongyan	0.0122	0.0031	GXfangchenggang	0.0506	0.0030
SXjinzhong	0.0081	0.0081	FJningde	0.0388	0.0010	GXqinzhou	0.0320	0.0062
SXyuncheng	0.0304	0.0005	JXpingxiang	0.0062	0.0019	GXguigang	0.0038	0.0127
SXxinzhou	0.0093	0.0056	JXyingtan	0.0401	0.0027	HaNsanya	0.0701	0.0114
SXlinfen	0.0126	0.0129	JXjian	0.0001	0.0116	SCzigong	0.0372	0.0018
NMGwuhai	0.0338	0.0130	JXyichun	0.0106	0.0063	SCpanzhihua	0.0340	0.0125
NMGchifeng	0.0226	0.0089	JXfuzhou	0.0149	0.0040	SCguangyuan	0.0083	0.0093
LNchaoyang	0.0176	0.0090	JXshangrao	0.0254	0.0134	SCsuining	0.0149	0.0015
LNhuludao	0.0178	0.0121	SDlaiwu	0.0166	0.0006	SCneijiang	0.0045	0.0191
JLsiping	0.0014	0.0032	SDheze	0.0087	0.0192	SCleshan	0.0267	0.0060
JLliaoyuan	0.0232	0.0066	HNhebi	0.0176	0.0014	SCnanchong	0.0022	0.0037
JLtonghua	0.0046	0.0042	HNluohe	0.0127	0.0038	SCmeishan	0.0083	0.0080
JLbaishan	0.0086	0.0048	HNsanmenxia	0.0076	0.0007	SCguangan	0.0144	0.0042
JLsongyuan	0.0080	0.0061	HNnanyang	0.0070	0.0048	SCdazhou	0.0005	0.0117
JLbaicheng	0.0040	0.0022	HNshangqiu	0.0052	0.0213	SCziyang	0.0105	0.0040
HLJjixi	0.0123	0.0008	HNxinyang	0.0076	0.0009	GZliupanshui	0.0504	0.0033
HLJhegang	0.0295	0.0031	HNzhoukou	0.0091	0.0009	GZanshun	0.0052	0.0205
HLJshuangyashan	0.0328	0.0056	HNzhumadian	0.0172	0.0044	YNqujing	0.0003	0.0217
HLJyichun	0.0231	0.0044	HBhuangshi	0.0058	0.0054	YNyuxi	0.0222	0.0023
HLJjiamusi	0.0377	0.0006	HBshiyan	0.0070	0.0062	ShXtongzhou	0.0334	0.0023
HLJqitaihe	0.0162	0.0129	HBezhou	0.0428	0.0029	ShXxianyang	0.0053	0.0067
HLJheihe	0.0040	0.0149	HBjingmen	0.0004	0.0070	ShXhanzhong	0.0169	0.0107
HLJsuihua	0.0112	0.0089	HBxiaogan	0.0029	0.0050	ShXyulin	0.0104	0.0031
JSsuqian	0.0037	0.0081	HuBhuanggang	0.0125	0.0055	GSjiayuguan	0.0823	0.0140
AHhuaibei	0.0321	0.0003	HuBxianning	0.0010	0.0043	GSjinchang	0.0435	0.0212
AHtongling	0.0309	0.0065	HuBsuizhou	0.0086	0.0004	GSbaiyin	0.0219	0.0081
AHhuangshan	0.0115	0.0011	HuNshaoyang	0.0214	0.0117	NXshizuishan	0.0100	0.0254
AHchuzhou	0.0012	0.0028	HuNzhangjiajie	0.0254	0.0026	NXwuzhong	0.0410	0.0198
AHfuyang	0.0103	0.0061	HuNyiyang	0.0064	0.0048			
AHsuzhou	0.0151	0.0091	HuNyongzhou	0.0026	0.0131			