The Economic Effects of Infrastructure on the Prefecture Level in China, Evidence from Historic and Modern Data

Thesis submitted in accordance with the requirements of the University of Liverpool for the degree of Doctor in Philosophy

by

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Declaration

I declare that the PhD thesis presented is completed by me from 2016 to 2021. I hereby declare that all the contents included are original and not included in a previous thesis or dissertation except for the source materials referenced in the list. I have read the University's current ethic guidelines. I have attempted to identify all the risks related to this research that may arise in conducting this research, obtained the relevant ethical and/or safety approval, and acknowledged my obligations and the rights of the participants.

Abstract

This dissertation comprises three essays that examine the economic effects of three different infrastructure types. In this dissertation, the author aims to find the initial incentive for the decision makers to build an infrastructure. The first essay uses the fixed effects model to examine the effects of the Grand Canal and major waterways on the wheat market integration in the mid-Qing period. Applying the methodology of Donaldson (2018), it demonstrates that the wheat price in cities along all waterways, including the Grand Canal, weakly responded to local weather conditions and strongly to price fluctuations in neighbouring cities. The second essay implements a quantitative method to investigate the transport efficiency and economic efficiency of urban rail transportation (URT) systems across Chinese cities. The Data Envelopment Analysis (DEA) is employed to generate production frontiers for economic and transport outcomes, one producing transportation turnover and the other serving economic objectives. After deriving the economic and transport efficiency, the essay uses the Tobit regression to estimate the factors affecting efficiency. The analysis clearly demonstrates that the URT infrastructure is more efficient at transporting passengers in the first-tier cities in China, but does a better job at improving GDP and economic attractiveness in other cities. The evidence thus, ex-post, suggests that the primary goal of building a URT might not be same for the policy makers in different sized cities. The third chapter estimates the effects of opening new airports on employment in 19 different sectors using prefecture level data from 2003 to 2018. By using difference in difference (DID) specification, it is found that the airport openings mainly brought significant growth in two sectors, wholesale & retail and transport & warehousing in the whole prefecture region. No significant signs were found in other sectors and the total employment. These findings could be attributed to the heterogeneous dependences of each sector on air traffic. To deal with endogeneity, an instrument variable estimated by distances to the nearest hub airport and the location of military airport is generated. The two-stage-least-square (2SLS) regression with instrument Variable (IV) suggests that the baseline model underestimate the significant effects on the wholesale & retail and transport & warehousing sectors.

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List of Abbreviations

CAAC: Civil Aviation Administration of China

CEIC: China Economic Information Centre

DEA: Data Envelop Analysis

DID: Difference in Difference

DMU: Decision Making Unit

HSR： High Speed Railway

LOP: Law of One Price

NBS: National Bureau of Statistics

NDRC: National Development and Reforming Commission

OLS: Ordinary Least Square

SMC: Small and Medium sized cities

2SLS: Two Stage Least Square

URT: Urban Rail Transportation

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Chapter 1 Introduction

As commonly known, China have witnessed a fast growing economy for last 30 years. A large amount of infrastructure investment significantly contributed to this rapid development. It is no doubt that the central government regarded infrastructures as an important financial tool to boom the economy. However, is it the predominant focus? Before this dissertation, two main questions should be asked in broad terms. First, what is the initial intention for decision makers to invest on infrastructures, for solving the civil issues or economic development? The second question might be related to local governors. As most of the projects should be applied and implemented by local governors, is there any other motivation for local governors to apply and build infrastructures?

My dissertation contributes to answer these two questions in three ways. As the primary concern of the infrastructure in historic period was comparably easy to identify, the first thesis directly investigated the economic effects of the Grand Canal on the market integration in pre-modern China. Comparing the transport and economic efficiency of metro systems, the second thesis aims to find the prior goal of building and operating infrastructure in modern days by ex-post quantitative research. The last thesis provides evidence of the effects of airports on the employment, which indicates that building and operating a new airport does not generally improve the overall employment level.

The second chapter is about the economic effects of a infrastructure project in history. China has a long history of building huge projects/projects. More than two thousand years ago, Qin Empire built several famous projects, two irrigation systems[1], national road network[2] and the Great Wall. In the following dynasties, the governors also

[1] Two irrigation systems are Dujiangyan and Zhengguoqu, completed roughly in 250 BC and 230 BC.
[2] The road network is called Qinzhidao and Qinchidao, which connected the capital of Qin to other regions.

built a series of massive infrastructures, when the national power was strong. The Grand Canal was a typical example, built in Sui Dynasty (581-618 AD), connecting the southern and northern regions afterwards. These infrastructures usually had a primary purpose, basically for political stability. For example, the prime goal of the Grand Canal was to transport the national tax of silver and grains to the capital in Ming and Qing Dynasties (1368 -1911), however, it also contributed to civil and commercial use and became the busiest trade route in pre-modern China. In spite of political uses, these infrastructures also significantly improve the national economy and life standard of residents.

Chapter 2 proves that the Grand Canal played a significant role in trade besides its political transport use. By using the monthly wheat prices in 18th and 19th century and measuring the price sensitivity to the weather, the result indicates that the cities along the Grand Canal reacted less sensitively to the local weather but strongly to the neighbouring markets. This presents that the infrastructure normally had impacts on more than its original function, even in the ancient times. Therefore, which impact is the prior focus becomes an interesting topic.

The second thesis (Chapter 3) estimates the transport efficiency and economic efficiency of URT systems. Compared to the research of inter-cities transport, like highways and high speed rails (HSR), the number of the researches of effects of URT is relatively less. Moreover, the inter-cities cooperation hardly happens in URT system, which makes it a better scope to investigate the thought of the local decision makers.

Chapter 3 implements the DEA method and Tobit regression to measures the transport efficiency and economic efficiency of 19 cities and concludes that larger cities relatively have higher transport efficiency, while the smaller ones have better performance on improving economic indicators. Taking a ex-post analysis, the civil use of the URT, the transport needs, might not be the primary purpose of the local decision makers, when applying the projects. They probably regard the infrastructure as an achievement for position promotion.

The third thesis (Chapter 4) examines the economic effects of another infrastructure, airport. Application of building civil airports became a trend for many medium and small cities. Due to the lack of passengers and flight route, many civil airports were not profitable and even temporarily close. This motivates the author that the economic effects of airports could be a more appropriate topic to examine the original incentive of the local decision makers. Compared to HSR as national macro planning, the airports application is a better representative of the local decision makers' thought. In addition, compared to national railway systems, the airports operation is more like a free market, the measurement of the economic effects of it is more convincing.

Chapter 4 uses difference in difference (DID) method to measure the effects of airports on 19 specific sectors. Wholesale & retail and transport & warehousing employment in the whole prefecture region are significantly improved by the appearance of the airport. The other sectors and total employmentare not significantly influenced. This implies that most of the airports in SMC could not have a significant benefit in overall employment level. Thus, it suggests the local governors to research the other economic advantages when considering the application of the resources.

In summary, fiscal budget becomes relatively contractional and the debt of local government has already reached a considerable level in recent years. The government, especially the local government could not invest all kinds of the infrastructure freely. This dissertation aims to research the economic benefits of several types of infrastructure and hope to provide some evidence to help local governors to allocate financial resources more efficiently.

Chapter 2 Water effects, Regional Differences on Market Integration in the Qing Dynasty, Evidence from Chinese Wheat Markets, 1738 -1820

Section 2.1 Introduction

Section 2.1.1 Background

Qing Dynasty (1644-1911), the last empire of China, is always described as autarky with a mainly agricultural economy. By the 1820s, China was experiencing a 'Prosperous and Golden Era' with population of approximately 400 million according to official census and estimated by the researchers (Liang, 1980; Madison, 2003).China's population constituted 36.6% of the global population at that time (Madison, 2003). Although the productivity of the Qing Empire fell behind European countries in the early stages of the industrial revolution, the nation still generated 33% of the global GDP, a significantly large volume of output (Madison, 2008). Despite a low level of urbanization, there was still an urban population of roughly 25 million and more than 300 cities (Roznan, 1977). The capital of the Qing Empire, Beijing, had a population of more than one million, who could not live without the business sector (Fudan University, 1982). Based on the information illustrated above, some questions could be asked: Does autarky truly describe China in that period? What was the level of marketization and commercialization in different regions? What were the main factors influencing the market integration? Is it possible to measure market efficiency and investigate the regional differences?

A buck of the literatures argues that the different regions of China did not share the same market efficiency. Keller and Shiue (2007) conclude that the regions in the lower Yangtze River and its tributaries had a higher level of market interaction than the other regions between 1742 and 1795. Chen (2010) claims that even in the province Guangdong, price correlations between cities were still significantly divergent. Yan and Liu (2011) and Li (2014) indicate that the southern regions generally had a higher level of market integration and the southern rivers even played a more important role in market integration than the northern rivers. It seems that the extent of market integration varied across the different regions. But what created this heterogeneity?

Among the factors affecting market integration, convenience of transport should be one of the main determinants, as it reduces the transportation cost and increases the volume and efficiency of trade. Skinner (1964, 1977a, 1977b) hypothesizes that navigable water routes were the main determinant of market integration in Qing Dynasty. Perkins (1969) points out that the transport cost of using the Yangtze River in the Qing Dynasty was approximately 1/5 to 1/3 of the land transport costs. A rich body of literature has investigated the impact of water transport on market efficiency (Evans, 1984; Wang, 1992; Wong and Perdue, 1992; Fan, 1993; Yan and Liu, 2011; Li, 2014). Moreover, the regional difference between the South and North has also been incorporated into the research of Keller and Shiue (2007), Yan and Liu (2011) and Li (2014). Keller and Shiue (2007) find that the waterway effects were only significant in the lower Yangtze Delta region in that period. The latter two papers include an interaction term between the river effects and the regional differences, concluding that only the rivers in the southern area played significant roles in market interactions. The literatures also discuss the effects of distance and political reasons on the market integration among the regions (Keller and Shiue, 2007; Yan and Liu, 2011; Li, 2014). Though many papers have demonstrated the importance of water transport for market integration, this thesis sheds new lights on each water route specifically, especially the Grand Canal. According to Yan and Liu (2011) and Li (2014), the rivers in the North hardly improved market efficiency in the mid-Qing Dynasty. However, as the Grand Canal connects the main river systems in the North and South, was the northern part of the Grand Canal postively improving the market integration? This chapter separately examines the effects of the Yangtze River system, the Yellow River system[3] and the Grand Canal to investigate whether they generated different impacts.

In addition to the waterway effects, referring to Yan and Liu (2011) and Li (2014), this chapter also incorporates and tests regional differences and political effects. Yan and Liu (2011) and Li (2014) both investigate the differences of market integration between the North and South and conclude that the southern region was more integrated than the North. This result is consistent with intuition, as the

[3] This paper would define the Huai River as a tributary of the Yellow River System.

Yangtze River and its tributaries, which covered the majority of the southern provinces and had the longest navigable year-round water route. Moreover, regional differences were also attributed to political administration. The inter-provincial border effects should also be considered as one of the determinants of market integration. Due to political reasons, cities in the same province should be more integrated. Another political effect is that of the capital city. Due to political and military reasons, the capital city always had a considerably higher proportion of population that did not engage in the agriculture sector in that period. In addition, the capital city normally had the most convenient transportation, both natural (rivers) and man-made (postal roads). Therefore, the capital city normally had a higher level of trading activities and enjoyed lower transport costs which contributed to a higher extent of the market economy.

Regarding the measurements of market integration, various methodologies have been implemented. Engel and Rogers (1993, 1996) use the price differences between cities and their volatilities to measure the market integration among American and Canadian cities. Their methodology is based on the Law of One Price. Fan and Wei (2006) use the exponential smooth threshold autoregressive (ESTAR) model to investigate the price dispersions among contemporaneous Chinese cities, a typical transitional economy. Other indicators to measure the market integration level of Chinese grain market in the Qing Dynasty include the price correlation between cities (Chen, 2010) and the cointegration of the price levels between city pairs (Keller and Shiue, 2007; Yan and Liu 2011; Li 2014). In these studies, the magnitude of market integrations is measured using the price information of city pairs. Following Donaldson (2018), market integration is measured by price responsiveness to the weather conditions of a city and neighbouring cities. Donaldson's work studies the effect of railways on the market integration of India in the Victorian era. In my paper, as the main route of trade, waterways played a similar role to the railways in the Victorian India. Therefore, the model might have similar explanatory power to describe the effect of waterways. This chapter slightly revises the methodology of Donaldson (2010) and use the grain data (1738 to 1820) to investigate two factors, the waterways and regional differences, which affected market efficiency in the Qing Dynasty.

Section 2.1.2 Motivation

According to the extant literatures, the availability of water transport is the most significant factor that improves market interactions, as water transport increases the trading opportunities and reduces transport costs (Skinner 1964, 1977a, 1977b; Perkins, 1969; Evans, 1984; Wang, 1992; Wong and Perdue, 1992; Fan, 1993; Yan and Liu, 2011; Li, 2014). However, to the best of my knowledge, it seems that there no relevant paper has separated different water systems from each other in this field. As the Grand Canal was one of the busiest water trade routes connecting the North and South in ancient China, the convenience of this transport brought many trading opportunities to the cities along it and hence improved the level of urbanization in these cities. A higher urbanization rate would further improve commercialization and market integration. However, referring to the previous articles, the rivers in northern China did not have a significant impact on market efficiency (Yan and Liu, 2011; Li, 2014). Did only the Southern part of the Grand Canal improve market integration but not the northern part? And if so, what caused it? Moreover, the conclusion that the northern rivers had considerably weaker effects than the southern rivers would leave the effects of the Huai River system ambiguous. It is difficult to define Huai River as a northern river or a southern river because it is actually the geographic boundary of the North and the South China. These considerations motivate me to focus on the effects of all waterways and man-made canal. In addition, this doctoral dissertation pays a great interest on the infrastructures, investigating the economic effects of a historic project could be a good start.

Second, there is a potential gap in Yan and Liu (2011) and Li (2014), both of which use wheat price in the North but rice price in the South. Their treatment may undermine their results. The regional difference between the South and the North might be created by the different commodities rather than regional traits. This chapter concentrates on one uniform grain, wheat, which was traded both in the South and in the North. Using the price of one single commodity is more reliable in investigating regional difference in market integration.

Third, the author believes that measurement of market integration in Donaldson (2018) could be used in estimating the effects of the water route, as the water transport in pre-modern period shared many common characteristics with railway in 19^{th} century. this chapter draws on Donaldson's model to explore research questions. It presents a new method of measuring the market integration that it studies how prices in a city respond to local weather conditions as well as other cities connected by railways. This is distinct from the conventional methodology of studying the relative price of city pairs.

Section 2.1.3 Contribution

The first contribution of this chapter is to distinguish the impacts of specific river system. To the best of my knowledge, this is the first attempt to conduct such an investigation. The finding in previous literatures that the northern rivers did not have strong impacts on improving the market integration is hardly believable because the Grand Canal connects the river system in the North to the river system in the South. Literal records show that the Grand Canal had high volumes of business activities in Qing Dynasty. Additionally, as noted above, it is difficult to classify the Huai River system because it delimits the North and the South. This chapter divides the rivers into three water systems[4], the Yellow River, the Grand Canal and the Yangtze River. The results show that all of the three river systems improved market efficiency of the Qing Dynasty. The Grand Canal and the Yellow River significantly reduced the sensitivity of wheat prices to local weather condition by 30.6% and 23.7%, respectively.

The second contribution is using the wheat price as a single and uniform commodity price to estimate market efficiency, which was not previously performed. The wheat prices used in this chapter cover 16 provinces, much larger than those studied by the extant research (Wang, 1992; Peng, 2005; Keller and Shiue, 2007; Yan and Liu, 2011; Li, 2014). As argued previously, using different commodities to measure market efficiency (Yan and Liu, 2011; Li, 2014) might generate ambiguous results because different kinds of grains might have different properties, which may respond differently to transport conditions. In order to

[4] There is no wheat price data of Guangdong and Guangxi provinces, hence, the Pearl River system is not included.

disentangle the effects of transport conditions from the effect of grain type, this chapter chooses a single commodity, wheat, to examine the factors affecting market efficiency. It presents a different result against the previous literatures that the North wheat market is more integrated. This makes the author wonder why the previous scholars tended to use rice price in the South as wheat price data is quite complete.

The final contribution is that this chapter interrogates previous finding on the regional differences between the South and North. According to the common view, having a huge water transport capacity, the southern region along the Yangtze River should have stronger market integration compared to the North. However, this thesis finds that wheat prices in the southern region reacted more strongly to local weather and the prices co-movements between neighbouring cities were weaker in the southern region. The responsiveness to local weather is 30% stronger than in the northern region and magnitude of the price co-movement with neighbouring cities was 7.4% weaker. These findings demonstrate that at least in the wheat market, the southern region did not have stronger market integration than the North.

Section 2.1.4 Structure

The rest of this chapter is organized as follows. Section 2.2 describes the basic information and institutions related to grain trade as well as the determinants of wheat prices. Section 2.3 presents the data and some patterns of it. Section 2.4 conducts some preliminary tests referring to the research questions. Section 2.5 implements the revised Donaldson framework and presents the results. Finally, offer some concluding remarks are placed in Section 2.6.

Section 2.2 Geographic and Institutional Background

Section 2.2.1 Water Systems and the Grand Canal

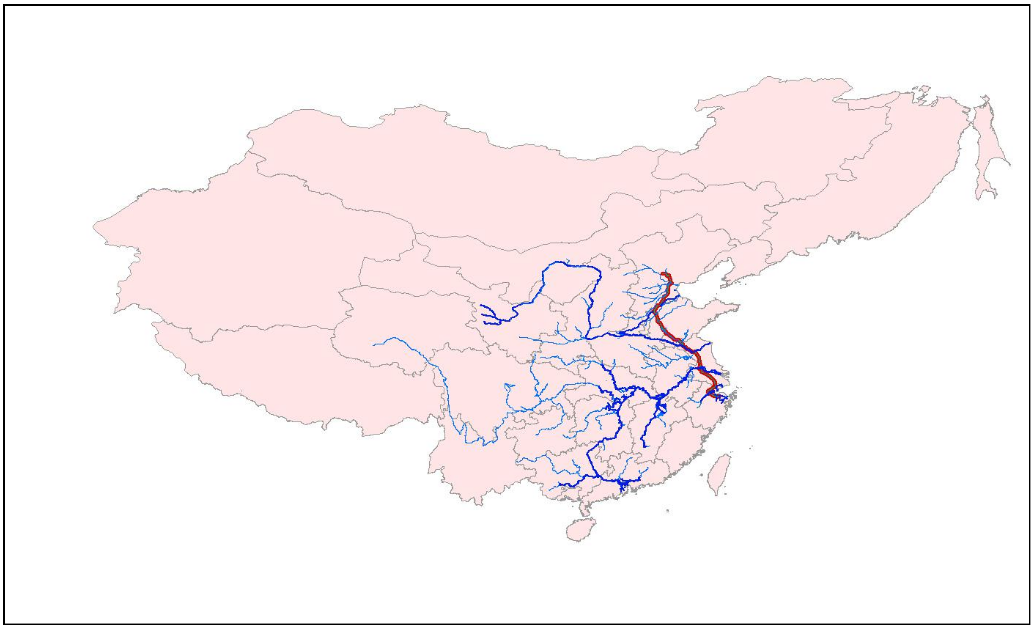
Starting from Beijing, the Grand Canal flowed through the provinces of Zhili, Shandong, Jiangsu and Zhejiang and ends in the city of Hangzhou. It is the longest canal in the world, at 1776km. it was once a crucial and busy transport route in the

Ming Dynasty and Qing Dynasty. Besides shipping grain and silver to the capital Beijing for political purpose, the Grand Canal also shipped other commodities for commercial use. Importantly, it linked the Yellow River, the Huai River and the Yangtze River, combining the northern regions and the southern regions. Many cities along the canal became economically prosperous and more urbanized because of intense commercial activities. As shown in Jing and Du (1997), cities along the Grand Canal, such as Huai’an, Linqing and Jining, which are underdeveloped contemporaneously, used to be very prosperous in the early and middle Qing Dynasty (Figure 2.1).

Figure 2.1 The Sketch Map of the Grand Canal

Source: www.chinatouristmaps.com

Figure 2.2 The Main River systems in China in 1820



Source: China Historical Geographic Information System (CHGIS), available at http://www.fas.harvard.edu/~chgis/index.html

The Yangtze River, the longest river in China, has the longest navigable waterways in China, when tributaries are included. In the period of Emperor Qianlong (1736-1796), the navigable Yangtze River and its tributaries were approximately 40,000 km in length in total, accounting for 80% of the navigable waterways in the nation.A total of 170,000 ships were sailing on the Yangtze River and its tributaries, accounting for more than 80% of the ships nationwide (Luo, 1991). The navigable waterway started from Yibin in the upper reaches and ended at the estuary, though the size of the ships allowed from Chongqing to Yichang was limited because of the rapids of the Three Gorges. Due to its dominant position in water transport, many researchers found that the Yangtze River water system or the southern rivers had a significant impact on market efficiency in the mid-Qing Dynasty. As shown in Figure 2.3, the middle reaches of the Yangtze River are from Yichang to Jiujiang, and the lower reaches are from Jiujiang to the estuary.

The extant literatures find that neither the Yellow River nor other northern Rivers played a significant role in market integration. In those discussions, this conclusion seems plausible since the Yellow River did not have the strong transport capability compared to the Yangtze River. However, the government spent 10% of the fiscal revenue on the maintenance of the Yellow River and the Grand Canal linked to it in Qing Dynasty (Naquin and Rawski, 1987), which might justify the importance of the inter-provincial grain transport via the Yellow River. According to Fan (2012), the Yellow River was navigable from Lanzhou in pre-modern China. Although the middle reaches and some tributaries had weak navigability due to gorges and rapids, there were still frequent regional transport activities for commercial purposes. In general, the natural constraints led less ships traveling long distance in the Yellower river compared to the Yangtze River. However, the Yellow River was still a main transport route for grains in short-distance regional trade. Intuitively, the Yellow River should have certain impacts on improving market efficiency, even if the impacts were not as great as the Yangtze River. Figure 2.3 demonstrates the two cut-off points for three segments of the Yellow River, namely Hekou and Mengjin, respectively. Fan (2012) also indicates that the Yellow River sometimes was not navigable as it froze. Therefore, this study aims to investigate if the impacts of the Yellow River on market integration were weaker and less significant than those of other rivers.

The Huai River is another important river system over 1,000 km in length, covering three provinces. Before 1855, the Huai River joined the Yellow River at Huai’an and flowed into the Yellow Sea. More importantly, Huai River marks the dividing line between the northern and southern China. The Huai River was extremely flood prone in the Qing Dynasty. The Qing government devoted a large amount of efforts into dealing with this issue, but with little effects. Between 1736 and 1911, the northern Anhui province (the Huai River Basin) only experienced 16 years without flooding, and in my study period, 1738-1820, there were only 6 years without flooding (Chen, 2009). Although the full range of the Huai River was navigable in the normal conditions of the Qing Dynasty (Tang and Kang, 1997), the transport condition was questionable in the flooding seasons. Apart from the question of whether the Huai River is defined as a northern or a southern river, the effects of the Huai River is ambiguous. As the Huai River joined the Yellow River in Huai’an and shared many common characteristics with the lower reaches of the Yellow River, this chapter would define the Huai River as a tributary of the Yellow River.

In 1855, the Yellow River flooded and changed course to flow through Shandong Province (seen in Figure 2.1). After that, the northern part of the Grand Canal gradually silted and lost its functionability (Jing and Du, 1997). Therefore, this chapter focuses on the period before 1855, when the Grand Canal was fully functionable. As the rivers were the main trade and transport routes especially for long distances, the Qing government established three large bureaus in charge of water traffic and waterway maintenance. These three bureaus had effective control over the waterways during the period of study.

Figure 2.3 Yellow River and Yangtze River in 1820

Section 2.2.2 Grain Trade

During Qing Dynasty, the agricultural sector dominated the preindustrial economy. Undoubtedly, grain was the main commodity in the market. In the mid- Qing Dynasty, there were more than 20 million urban population purchasing grains on the market. As farmers had to pay tax in silver, they also needed to trade a proportion of their crops in the market. There was a large internal grain market in that era. Marks (1991) estimates that more than 20% of the rice produced in

Guangdong was finally traded in the market, while Fang et al. (2000) estimate that the trade volume of grains in China was about 2.6 million tons annually during the 18-19th centuries.

Moreover, in the mid-Qing Dynasty, the production of grains became geographically imbalanced; some areas, such as the lower Yangtze River area, became significantly short of grains due to cash crop cultivation (Wang, 1992). Market forces encouraged the grains to flow from the grain-sufficient areas to grain-deficient regions. Also, the availability of long-distance trade encouraged the flow of other commodities. To make more profit, merchants could ship cash crops (e.g. cotton fabrics, silk fabrics and tea) on the return trip, which improved the specialization of crops in different regions and hence stimulated the grain trade in cash crop farming region (grain import region). In conclusion, grains were traded on large scales in the Qing Dynasty.

Section 2.2.3 Institutions

In the traditional view, market vitality was limited by the centralized and imperial administration of the Qing Dynasty. However, if delving deeper into the institutional arrangements, it will find that the policies were actually market-friendly.

First, in general situations, the Qing government did not make frequent interventions into commercial activities. The official business tax was remarkably low in the 18th century. Commercial activities were mainly regulated by informal rules in the form of family bylaws, lineage rules and guild regulations (Ma, 2004; Wong, 2004). In other words, business was less regulated by the state but largely operated along the market principle. Even in the case of grains, the government implemented flexible policies and encouraged private merchants (Li, 2014). From the mid-18th century, trade barriers were removed and the private institutions such as self-governing guilds were officially encouraged to participate in the grain trade (Mann, 1987; Dunstan, 2006). In contrast to the traditional view that the Qing government was hostile to commerce, it was actually one of the most pro-commercial regimes in Chinese history (Perkins, 1969).

Besides encouraging private institutions, the Qing government imposed laws and orders and established public institutions to support grain trade. One approach was the establishment of three bureaus (noted above) to maintain the main waterways to guarantee the shipment of grains. A system of brokerage was also established in which authorized licensed brokers to supervise payment in trade, delivery and the quality and quantity of goods. As the brokerage system served as an intermediate of exchange (Mann, 1987), this para-bureaucratic institution not only reduced direct intervention in the market but also contributed to its healthy development.

Grains, the most important good and the strategic resource in pre-modern era, were the chief and prior concerns of the state. The Qing state set up a series of approaches to maintain food security. The cornerstone of all these measures was the nation-wide granary reserve system. The central government set the target of storage for those granaries, which were managed by local governments to deal with potential famines. There were three kinds of granary, Changping Cang[5], She Cang and Yi Cang[6]. The primary function of the granary system was to store grains in harvest years and release food at the times of shortage. Though many researchers have estimated that granaries storage only accounted for less than 8% of national production in the 18th century, the actual amount was rather large (Liu, 1980; Marks, 1991; Shiue 2004). During the years 1764-1766, state records showed that there were 40.6 million shi[7] of unhusked grains stored in the granaries (Chuan and Kraus, 1975). The government did not interfere with normal market activities when there was no famine. On the contrary, the system increased grain trade activities as the granaries needed to buy reserves in the harvest time and sometimes sell it to avoid spoilage or food shortage in springs. As the grains were normally stored for three years according to regulations, presumably at least one third of the stored grains needed to be replaced in each year (Chuan and Kraus, 1975). Therefore, this price stabilization and food reserve policy contributed to higher grain exchange in market.

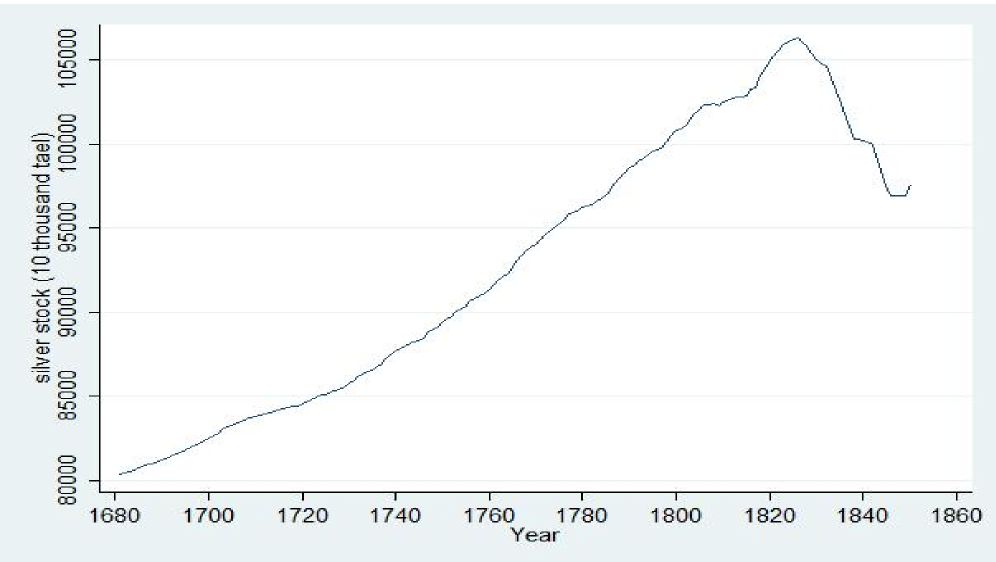
Section 2.2.4 The Golden Age of the Qing Dynasty

The official demographic records show that the population of China grew to more than 400 million in the early 19th century (Liang, 1980), without any apparent

[5] Changping Cang was mainly supplied and governed by government.
[6] She Cang and Yicang were mainly sponsored by private charity and community.
[7] Shi is a unit of volume which is approximately 103.6 litres.

reduction in GDP per capita (Baten et al., 2010). Maddison (2009) estimates that China was the largest economy in the 18th and early 19th century in the world, producing approximately one third of the global output. The years of Emperor Qianlong (1736-1795) and Emperor Jiaqing (1796-1820) are usually defined as the mid-Qing period. In particular, the period of Qianlong (1736-1795) experienced a rapid population growth, which can be attributed to progress in agricultural production (Perkins, 1969), political stability and economic prosperity (Wang, 1992). All of these effects spurred long distance trade, commercialization and urbanization, which made the market more integrated, differentiated and competitive (Naquin and Rawski, 1987). Moreover, from 1736 to 1820, it is estimated that China generated approximately 180 million tael[8] silver net inflow in international trade (Li, 2009). The continuous silver inflow in this period ensured a sufficient amount of currency in circulation, hence encouraging the economic prosperity and commercialization. Figure 1.4 presents some trend of money stock. As shown, most years before 1820 had surplus in the balance of payment which increased the amount of money in circulation.

Figure 2.4 Estimated Annual Silver Stock (Money Supply)



Source: Li (2009).

[8] Tael is a unit of weight which is approximately 37.3 grams.

However, the prosperity of the Golden Age ceased in the first half of the 19th century. Population stalled and the balance of payment began to show deficits in the 1830s (Figure 2.4). The Opium War (1839-1842) further weakened the regime of the Qing government. Following the Taiping Rebellion (1851–1864) and the Second Opium War (1856-1860), the economy and political stability of the Qing Dynasty considerably deteriorated. The population, GDP per capita and living standard began to gradually decrease, which indicated the wane of the Qing Dynasty. Given the turbulent events with the latter half of the 19th century, which had severe effects on the grain prices, this chapter adopts the era of Emperors Qianlong and Jiaqing (1738-1820) for studying market integration. As noted above, this period was described as "economically and politically stable." Consistent growth ensured that the secular change in the grain prices was mainly affected by market factors rather than shocks with politics, war or climate. Moreover, this period was dominated by wooden river boats in river systems, before the advent of steam engine ships and railways that would revolutionize transportation. In addition, in this period, the three bureaus mentioned in the above sections still functioned well to maintain the navigability of the Yellow River, the Huai River and the Grand Canal. After 1820, however, it became increasingly difficult to ship grains to the North by the river systems (Dodgen, 1991). In 1855, the Yellow River changed its course and the northern part of the Grand Canal began to silt, which made it lose its functionality. Since 1870s a large volume of trade was transported by sea. In conclusion, the period of 1738-1820 is the appropriate time frame to study the effects of water transport and regional difference. During this period the water transport was still the main one and the transport conditions was still completely capable.

Section 2.3 Data

Section 2.3.1 General Description

This chapter uses detailed grain price data and geographical data. The grain price data is collected from the Qing Dynasty Grain Price Database[9] (Qing Dai Liang Jia Zi

[9] The database is held at the Institute of Modern History, Academia Sinica, in Taiwan. The digitally online resource is available at http://mhdb.mh.sinica.edu.tw/foodprice/.

Liao Ku) compiled by Professor Wang Yeh-Chien and his collaborators. The price records were sourced from the official archives of local governments and the central government. The data contain monthly prices for up to 20 commodities at the prefecture level (not all grains were reported in every region). In this chapter, only wheat price data are used as they cover far more cities compared to other grains. The data are believed to be highly reliable in the mid-Qing Dynasty as the administration was still efficient. Chuan and Kraus (1975) and Wang (1978) have both accept the reliability of data.

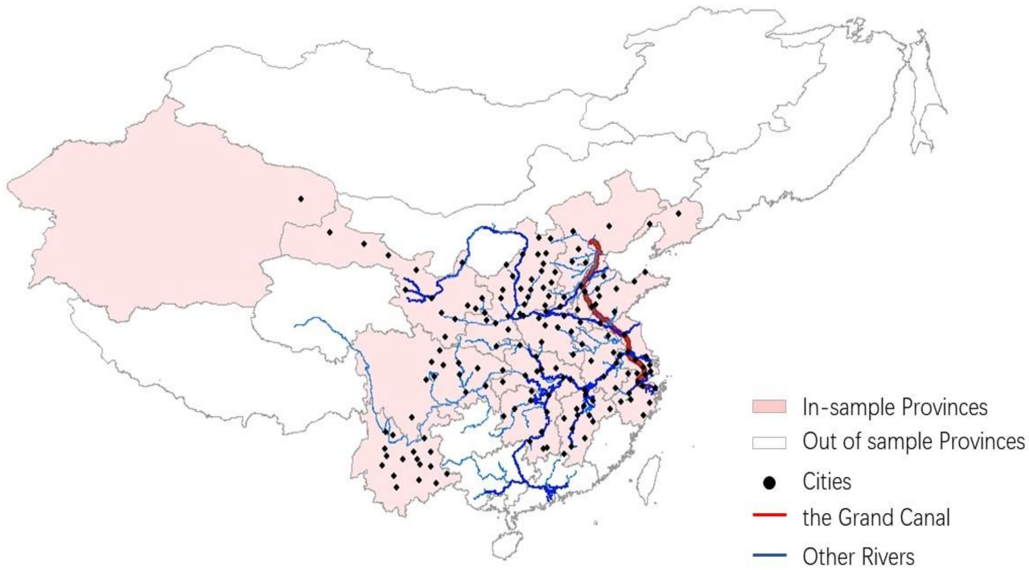
The study period (1738-1820) is based on both quantitative and qualitative reasons. Although the start year of the database is 1736, there were nearly no data in the first two years. Hence, the study uses data starting in January, 1738. The end year is chosen as the last year of Emperor Jiaqing. The regime of Jiaqing (1796-1820) is normally regarded as the turning point in the Qing Dynasty. After the reign of Jiaqing, the balance of trade presented deficits and a series of political instabilities gradually weakened the Qing Dynasty. Moreover, the post-Jiaqing era witnessed the advent of modern means of transport (steam engine ships and railways), which redefined China's inland transportation.

Geographical data are collected from the China Historical Geographic Information System (CHGIS) which provides geological information for the year 1820. With the help of the database, three datasets are created: the coordinates of cities, the shapefile for waterways and the shapefile for prefectures. The coordinates are used to measure the distance between cities and waterways, which determines whether a city is close to a major waterway. The shapefile of prefectures is used to generate the neighbourhood relationship.

Section 2.3.2 Grain Price Data

The database records both the monthly minimum and maximum price. I follow the common practice in the literature and use the average price between the minimum and the maximum (Marks, 1991; Keller and Shiue, 2007; Yan and Liu, 2011; Li, 2014). The wheat price data cover the period of 1738-1820, totalling 83 years (996 months) and 170 cities[10] from 16 provinces. Figure 2.5 presents the provinces and the cities in the sample. Table 2.1 presents the number of cities and number of observations contained in each province. The number of observations varies by city because different cities had different numbers of missing values.

Figure 2.5 Map of China with Sample Provinces, Sample Cities and waterways



Source: original source is from http://sites.fas.harvard.edu/~chgis/. Only the cities with wheat prices are kept.

[10] The list of the cities are given in Appendix A.1.1

Table 2.1 Provincial Statistics

Province	No. of Cities	No. of Observation	Province	No. of Cities	No. of Observation
Shandong	12	9062	Henan	12	8861
Jiangsu	10	8248	Anhui	9	7481
Zhejiang	10	7779	Jiangxi	14	11742
Zhili	5	3750	Hubei	10	7632
Fengtian	2	1099	Hunan	9	7804
Shanxi	20	16678	Sichuan	13	9003
Shaanxi	11	9295	Yunnan	19	13301
Gansu	13	10976	Xinjiang	1	393

Source: Data is collected from Qing Dynasty Grain Price Database (Qing Dai Liang Jia Zi Liao Ku) available at http://mhdb.mh.sinica.edu.tw/foodprice/

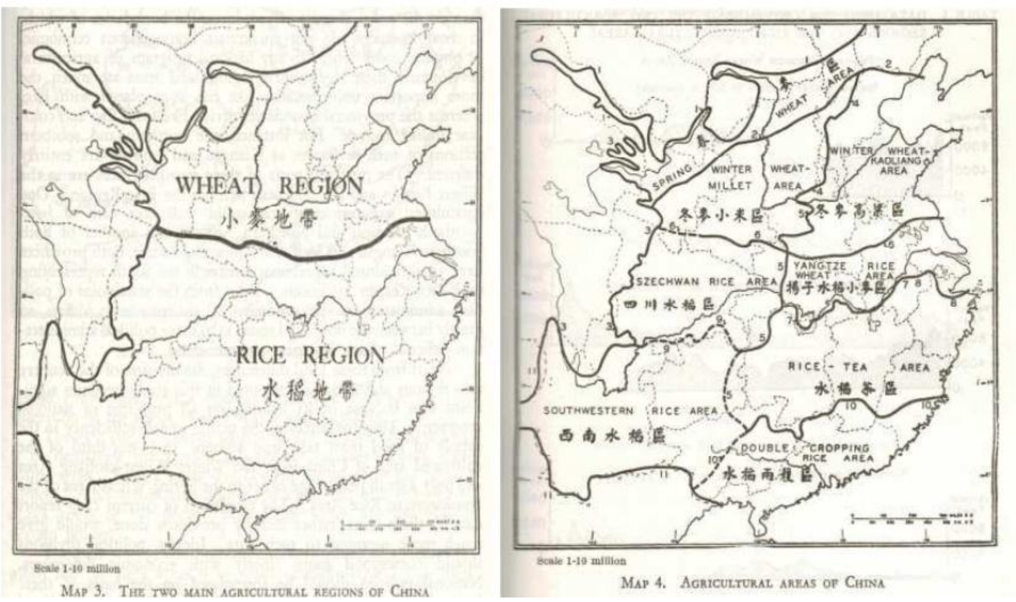
Table 2.2 presents the mean price, the minimum price, and the maximum price by province. The table reveals high levels of heterogeneity within each province. It seems that the northern provinces and the more developed provinces along the Grand Canal had relatively higher wheat prices. A surprising finding is that the prices in the North are relatively higher than the prices in the South. As traditionally known, the northern area was specialized in the cultivation of wheat, while the southern area grew rice (seen in Figure 2.6). If the southern regions were net importers of wheat, the price should have been higher than that in the North because of trading costs. A preliminary quantitative analysis and some possible explanations for this are given in Section 2.3.3 and 2.4.2.

Table 2.2 Wheat price by province

Province	Average Price	Min Price	Max Price
Shandong	1690	600	5240
Jiangsu	1447	400	4200
Zhejiang	1262	700	2450
Zhili	2043	910	7250
Fengtian	2014	1080	3545
Shanxi	1951	840	3980
Shaanxi	1565	345	9075
Gansu	1105	410	4480
Xinjiang	1544	1210	2560
Henan	1223	450	3900
Anhui	1232	565	3170
Jiangxi	1253	540	1860
Hubei	1170	515	3000
Hunan	1068	605	1885
Sichuan	1104	380	4020
Yunnan	1297	350	4190

Source: Same as Table 2.1. Unit: Silver Tael per Shi*1000

Figure 2.6 Crop Area in Qing Dynasty



Source: Buck (1937).

Section 2.3.3 Geographic Data

This section uses the China Historical Geographic Information System (CHGIS) database to construct the geographical variables. Geo-referenced information on cities' coordinates, regional borders and waterways are extracted from the 1820 digital map.

a few small and non-navigable rivers that were not connected to the three main waterways (Yangtze River, Yellow River and the Grand Canal) are dropped. The remaining waterways are shown in Figure 2.5. It is apparent that the Yangtze River and its tributaries had the longest navigable waterways. The Yellow River system is the major river system of North China. It should be noticed that the Huai River is defined as a tributary of the Yellow River, because it joins the Yellow River in the lower reaches and flows to the same estuary. The cities are shown as points on the map. I construct three geographic variables for each city. First, the river dummy is 1 if the city is within 50km of a waterway in straight line distance, otherwise 0. Second, the south dummy is 1 if the city is in the south region[11], otherwise 0. Third, the capital dummy is to capture the political and urbanization effects of provincial capitals. The capital dummy equals 1 if the city is the capital of a province or the nation. Detailed information is given in Table 2.3.

The analysis also needs a neighbourhood relationship among cities, which is defined by contiguity. Two other dummy variables are generated to measure the river connection effect and the provincial border effect. The river connection dummy equals 1 if two adjacent cities are both located within 50km of waterways that are connected. The provincial border dummy equals 1, when two adjacent cities are in the same province.

[11] The provinces of Jiangsu, Zhejiang, Anhui, Hubei, Hunan, Sichuan and Yunnan are defined as southern regions. And the other cities are northern.

Table 2.2 Description and Definition of Dummy Variables

Dummy Variable	Definition
Yangtze River Dummy: YT_i	The dummy equals 1, when the straight line distance from city i to the Yangtze River or its tributaries is less than 50km, otherwise 0.
Yellow River Dummy: YR_i	The dummy equals 1, when the straight line distance from city i to the Yellow River or its tributaries is less than 50km, otherwise 0.
Grand Canal Dummy: G_i	The dummy equals 1, when the straight line distance from city i to the Grand Canal or its tributaries is less than 50km, otherwise 0.
Capital Dummy: C_i	The dummy equals 1, when city i is the capital of the province or the whole country, otherwise 0.
South Dummy: S_i	The dummy equals 1, when city i is located in the provinces of Jiangsu, Zhejiang, Anhui, Hubei, Hunan, Jiangxi, Sichuan or Yunnan, otherwise 0.
River Connection Dummy: R_{ij}	The dummy equals 1, when cities i and j are located within 50km in straight line distance to waterways which could connect them. Otherwise 0.
Intra-Provincial Dummy: Pro_{ij}	The dummy equals 1, when cities i and j are located in the same province. Otherwise, 0.

Table 2.4 presents the basic statistics for each category of cities. It could be seen that cities close to the Grand Canal and the Yellow River, northern cities and the capital cities had relatively higher prices, which is consistent with Table 2.2. Regarding the regional differences, it is apparent that wheat prices in the South were notably lower than those in the North. It is plausible that the wheat in the southern region was not transported from the North due to the transport costs. If this statement holds, there could be only one reasonable explanation that the wheat traded in the South was also grown there. As additional evidence, the price volatility was higher in the cities close to the Yellow River, in northern cities and in capital cities. Engel and Rogers (1993, 1996) use price volatility as an indicator of

market integration. If the standard deviation of these wheat prices is used as the measurement of market integration, It should be concluded that the cities close to the Yellow River and the northern cities had a relatively low level of market integration, consistent with Yan and Liu (2011) and Li (2014). However, based on the higher volatility, It could also be concluded that capital cities had relatively lower market integration, which is counter-intuitive. With a relatively higher urbanization rate, commercial activities and more convenient transport access to all cities within the province, provincial capital cities should have had relatively a higher level of market integration. Therefore, the reliability of this indicator of market integration is questionable. Moreover, the other factors, such as weather shocks, could also contribute to a volatile price fluctuation, which could not be presented in Table 2.4. Section 2.4.3 would implement the methodology used by Engel and Rogers (1996) and see the main determinants of market integration.

Table 2.3 Basic Descriptive Statistics of the Wheat Price by Categories

Categories of Cities	No. of Cities	Average Price	Standard Deviation	Categories of Cities	No. of Cities	Average Price	Standard Deviation
Cities Close to Yangtze River	45	1.283	230	Southern Cities	88	1.257	246
Cities Close to Yellow River	33	1.497	432	Northern Cities	95	1.616	426
Cities Close to the Grand Canal	25	1.521	319	Capital Cities	16	1.534	412
Cities Close to no River	89	1.503	411				

Note: $\text{Average Price}_{\text{group}} = \frac{\sum_i \text{Avrage Price}_i}{n}$ and $\text{Standard Deviation}_{\text{group}} = \frac{\sum_i \text{standard deviation}_i}{n}$. i refers to the city i for each category and n is the number of cities for each category. The unit of the price is silver tael.

Section 2.3.4 Seasonality

The grain market is sensitive to seasons. In general, in the harvest season, the supply should be relatively sufficient which would reduce the price. Moreover, as a perishable commodity, the seasonal pattern should be stronger than durable goods. In the Qing Dynasty, there was spring wheat and winter wheat, grown in colder and warmer regions, respectively. The winter wheat was harvested from May to June, the spring wheat from July to August. The cultivated area of the winter wheat was larger than that of the spring wheat (Perkins, 1969). Figure 2.6 also shows that most of the northern area to the south of the Great Wall was actually the area of winter wheat. This could imply that the harvest season would increase the supply and hence reduce the market price. I use the seasonal variation (SV) of Li (2014) to measure the monthly deviation from the annual average.

$$SV_m = (\sum \frac{P_{i,y,m}}{\overline{P_{i,y}}}) * (N * T)^{-1} \quad (2.1)$$

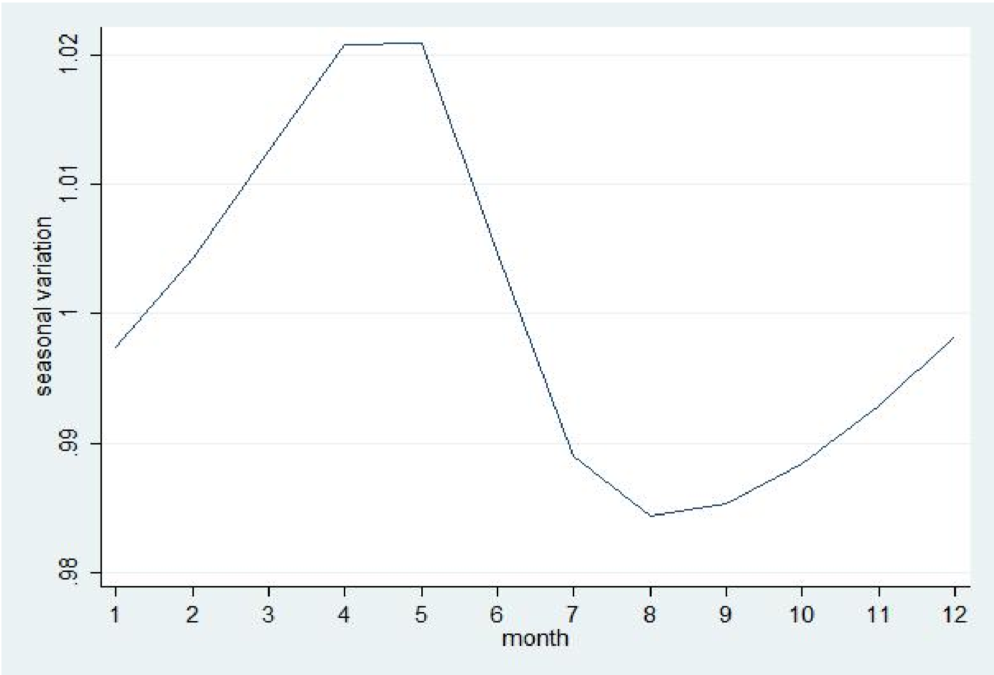
$P_{i,y,m}$ refers to the price of city i in the month m in year y.

$\overline{P_{i,y}}$ refers to the average price of city i in year y.

N and T refer to the number of cities and years.

Figure 2.7 presents the seasonality generated by Equation (2.1). It can be seen that the absolute change of the price was negligible, fluctuating only between 98.4% and 102.1% of the average annual price. The peak price was in April and May while the minimum price was in August and September. Li (2014) explains that this situation can be accounted for by the rational expectations of farmers. As a precautionary move, farmers tended to smooth their supply to the market to avoid potential food shortages in later seasons. I assume that this seasonal pattern is relevant to the timing of tax payments. In the mid-Qing Dynasty, the government collected farmland taxes twice annually. The two tax collection periods were called Shang Mang (first busy time in the year), from February to May, and Xia Mang (second busy time in the year), from August to November, respectively (Shi, 1995). The tax of Xia Mang, or the Autumn Tax, was the main farmland tax in both the Ming and Qing Dynasties. Therefore, the reason that the price was lowest in August and September might be related to the timing of tax payments, when farmers had to sell grains to pay tax in silver. The extra supply of grains increased the supply in the market and drove down the price. Nevertheless, no matter what caused the seasonal patterns, seasonality should definitely be dealt with in the empirical analysis.

Figure 2.7 Seasonal Variation of the Wheat Price



Section 2.3.5 Investigation Period

The period of study is from 1738 to 1820, covering the regimes of the Emperors Qianlong (1736-1795) and Jiaqing (1796 – 1820). This period is also known as the mid-Qing era ('Golden Age'). The main reason to start the analysis from 1738 is data driven. The database started in 1736, but, as noted above, more than 50% of the cities had no records before 1738, while in 1738, 157 out of 183 cities did have records. The final year is determined for historical reasons. The regime of Emperor Daoguang (1820-1850) is always regarded as the turning point to the age of recession, so the time period was cut at 1820 to make the price dynamics more consistent. As mentioned, the Golden Age should have had more powerful control from the central court to local administrators. Therefore, the data quality should be more reliable and accurate for this period. In addition, the Yellow River flooded in

1855 changed the course of that river and devastated the navigability of the northern canal. As the main focus of the study is on the water effects, I only investigate the time before the change of river courses. More importantly, the period of 1738 - 1820 excludes the factor of transportation technology improvements, which negatively affected the river effects in the analysis. Before the introduction of steamships and railways after the 1850s, the junks (Chinese sailboats) on the inland rivers were still the main transportation method for the trade in grains. In conclusion, the economic effect of the Grand Canal kept constant in the selected time period due to the well reserve of the navigability and lack of steam boats and sea transport in later 19th century. More importantly, prosperity and strong political control makes the data more reliable than later times. Equation 2.2 calculates the annual average prices in national level. As seen in Figure 2.8, the wheat price experienced a general growth before in 1820, which correlated with the trend of silver inflow in that era.

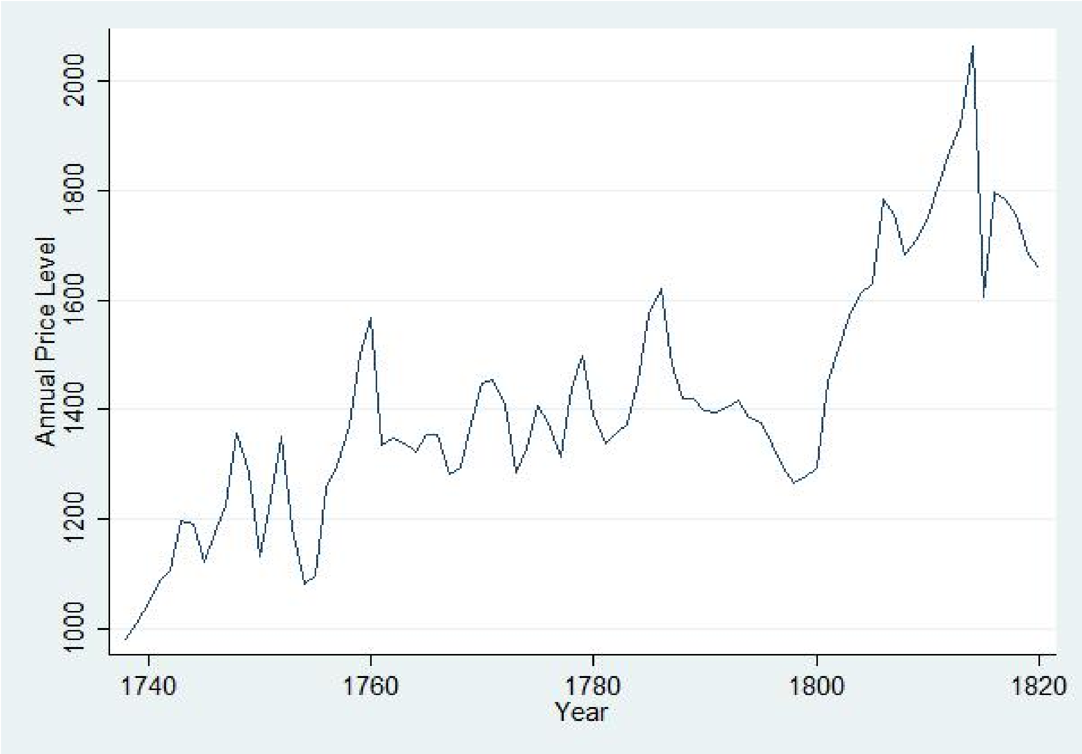
$$\overline{P_y} = \frac{\sum \overline{P_{i,y}}}{N} \qquad (2.2)$$

$\overline{P_y}$ refers to the national price level in year y.

$\overline{P_{i,y}}$ refers to the average price of city i in year y.

N refers to the number of cities.

Figure 2.8 Annual Wheat Price Level from 1738-1820 (unit: silver tale per shi *1000)

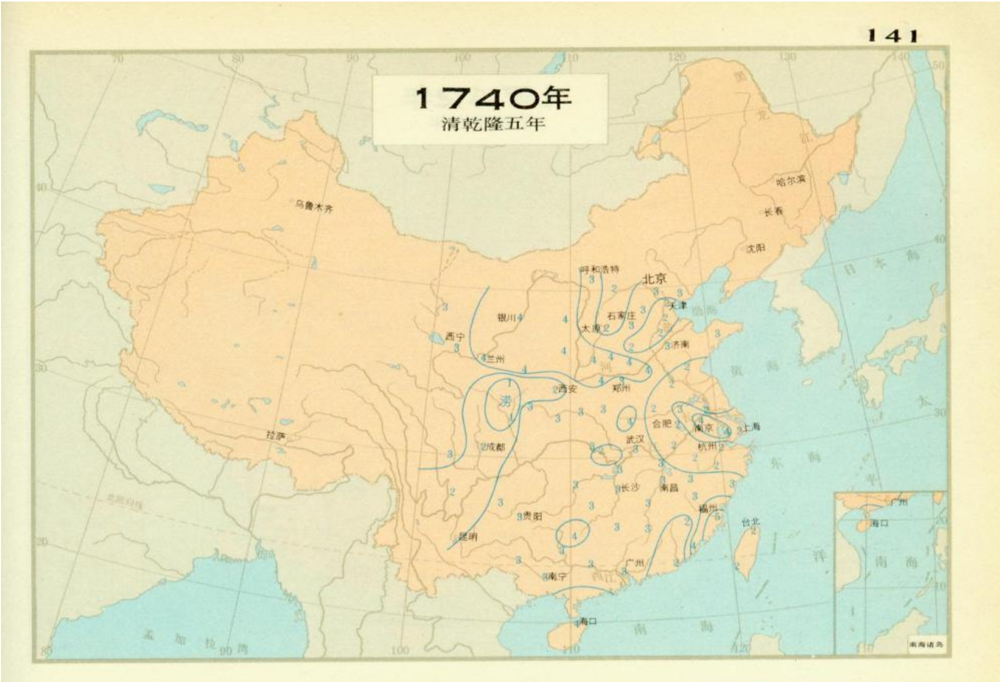


Section 2.3.6 Weather Condition

Following Donaldson (2018), market integration is measured by the responsiveness of local prices to neighbouring prices and to local weather conditions. Weather conditions had a significant impact on the yield of grains and hence affected the market price. If the economy was less integrated with the external market, then the price reaction to local weather conditions would be more sensitive. One could hypothesise that favourable local weather conditions would reduce grain prices, while unfavourable weather conditions would push them up. If it could buy from external market, the effects of the weather would be lessened. Hence, the magnitude of the price reaction to the weather could measure the openness of the local market to the external market.

The weather data are collected from the weather maps published by the State Meteorological Administration (1981). For example, Figure 2.9 presents the precipitation map for 1740., one page of that weather map The weather index is measured annually and ranges from 1 to 5. The index of 3 is the most favourable condition, while indices 1 and 5 represent severe drought and severe flood, respectively.

Figure 2.9 One page as An Example in Map of Droughts and Floods in China in the Past 500 Years (Zhongguo Jin Wubainien Hanlao Fenbu Tuji).



Source: State Meteorological Administration (1981)

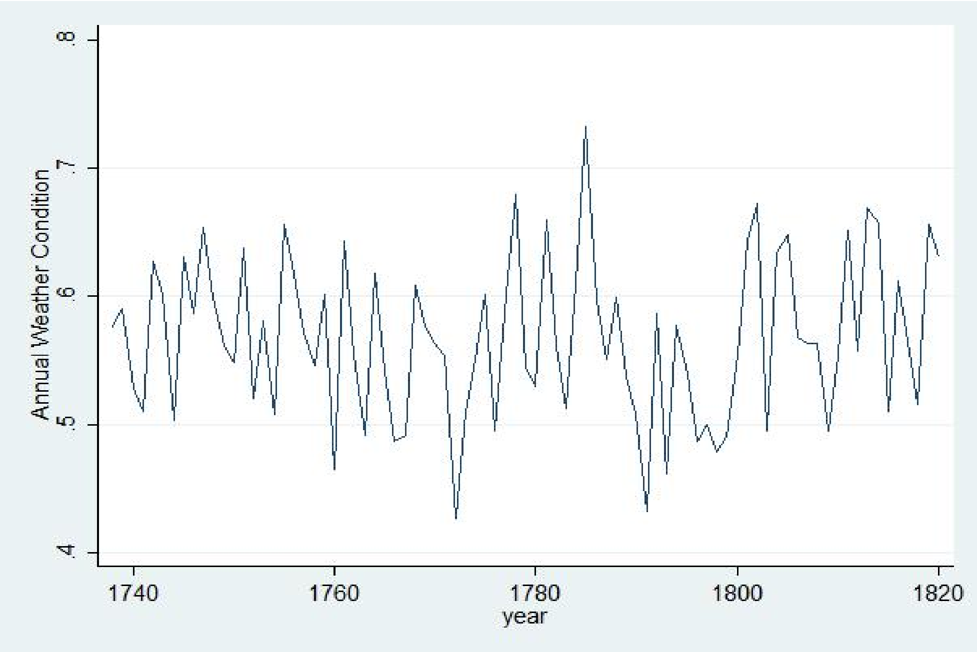
The measurement of weather conditions is defined in Equation (2.3). $\boldsymbol{w_{it}}$ takes values 1/3, 2/3 and 1, with larger values corresponding to more unfavourable weather. Figure 2.10 plots the average weather index of all cities by year. It could be seen that most of the years had relatively good weather (index below 2/3) nationwide.

$$\boldsymbol{w_{i,y}} = \left(\left|\boldsymbol{index_{iy}} - \boldsymbol{3}\right| + \boldsymbol{1}\right) * \frac{\boldsymbol{1}}{\boldsymbol{3}} \qquad (2.3)$$

$\boldsymbol{Index_{i,y}}$ refers to the weather conditions index for city i in year y.

$\boldsymbol{w_{i,y}}$ refers to the weather conditions for city i in year y.

Figure 2.10 Annual Average Weather Conditions of All Cities



Note: $\boldsymbol{Annual\ Weather\ Condition_y} = \frac{\sum \boldsymbol{W_{i,y}}}{\boldsymbol{N}}$, where $\boldsymbol{w_{i,y}}$ and $\boldsymbol{N}$ refer to the weather conditions for city i in year y and number of cities in the sample, respectively.

Section 2.4 Preliminary Research

Section 2.4.1 General Introduction

This section uses some preliminary research to generate an initial understanding of the wheat market. The main research targets in this chapter are the effects of the waterways and the regional differences. The following two sub-sections both focus on the effects of these two aspects. Section 2.3.3 considers the apparently anomalous fact that the southern wheat price was relatively lower than its northern counterpart, a point which has not been considered in the previous literatures. The fact that the South had lower prices proves that the wheat in the southern market may not have been shipped from the North. However, it runs against the common knowledge that the northern regions mainly specialised in wheat plantations (Perkins, 1969). Therefore, Section 2.4.2 investigates whether the lower wheat price in the South was caused by some other reasons. If the latter conclusion holds, the only implication possible is that the wheat market in the southern region was not supplied by northern wheat. Moreover, this preliminary research could also examine the effects of the rivers and canal on the prices. According to the low transport costs, we might expect that the river would have a positive impact on reducing wheat prices. Hence, Section 2.4.2 uses a simple ordinary least square (OLS) robust regression to estimate the effects of water transport, the southern regions and some other control factors on the prices.

Regarding the measurement of market integration, this preliminary research follows Engel and Rogers (1993, 1996) in measuring the extent of market integration. Price dispersion is measured in terms of the price differences between the two cities and is regarded as an indicator of the market integration between pairs of cities. If the market integration level is high between the regions, the prices would converge to a uniform value for different markets. Even considering the existence of trade costs, the price dispersion between two cities could be very small and constant, reflecting transport costs. Section 2.4.3 calculates the price dispersion and uses it as the dependent variable to estimate the effects of each factor on it. The river effects and the regional differences are still the key points in this study. It could be intuitively hypothesised that rivers should reduce the extent of price dispersion (trade costs) and two cities in the same region (both in the South or the North) might have a lower price dispersion compared to two cities located in different regions. Control variables like distance and capital dummy are also included.

Section 2.4.2 Determinants of the Price Estimation

Section 2.3.2 and 2.3.3 show that the southern region had a relatively lower wheat price level, which seems to present that the wheat trade in the southern market was not transported from the North. However, the basic statistics in Section 2.3.2 and 2.3.3 do not exclude the other external factors. It is possible that the low price level in the South is attributable to other endogenous factors. Therefore, this section tries to implement a very simple ordinary least square estimation to see if the low prices in the southern region were really affected by the location. The model and the determinants included are shown in Equation (2.4). The current research incorporates the river effects and weather conditions, which are assumed to be determinants of the price level. Moreover, endogenous city effects, seasonal patterns and yearly patterns are the control variables in the equation in order to generate a more specific result. Incorporating these factors could make it clearer to investigate whether the location of a city in the South really had a lower wheat price level. Prior to the quantitative analysis, it is assumed that severe weather conditions would increase the price level and the waterway effects might reduce the price level due to low transportation costs. The capital effects might be the same as the river effects, according to the convenience of transport, economies of scale and agglomeration effects

$$P_{i,m,y} = \beta_0 + \beta_d + \beta_m + \beta_y + \beta_1 w_{iy} + \beta_2 G_i + \beta_3 YT_i + \beta_4 YR_i + \beta_5 C_i + \beta_6 S_i + \epsilon_{i,m,y} \tag{2.4}$$

$P_{i,y,m}$ refers to the logrithm price of city i in the month m in year y.

w_{iy} refers to the weather conditions for city i in year y.

β_d, β_m and β_y refers to the district, monthly and yearly effect, respectively.

YT_i, C_i, G_i, YR_i and S_i are the dummy variables of the Yangtze River, capital, Grand Canal, Yellow River and the southern region, respectively. The detailed definition can be seen in Table 2.3

The regression results are shown in Table 2.5. Column (1) and (2) present the OLS estimates and the Robust estimates, respectively. The independent variables in the two regressions nearly share the same pattern, which have all the coefficients significant at 1% level. Table 2.5 apparently indicates that a location in the South contributes a 20.5% reduction in price, ceteris paribus. Consistent with the basic statistic in Tables 2.2 and 2.4, this consequence confirms that the factor of location in the South significantly reduces the wheat price level, which reflects that at least a large proportion of the wheat traded in southern markets was not transported from the North, considering the profitability. This finding has never been described by the previous literature (Wang, 1992; Keller and Shiue, 2007; Yan and Liu, 2011; Li, 2014). Considering the arbitrage, it could be boldly implied that southern grown wheat might probably even have been traded from the South *to the* North. However, it is commonly known that the main region of wheat grown in the Qing Dynasty, indeed even in contemporary China, is the northern region, something also observable in Figure 2.6. Perkins (1969) and Guo (1995) also argue that the northern region was the main wheat-producing area. Did the southern region grow wheat and even supply it to the northern market? Actually, in the Qing Dynasty, many southern regions double-cropped, growing wheat in winter and harvesting it in May, and then growing rice in summer and harvesting it around October (Guo, 2012). Guo (1994) points that the annual rice-wheat rotation dominated the lower Yangtze River reaches (South of Jiangsu and Zhejiang) and the basin of the Huai River in the Qing Dynasty. Guo (2012) also argues that double cropping widely applied to the whole basin of the Yangtze River Systems. He claims that some prefectures in Hubei province had more than 70% of their farmland devoted to growing wheat, while even the lowest had more than 40%. Also, 4 prefectures in Hunan province also had more than 50% of their farmland growing wheat. Wheat cultivation also applied to Sichuan, Fujian and even Guangdong province. Wu (1985) estimated that 22.4% of the southern paddy fields grew rice-wheat rotations in the Qing Dynasty. Therefore, considering the results of the preliminary research, it could be concluded that the southern wheat market was generally supplied by southern-grown wheat rather than wheat transported from the north to the southern market. This result has never been considered by the previous literatures (Wang, 1992; Keller and Shiue, 2007; Yan and Liu, 2011; Li, 2014).

Moreover, the effects of weather conditions were significant in that unfavourable conditions would push up the price. If the weather conditions changed from favourable (index=1/3) to less favourable (index=2/3) or from less favourable to extremely unfavourable (index=1), the price would increase by 2%, which is in line with expectations. It is clear that all three waterways had a significant impact on reducing grain prices, attributable to the large amount of trade activities and the low transportation costs. The effects of the Yellow River and the Yangtze River were significant and considerable, causing prices in adjacent cities to be 53.3% and 42.7% lower than the other region, ceteris paribus. However, the capital effects were not as expected in the original hypothesis. It was assumed that the capital would have lower prices due to convenience of transport and economies of scale. In contrast, the results here show that prices in the capital city were 5% higher than in other cities, all other factors being equal. This result might be explained by the pressure of a higher urban population (demand-side effect) or by the relative economic prosperity (monetary effect) of the capital city. A high price level does not totally contradict a high level of market integration; other factors, such as the urbanization rate, other trade costs and the money circulated in the market, would all contribute to higher prices. Therefore, the effects of the capital will be further investigated in later sections.

Table 2.4 The Results of Equation (4) in OLS Regression and Robust Regression

Dependent Variable: Log value of mean price	(1)	(2)
Weather Condition	0.062***	0.062***
	(0.000750)	(0.000784)
Canal Dummy	-0.126***	-0.126***
	(0.0109)	(0.00955)
Yellow River Dummy	-0.533***	-0.533***
	(0.0109)	(0.00846)
Yangtze River Dummy	-0.427***	-0.427***
	(0.0101)	(0.0130)
Capital Dummy	0.0519***	0.0519***
	(0.0104)	(0.0138)
South Dummy	-0.382***	-0.382***
	(0.0112)	(0.0120)
Constant	4.936***	4.936***
	(0.0106)	(0.00973)
Seasonal Effects	YES	YES
City Fixed Effects	YES	YES
Yearly Effects	YES	YES
Robust Regression		YES
Observations	140172	140172
R-square	0.68	0.68

Note: The value in parentheses is the standard error, and the *, **, *** presents the significance level at 10%, 5% and 1%, respectively.

Section 2.4.3 Determinants of Price Dispersions with OLS Estimation

Based on the theory of Law of One Price (LOP) (Friedman, 1953), another measurement of integration, price dispersion is illustrated by Engel and Rogers (1993, 1996). According to the LOP, the same quality of goods should have the same price in all locations when the different markets are integrated. However, as the trade cost has always existed, in the real world it can only be said that the price difference between cities should be very small due to limited opportunities for arbitrage. Therefore, Engel and Rogers (1993, 1996) use the price dispersion as an indicator of market integration. The price dispersion is expressed by the difference between the logarithm value of prices in two cities. According to the LOP, a low price dispersion represents a high level of market integration. In extreme cases, if the price dispersion in the long-term converges to 0, it could be said that the two regions might be integrated as a single market. Equation (2.5) represents the price dispersion between two cities. The value of the price dispersion reflects a negative relation with the market integration.

$$PD_{ij,m} = |\log P_{i,m} - \log P_{j,m}| \qquad (2.5)$$

$P_{ij,m}$ refers to the price dispersion between city i and j in month m.

Then model (2.6) is employed to examine the effects of all the factors on market integration. In model (2.6), PD_{ij} is the price dispersion in the long term, which equals the arithmetic mean of $PD_{ij,m}$. w_{ij} is the weather difference between the two cities i and j, which equals the arithmetic mean of $|w_i - w_j|$. R_{ij} is the indicator of the river effects, which equals 1 if the two cities i and j are located in the same water system (Yellow River, Yangtze River or the Grand Canal), otherwise 0. Pro_{ij} measures the provincial border effects, which equals 1 if the two cities i and j are in the same province, otherwise 0. The dis_{ij} is the logarithm of the straight line distance between city i and j. C_{ij} describes the capital effects, which equals 1, when at least one of the cities of i and j is the capital city. SR_{ij} refers to the same region effects, which equals 1 when both city i and j are located in the South or both in the North.

$$\mathrm{PD_{ij}} = \beta_0 + \beta_1 \mathrm{w_{ij}} + \beta_2 \mathrm{R_{ij}} + \beta_3 \mathrm{Pro_{ij}} + \beta_4 \mathrm{dis_{ij}} + \beta_5 \mathrm{C_{ij}} + \beta_6 \mathrm{SR_{ij}} + \varepsilon_{ij} \qquad (2.6)$$

Table 2.6 presents the empirical results of model (2.6) by OLS regression and robust regression. As the price dispersion (dependent variable) and market integration are negatively correlated, the effects of the independent variable on market integration are inverse to the signs shown in Table 2.6. In general, the signs of all the determinants are as expected and all the coefficients are significant at 1% level, except the capital effects (column 1), at 5% level. First, waterway effects are as expected, meaning that it could reduce the price dispersion by 1.8% if the two cities are located in the same river system. It is clear that long distances significantly increase the price dispersion level, with a 1% increase of distance increasing 0.057% of the price dispersion. Moreover, the weather differences also widen the gap in the price differences. Cities in the same province, both in the South or both in the North, have a relatively low level of price dispersion. In this part, the capital effects make it apparent that being a capital improves market interaction between the two cities, making the price differences smaller. Therefore, the empirical results of the preliminary research are consistent with the assumption made in the previous paragraph, which fits our expectation before using the methodology revised from Donaldson (2018). As the R-square is only at 10%, this suggests that OLS is not an appropriate specification for estimating the factors of market integration.

Table 2.5 Determinants of the Price Dispersion

Dependent Variable: Price Dispersion	(1)	(2)
Capital Effects	-0.009**	-0.009***
	(0.00347)	(0.00327)
River Effects	-0.018***	-0.018***
	(0.0042)	(0.0038)
Distance Effects	0.057***	0.057***
	(0.0023)	(0.0022)
Provincial Border Effects	-0.062***	-0.062***
	(0.0060)	(0.0050)
The Southern/Northern Border Effects	-0.021***	-0.021***
	(0.0028)	(0.0028)
Weather Difference Effects	0.075***	0.075***
	(0.0087)	(0.0095)
Constant	-0.033**	-0.033**
	(0.0156)	(0.0146)
OLS	Yes	
Robust Regression		Yes
Observations	16,618	16,618
R-square	0.1009	0.1009

Note: The value in parentheses is the standard error, and the *, **, *** presents the significance level at 10%, 5% and 1%, respectively.

Engel and Rogers (1996) also suggest another method to measure market integration and/or the level of LOP, namely, the volatility of the price dispersion series. If two markets are highly integrated, the price dispersion would be relatively constant and would be close to the trade costs between the two regions. If the two cities did not have grain exchange, the pattern of the price dispersion would be more volatile. Due to the relation between the volatility of the price dispersion and market integration, low volatility actually expresses high market integration. This section uses the standard deviation of $\mathrm{PD}_{\mathrm{ij,m}}$ as the measurement of market integration and implements an alternative check for model (2.6). Equation (2.7) presents the model for the robustness check. It is apparent that the model is nearly the same of model 2.6 except the dependent variable changes, which still focuses on the effects noted above on market integration. $\mathrm{SD_{ij}}$ is the standard deviation of $\mathrm{PD_{ij,m}}$, which represents the level of market integration. Other dependent variables are the same as model 2.6

$$\mathrm{SD_{ij}} = \beta_0 + \beta_1 \mathrm{w_{ij}} + \beta_2 \mathrm{R_{ij}} + \beta_3 \mathrm{Pro_{ij}} + \beta_4 \mathrm{dis_{ij}} + \beta_5 \mathrm{C_{ij}} + \beta_6 \mathrm{SR_{ij}} + \epsilon_{ij} \qquad (2.7)$$

Table 7 (columns 3 and 4) shows the results of this alternative check. The majority of the effects are significant and the same sign with the original quantitative conclusion, except for the capital effects. This clearly shows that cities along the same river systems or in the same province or same region had a lower volatility in the price dispersion. On the other hand, cities with a longer distance or larger weather differences influenced the extent of the LOP negatively. The only difference in the robustness check is in the capital effects, with columns (3) and (4) demonstrating that the impact of being a capital on the volatility of the price dispersion is small and insignificant. However, this is not important as the factor of capital is not the focus of this chapter.

In conclusion, the current research uses the measurement of market integration proposed by Engel and Rogers (1996), confirming most of our expected results proposed in Section 2.4.3, which is also consistent with the effects of the determinants illustrated in Engel and Rogers (1996), Fan and Wei (2006), Shiue and Keller (2007), Yan and Liu (2011) and Li (2014). This provides a reference to this chapter before the new methodology is implemented in Section 2.5. Again, due to the low value of goodness of fit, it suggests to use another methodology to estimate the effects of each variable.

Table 2.6 Determinants of the Volatility of Price Dispersion

Dependent Variable: Standard Deviation of Price Dispersion	result of model 2.6	result of model 2.6	(3)	(4)
Capital Effects	-0.009**	-0.009***	0.000	0.000
	(0.00347)	(0.00327)	(0.00133)	(0.00127)
River Effects	-0.018***	-0.018***	-0.012***	-0.012***
	(0.0042)	(0.0038)	(0.0016)	(0.0014)
Distance Effects	0.057***	0.057***	0.038***	0.038***
	(0.0023)	(0.0022)	(0.0009)	(0.0009)
Provincial Border Effects	-0.062***	-0.062***	-0.019***	-0.019***
	(0.0060)	(0.0050)	(0.0023)	(0.0022)
The Southern/Northern Border Effects	0.021***	0.021***	0.006***	0.006***
	(0.0028)	(0.0028)	(0.0011)	(0.0011)
Weather Difference Effects	0.075***	0.075***	0.045***	0.045***
	(0.0087)	(0.0095)	(0.0033)	(0.0033)
Constant	-0.033**	-0.033**	-0.050***	-0.033**
	(0.0156)	(0.0146)	(0.0060)	(0.0062)
OLS	Yes		Yes	
Robust Regression		Yes		Yes
Observations	16,618	16,618	16,618	16,618
R-square	0.1009	0.1009	0.1893	0.1893

Note: The value in parentheses is the standard error, and the *, **, *** presents the significance level at 10%, 5% and 1%, respectively.

Section 2.5 Methodology

Section 2.5.1 Theoretical Framework

This section explains the methodology used by Donaldson (2018), who researched the economic effects of the railways in India in the Victorian era. Donaldson hypothesises that the railways would bring a low trade cost and hence improve market integration and market interaction. Hence, as the main trade routes with a low transport cost, water routes in pre-modern China might play a similar role in the current research to the role of the railways in India in the colonial era. Donaldson predicts that the responsiveness of the price in a region to local weather conditions is weaker when the region has low trade costs and conveniently connected to external market. Moreover, as it connects to the external market, it might have a strong reaction to the external weather conditions. Donaldson's (2018) model is shown in Equation (2.8).

$$lnp_{dt} = \beta_d + \beta_t + \beta_{dt} + \chi_1 Rain_{dt} + \chi_2 Rail_{dt} * Rain_{dt} + \chi_3 \left(\frac{1}{N_d}\right) \sum_{o \in N_d} Rain_{ot} + \chi_4 \left(\frac{1}{N_d}\right) \sum_{o \in N_d} (Rain_{ot} * Rail_{odt}) + \varepsilon_{dt} \quad (2.8)$$

lnp_{dt} is the logarithm value of the grain price in district d and time t.

$Rain_{dt}$ represents the local rainfall (weather conditions) in district d and time t.

$Rail_{dt}/Rain_{ot}$ are dummy variables, which equals 1 when district d/o has access to the railway in time t, otherwise 0. District o is a neighbour city close to district d.

$Rail_{odt}$ is a dummy variable, equal to 1, when the railway connects the regions between district o and d.

β_d, β_{dt} and β_t are the control effects for district and time for any unobservable variables.

From Equation (2.8) we can conclude the two measurements of market integration. One is the responsiveness of local prices to local weather conditions. And the other is the responsiveness of local prices to the weather conditions of the other regions. The interaction terms of $\sum_{o \in N_d} (Rain_{ot} * Rail_{odt})$ and $Rail_{dt} * Rain_{dt}$ are used to measure changes in responsiveness when there is a railway connection. If there is no railway connection in district d, the term $\sum_{o \in N_d} (\mathrm{Rain}_{ot} * \mathrm{Rail}_{odt})$ and $\mathrm{Rail}_{dt} * \mathrm{Rain}_{dt}$ would equal 0. Therefore, χ_1 and χ_3 would represent the sensitivity of the responsiveness of local prices to the local weather and the neighbouring region's weather. If there is a railway connection in district d, then the two responsiveness would be represented by the coefficient $\chi_1 + \chi_2$ and $\chi_3 + \chi_4$. In Donaldson (2018), because a large volume of rainfall would increase the yield in the area and the market supply and hence reduce market prices, the signs of χ_1 and χ_3 are expected to be negative. As a railway connection in district d would weaken the reaction of local prices to local weather conditions and cause them to rely more on the neighbouring price, the sign χ_2 contrasts with χ_1 and the sign χ_4 is the same as χ_3.

In this chapter, the model is slightly revised. Firstly, the responsiveness to the weather conditions of neighbouring regions is replaced by the responsiveness to the grain prices of neighbouring regions. The reason for this change is that the correlation of local weather conditions and neighbouring weather conditions is highly correlated, which might cause multicollinearity and misspecification. It can be seen in Figure 2.9 that the weather condition index is not very specific to the prefecture level, and the same weather condition data might appear in more than one province. Therefore, the weather condition data in a city are highly likely to be the same as in its neighbouring cities. The practical results also prove the potential existence of multicollinearity. The means of all the correlations between each two neighbouring cities' weather are more than 0.8. Hence, in order to utilise the two measurements of market integration simultaneously, it is necessary to keep the responsiveness of local prices to local weather conditions and change the second responsiveness to the neighbouring city prices rather than neighbouring weather shocks. Because the railways in colonial India and the river routes in pre-modern time carried the most responsibility of transport, the railway variables are substituted for the river variables in this study. As it is necessary to investigate the regional differences between the North and the South, this factor is also included in the model. Moreover, the intra-provincial border effects and the capital effects are controlled in the model (see Equation (2.9)). The model implements panel data analysis to control the fixed effects of each city.

$$lnp_{it} = \beta_d + \beta_y + \beta_s + \chi_1 w_{it} + \chi_2 YT_{it} * w_{it} + \chi_3 YR_i * w_{it} + \chi_4 G_i * w_{it} + \chi_5 C_i * w_{it} + \chi_6 S_i * w_{it} * + \chi_7 \left(\frac{1}{N_i}\right) \sum_{j \in N_i} p_{jt} + \chi_8 \left(\frac{1}{N_i}\right) \sum_{j \in N_i} p_{jt} * R_{ij} + \chi_9 \left(\frac{1}{N_i}\right) \sum_{j \in N_i} p_{jt} * S_i + \chi_{10} \left(\frac{1}{N_i}\right) \sum_{j \in N_i} p_{jt} * C_i + \chi_{11} \left(\frac{1}{N_i}\right) \sum_{j \in N_i} p_{jt} * Pro_{ij} + \varepsilon_{it} \quad (2.9)$$

In the model, lnp_{it} is the logarithm value of the wheat price in city i and time t. w_{it} represents the local weather conditions in city i and time t. YR_i, YT_i and G_i are dummy variables, which equal 1 when city i is close to the Yangtze River, the Yellow River or the Grand Canal, respectively, otherwise 0. C_i and S_i are the dummy variables, which equal 1 when city i is in the South or is a capital city. p_{jt} represents price in city j and time t, while city j is the neighbouring city of prefecture i. R_{ij} and Pro_{ij} are the dummy variables, which equal 1 when cities i and j have a river connection or are located in the same province, otherwise, 0. β_d, β_y and β_s are the control effects for each district, year and season, and represent the unobservable geographic and political factors for the price. Detailed information and a definition of the variables illustrated in this paragraph can be found in Section 2.3.

Based on the weather condition data, w_{it} is equal to 1/3, 2/3 and 1, and represents the favourable, less favourable and unfavourable weather conditions, respectively. An increase in w_{it} means a more severe weather condition, which could reduce the local yield and supply in the market and hence increase prices. Therefore, it would assume the sign of χ_1 to be positive. The interaction term of the effects of the Yellow River, the Yangtze River, the Grand Canal, capital cities and the southern region with local weather conditions aggregately expresses the responsiveness of local prices to local weather conditions. It is assumed that all these effects improved market efficiency; therefore, the signs χ_2 , χ_3, χ_4, χ_5 and χ_6 should be negative, weakening the reaction to local weather conditions. Considering the responsiveness of local prices to neighbouring prices, it is assumed to be positively correlated. Therefore, the sign χ_7 would also be positive. Together with the mean value of the prices in the neighbouring regions, their interaction with the effects of the river, the southern region, and capital cities aggregately determine the correlation between the market prices of the local region with neighbouring regions. As all those factors are assumed to improve market integration, the signs of χ_8, χ_9 and χ_{10} are assumed to be the same as the sign χ_7. Li (2014) indicates that the provincial border effect is also significantly strong. Cities within the same province had a higher level of market interaction due to political reasons. Hence, the interaction term $w_{jt} * Pro_{ij}$ is incorporated to measure whether two cities in the same province would improve the correlation between them. The sign χ_{11} is expected to be positive.

Section 2.5.2 Hausman Test

In order to explain some unobservable factors, the model includes the effects of the seasonal pattern, annual pattern and the fixed effects of each city. The city effects are assumed to be fixed. Before using the fixed effects, the Hausman Test (Hausman, 1978) was conducted to see if the fixed effects are more appropriate than random effects. The statistics of the Hausman test between random effects and fixed effects are 1259.1, and the p-value is 0.0000. Therefore, the null hypothesis is rejected, meaning that a fixed effect panel analysis is more appropriate for the model.

Section 2.5.3 Empirical Findings

The results are shown in Table 2.8. The two main factors for the thesis are the waterway effects and the regional differences between the South and the North. Column (1) only includes the river effects in the interaction term. It can be seen that the sign of the weather condition variable is positive and significant, which means that poor weather increased the grain prices, and the sensitivity of the responsiveness of weather conditions to local prices is 0.16. At the same time, all three river interaction terms show a negative sign and are significant. This suggests that local prices would be less responsive to local weather conditions if the city connects with any of the three river systems. Unlike the results in Yan and Liu (2011) and Li (2014), this result indicates that even the northern rivers (part of the Grand Canal and the Yellow River System) improved market integration, which presented a weaker correlation between local prices and local weather conditions. The three river systems reduced the sensitivity of the responsiveness by 0.045,0.040 and 0.270. The Grand Canal seems to have a stronger capability for market integration. However, the sign of the interaction term of the capital is not as expected. The capital effects are always ambiguous in this research, and have seldom been discussed in the previous literature. As noted, the capital region might have had a higher market integration due to its convenient transport links and high level of trade. However, it is also plausible that the market in the capital was very sensitive to any changes as there were a large population of urban residents who did not have a large reserve of grains at home. These two reasons would affect the market in the capital simultaneously. Here, the empirical results demonstrate that capital cities reacted more sensitively to the local weather, by 0.138. The other indicator of market integration presents a same result. It shows that local prices and prices in the neighbouring regions were positively correlated. And if the region and the neighbouring regions were connected with a river route, the correlation between the prices in neighbouring markets would be further improved. Therefore, the river effects improved market integration significantly, both in terms of the reaction of local prices to local weather conditions and to neighbouring prices.

Column (2) in Table 2.8 adds the factor of the South in the responsiveness to local weather. The results show that all the coefficients and the significance of the variables are consistent with column (1), while the three rivers reduced the responsiveness of local prices to the local weather, while the capital city responded more sensitively. However, the sign of the South region is not as expected as in the previous research (Yan and Liu, 2011; Li, 2014), but consistent with the result in Section 2.4. It is commonly agreed that the southern market was more integrated than the northern market (Yan and Liu, 2011; Li, 2014). However, the results in column (2) seem to offer a different view, showing that the prefectures in the southern region reacted more strongly to local weather conditions, by 0.025. Was this sensitive responsiveness caused by low market integration or higher demand-side pressures such as the capital city? As the main food source of the South is rice, the assumption of the demand-side pressure seems not to hold.

Column (3) in Table 2.8 presents the model adding the interaction of the South with the mean price of the neighbouring cities. As can be seen, the significance level and the value of the coefficients for other variables are comparable and consistent with columns (1) and (2). The two new variables in column (3) might explain the factors of the South and the capital as a supplement of column (2). The sign of the interaction term of the South dummy with the mean of the neighbouring prices is negative, which means that the co-movement and the correlation between the region and its neighbouring regions were weaker in the southern area. From the empirical results, it can be concluded that the elasticity of the neighbouring prices to local prices is 0.808 in the North, but falls by 0.037 in the southern region. This result would help us to understand the regional effect finding in column (2), which demonstrates that the strong responsiveness of local prices to the local market in the South can be attributed to weak market integration rather than to the demand-side effect, because the demand-side pressure should also push up the price of the neighbouring price. However, the interaction of the capital variable with the mean of the neighbouring prices shows a different pattern with the South effect. The positive sign means a higher interaction between the local market and the neighbouring regions for the capital city. This higher market interaction of capital cities might explain the reason for the strong responsiveness of local prices to local weather, and it might not have been caused by the low level of market integration but rather the high demand effect.

Finally, column (4) adds the provincial border effect into the equation, giving us a complete model in Equation (9). All the findings are robust to the previous results. The result of the provincial effect is also as expected and statically significant. For cities in the same province, this improves the interaction between the neighbouring prices and the region itself, which increases the elasticity between the city and its neighbours, by 0.294.

Based on all of the results in columns (1), (2), (3) and (4) of Table 2.8, the chapter generates consistent results for the determinants of market integration. First, all the waterways, including the northern rivers, improved market integration, which led the region to rely less on local market supply and more on the prices in other regions. This result differs slightly from those of Yan and Liu (2011) and Li (2014). However, it can be explained by the fact that the Grand Canal and the lower reaches of the Yellow River (Fan, 2012) had frequent trade and transport vessels, although possibly not as many and not as frequently as in the Yangtze River. Among all the water systems, the Grand Canal had a highest impact on reducing market differences. The second finding is that the capital city probably had stronger market integration, as reflected in a high price co-movement between cities. As is commonly known, the capital city normally had convenient connections to other cities, as well as a high urbanisation rate. Both reasons would improve the trade volume and market integration. The empirical results confirm that the high market integration of the capital cities, whose prices reflected a strong co-movement with prices in the neighbouring regions. On the other hand, the strong responsiveness of local prices to the local weather conditions of the capital city could be attributed to high demand, which would heighten price sensitivity to any changes in the short term, including local weather shocks, as the capital city is normally a net grain-importing city. The third result differs somewhat from the previous literature. In most previous studies, it has been proposed that the southern region should have a higher degree of market integration than the northern region due to the convenient water transport routes. However, the negative effect of the southern location on market integration is solid and significant in this research, as columns (2), (3), (4) show. Does this mean that the southern region really had weak market integration and high trade costs? Based on this study's empirical findings, the southern regions were at least weak in the wheat market, even if it did not apply to other commodities. In the previous literatures (Keller and Shiue, 2007; Yan and Liu, 2011; Li, 2014), the result for regional differences show that the southern region had the stronger market integration than the northern. However, their comparison of regional differences between the South and the North is based on an estimation of measuring different grains. The previous literatures used rice price data to measure southern market integration, but wheat price data for the northern region. Therefore, this regional difference may probably be caused by the endogenous differences in the grains. The current study uses a single commodity term, wheat, to measure market integration. At the very least, the unity of the commodity would generate a more powerful consequence of the effect in this specific commodity market. Regarding the weak wheat market integration in the South, this could be explained in three ways. As with the conclusion generated in the preliminary research (Section 4.2), the southern wheat price was always lower than the northern wheat price, which implies that the southern wheat price market might not have been supplied with northern grown wheat. Therefore, trading activities were limited to the regional level rather than the national level. A small level and scale of trade means low market integration. Due to the price differences between the South and the North, it is even possible that southern-grown wheat was transported to the northern region. In this case, the northern region might have been more integrated into the national wheat trade. The second reason might be the low quantity of demand. In the southern region, the staple food was rice, which might have led to limited demand for wheat in the local market. As the limited demand for wheat would be sufficiently satisfied by local supply or supply from adjacent regions, market interaction in wheat would be low and there would be no incentive to transport the wheat to the region due to the relatively high trade costs. The third reason is related to opportunity costs and opportunity profits. It has been claimed that the spoilage rate and the transport costs of wheat are greater than for rice (Deng, 1994, 1995; Yan and Liu, 2011; Li, 2014). As the main consumption area of rice, merchants would have been more willing to transport rice within the southern regions due to the lower costs and higher profitability. Given the large demand for rice, it would be relatively less price elastic than wheat, which would help merchants anticipate more stable revenue and minimize the risk of loss. On the other hand, since the staple diet in the northern region was (and is) mainly wheat and flour, the wheat trade must have been more circulated there, and hence a higher level of trade volume generated a higher market integration. In conclusion, in the wheat trade, the extent of market integration in the South lagged behind that of the North.

Table 2.7 Results of Model 2.9

Dependent Variable: Log Value of Wheat Price	(1)	(2)	(3)	(4)
Weather Condition	0.161***	0.133***	0.122***	0.111***
	(0.0251)	(0.0290)	(0.0290)	(0.0286)
Canal*Weather Condition	-0.0445***	-0.0509***	-0.048***	-0.034**
	(0.0017)	(0.0169)	(0.0169)	(0.0167)
Yangtze River Dummy* Weather Condition	-0.027**	-0.034**	-0.030**	-0.031**
	(0.0131)	(0.0136)	(0.0136)	(0.0134)
Yellow River Dummy* Weather Condition	-0.040***	-0.032**	-0.031**	-0.0263*
	(0.0270)	(0.0.0140)	(0.0140)	(0.0138)
Capital Dummy* Weather Condition	0.138***	0.138***	0.107***	0.106***
	(0.0202)	(0.0202)	(0.0203)	(0.0200)
South Dummy* Weather Condition		0.025**	0.036***	0.033***
		(0.0128)	(0.0128)	(0.0127)
Mean of Neighbour Cities Prices	0.803***	0.803***	0.808***	0.594***
	(0.0029)	(0.0029)	(0.0032)	(0.0056)
Mean of Neighbour Cities Prices* River Connection Dummy	0.167***	0.167***	0.171***	0.191***
	(0.0052)	(0.0052)	(0.0053)	(0.0053)
Capital Dummy*Mean of Neighbour Cities Prices			0.084***	0.040***
			(0.0065)	(0.0065)
South Dummy* Mean of Neighbour Cities Prices			-0.037***	-0.074***
			(0.0040)	(0.0040)
Provincial Border Dummy * Mean of Neighbour Cities Prices				0.294***
				(0.0063)
Constant	2.955***	2.955***	2.966***	2.966***
	(0.0119)	(0.0119)	(0.0120)	(0.0120)
District Fixed Effects	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES
Season Effects	YES	YES	YES	YES
Observations	137450	137450	137450	136946
Within R2	0.6429	0.6429	0.6436	0.6509

Note: The value in parentheses is the standard error, and the *, **, *** presents the significance level at 10%, 5% and 1%, respectively.

Section 2.5.4 Robustness Check

In this section, I implement two alternative checks to support the findings from Section 2.5.3. In the original model (2.9), the river effects on the responsiveness to local weather conditions are separated into three specific water systems, while the effects on the neighbouring regions are aggregated to all of them in the variable "river connection between cities". The first robustness check replaced the three separate water effects for the responsiveness to local weather conditions to a single term 'river *weather index' while adding three interaction terms for the three specific water river dummies with the neighbouring regions' prices instead of the original term of $\left(\frac{1}{N_i}\right)\sum_{j\in N_i} w_{jt} * R_{ij}$. The model is shown in Equation (2.10).

$$lnp_{it}= \beta_d+\beta_y + \beta_s + \chi_1 w_{it} + \chi_2 R_i * w_{it} + \chi_3 C_i * w_{it} + \chi_4 S_i * w_{it} *+ \chi_5 \left(\frac{1}{N_i}\right)\sum_{j\in N_i} p_{jt} + \chi_6 YR_i * \left(\frac{1}{N_i}\right)\sum_{j\in N_i} p_{jt} + \chi_7 YT_i * \left(\frac{1}{N_i}\right)\sum_{j\in N_i} p_{jt} + \chi_8 G_i * \left(\frac{1}{N_i}\right)\sum_{j\in N_i} p_{jt} + \chi_9 \left(\frac{1}{N_i}\right)\sum_{j\in N_i} p_{jt} * S_i + \chi_{10} \left(\frac{1}{N_i}\right) \sum_{j\in N_i} w_{jt} * C_i + \chi_{11} \left(\frac{1}{N_i}\right)\sum_{j\in N_i} p_{jt} * Pro_{ij} + \varepsilon_{dt} \qquad (2.10)$$

R_i is the dummy variable, equaling 1, when the city i is close to any water system.

The results are shown in Table 2.9. Compared to column (1), columns (2) and (3) add the effects of the southern regions and the provincial borders into the regression. The results are consistent compared to model 2.8. First, the rivers reduced the local price reaction to local weather shocks. The South had weakened market integration, which led local prices to be strongly sensitive to the local weather and to a low extent of co-movement with neighbouring prices. The capital effects reacted strongly, both to local weather changes and to the neighbouring price changes. The interaction term of the Yellow River dummy, the Yangtze River dummy and the Grand Canal dummy with the river connection term show results consistent with the previous model. In model (2.10), it is clear that all three water systems significantly improved the correlation and interaction between local prices and neighbouring prices. The basic idea behind using this model is to ascertain whether all the rivers, including the northern rivers, improved market integration between neighbouring markets. From its interaction terms, all the three rivers significantly improved the price co-movements and convergence between the neighbouring prefectures. And the Grand Canal had the largest impacts compared to other river systems.

Table 2.8 Results of the Robustness Check for Model (2.10)

Dependent Variable: Log Value of Wheat Price	(1)	(2)	(3)
Weather Condition	0.053*** (0.0086)	0.053*** (0.0097)	0.039*** (0.0096)
River*Weather Condition	-0.036*** (0.01111)	-0.035*** (0.01111)	-0.032** (0.0111)
Capital Dummy* Weather Condition	0.139*** (0.0202)	0.108*** (0.0203)	0.109*** (0.0200)
South Dummy* Weather Condition		0.029*** (0.0112)	0.027** (0.0110)
Mean of Neighbour Cities Prices	0.817*** (0.0028)	0.829*** (0.0032)	0.621*** (0.0056)
Yangtze River Dummy*Mean of Neighbour Cities Prices	0.164*** (0.0063)	0.196*** (0.0070)	0.181*** (0.0075)
Yellow River Dummy*Mean of Neighbour Cities Prices	0.142*** (0.0076)	0.119*** (0.0077)	0.121*** (0.0076)
Grand Canal Dummy*Mean of Neighbour Cities Prices	0.028*** (0.0073)	0.040*** (0.0075)	0.102*** (0.0075)
Capital Dummy*Mean of Neighbour Cities Prices		0.084*** (0.0065)	0.041*** (0.0065)
South Dummy* Mean of Neighbour Cities Prices		-0.058*** (0.0046)	-0.093*** (0.0046)
Provincial Border Dummy * Mean of Neighbour Cities Prices			0.289*** (0.0064)
Constant	0.656*** (0.0120)	0.668*** (0.0120)	0.702*** (0.0119)
District Fixed Effects	YES	YES	YES
Year Effects	YES	YES	YES
Season Effects	YES	YES	YES
Observations	137450	137450	136946
Within R2	0.6426	0.6435	0.6504

Note: The value in parentheses is the standard error, and the *, **, *** presents the significance level at 10%, 5% and 1%, respectively.

The second robustness check uses the three specific water determinants instead of the total river effects in both the responsiveness to the local weather and the neighbouring prices. The model is shown in Equation (2.11) and the results are given in Table 2.10, which show that the results are consistent with model (2.9) and model (2.10), providing solid support for the quantitative analysis results for this chapter.

$$lnp_{it}= \beta_d+\beta_y+\beta_s+\chi_1 w_{it}+\chi_2 YT_{it}*w_{it}+\chi_3 YR_i*w_{it}+\chi_4 G_i*w_{it}+\chi_5 C_i *w_{it}+\chi_6 S_i*w_{it}+\chi_7\left(\frac{1}{N_i}\right)\sum_{j\in N_i}p_{jt}+\chi_8 YR_i*\left(\frac{1}{N_i}\right)\sum_{j\in N_i}p_{jt}*R_{ij}+\chi_9 YT_i *\left(\frac{1}{N_i}\right)\sum_{j\in N_i}p_{jt}*R_{ij}+\chi_{10}G_i*\left(\frac{1}{N_i}\right)\sum_{j\in N_i}p_{jt}*R_{ij}+\chi_{11}\left(\frac{1}{N_i}\right)\sum_{j\in N_i}p_{jt}*S_i +\chi_{12}\left(\frac{1}{N_i}\right)\sum_{j\in N_i}p_{jt}*C_i+\chi_{13}\left(\frac{1}{N_i}\right)\sum_{j\in N_i}p_{jt}*Pro_{ij}+\varepsilon_{dt} \quad (2.11)$$

Table 2.9 Results of the Second Robustness Check for Model (2.11)

Dependent Variable: Log Value of Wheat Price	(1)	(2)	(3)
Weather Condition	0.056***	0.044***	0.040***
	(0.0084)	(0.0096)	(0.0096)
Canal*Weather Condition	-0.034**	-0.037**	-0.037**
	(0.0168)	(0.0170)	(0.0168)
Yangtze River Dummy* Weather	-0.0358***	-0.040***	-0.038***
Condition	(0.0132)	(0.0136)	(0.0134)
Yellow River Dummy* Weather	-0.047**	-0.035**	-0.029**
Condition	(0.0132)	(0.0140)	(0.0139)
Capital Dummy* Weather	0.140***	0.109***	0.110***
Condition	(0.0202)	(0.0203)	(0.0200)
South Dummy* Weather Condition		0.034***	0.033***
		(0.0129)	(0.0127)
Mean of Neighbour Cities Prices	0.817***	0.829***	0.621***
	(0.0028)	(0.0032)	(0.0056)
Yangtze River Dummy*Mean of	0.164***	0.197***	0.181***
Neighbour Cities Prices*	(0.0063)	(0.0070)	(0.0069)
Yellow River Dummy*Mean of	0.142***	0.119***	0.121***
Neighbour Cities Prices*	(0.0076)	(0.0077)	(0.0076)
Grand Canal Dummy*Mean of	0.028***	0.041***	0.103***
Neighbour Cities Prices*	(0.0074)	(0.0075)	(0.0076)
Capital Dummy*Mean of		0.084***	0.041***
Neighbour Cities Prices		(0.0065)	(0.0065)
South Dummy* Mean of		-0.058***	-0.093***
Neighbour Cities Prices		(0.0040)	(0.0046)
Provincial Border Dummy * Mean			0.289***
of Neighbour Cities Prices			(0.0064)
Constant		0.668***	0.702***
		(0.0120)	(0.0119)
District Fixed Effects	YES	YES	YES
Year Effects	YES	YES	YES
Season Effects	YES	YES	YES
Observations	137450	137450	136946
Within R2	0.6426	0.6436	0.6504

Note: The value in parentheses is the standard error, and the *, **, *** presents the significance level at 10%, 5% and 1%, respectively.

Section 2.6 Conclusions and Implications

This chapter is the first attempt to use the fixed panel data analysis generated by Donaldson (2018) to check the determinants of market integration in the mid-Qing

Dynasty (1738-1820). Historical wheat prices and the geographical data depict the heterogeneous characteristics for each prefecture. First, the results show the significant impacts of both the southern and northern river routes on improving market efficiency in pre-modern China. The Grand Canal had the strongest, or at least equally strong, effects on market integration compared to the other –natural - waterways. The southern market for wheat was not as claimed in previous papers. From the current study, the southern wheat market was weaker than the northern market, something which could be attributed to limited demand and trade volume. This finding does not deny the transport advantage of the Yangtze River, as wheat was not the most important commodity traded in the South. However, it does demonstrate that at least not all the commodity markets in the South were stronger than in the North from the perspective of market integration. The capital city effects are complex and need unpacking. Capital cities simultaneously responded sensitively to local weather shocks and changes in neighbouring prices. This might be the reason for the high urbanisation rate, as when the local weather changed, people were more precautionary and stored food at home, since a large number of people in the provincial capitals could not produce their own grain. The provincial border effect is also very significant[12]. This finding proves that political reasons were as important as geographic reasons, which enhanced market connections within the province.

Three main limitations exist in this chapter. The first is that the weather condition data is too general. As seen in Figure 2.9, a number of cities in some provinces may have shared the same weather index, something which would cause problems for this study's quantitative analysis. In order to eliminate multicollinearity, it was not possible to use the weather data for both the region and for neighbouring cities. The second problem is that wheat might not have been the leading commodity in the South, something which may weaken the results of the analysis. However, if I had used the wheat price in the North and the rice price in the South, the results would also have lacked reliability. In this case, the regional difference might have been generated by the endogenous differences between the

[12] In order to control the provinces more effectively, the provincial border is always not consistent with the geographical borders (mountains or rivers), hence the provincial governor is hard to rebel against the central government and defend the launching by the central army.

two grains rather than the regional difference in and of itself. Therefore, it was deemed more effective to identify a single commodity which was circulating widely both in the South and in the North. The third weakness is that the study only measures interaction between a city and its neighbouring regions. However, market integration might apply to greater distances.

These limitations imply some implications for future research. The first is that it might need to collect more detailed climate data at the prefecture level which would see to determine if regions along rivers responded strongly to weather shocks in neighbouring regions, as in the methodology used by Donaldson (2018). The second improvement concerns the selection of the commodity. As the wheat trade might not have been the main trading activity in the South, its price could not have represented the general market situation in the South. Therefore, another commodity might be needed to measure the regional differences for both the South and the North. For example, the silk price might be a good tool. The third improvement concerns the market interaction between cities. It is possible to generate a new equation to measure the co-movement of the city not only as it relates to neighbouring cities but also to greater distances. Moreover, as the urbanised population pressure on the capital effects is discussed here, it might be better to collect data on the urbanisation rate to describe the demand effect more clearly.

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Section 2.8 Appendix for Chapter 1

A.1.1 List of the prefecture level unit in Chapter 1

Name in Chinese	City	Name in Chinese	City
東昌[府]	DONGCHANG	霍[直隸州]	HUO
济南府	JINAN	絳[直隸州]	JIANG
济宁（直隶州）	JINING	解[直隸州]	XIE
临清	LINQING	遼[直隸州]	LIAO
兖州府	YANZHOU	潞安[府]	LU'AN
常州府	CHANGZHOU	寧武[府]	NINGWU
淮安府	HUAI'AN	平定[直隸州]	PINGDING
苏州府	SUZHOU	平陽[府]	PINGYANG
徐州府	XUZHOU	蒲州[府]	PUZHOU
扬州府	YANGZHOU	沁[直隸州]	QIN
镇江府	ZHENJIANG	朔平[府]	SHUOPING
杭州[府]	HANGZHOU	太原[府]	TAIYUAN
嘉興[府]	JIAXING	隰[直隸州]	XI
承德府	CHENGDE	忻[直隸州]	XIN
定（直隶州）	DING	澤州[府]	ZEZHOU
河间府	HEJIAN	歸綏(歸綏六廳)[道]	GUISUI
宣化府	XUANHUA	鳳翔[府]	FENGXIANG
易（直隶州）	YI	鄜[直隸州]	LU
曹州[府]	CAOZHOU	漢中[府]	HANZHONG
登州[府]	DENGZHOU	乾[直隸州]	QIAN
莱州府	LAIZHOU	商[直隸州]	SHANG
青州府	QINGZHOU	綏德[直隸州]	SUIDE
泰安府	TAI'AN	同州[府]	TONGZHOU

武定府	WUDING	西安[府]	XI'AN
沂州府	YIZHOU	興安[府]	XING'AN
江宁府	JIANGNING	延安[府]	YAN'AN
松江府	SONGJIANG	榆林[府]	YULIN
太仓（直隶州）	TAICANG	安西[直隷州]	ANXI
通（直隶州）	NANTONG	甘州[府]	GANZHOU
湖州[府]	HUZHOU	鞏昌[府]	GONGCHANG
金華[府]	JINHUA	階[直隷州]	JIE
衢州[府]	QUZHOU	涇[直隷州]	JING
寧波[府]	NINGBO	蘭州[府]	LANZHOU
紹興[府]	SHAOXING	涼州[府]	LIANGZHOU
台州[府]	TAIZHOU	寧夏[府]	NINGXIA
溫州[府]	WENZHOU	平涼[府]	PINGLIANG
嚴州[府]	YANZHOU	秦[直隷州]	QIN
奉天[府]	FENGTIAN	慶陽[府]	QINGYANG
錦州[府]	JINZHOU	肅[直隷州]	SUZHOU
保德[直隷州]	BAODE	西寧[府]	XINING
代[直隷州]	DAI	哈密[直隷廳]	HAMI
大同[府]	DATONG	陳州[府]	CHENZHOU
汾州[府]	FENZHOU	光[直隷州]	GUANGZHOU
歸德[府]	GUIDE	鄖陽[府]	XUNYANG
河南[府]	HENAN	寶慶[府]	BAOQING
懷慶[府]	HUAIQING	常德[府]	CHANGDE
開封[府]	KAIFENG	長沙[府]	CHANGSHA
南陽[府]	NANYANG	辰州[府]	CHENZHOU
汝[直隷州]	RU	桂陽[直隷州]	GUIYANG
陝[直隷州]	SHAN	衡州[府]	HENGZHOU
衛輝[府]	WEIHUI	澧[直隷州]	LI

許[直隸州]	XU	永州[府]	YONGZHOU
彰德[府]	ZHANGDE	岳州[府]	YUEZHOU
池州[府]	CHIZHOU	保寧[府]	BAONING
滁[直隸州]	CHU	成都[府]	CHENGDU
廣德[直隸州]	GUANGDE	重慶[府]	CHONGQING
徽州[府]	HUIZHOU	嘉定[府]	JIADING
六安[直隸州]	LIU'AN	邛[直隸州]	QIONG
廬州[府]	LUZHOU	夔州[府]	KUIZHOU
泗[直隸州]	SI	龍安[府]	LONG'AN
太平[府]	TAIPING	綿[直隸州]	MIAN
潁州[府]	YINGZHOU	茂[直隸州]	MAO
撫州[府]	FUZHOU	寧遠[府]	NINGYUAN
贛州[府]	GANZHOU	石砫[直隸廳]	SHIZHU
廣信[府]	GUANGXIN	順慶[府]	SHUNQING
吉安[府]	JI'AN	綏定[府]	SUIDING
建昌[府]	JIANCHANG	澂江[府]	CHENGZHOU
九江[府]	JIUJIANG	楚雄[府]	CHUXIONG
臨江[府]	LINJIANG	大理[府]	DALI
南安[府]	NANAN	東川[府]	DONGCHUAN
南昌[府]	NANCHANG	廣南[府]	GUANGNAN
南康[府]	NANKANG	廣西[直隸州]	GUANGXIN
寧都(寧州)[直隸州]	NINGDU	景東[直隸廳]	JINGDONG
饒州[府]	RAOZHOU	開化[府]	KAIHUA
瑞州[府]	RUIZHOU	麗江[府]	LIJIANG
袁州[府]	YUANZHOU	臨安[府]	LIN'AN
安陸[府]	ANLU	蒙化[直隸廳]	MENGHUA
德安[府]	DE'AN	普洱[府]	PU'ER
漢陽[府]	HANYANG	曲靖[府]	QUJING

黄州[府]	HUANGZHOU	順寧[府]	SHUNNING
荊門[直隷州]	JINGMEN	武定[直隷州]	WUDING
施南[府]	SHINAN	永北[直隷廳]	YONGBEI
武昌[府]	WUCHANG	雲南[府]	YUNNAN
襄陽[府]	XIANGYANG	昭通[府]	ZHAOTONG
宜昌[府]	YICHANG	鎮沅[直隷廳]	ZHENYUAN

A.2.2 The map of neighbouring cities and the waterways

Source: http://sites.fas.harvard.edu/~chgis/

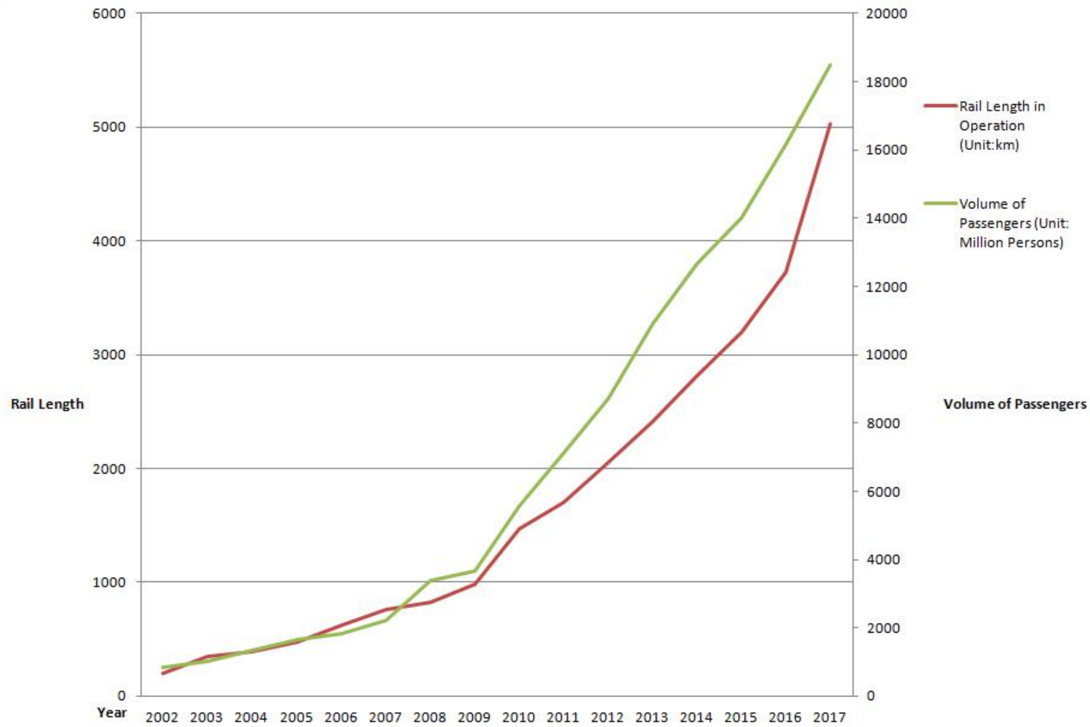
Chapter 3 Transportation or Economic Purpose? A Non-parametric Approach Analysing Urban Rail Transportation in China

Section 3.1 Introduction

Recent decades have witnessed an economic boom in China. Accompanying economic prosperity, a large number of population conglomeration have become a huge pressure for metropolises. The increasing number of urban residents and the concomitant rise in the number of private cars have overburdened urban roads in many Chinese cities. In order to deal with congestion, URT systems, including metros, light rail systems, and trams have appeared gradually in most large cities. According to the China Urban Rail Transit Association (CURTA) (2017)[13], there was a total 5,033km of urban rail lines operating in 34 cities and 6,246km under construction in mainland China at the end of 2017. Figure 3.1 shows the length of the constructed urban railways and the passenger turnover from 2002 to 2017. It can be seen that the development of URT accelerated after 2008. By the end of 2017, the length of URT lines in operation was 25 times that in 2002.

[13] The source is 'The statistics and analysis report of urban rail transit in 2017', available at: http://www.camet.org.cn/index.php?m=content&c=index&a=lists&catid=18&page=2.

Figure 3.1 The Development of the Urban Rail Transportation in China



Source: Annual Statistics and Analysis Report of the China Urban Rail Transit Association

Remarkably, the URT system does not make profit in most cities. According to the China Urban Rail Transit Association (2017), in only 4 out of 35 cities the URT system made profit in 2017. Nationally, the average operating cost was 28.1 RMB/km, while the average operating revenue was 13.2 RMB/km in 2017. Liu and Ouyang (2007) reported that the average building cost of underground metro lines was around 600 million RMB per kilometre. Based on this cost and the most cities' average ticket price, 3-5 RMB[14], it can be calculated that a 30km metro line needs 150 million passengers to cover the total construction cost in 30 years excluding the interest payments and operation costs. It was reported that the annual operating revenue of the URT system in Beijing only accounted for only 30% of the operating cost in 2002, and Line 13 alone suffered a loss of 80 million RMB in the first year of operation (Huang, 2013). Therefore, given the cheap tickets but huge construction costs, the URT system is generally not a profitable project. Instead, it is more like a public facility that serves public benefits. What are these benefits? Mu (2012)

[14] Source: https://www.sohu.com/a/211065030_729676

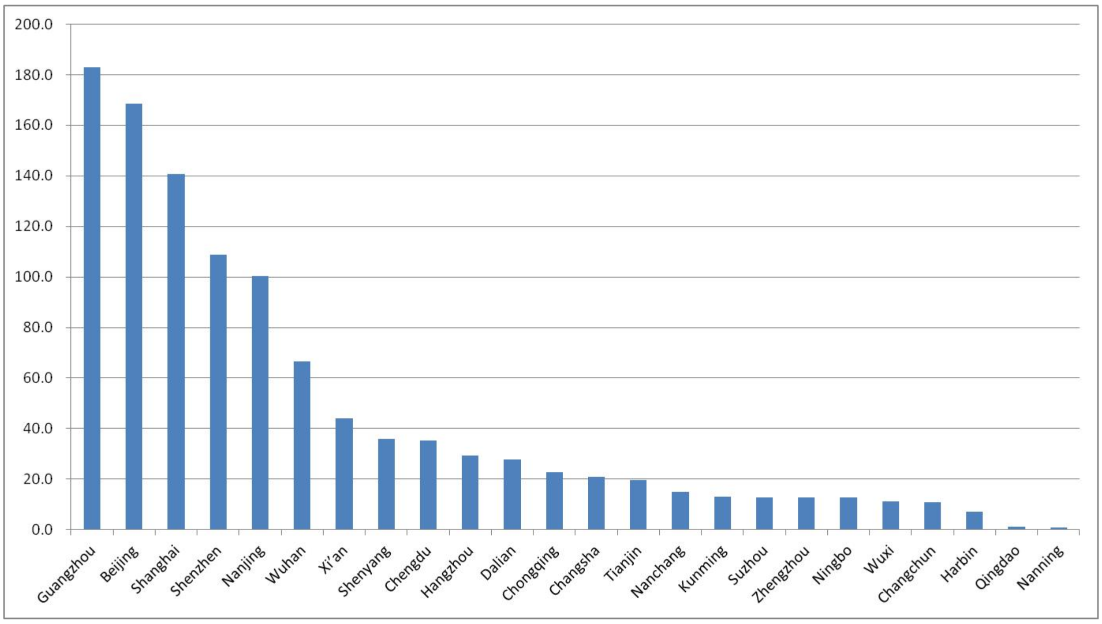
classified the benefits into three categories, transportation benefit, environmental benefit and social benefit. The transportation benefit includes increasing transport opportunities, saving transport time, enhancing labour productivity, reducing accidents and substituting for road traffic. The environmental effects encompass energy saving and reduction of pollution and noise. The increases of land price, working opportunities, competitiveness of a city and the economy are defined as the social benefits. Because of the existence of positive externalities, governments are motivated to build and operate URT systems in spite of financial losses thereby incurred.

Naturally, a city with a larger population has a higher demand for transport needs. Tan (2001) pointed out that the travel intensity of the residents is from 2.5 to 3 times per day in most of the first- and second-tier cities in China. By the end of 2016, all cities with URT system had more than 5 million permanent residents. There is also a positive relationship between passenger turnover and urban population. In 2016, the URT passenger turnover was greater than 1 billion people in four cities, which are Beijing (3.65 billion), Shanghai (3.4 billion), Guangzhou (2.57 billion) and Shenzhen (1.3 billion). Those four cities happen to be the first-tier cities[15], which have the largest GDP and the longest URT lines. By the end of 2016, 16 cities, including the top 4 cities, had annual URT turnovers greater than 100 million passengers. Figure 3.2 presents the ratio of the number of passengers to the population of permanent residents in 2016. In terms of the passenger-to-population ratio, the top four were again in the top tier. In these cities the annual number of passengers exceeded 100 times as much as the population. The average ratio was 46, and only 3 cities had a ratio that was less than 10. New York, London, Madrid and Paris have approximately 150 times[16] of annual passengers to their population in 2018. Comparing to the same ratio in western countries, the URT systems of top tier cities in China functioned well in transporting passengers.

[15] There is not a strict definition of the fist-tier cities or Chinese city tier system. It generally represents the most developed and densely populated urban metropolises that have huge economic, cultural and political influence in China. The consensus is that four cities belong to first-tier: Beijing, Shanghai, Guangzhou and Shenzhen, which are also the top 4 in the rank of GDP level.

[16] The data of URT passenger volume are from Wikipedia and the population data is from CEIC.

Figure 3.2 The Ratio of the Annual Number of Passengers to the Population of Permanent Residents in 2016



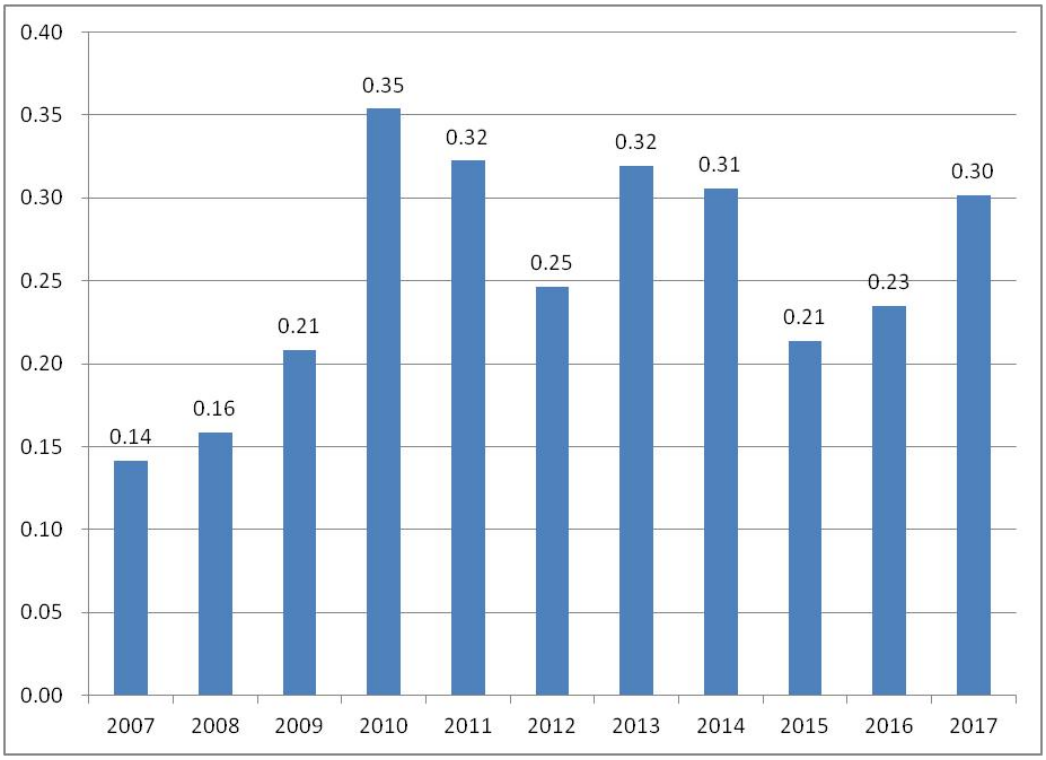
Source: Passengers data is from Annual Statistics and Analysis Report of CURTA and population data is from CEIC.

URT system is also an important component of the low-carbon economy. First, the energy consumption of a URT system is considerably lower than that of private cars and buses. Based on per km per person numbers, the energy consumption of the URT system is only 31.3% and 8.4% of those of buses and private cars, respectively (Jiang and Bai, 2010). Second, a URT system reduces air pollution and greenhouse gas emissions. Jiang and Bai (2010) estimated that if the passenger throughput of a URT system was around 50% of its full capacity, the emission of carbon dioxide and nitrogen oxides could be reduced by 92% and 86%, respectively, compared to road traffic. According to Li (2007), emissions of sulphur dioxide by a URT system is half of that of private cars. Moreover, the URT system reduces noise and traffic land use.

Besides alleviating the traffic burden and improving the environment, the incentive for career promotion of the local governors might also be an important factor that government officers take into consideration. In China, the promotion of local government leaders is generally determined by the upper level of the Party committee (Yang, 2014). The economic performance of the city is the leading factor in the evaluation of career promotion for the mayors and municipal Party committee secretaries (Zong, 2013; Luo, She and Chen, 2015). Luo, She and Chen's (2015) quantitative analysis find that the GDP growth rate significantly improves the promotion chances of the local governors. Therefore, when evaluating the potential of an URT system, local government leaders tend to consider the political benefits as well. First, building the URT system will directly boost urban GDP and create a large number of jobs in both the construction and operation stages. In this way, large public investments such as the URT system will substantially improve the local economic performance, which generates political benefits to local government servants. For example, Shen (2004) estimated that the URT project in Chongqing generated more than 10 billion RMB's GDP both directly and indirectly, and the economic multiplier of the investment of the URT project was around 3. The URT system and URT-related business opportunities also provide extra jobs for the residents. Wei (2017) points that the URT system in Xi'an needed more than 1,000 employees to operate and also created jobs in the supporting facilities and advertising companies. Second, the introduction of the URT system increases the land prices in surrounding areas. In Hong Kong and Japan, the government uses revenues from real estate projects along metro lines to cover the construction cost of metro lines (Jin, 1998; Ye, Hu and Gu, 2002). This also happens to mainland China. Planning URT lines could increase the land price, thus increases the local fiscal revenue by land sales. According to the data of Ministry of Finance data, revenues from land transactions and property tax from real estate projects along URT lines constitute an important source of income for local governments in China. In the period 2009-2017, revenues from land transaction accounted for 27% of the total fiscal revenue on average, seen in Figure 3.3. As the fiscal revenue is divided to the local and the central fiscal revenue, the percentage of the revenue from land sales to the local fiscal revenue is even higher. Therefore, by building the URT system, Chinese local governments may supplement their fiscal budget with revenues, which could be used to provide other public facilities or services, such as education, sanitation and social security. These are also the criteria to evaluate the performance of the local government officers (Zhang, 2003).

Additionally, better urban transport and public services will attract more talents to the city, who will also create economic growth and provide tax revenue to the local government afterwards (Xu, 2002; Song & Zhang, 2010). Hence local governments may have a strong economic incentive to build the URT system. In other words, Building the URT systems might create more GDP and employment, more revenue from land sales and property taxes, hence enhancing the attractiveness of the city to skilled workers. Based on the economic advantages that the URT could achieve, the local government leaders are very willing to apply for the project even if it is not highly needed from the perspective of transportation. Economic incentive in URT construction is not unique to China. Pickrell (1989) reported that the estimated cost was always lower than the actual cost and the estimated traffic always higher than the actual traffic in many URT projects in US, when the government was planning the project. His finding indicates that transport need was not the only initiative in planning URT systems that the American local governors also tended to make the projects approved by overestimating the revenue and underestimating the budget

Figure 3.3 The Percentage of Land Sales Revenue to National Fiscal Revenue



Source: CEIC

A side effect of URT is that it increases the house prices along it. Wei (2007) reports that property price along metro lines increased significantly within 1 year after the construction in Panyu, a district of Guangzhou. Ye and Cai (2002), Chen, Lin and Liu(2005), Wu (2011), Chi (2012) and Wei (2017) have made similar observations in Shanghai, Beijing, Wuhan, Shenyang and Xi'an. But it is not the main focus of this chapter.

Due to its economic benefits, a large number of local governments devoted a large amount of effort to applying, planning and constructing the URT projects in last 10 years. After a rapid booming in the last decade, the central government finds that URT of some cities are over-developed, which led to a high fiscal burden to subsidize the operation and pay interests on financing cost. The central government became unwilling to see increasing debts and inefficient allocation of the resources if the cities do not necessarily need the URT project in transporting passengers. In 2018, the State council changes the criteria[17] to apply for the new URT project. And considering the new request, whose details are shown in Section 3.2.1, URT application of 14 cities are denied by the central government due to high liability ratio, insufficient GDP level, insufficient fiscal budget or low level of population.

This chapter analyses and compares the efficiencies of Chinese URT system in providing public transit and meeting economic objectives. This aims to investigate whether Chinese URT systems are built primarily to serve the transport function or the economic incentives of the local governments, and to explore potential heterogeneity among different types of Chinese cities.

Data Envelopment Analysis (DEA) was used to evaluate the efficiencies of the URT systems in the provision of transportation and economic objectives. After dealing with the results generated from DEA, this chapter implements the Tobit regression model to ascertain whether the top cites relatively have a different efficiency pattern compared to other cities. The results show that top cities relatively have the higher transport efficiency while the small and medium cities[18] (SMC) have higher economic efficiency. These results, ex-post, implies that the local governments of those non-top cities (SMC) mainly concentrate on economic

[17] The regulation document could be found in the link: http://www.gov.cn/zhengce/content/2018-07/13/content_5306202.htm.
[18] SMC are the synonym of non-first tier cities in this dissertation.

advantages rather than dealing with transport needs when considering and applying for the URT project. The practical results also show that URT systems in most of the cities produce the economic benefit on a decreasing return to scale, which suggests local governments that further investment on the URT project might be less effective approach in improving the economy of the city.

The first motivation of this chapter is that it is the first attempt to study the transportation and economic benefits of the URT system using all the URT data in China mainland. To my best knowledge, although numerous studies on the economic or social benefits of the URT systems are conducted in individual Chinese cities. There is few estimating the effects gathering all the cities. Second, there is nearly no previous research investigating the heterogeneity between different types of cities. This chapter try to see if building URT is necessary for different type of cities. Third, it is also the first time that DEA-Tobit two-step estimation has been applied to the analysis of URT efficiency in China. Most importantly, the empirical evidence may help the decision makers to review the effects of the existed projects and rethink of their new URT development strategy. As the most of the developing countries have no URT or only have URT systems in their national-core cities. This chapter offers some new sights for other developing countries that whether a regional-core city should build more URT lines.

The rest of the study is organised as follows. Section 3.2 overviews the institutional background and policies that governs URT planning and construction in China. Section 3.3 reviews the DEA and Tobit regression model literature and empirical studies on China’s URT systems. Sections 3.4 and 3.5 present details of the methodology and data description. Section 3.6 presents the analytical results. Section 3.7 offers some concluding the findings and give implications to the projects applicants and approver.

Section 3.2 Background and Institutions

Section 3.2.1 Requirements of applying URT system

The central government has very clear criteria[19] to determine which city is eligible to apply for a URT project. In 2003, the State Council mandated that cities with an urban population of over 3 million, 10 billion RMB of local fiscal revenue and 100 billion RMB of GDP were qualified to apply for a URT system. However, due to high construction costs and operating losses, most cities satisfying these conditions accumulated huge debts after they constructed a system. In 2018, the qualification conditions were raised to 30 billion RMB of local fiscal revenue and 300 billion RMB of GDP in an attempt to keep smaller cities out of the URT club. To avoid operating losses, the central government also requests that the expected passenger flow should be no less than 7000 people per day per kilometre in the short run and 30,000 people per day per kilometre in the long run.

Section 3.2.2 The Process of URT System Application and Approval

According to the official file, "Strengthening the Management of Planning and Constructing the URT", published by the National Development and Reforming Commission (NDRC) in 2015, the process is quite complicated and involves numerous bureaus authorisation.

In the first step, the local government (prefecture level) delegates a professional company to draw up a network plan and a construction plan. The network plan is a long-term plan which specifies the full network, the operation system, station locations, type of train/carriage, etc. Passenger turnover forecast is the most important component of the network plan. The construction plan deals with short-term objectives. It provides more detail on the lines to be constructed in the near future. It also provides information on project budget and financing methods.

The network plan and the construction plan are combined into a preliminary version of a URT network plan and handed to the Provincial Development and Reform Commission for approval. After approval, the preliminary plan is examined by the National Environmental Protection Agency and China's Earthquake

[19] The regulation document could be found in the link: http://www.gov.cn/gongbao/content/2003/content_62476.htm.

Administration. Next, the land use by the planned URT project should be approved by the National Ministry of Housing and Urban-Rural Development. After approval by these authorities, it is submitted to the NDRC, which then commissions the China International Engineering Consulting Corporation (CIECC) to evaluate the project and make detailed comments on feasibility. If the feedback is positive, the NDRC will hand it over to the State Council for final approval.

After the URT project is officially approved with a green light from the State Council, the local government should compose a report on the project's feasibility. This report should encompass many aspects of the project, including engineering feasibility, locations of stations, passenger turnover forecast, a geological investigation, an environmental impact survey, social stability analysis, an energy saving study, a security assessment, among others. After approval of the feasibility report by the specialists commissioned by the NDRC again, the project enters the construction stage.

Due to the complicated procedures of project application, it generally takes more than 5 years before the stage of construction is reached. Thus, the local governors should be careful to decide whether to devote limited resources and workloads to the project. If it is not approved, this long time process might lead the city missing a lot of other development opportunities.

Section 3.3 Literature Review

In this chapter, the DEA methodology is implemented. DEA was first proposed by Charnes, Cooper and Rhodes (1978) to estimate the production frontier and construct measures of efficiency using linear programming techniques. The initial model was based on the assumption of constant returns to scale and was named the CCR model. Banker, Charnes and Cooper (1984) revised the CCR model to allow varying returns to scale. Their model was thus called the BCC model. There are three advantages of the DEA method in efficiency analysis. First, it allows researchers to construct the production frontier directly from data without making any assumption on the production function. Second, it is far more convenient than the conventional parametric methods in handling multi-output technologies. Third, by computing the optimal output, it is convenient to construct measures of efficiency.

In Chinese studies, DEA has been used to study the efficiency of various types of economic agents, especially when it is difficult to measure output by revenue. Topics include hospitals and nursing facilities (Jiang and Zhou, 2017; Zeng et al., 2018), the tourism sector (Ren, 2018), inter-city transportation infrastructure (Dong et al., 2018), and security companies (Song, 2017). As far as I know, no researcher has applied DEA to study the efficiency of Chinese URT systems.

A rich body of the literature has studied the economic impact of URT system using Chinese data. Ma et.al (2001) implements the linear regression based on the Taylor expansion of the CES production function of three elements of Rank Two to investigate the contribution of the construction of infrastructures to economic growth. Using data in Shenyang from 1985 to 1999, they derive how much GDP growth is contributed by infrastructure investment and the production (GDP) elasticity of the investment of infrastructure. This method is quite applicable, however, there is only 15 annual data, which brings limitation to the model. By estimating a Solow growth model, Liu (2002) investigated the relationship between GDP, public investment and private investment using data from 29 provinces spanning 5 years. Liu concludes that the output elasticity of public investment was significantly higher than that of private investment. Decomposing public investment into various categories, it found that the investment on infrastructure had the highest elasticity of generating GDP.

Regarding the economic impacts of URT systems, many studies have identified a significant effect on property prices. Ye and Cai (2002) implement the land function method to estimate the house price difference regarding the effects of the distance to the metro station. Using practical data from Shanghai, the scholars conclude that the price difference is larger in areas located further from the city centre and is also larger if the house is very close to the metro station compared to properties nearby but not close to a metro line. The paper itself points out two shortcomings: a lack of data and a lack of independent factors to the house price difference. Using the same method, Li’s (2004) estimation of housing price changes after metro lines open generates similar results. Revising the method of Ye and Cai (2002), Chen, Lin and Liu (2005) add one more variable-time-into the model. They find that house price increases along Line 13 in Beijing would be smaller in suburban areas, a finding which is not consistent with Ye and Cai (2002). More importantly, the price increases are positively correlated with time, i.e., the longer the metro has been operating, the higher the prices are. Wu (2011) uses a similar methodology to estimate the effects on house prices in Wuhan, generating similar results with Chen, Lin and Liu (2005). The finding of house price increase presents the sight that building URT raises the land price as well at some extent.

Other researchers have identified a significant impact of URT systems on local GDP. According to Zhang and Chen’s (2006) estimate, a URT project that costs 3.76 billion RMB in Chongqing increased local GDP by about 6.9 billion RMB in the first year. That is, the economic multiplier was 1.84 in the first year. A major limitation of their analysis is the small sample size, only nine observations. Zhou and Zhang (2013) studied the economic effect of urban rail transport based on system dynamic model using Beijing data from 2001 to 2010. The economic effect of URT in this article is regarded as improving the population agglomeration, which thus increases the land value, enhances the prosperity of the commercial service, and promotes the regional economic development. The findings conclude that the increase of passenger capacity is positively correlated with its economic effect and the stimulation increases passenger traffic to improve the speed of its economic effects in the short term, while it shows less relation between these two in the long term. Li, Hu and Guo (2017) estimated the effect of URT systems on local GDP using panel data for all cities in China. By controlling other transportation investment in the fixed effects model, they concluded that the output elasticity of URT investment was 0.025. By dividing the sample into small cities (urban population below 3 million) and large cities (urban population greater than 3 million), they found that the effect of URT investment on GDP was significant only among large cities. However, since most of the small cities did not have their URT systems during the study period, the sample of small cities might be too small. This paper is the only one the author found that gathers all the China URT data and compares the different between different sized cities.

Finally, some researchers have explored other socio-economic impacts of a URT system. Li (2007) used the input-output model to estimate the strength of the forward and backward linkages generated by a URT system. He concluded that the strongest forward linkage was associated with the real estate industry, while the construction industry had the strongest backward linkage. Jiang and Bai (2010) employ the Multi-layer Fuzzy Comprehensive Evaluation model (MFCE) to evaluate the environmental benefits of Wuhan's No. 2 metro line. They weigh several environmental effects, including energy saving and emission reductions, and the overall conclusion was "quite environmentally efficient." Mu (2012) uses the same method to analyse the benefits of Chengdu's No. 2 metro line. They consider transportation, environmental, and economic benefits and asked 100 specialists to give their satisfaction score for each benefit. The overall score is "quite satisfactory." The disadvantage of this method is that the scores are set by specialists, which may not be objective. Zhu (2015) considers a wide range of socio-economic effects and uses cost-benefit analysis to estimate the overall benefit of URT projects. By converting all externalities into monetary values, he was able to evaluate the aggregate benefit of the URT system.

The DEA methodology implementation in this chapter is closely related to that Bertoméu-Sánchez and Estache (2017), who compared the efficiencies of Spain's transportation infrastructure in enhancing transport mobility and Madrid's political centrality. They measured transport mobility by freight and passenger turnover and the centrality of Madrid by its population and income as shares of national totals. They argued that the political objective might have played an important role in the decision of building transportation infrastructure because politicians wanted to win more votes by improving the economy of the central city (Madrid). Using DEA, they found that the project of the railways and motorways played a better role in serving the political goal (centralization) than the transport goal (mobility). Similar to Bertoméu-Sánchez and Estache (2017), this chapter argues that Chinese URT projects also serve two objectives: the transportation needs and political goals (improving cities' attractiveness). As demonstrated in Section1.1, URT projects generate strong boosts to the local economy, create more revenue from land sales and they add to the attractiveness of the city, which are directly linked to the promotion of local government officials. Though the final approval rights are in the hands of the NDRC., the local government officials could enjoy the most of economic and promotion benefit. It leads to strong incentives to draft URT plans for state approval. Notably, the political incentives differ widely in China and in Spain. By analysing the transportation efficiency and the economic (political) efficiency of the URT systems in China, this chapter sheds further light on the motivation behind the decision of building large public transportation infrastructures.

After generating DEA results, the Tobit regression model is used to examine the factors contributing to the heterogeneity of efficiency. A DEA-Tobit two stage approach is widely used to analyse the determinants of efficiency. Grigorian and Manole (2006) use this two-stage approach to evaluate the factor of commercial bank performance in economic reforming countries in the 1990s. They argue that a censored Tobit model is an appropriate approach to estimate efficiency as it only ranges from 0 to 1. Afonso and Aubyn (2006) use a similar method to conclude that the school score efficiency is significantly affected by GDP per capita. In China, Tu and Wu (2006) Shi and Shen (2008) also use the Tobit model to find the determinants of resource efficiency after generating efficiency from a super-DEA model. Yang, Shao and Hu (2010) estimate provincial environmental efficiency and implement the Tobit model to confirm the relationship between efficiency and GDP per capita.

Section 3.4 Methodology

In this chapter, the URT system in each city is treated as a decision making unit (DMU). Wherever the annual observations are pooled together, the same URT system in different years is treated as different DMUs.

This chapter adopts the BCC model (Banker, Charnes and Cooper, 1984), which allows a variable return to scale. Compared to the CCR model, the BCC model also has the advantage of separating technical efficiency from scale efficiency. The output oriented approach is adopted to define efficiencies. The reason would be explained after introduction of the input and output information. Specifically, technical efficiency is defined as the ratio of actual output to the best possible output given the inputs, and scale efficiency determines whether the technology is operating at increasing, constant, or decreasing returns to scale. If the production frontier is increasing returns to scale in the early stage of production and eventually begins to decrease returns to scale when output/input increases, optimal scale efficiency (maximal average output) is achieved when the technology is operating at constant returns to scale.

Figure 3.4 illustrates the concepts of technical efficiency and scale efficiency using a technology that produces one output using one input. The curve AEC is the production frontier generated by the data (all the points except D and B). As seen, this PPC curve could envelop all of those points. As mentioned in the last paragraph, the technical efficiency measures the distance from the actual output from the maximum possible level of output given the input. Since points A, E and C are located on the production frontier, they are technically efficient. The other points from F to L are technically inefficient. The scale efficiency measures the distance from the maximum output level to that of a constant-returns-to-scale technology generated by the same data. Therefore, for all the points within the production feasibility set, only point E is scale efficient because the slope of point E on AEC curve is the largest (OE is the tangent line of point E). In other words, the point E is the one with the largest productivity (output/input). Using point F as an example, the efficiency measures are defined as follows:

Real Input level: OB. Real output level: BF

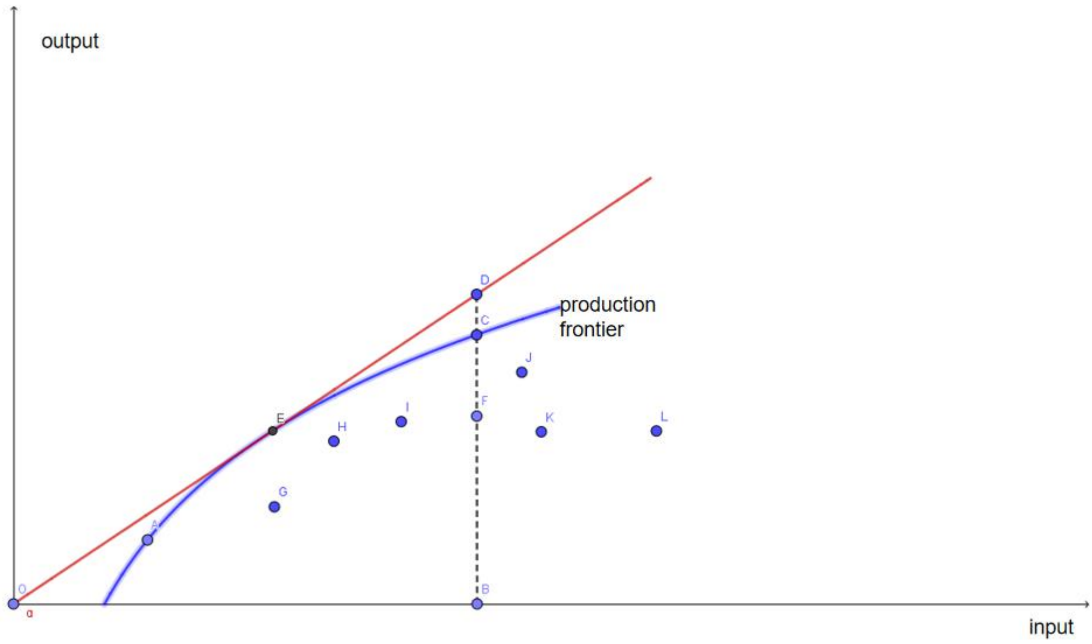
Technical efficiency: BF/BC. BC is the largest output level, given OB input.

Scale efficiency: BC/BD. BD is the output level with the largest productivity on line OE given OB input.

Overall efficiency: BF/BD=technical efficiency * scale efficiency.

In this case, for point C, the technical efficiency equals 1. And for point E, technical efficiency and scale efficiency are both equal to 1.

Figure 3.4 An Example of Efficiency Estimation with One input and One output.



The technical efficiency can be solved by the following linear program:

$\max \theta$ subject to $-\theta \boldsymbol{q_i} + Q\boldsymbol{\lambda} \geq 0$

(3.1)

$\text{s.t.}\, \boldsymbol{x_i} - \boldsymbol{X\lambda} \geq \boldsymbol{0}$ (3.2)

$\text{s.t.}\, \boldsymbol{1}^{'}\boldsymbol{\lambda} = 1 \; and \; \boldsymbol{\lambda} \geq 0$ (3.3)

where θ is the overall efficiency that the chapter aims to derive. $\boldsymbol{x_i}$ and $\boldsymbol{q_i}$ are the vectors of inputs and outputs for DMU i, respectively. If there are M inputs and N outputs. $\boldsymbol{x_i}$ and $\boldsymbol{q_i}$ are $M * 1$ and $N * 1$ vectors, respectively. X and Q are the matrices of inputs and outputs for all DMUs. Hence, if there are I DMUs, X and Q will be $M * I$ and $N * I$ matrices, respectively. $\boldsymbol{\lambda}$ is a $I * 1$ vector.$\boldsymbol{1}^{'}$ is a row vector equals [1,1,1,1…].

$(X\boldsymbol{\lambda}, Q\boldsymbol{\lambda})$ is the projection of the vector $(\boldsymbol{x_i}, \boldsymbol{q_i})$ onto the production frontier, so that $\boldsymbol{Q\lambda}$ represents the optimal output given $\boldsymbol{x_i}$. The technical efficiency of DMU *i* is then defined as the ratio of the actual output $\boldsymbol{q_i}$ to optimal output $\boldsymbol{Q\lambda}$, which is the solution $\boldsymbol{\theta_T}$ to the linear program. Finally, Equation (3.3) is the constraint of convexity, which allows for variable returns to scale.

Without the Equation (3.3), the solution θ corresponds to the technical efficiency for a constant return to scale technology or equivalently the overall efficiency.

Generating the technical efficiency θ_T and the overall efficiency θ from equation 3.1-3.3, the scale efficiency is derived as $\frac{\theta_T}{\theta}$. From practical scope, the technical efficiency measures to what extent resources are misallocated in the production process, and the scale efficiency measures whether the production is operating at its optimal size. On the other hand, the technical efficiency represents short-run effects, while the scale efficiency captures long-run effects.

This chapter considers two production processes, corresponding to two functions of a URT system: generating traffic and serving economic/political purposes. Identical inputs are assumed for both the economic and transportation purpose, which are the length of rails in operation, the number of carriages in operation, and the population of the city. The output differs between the two purposes. For the transportation purpose, it is measured by the number of passengers. For the economic purpose, 3 outputs are considered: local GDP, fiscal expenditure of the local government, and the ratio of permanent resident population to the population of registered residents.

The number of passengers is used to estimate the performance of the URT system in creating passenger turnover. A large number indicates higher traffic and better performance. Because a larger population will inevitably induce a larger passenger turnover, population is included as an additional input in the production process.

From the angle of economic effects, GDP is apparently the main indicator of economic performance after the construction and operation of the URT system. Fiscal expenditure is included as an economic output to proxy the budget size and the financial status of the local government. As previously discussed, URT systems boost property prices along metro lines, resulting in higher fiscal revenue from land sales. Consequently, URT systems may indirectly push up local fiscal expenditure. The ratio of the permanent resident population to the population of registered residents is used to measure the attractiveness of the city. A higher ratio means that the city has attracted more migrant workers and talents by providing more job opportunities. Because cities with a larger population are more likely to have higher

GDP and fiscal expenditure, population is also considered as an input in the production of economic objectives.

Because the amount of the input (population, URT length) is relatively fixed in the short run, the output-oriented approach is more appropriate for estimation.

After obtaining the results of efficiency, this chapter employs a Tobit regression to investigate the heterogeneity of efficiency in different categories of the city. The Tobit model is designed for the dependent variable with a truncated value. As the range of efficiency is from 0 to 1, the Tobit model fits better than other models. Regression model (3.4) is shown as follows:

$$E_{it} = \beta_1 citytype1 + \beta_2 citytype2 + \beta_3 citytype3 + \beta_4 P_{it} + \beta_5 emp + \beta_6 bus + \beta_7 OY_{it} + \mu_t + \varepsilon_{it} \quad (3.4)$$

E_{it} is the efficiency for city i in year t. As the chapter evaluates transport efficiency and economic efficiency, it would deal with the regression twice for different dependent variables. As this chapter treat each city in each year as an independent DMU, E_{it} is actually a cross-sectional data.

$citytype1$,2 and 3 are the dummy variables of three different groups of SMC. $citytype1$ equals 1 when the city is a provincial capital or sub-provincial city, otherwise 0. $citytype2/3$ equals 1 if the city is a municipality/ordinary prefecture-level city, otherwise 0. In other words, for the four top cities, the three dummies are all equal to 0. Therefore, the sign of β_1, β_2 and β_3 would present the difference in efficiencies between the first-tier cities and the other cities. As this chapter hypothesizes that top cities might have a higher transport efficiency due to the agglomeration effects caused by longer rail length, the sign of β_1, β_2 and β_3 is expected to be negative. However, the sign of β_1, β_2 and β_3 are expected to be positive in regressing the economic efficiency, because improving the economic performance is more difficult in the top cities owing to a relatively larger economic stock.

P_{it}, is the city's labour productivity in city i and time t. GDP per capita is used to quantify it in this model. The first-tier cities usually have higher GDP per capita or productivity. emp_{it} is logarithm value of the employment population, which is larger in the main metropolises. P_{it} and emp_{it} are two control variables for this model. Representing the average productivity of a city, β_4 is expected to be positive in transporting efficiency regression as the higher productivity in top cities is positively correlated to the working ability of URT staff. On the other hand, β_4 is also expected to be positive as the higher productivity could benefit the economic performance. The employment number could have a positive effect on improving economy and also a high demand pressure on public transporting. Therefore, β_5 is expected to be positive both in the transporting and economic efficiency regressions.

Another control variable, bus, is the logarithm value of no. of bus in city i in time t. Owning more buses presents a higher demand pressure on public transport and better capability of coordinating and managing traffic. Simultaneously, proving a better public transport should contribute to a better economic performance. Hence it should give a positive β_6 of transporting efficiency and economic efficiency regression. OY_{it} is the time length of the operation (in years) of the URT in city i. As the length of the rail is included in the DEA analysis, it uses operating years to represent it. This aims not only to investigate the time trend of the efficiency, but also to see if the overall efficiency could be improved when the rail length gradually increases. Similarly to the expectation of the effect of top cities, it expects that a longer distance and more lines (higher years) could lead the efficiency to increase at some extent. On the other hand, accompanied by the years growing, the increase of URT might be decreasingly productive in improving economy due to the large amount of economic stock.

The chapter focuses on the signs and coefficients of three city categories. As known, the different categories of cities are determined by political and historical reasons rather than economic reasons. The political status of these cities has hardly changed since 1949. Therefore, these variables could be treated as quasi-exogenous, which avoids the endogeneity problem.

Software DEAP 2.1 is used to fulfil the research in this chapter. This software is specifically designed for different DEA models and widely applied by a wide range of references.

Section 3.5 Data

As noted, the two technologies employ three inputs to produce a total of four outputs. Data on the length of URT lines and the number of URT carriages are collected from multiple sources, the main ones being the National Bureau of Statistics (NBS) and the CEIC database[20]. Missing observations are replaced by data extracted from the Yearbook of Transportation and Communication and the Annual Statistics and Analysis Report of the CURTA. A major drawback of the line length data provided by the NBS or the CEIC is that they report end-of-year values, which may overstate the length of URT lines in operation during the year. For example, if a metro line is open to traffic on December 30, it will generate very little passenger flow in that year. If the full length of this metro line is counted as input in the year, efficiency will be underestimated. This simple example illustrates that a better measure of line length should account for time of operation. Consequently, the value of this variable in any year is redefined as the sum of (1) the length of URT lines that were in operation at the beginning of the year, and (2) the length of URT lines that were put into service during the year multiplied by total months it operatesand divided by 12 months. For example, if a metro line is put into service on July 1 and is 18 kilometres in length, it will be counted as 9 kilometres in that year.

Data on the number of URT passengers are mainly collected from the Yearbook of Transportation and Communication and the Annual Statistics and Analysis Report of CURTA. Some missing observations are replaced by values extracted from the Economic and Social Development Statistical Bulletin released by local governments. All other data are extracted from the CEIC database.

[20] Source: www.ceicdatabase.com

Table 3.1 Summary Statistics

Variable	Category	Unit	Min	Max	Mean	St. Dev
Length of URT lines in operation	input	Km	0.45	617.50	108.00	127.94
Number of URT carriages in operation	input		7	5210	712	1038
Population of permanent residents	input	Thousand Persons	5371.4	30484.3	12363.9	6510.7
Number of passengers	transport output	Thousand Persons per year	68	377706	499607.5	831546
GDP	Economic output	Billion RMB	115.02	2817.87	882.32	565.80
Ratio of permanent residents to registered residents	Economic output	N/A	0.87	4.55	1.37	0.652
Fiscal expenditure of local government	Economic output	Million RMB	7006	691894	133543	130867
Bus no.	Tobit model		3017	25624	9200	5241
Total employment	Tobit model	Thousand persons	845.9	17175.2	5531.3	4553.3

As the cities opened their first metro lines in different years, we have an unbalanced panel. Table 3.2 presents the cities and the numbers of observations. Because each city in each year is treated as an independent DMU, in total there are 24 cities and 190 observations. Data are missing for Suzhou and Wuxi in 2016 and Shenzhen in 2006. Among the 24 cities, 10 have more than 10 observations, while 7 have no more than 3 observations. The first four cities in Table 3.2 - Beijing, Shanghai, Guangzhou and Shenzhen (bold text) - are regarded as first-tier cities, which are also coincidentally top 4 in the rank of GDP. In the academic field, there is not a strict definition and measurement of Chinese city tier systems. The judging standards vary: consumer behaviour, income level, population size, infrastructure, talent pool and business opportunities, among other factors. In China, first-tier cities commonly refer to the four named ones. Yi Cai Global (2017) published a tiered list of 338 Chinese cities based on the scopes of commercial conglomeration, transportation accessibility, residents activeness, lifestyle variety and future development. In this ranking, Beijing, Shanghai, Guangzhou and Shenzhen are still the top 4. Owing to their prosperity, large transport needs, and relatively large fiscal budgets, the top 4 cities built their first metro lines relatively early and now their URT systems are much more developed than those of the other cities. As normally the large and prosperous cities have larger transport needs, this chapter hypothesises that, regarding the URT systmes of the large cities, the efficiency of transporting passengers should be comparably higher than that of the other cities and the contribution to economic growth might be not as large as that of the other cities. In other words, the non-first tier cities (SMC) mainly consider URT construction as an economic boost while the large and more prosperous cities might be more likely to see the URT as a way to lessen traffic pressure.

Table 3.2 Summary of the observations in each city

City	Observed Period	No. of Observation	Population of Permanent Residence in 2016 (Thousand)	GDP in 2016 (Billion RMB)
Beijing	**2002-2017**	**16**	**21729**	**2566.91**
Shanghai	**2002-2016**	**15**	**24197**	**2817.87**
Guangzhou	**2002-2016**	**15**	**14043.5**	**1954.74**
Shenzhen[21]	**2005-2016**	**11**	**11908.4**	**1949.26**
Tianjin	2005-2016	12	15621.2	1788.54
Nanjing	2005-2016	12	8270	1050.3
Suzhou	2012-2015	4	10647.4	1547.51
Wuxi	2014-2015	2	6529.0	921.00
Chongqing	2004-2016	13	30484.3	1755.93
Changchun	2002-2016	15	7534.3	598.64
Wuhan	2004-2016	13	10766.2	1191.26
Dalian	2002-2016	15	5956	681.02
Shenyang	2010-2016	7	8292	554.64
Chengdu	2010-2016	7	15917.6	1217.02
Xi’an	2011-2016	6	8832.1	628.27
Hangzhou	2012-2016	5	9188	1131.37
Ningbo	2014-2016	3	7875	868.65
Kunming	2013-2016	4	6728	430.00
Qingdao	2015-2016	2	9204	1001.13
Zhengzhou	2014-2016	3	9723.9	811.40
Changsha	2014-2016	3	7645.2	935.70
Harbin	2013-2016	4	9620.5	610.16
Nanning	2016	1	7062.2	370.33
Nanchang	2016	1	5371.4	440.17

Section 3.6 Findings

This section presents the empirical estimates from the DEA-Tobit model. The efficiencies of the transport are discussed first, followed by economic efficiency.

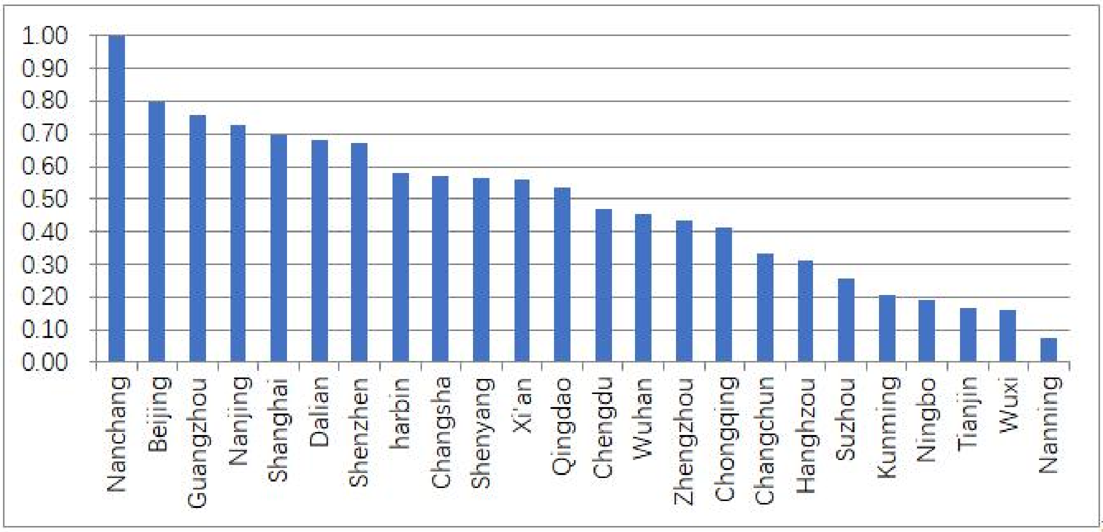
[21] The data in 2006 of Shenzhen is not found, therefore, there is only 11 observations of Shenzhen

Section 3.6.1 Transport Technical efficiency

Figure 3.5 presents the average transport technical efficiency for each city. Obviously, there are huge differences in technical efficiency across cities. The most efficient city is Nanchang (1.0) and the least efficient city is Nanning (0.08). It happens that the URT system in both cities went into operation too late, in the end of 2016, which makes these data less comparable to other data in the sample. Thus, these two cities are likely to be outliers in the sample. Remarkably, the technical efficiency is higher than 0.67 in all first-tier cities, while the average technical efficiency of the other cities is only 0.48. If we exclude Nanchang from the sample, the efficiencies of other cities do not change. As the overall efficiencies of these two cities are quite low, excluding them does not change the production frontier. In the new sample, Beijing, Guangzhou, Shanghai and Shenzhen rank the first, second, fourth and sixth among all the cities for technical efficiency. Thus, the empirical evidence indicates that the first-tier cities have higher technical efficiency. In other words, the URT systems in these four cities are more efficient at transporting passengers and reducing road traffic pressure than those in the other cities. Interestingly, CURTA reported that only the URT systems in Beijing, Guangzhou, Shenzhen and Wuhan were able to yield positive profits in the years 2016 and 2017, and the URT system in Nanjing was profitable prior to 2015. Considering the fact that large traffic generates ample operating income, it is not surprising at all that cities with positive profits are also cities with high technical efficiencies in transportation. Another finding is that the URT systems in cities with high technical efficiency usually have longer lines and were built earlier. The correlation between line length in 2016[22] and the average technical efficiency is 0.59. In other words, the URT system with longer lines is usually more technically efficient. This might be attributed to high productivity of labour and management system with the long period operation experience.

[22] Because length data are missing in 2016, we use the 2015 values for Suzhou and Wuxi.

Figure 3.5 The Average Transport Technical Efficiency by City



In order to examine our implication, Figure 3.6 plots the transport technical efficiency of the first-tier cities by year. Three of them have an increase trend of the technical efficiency time, and approached to 1 in recent years. Even though there was a sudden decline during 2010-2011, the technical efficiency of Shenzhen improved thereafter. Metro network expansion may explain the increase in technical efficiency in these cities. The first-tier cities manifest their leading position in technical efficiency when we examine the 2016 result only (seen in Figure 3.7). The average technical efficiency of the first-tier cities was 0.9 in 2016, while the average of the other cities was only 0.44. In sum, the URT systems in the first-tier cities generally have a higher technical efficiency in transporting passengers and the efficiencies increase by the time or the increase of the rail length.

Figure 3.6 The Transport Technical Efficiency of the first-tier Cities by Year

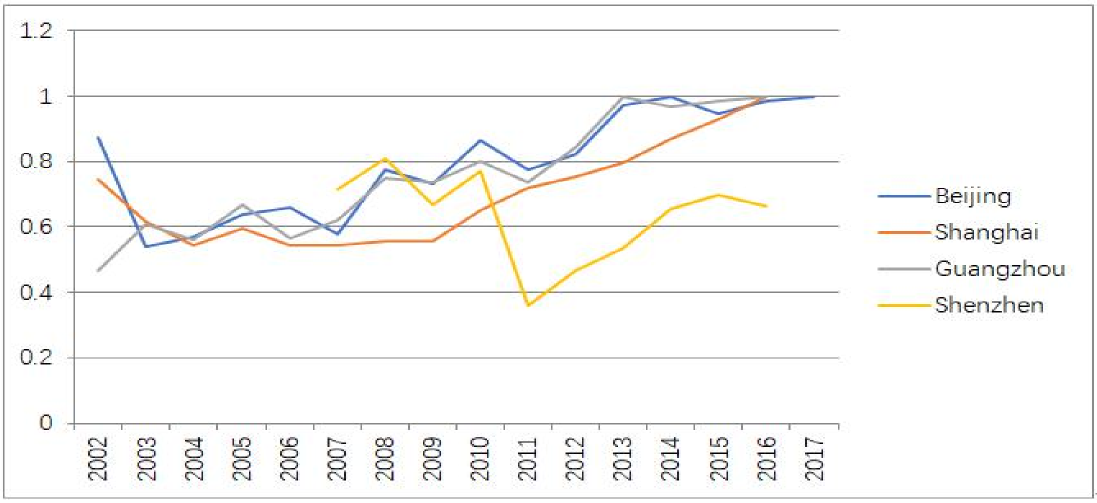
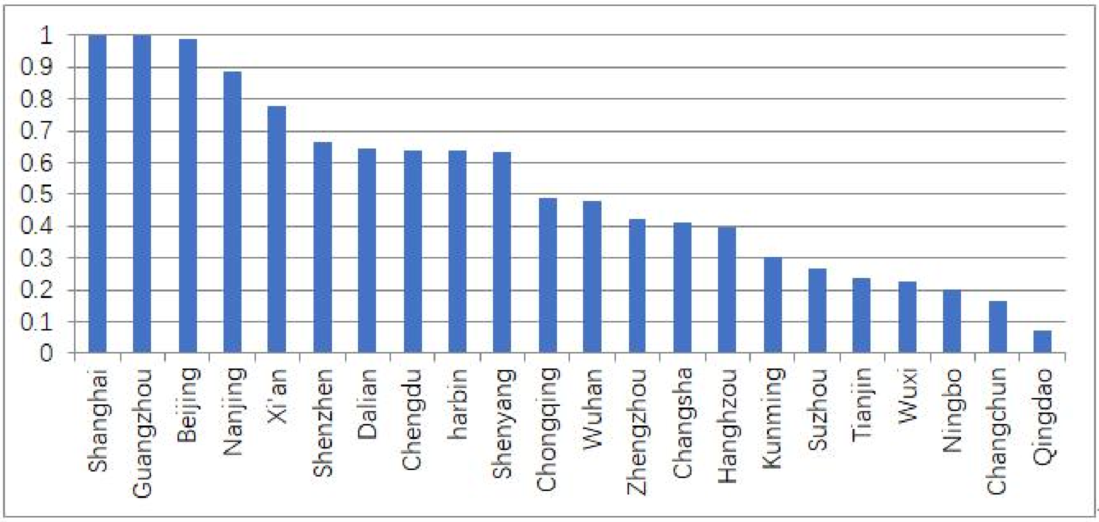


Figure 3.7 The Transport Technical Efficiency in 2016 by city[23]



Section 3.6.2 Transport Scale Efficiency

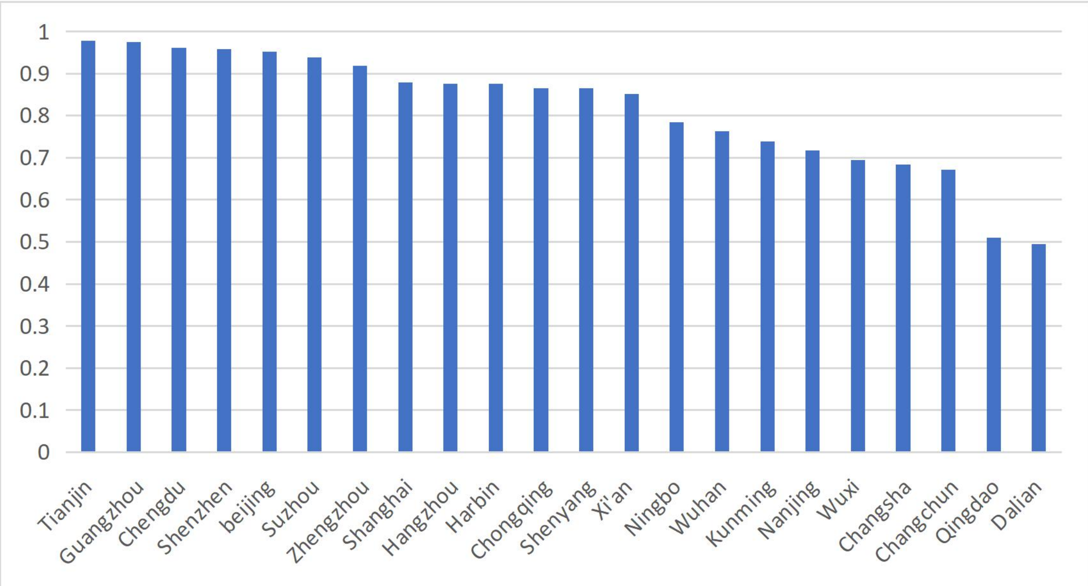
The scale efficiency measures whether the URT system is operating at its optimal size. As shown in Figure 3.4, Section 3.4, scale inefficiency arises when the URT system is either too large or too small. Whether the URT system is too large or too small depends on the returns to scale. If the technology exhibits increasing returns to scale, output (passenger turnover) will increase at a higher rate than inputs (URT infrastructure and population). It recommends that the government can increase the operating efficiency of the URT system by expanding the network. Conversely, if

[23] We use the 2015 values for Suzhou and Wuxi, because the 2016 data are missing.

the production exhibits decreasing returns to scale, the government may postpone future investment in the URT system without creating much congestion.

Figure 3.8 presents the average transport scale efficiency of each city over the study period. It shows that the highest efficiency was in Tianjin (0.98). All four top cities are located in the high efficiency zone. The average efficiency of Guangzhou (second), Shenzhen (fourth), Beijing (fifth) and Shanghai (eighth) is 0.94, while the average efficiency of the other cities is 0.75, or 0.79 excluding Nanchang and Nanning. Thus, the data suggest that the tier one cities have relatively high scale efficiencies compared to the rest of the sample.

Figure 3.8 The Average Transport Scale Efficiency by City[24]



A scale efficiency index that is strictly smaller than one does not reveal whether the URT system is below or above the optimal scale. The exact status of returns to scale is shown in the Appendix A.3.1. Time series plots could reveal more information. Although the average scale efficiencies of Shanghai, Hangzhou and Harbin are similar (see Figure 3.8), Figure 3.9 shows that they have evolved in quite different ways. The scale efficiency of Shanghai remained at one or close to one for many years before 2009, which indicates constant returns to scale during this period. After that, the efficiency index plunged to 0.776 in 2010 and further

[24] Outliers of Nanchang and Nanning are excluded.

decreased to 0.768 in 2016. Data shows a sharp increase in metro lines and carriages in Shanghai from 2009. Thus, it is very likely that this increase amount of input pushes the production over the constant return to scale then fell into the region of decreasing returns to scale. This was confirmed by the information in Table 3.3 and the Appendix. A.3.1. In contrast, the scale efficiency indices of Hangzhou and Harbin were on the rise, yet they were still some distance from 1. Given the fact that the URT systems in both cities kept on expanding during the same period, this corresponds to the fact that they were still operating in the region of increasing returns to scale.

Figure 3.9 The Transport Scale Efficiency of Three Cities by Year

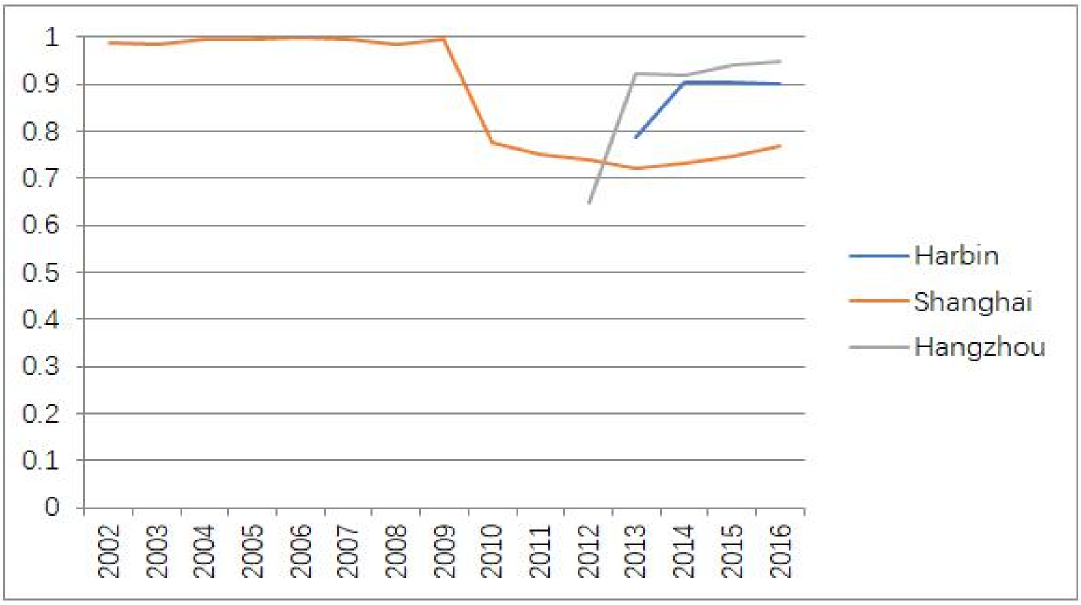


Table 3.3 presents the scale efficiencies in 2016 derived by DEAP software[25]. I also indicate whether it corresponds to increasing returns to scale or decreasing returns to scale, which is provided by the software 'DEAP 2.1'. The detailed information could be checked in the Appendix A.3.1. It can be seen that only Beijing, Shanghai and Chongqing demonstrate decreasing returns to scale. While Guangzhou and Suzhou show constant returns to scale, Shenzhen, Tianjin and Chengdu are very close to 1. Therefore, all four tier one cities have crossed or are close to the stage of constant returns to scale. Moreover, Tianjin is close to constant

[25] 2015 values are reported for Suzhou and Wuxi, because data for 2016 are missing.

returns to scale and Chongqing has entered decreasing returns to scale, which implies that the decreasing return to scale is positively correlated to the operation length (input) and time. All the other cities are still operating with increasing returns to scale. To sum up, in 2016, the URT systems in Beijing, Shanghai and Chongqing have passed their optimal scales and further expansion of these URT systems won't increase optimal passenger volume proportionally. For these cities, it is time to slow down their URT investment as the decreasing marginal benefit. URT systems in Guangzhou, Suzhou, Chengdu and Shenzhen are either at or close to their optimal scales. If these URT systems are expanded by the same proportion as the population, passenger flow will increase proportionally and in the highest optimal output. As for the rest of the cities, it is encouraged to expand their URT systems as the population increases. This will generate a relatively larger amount of output (passenger turnover).

Table 3.3 Transport Scale Efficiency and Returns to Scale by City in 2016

City	Scale Efficiency	Returns to Scale	City	Scale Efficiency	Returns to Scale
Beijing	**0.932**	**drs**	Dalian	0.314	irs
Shanghai	**0.768**	**drs**	Shenyang	0.938	irs
Guangzhou	**1**	**crs**	Chengdu	0.997	irs
Shenzhen	**0.979**	**irs**	Xi'an	0.931	irs
Tianjin	0.995	irs	Hanghzou	0.949	irs
Nanjing	0.63	irs	Ningbo	0.92	irs
Suzhou	1	crs	Kunming	0.811	irs
Wuxi	0.785	irs	Qingdao	0.892	irs
Chongqing	0.966	drs	Zhengzhou	0.933	irs
Changchun	0.872	irs	Changsha	0.857	irs
Wuhan	0.959	irs	harbin	0.902	irs
			Nanning	0.556	irs
			Nanchang	0.339	irs

Section 3.6.3 Overall Transport Efficiency and Tobit Regression

The overall efficiency is defined as the product of scale efficiency and technical efficiency. As the average technical efficiency and average scale efficiency of the first-tier cities both rank high, so must be their overall efficiency. Figure 3.10 justifies the conjecture. There the first-tier cities rank one to four in the overall efficiency. In other words, the URT systems of the first-tier cities demonstrate a higher level of efficiency in generating passenger traffic than those of other cities. The pattern does not change when the latest data is considered (Figure 3.11). In other words, the URT systems in the first-tier cities fulfil the transport needs to a significantly higher extent than those in the other cities, in spite of the higher level of input.

Figure 3.10 Average Overall Efficiency of Transport by City

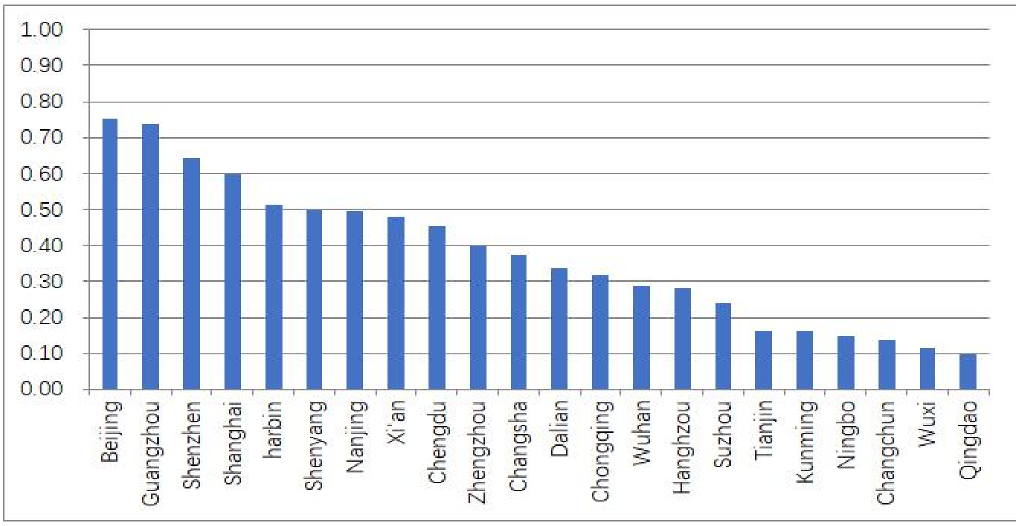
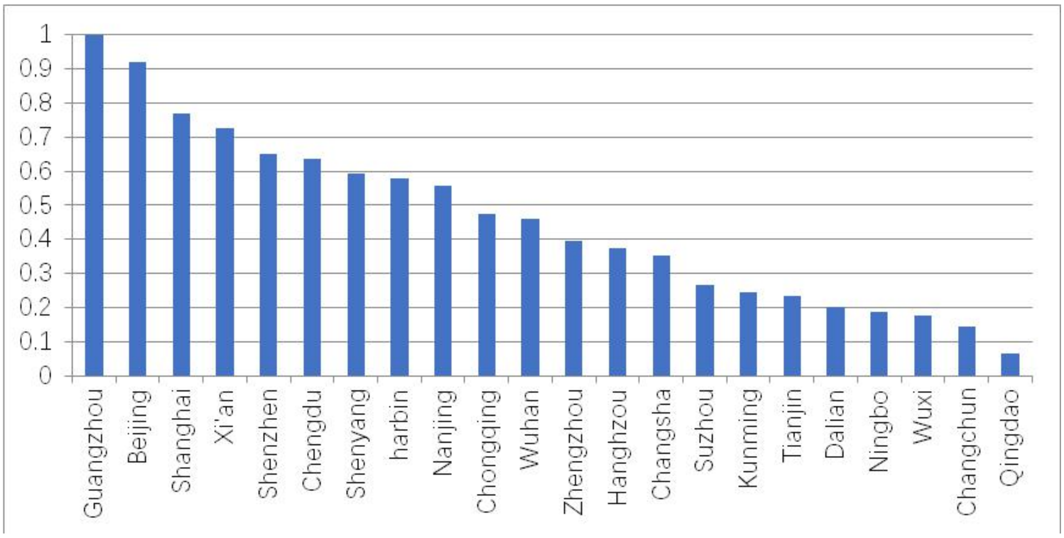


Figure 3.11 Overall Efficiency of Transport by City in 2016[26]



After the simple observing and ranking the efficiency results, the Tobit regression is employed to specifically estimate whether the first-tier cities have a significant effect on the transport efficiency. Table 3.4 presents the results from the model (3.4)[27]. As shown, the sings of three other city categories are all positive and significant at 5% or 1% level. This confirms that the non-first tier cites have lower transport efficiency. Among them, the other municipality cities (Tianjin and Chongqing) have the most negative effects on the transport efficiency at -0.371. The GDP per capita, the index of the productivity, contributes to a significantly positive effect on transport efficiency at 1% level. This is to say that a general productive city is also more efficient in transporting passengers. The level of employment also significantly improves the transport passengers as expected. 1% increase in employment level would cause the efficiency to increase by 0.07. The effect of bus is as expected as well. A higher number of buses means a better traffic coordination and management. Moreover, it could also mean that there is a high demand of public transport of cities, which leads the output of the transport efficiency to increase. The effect of the operation years is positive, which presents that the transport efficiency gradually increases as the operation length (both in years and in km) increases. However, the coefficient of the operation years is only positively significant at 10% level.

[26] 2015 values are reported for Suzhou and Wuxi, because the 2016 data are missing.
[27] Nanning and Nanchang are excluded in regression.

Table 3.4 Tobit Regression of Transport Overall Efficiency

Dependent Variable: Transport Overall Efficiency	Coefficient (standard error)
Provincial Capital or Sub-provincal City dummy	-0.107** (0.051)
Municipality City dummy	-0.371*** (0.046)
Other SMC dummy	-0.278*** (0.091)
Log value of GDP per capita	0.098*** (0.027)
Log value of employment	0.070** (0.030)
Log value of Bus	0.118** (0.046)
Operating Years	0.006* (0.003)
Time Effects	YES

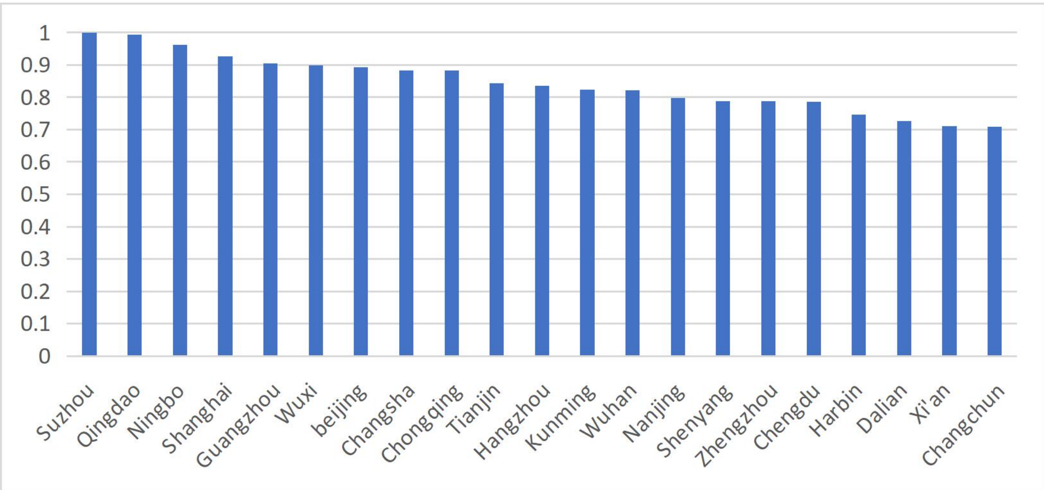
Note: The value in parentheses is the standard error, and the *, **, *** presents the significance level at 10%, 5% and 1%, respectively.

Section 3.6.4 Economic Technical Efficiency

The average technical efficiency for the economic performance demonstrates a different pattern. In this chapter, the attractiveness of the city, an output, is measured by the ratio of the permanent resident population to the registered resident population. This ratio is exceptionally high in Shenzhen for historical reasons. The city remained a small town in Guangdong province until the 1980s, in which year it was designated as one of China's special economic zones. Unlike conventional Chinese cities, Shenzhen does not have a large native (registered) population. The registered population of Shenzhen was only around 4 million in 2017, while the other first-tier cities all have registered population more than 10 million. With a small registered residents' population and a large permanent resident population (immigrants), the attractiveness measure is artificially high for Shenzhen in the data. The ratio is between 0.9 and 1.5 for most of other cities, but around 4 for Shenzhen (see Table 3.1). As attractiveness is one of the outputs, estimation would not be consistent if Shenzhen is included, which would expand the production frontier and make other cities' efficiency to be extremely low. Therefore, Shenzhen's data is out of sample, so are the Nanchang and Nanning as explained before. The DEA method including these three outlier cities are also included in the Appendix A.3.2 and the DEA estimation without them are put in A.3.3.

From Figure 3.12, it shows that the highest technical efficiency is Suzhou at 1.0 and the lowest is Changchun at 0.71. The top cities, Shanghai, Guangzhou and Beijing ranked 4th, 5th and 7th highest in the range. From average technical efficiency, it did not show much difference between the first-tier cities and other cities. It seems that URT in most of the cities have a relatively high technical efficiency in improving economic performance.

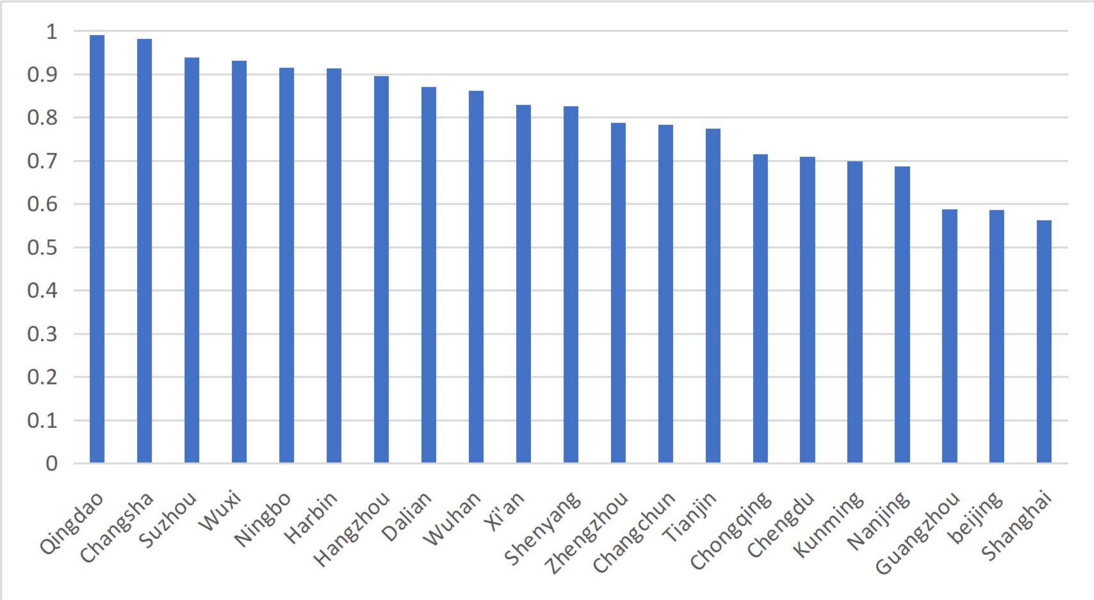
Figure 3.12 Average economic Technical Efficiency by City



Section 3.6.5 Scale Efficiency of Economic Perspective

Figure 3.13 presents the average scale efficiency of each city (excluding two outliers). Qingdao features the highest scale efficiency among all the cities. All the first-tier cities all fall behind. Ranking from lowest to highest, there are Shanghai, Beijing, Guangzhou, which are all first tier cities. The possible explanation is that too much input contributes to a low production possibility compared to the optimal productivity.

Figure 3.13 Average Economic Technical Efficiency by City



As with what has been discussed in Section 3.6.2, the average value of any city does not show the exact returns to scale for a given year. Table 3.5 presents the situation of returns to scale for all cities in 2015. All cities exhibited decreasing returns to scale, except for Qingdao. Generally speaking, the results suggest that in most cities, the expansion of URT systems (as well as population) would not generate a proportional increase in GDP, fiscal expenditure, and city attractiveness, even if the URT systems were operating with full technical efficiency. The situation is much more severe in the first-tier cities. An interesting finding from the results is that the general scale efficiency of each city gradually rises through the time. Seen in A.3.3, it shows most of the cities had a lower scale efficiency at the beginning stage and tended to grow afterwards.

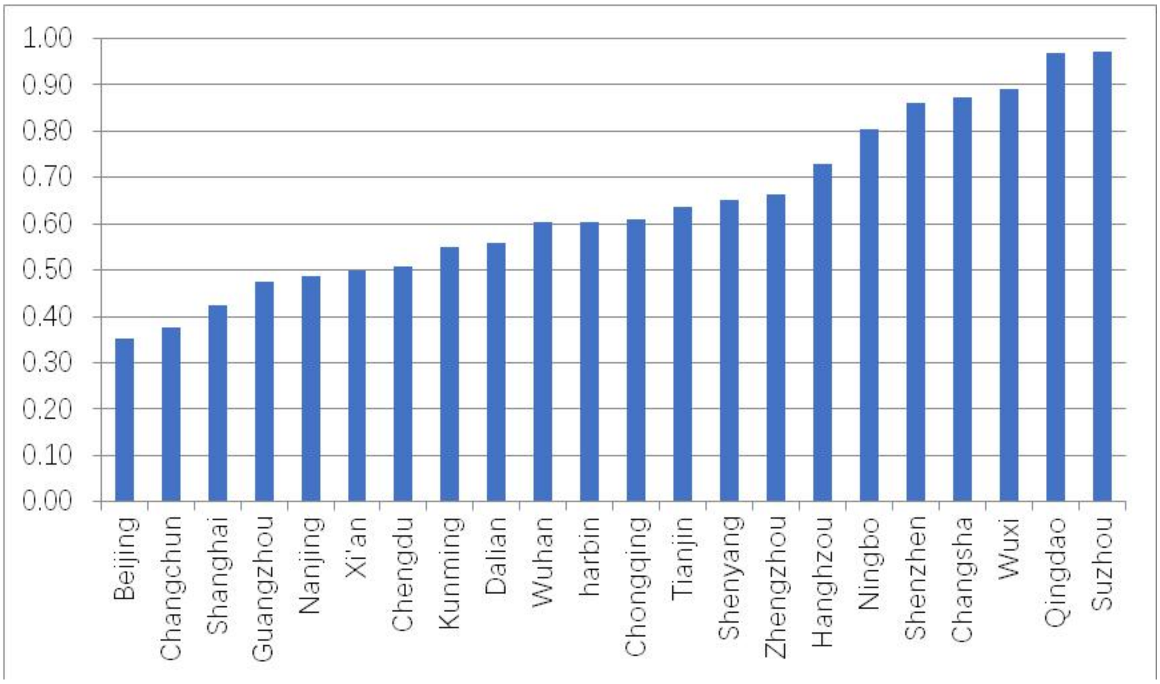
Table 3.5 Economic Scale Efficiency and Return to Scale by City in 2016

City	Scale efficiency	Return to scale	City	Scale efficiency	Return to scale
beijing	0.8	drs	Dalian	0.74	drs
Shanghai	0.76	drs	Shenyang	0.732	drs
Guangzhou	0.535	drs	Chengdu	0.778	drs
Tianjin	0.993	drs	Xi'an	0.815	drs
Nanjing	0.486	drs	Hangzhou	0.852	drs
Suzhou	0.879	drs	Ningbo	0.956	drs
Wuxi	0.863	drs	Kunming	0.592	drs
Chongqing	0.682	drs	Qingdao	1	crs
Changchun	0.765	drs	Zhengzhou	0.796	drs
Wuhan	0.784	drs	Changsha	0.996	drs
			Harbin	0.939	drs

Section 3.6.6 Overall Economic Efficiency and Tobit regression

The previous analysis revealed relatively low technical efficiency and scale efficiency in three out of four first-tier cities, namely Beijing, Shanghai, and Guangzhou. Their overall efficiencies should be lower than those of the other cities, too. This is indeed the case. In Figure 3.14, Beijing, Shanghai and Guangzhou rank in first, third and fourth place, respectively, among all cities' overall efficiency (lowest to highest). To conclude, the URT systems of the first-tier cities, except for Shenzhen, served the economic objectives much less effectively than the URT systems in the other cities did. The initial motivation to build a URT of the local government of the first-tier cities is less likely to be the economic incentive compared to the other cities.

Figure 3.14 Average Overall Economic Efficiency by City



Putting economic efficiency into Tobit regression estimation generates a more detailed analysis. Table 3.6 presents the results using model (3.4). As shown, the three city dummies are all positive and significant. Two of them are significant at 5%, and only the provincial capital dummy is at 10%. The findings show that non-first tier cities relatively have a higher economic efficiency. Among them, the ordinary prefecture level city, with not any special political status, has the strongest positive impact on economic efficiency. This confirms that the URTs in SMC improved the economic more efficiently than those in top cities. The coefficient of the GDP per capita contributes to a significantly positive effect on economic efficiency as expected. This shows that productivity drives higher economic efficiency. From the results, the effects of employment and buses are positive and negative, respectively, but not significant. The sign of the operating years are negative and significant at 5% level. This is to say, the overall efficiency becomes decreasing by the growth of time and rail length. This might be the reason that too much output accumulated causes a decreasing marginal production.

Table 3.6 Tobit Regression of Economic Overall Efficiency

Dependent Variable: Transport Overall Efficiency	Coefficient (standard error)
Provincial Capital or Sub-provincal City dummy	0.100* (0.060)
Municipality City dummy	0.108** (0.053)
Other SMC dummy	0.221** (0.110)
Log value of GDP per capita	0.079** (0.033)
Log value of employment	0.031 (0.033)
Log value of Bus	-0.055 (0.044)
Operating Years	-0.007** (0.003)
Time Effects	YES

Note: The value in parentheses is the standard error, and the *, **, *** presents the significance level at 10%, 5% and 1%, respectively.

Section 3.7 Conclusions and Recommendations

URT systems in China serve dual purposes. They are powerful infrastructure projects that solve urban congestion on one hand, and are handy tools to promote local economy on the other. Chinese local governments are particularly interested in building URT systems in last decade. Given China’s fast urbanization process and rapid economic development, it is difficult to tell which incentive dominates the decision of building URT systems. This chapter estimates two separate influences of Chinese URT systems, one is the number of passengers and the other one is economic performance. By ex-post analysis of evaluating the efficiency by DEA-Tobit two stage analysis, it implies which objective played the dominant role in URT construction and operation. Specifically, cities that are more efficient at delivering passengers are likely those that prioritize transport needs, while cities that are more efficient at generating economic outcomes are likely those that prioritize economic objectives.

Overall, the results show that the URT systems in non-first-tier cities have been more efficient in boosting local economic performance than creating passenger traffic, while the URT systems of the first-tier cities generally perform more efficiently in transporting passengers. By ex-post analysis, it could imply that the decisions of constructing URT systems in non-first-tier cities are more likely to be based on the economic objective, whose transport needs for URT are not as urgent as the first-tier cities'. Based on the result, it could boldly imply that the primary goal of the first-tier city is to solve urban transportation problems, but to fulfil the economic progress, which is the most important assessment field for the local governonrs in their career performances. Our preliminary analysis also indicates that the economic incentive is stronger in cities with low political status.

Regarding technical efficiency, the first-tier cities have used inputs more efficiently at creating passenger traffic, while the other cities are better at improving economic performance. Moreover, it is found that technical efficiencies are positively correlated with an increase in inputs for both transport and economic objectives, especially in the first-tier cities, which are now mostly close to 1. Therefore, in order to improve the technical efficiency of those other cities that have lower efficiency, it might be recommended that they increase investment in the URT system. But this increase in technical efficiency only means improving the output level to reach the potential optimal level; it is not strictly synonymous with improving productivity and nor is it necessarily cost-worthy.

Turning to scale efficiency, the results present that most of the SMC's transport efficiencies are in increasing return to scale. This is to say, increasing input could enhance the potential productivity. On the other hand, most of the cities' economic efficiencies are in decreasing return to scale, which suggests that it might not be the most efficient way to improve the economy by investment in URTs.

Tobit regression reveals that the top cities are higher in transport overall efficiency and lower than other cities in economic overall efficiency. This is consistent with the facts that most of SMCs do not have profit from URT operation. This gives a summary for the central governors to re-investigate local decision makers' primary motive of applying URT. The results tell us it might not be urgent for some SMC to build URTs in delimiting the transporting pressure. In addition, the negative sign of the operation years on economic efficiency also illustrate that increasing investment would reduce the efficiency on economic performance. In other words, the economic benefits might not as large as before by adding investment on URTs. Generally speaking, central government should seriously examine the transport necessity of building URT lines and not use them as effective fiscal policies in the top cities.

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Section 3.9 Appendix for Chapter 2

A.3.1 DEA Results- Transport Perspective

City	year	overall	technical	scale	Variable Return to Scale
beijing	2002	0.869	0.873	0.995	irs
beijing	2003	0.54	0.542	0.997	irs
beijing	2004	0.568	0.569	0.998	irs
beijing	2005	0.636	0.637	0.998	irs
beijing	2006	0.658	0.659	0.998	irs
beijing	2007	0.577	0.578	0.998	irs
beijing	2008	0.774	0.774	0.999	irs
beijing	2009	0.733	0.734	1	crs
beijing	2010	0.864	0.864	1	crs
beijing	2011	0.696	0.775	0.898	drs
beijing	2012	0.706	0.824	0.857	drs
beijing	2013	0.828	0.974	0.85	drs
beijing	2014	0.86	1	0.86	drs
beijing	2015	0.86	0.946	0.909	drs
beijing	2016	0.92	0.987	0.932	drs
beijing	2017	0.951	1	0.951	drs
Shanghai	2002	0.737	0.746	0.988	irs
Shanghai	2003	0.607	0.617	0.984	drs
Shanghai	2004	0.542	0.544	0.996	irs
Shanghai	2005	0.592	0.594	0.996	irs
Shanghai	2006	0.545	0.546	0.999	drs
Shanghai	2007	0.543	0.545	0.997	irs
Shanghai	2008	0.546	0.555	0.983	drs
Shanghai	2009	0.556	0.559	0.994	drs
Shanghai	2010	0.505	0.651	0.776	drs
Shanghai	2011	0.54	0.72	0.75	drs
Shanghai	2012	0.558	0.755	0.74	drs
Shanghai	2013	0.576	0.797	0.723	drs

Shanghai	2014	0.637	0.87	0.732	drs
Shanghai	2015	0.694	0.929	0.747	drs
Shanghai	2016	0.768	1	0.768	drs
Guangzhou	2002	0.4	0.466	0.859	irs
Guangzhou	2003	0.589	0.607	0.971	irs
Guangzhou	2004	0.522	0.56	0.932	irs
Guangzhou	2005	0.623	0.667	0.935	irs
Guangzhou	2006	0.546	0.566	0.965	irs
Guangzhou	2007	0.618	0.622	0.995	drs
Guangzhou	2008	0.744	0.748	0.995	drs
Guangzhou	2009	0.736	0.736	0.999	irs
Guangzhou	2010	0.798	0.803	0.994	irs
Guangzhou	2011	0.738	0.738	1	crs
Guangzhou	2012	0.845	0.845	1	crs
Guangzhou	2013	1	1	1	crs
Guangzhou	2014	0.947	0.969	0.977	irs
Guangzhou	2015	0.977	0.986	0.991	irs
Guangzhou	2016	1	1	1	crs
Shenzhen	2005	1	1	1	crs
Shenzhen	2007	0.627	0.717	0.876	irs
Shenzhen	2008	0.715	0.81	0.882	irs
Shenzhen	2009	0.657	0.668	0.984	irs
Shenzhen	2010	0.759	0.771	0.984	irs
Shenzhen	2011	0.354	0.362	0.978	irs
Shenzhen	2012	0.443	0.468	0.945	irs
Shenzhen	2013	0.513	0.537	0.955	irs
Shenzhen	2014	0.636	0.655	0.972	irs
Shenzhen	2015	0.689	0.699	0.986	irs
Shenzhen	2016	0.652	0.666	0.979	irs
Tianjin	2005	0.032	0.033	0.968	drs
Tianjin	2006	0.048	0.049	0.976	drs
Tianjin	2007	0.097	0.099	0.978	drs
Tianjin	2008	0.122	0.125	0.976	drs

Tianjin	2009	0.132	0.136	0.972	drs
Tianjin	2010	0.145	0.15	0.97	drs
Tianjin	2011	0.148	0.153	0.97	drs
Tianjin	2012	0.127	0.129	0.986	irs
Tianjin	2013	0.261	0.266	0.983	drs
Tianjin	2014	0.321	0.327	0.982	drs
Tianjin	2015	0.306	0.312	0.98	drs
Tianjin	2016	0.235	0.236	0.995	irs
Nanjing	2005	0.052	1	0.052	irs
Nanjing	2006	0.332	0.489	0.678	irs
Nanjing	2007	0.458	0.646	0.71	irs
Nanjing	2008	0.593	0.807	0.735	irs
Nanjing	2009	0.649	0.862	0.753	irs
Nanjing	2010	0.423	0.476	0.887	irs
Nanjing	2011	0.521	0.562	0.927	irs
Nanjing	2012	0.577	0.62	0.931	irs
Nanjing	2013	0.655	0.715	0.917	irs
Nanjing	2014	0.481	0.586	0.821	irs
Nanjing	2015	0.499	0.776	0.644	irs
Nanjing	2016	0.558	0.885	0.63	irs
Nanjing	2017	0.64	1	0.64	irs
Suzhou	2012	0.186	0.216	0.862	irs
Suzhou	2013	0.214	0.236	0.905	irs
Suzhou	2014	0.299	0.302	0.988	drs
Suzhou	2015	0.267	0.268	1	crs
Wuxi	2014	0.059	0.098	0.604	irs
Wuxi	2015	0.176	0.225	0.785	irs
Chongqing	2004	0.009	1	0.009	irs
Chongqing	2005	0.12	0.139	0.862	irs
Chongqing	2006	0.257	0.29	0.887	irs
Chongqing	2007	0.343	0.378	0.905	irs
Chongqing	2008	0.408	0.451	0.905	irs
Chongqing	2009	0.346	0.384	0.9	irs

Chongqing	2010	0.302	0.331	0.913	irs
Chongqing	2011	0.308	0.312	0.988	irs
Chongqing	2012	0.354	0.358	0.987	irs
Chongqing	2013	0.391	0.393	0.994	drs
Chongqing	2014	0.395	0.402	0.984	drs
Chongqing	2015	0.454	0.476	0.954	drs
Chongqing	2016	0.474	0.49	0.966	drs
Changchun	2002	0.169	1	0.169	irs
Changchun	2003	0.159	1	0.159	irs
Changchun	2004	0.179	0.778	0.23	irs
Changchun	2005	0.181	0.563	0.321	irs
Changchun	2006	0.083	0.117	0.71	irs
Changchun	2007	0.108	0.13	0.832	irs
Changchun	2008	0.125	0.149	0.841	irs
Changchun	2009	0.132	0.156	0.85	irs
Changchun	2010	0.114	0.137	0.832	irs
Changchun	2011	0.132	0.16	0.825	irs
Changchun	2012	0.113	0.135	0.836	irs
Changchun	2013	0.147	0.172	0.855	irs
Changchun	2014	0.155	0.182	0.856	irs
Changchun	2015	0.141	0.162	0.872	irs
Changchun	2016	0.145	0.167	0.872	irs
Wuhan	2004	0.087	1	0.087	irs
Wuhan	2005	0.064	1	0.064	irs
Wuhan	2006	0.104	0.135	0.77	irs
Wuhan	2007	0.128	0.166	0.772	irs
Wuhan	2008	0.153	0.198	0.772	irs
Wuhan	2009	0.182	0.236	0.773	irs
Wuhan	2010	0.206	0.242	0.853	irs
Wuhan	2011	0.394	0.413	0.956	irs
Wuhan	2012	0.312	0.315	0.988	irs
Wuhan	2013	0.534	0.556	0.961	irs
Wuhan	2014	0.505	0.516	0.978	irs

Wuhan	2015	0.633	0.638	0.991	irs
Wuhan	2016	0.461	0.481	0.959	irs
Dalian	2002	0.449	1	0.449	irs
Dalian	2003	0.361	0.804	0.449	irs
Dalian	2004	0.354	0.765	0.463	irs
Dalian	2005	0.377	0.767	0.492	irs
Dalian	2006	0.453	1	0.453	irs
Dalian	2007	0.362	0.733	0.494	irs
Dalian	2008	0.44	0.949	0.463	irs
Dalian	2009	0.428	0.844	0.507	irs
Dalian	2010	0.228	0.393	0.579	irs
Dalian	2011	0.252	0.429	0.589	irs
Dalian	2012	0.266	0.447	0.596	irs
Dalian	2013	0.314	0.513	0.611	irs
Dalian	2014	0.271	0.447	0.607	irs
Dalian	2015	0.156	0.45	0.347	irs
Dalian	2016	0.202	0.642	0.314	irs
Shenyang	2010	0.19	0.383	0.496	irs
Shenyang	2011	0.354	0.403	0.877	irs
Shenyang	2012	0.49	0.53	0.925	irs
Shenyang	2013	0.572	0.61	0.938	irs
Shenyang	2014	0.672	0.715	0.94	irs
Shenyang	2015	0.629	0.669	0.939	irs
Shenyang	2016	0.594	0.633	0.938	irs
Chengdu	2010	0.274	0.298	0.917	irs
Chengdu	2011	0.379	0.42	0.902	irs
Chengdu	2012	0.446	0.453	0.985	irs
Chengdu	2013	0.485	0.508	0.955	irs
Chengdu	2014	0.483	0.497	0.971	irs
Chengdu	2015	0.472	0.474	0.995	irs
Chengdu	2016	0.637	0.639	0.997	irs
Xi'an	2011	0.298	0.506	0.588	irs
Xi'an	2012	0.37	0.431	0.858	irs

Xi'an	2013	0.394	0.441	0.894	irs
Xi'an	2014	0.325	0.355	0.916	irs
Xi'an	2015	0.774	0.844	0.917	irs
Xi'an	2016	0.725	0.779	0.931	irs
Hangzhou	2012	0.15	0.23	0.649	irs
Hangzhou	2013	0.225	0.244	0.923	irs
Hangzhou	2014	0.313	0.34	0.92	irs
Hangzhou	2015	0.343	0.365	0.941	irs
Hangzhou	2016	0.374	0.394	0.949	irs
Ningbo	2014	0.121	0.194	0.623	irs
Ningbo	2015	0.144	0.178	0.809	irs
Ningbo	2016	0.186	0.202	0.92	irs
Kunming	2013	0.032	0.059	0.542	irs
Kunming	2014	0.142	0.179	0.796	irs
Kunming	2015	0.232	0.288	0.806	irs
Kunming	2016	0.245	0.303	0.811	irs
Qingdao	2015	0.128	1	0.128	irs
Qingdao	2016	0.065	0.073	0.892	irs
Zhengzhou	2014	0.316	0.347	0.911	irs
Zhengzhou	2015	0.407	0.446	0.911	irs
Zhengzhou	2016	0.395	0.423	0.933	irs
Changsha	2014	0.354	0.687	0.515	irs
Changsha	2015	0.413	0.607	0.681	irs
Changsha	2016	0.353	0.412	0.857	irs
Harbin	2013	0.34	0.431	0.789	irs
Harbin	2014	0.514	0.568	0.905	irs
Harbin	2015	0.626	0.692	0.905	irs
Harbin	2016	0.577	0.639	0.902	irs
Nanning	2016	0.043	0.077	0.556	irs
Nanchang	2016	0.339	1	0.339	irs

A.3.2 DEA Results-Economic Perspective

City	year	overall	technical	scale	Variable

					Return to Scale
beijing	2002	0.254	0.36	0.706	drs
beijing	2003	0.242	0.37	0.655	drs
beijing	2004	0.267	0.412	0.649	drs
beijing	2005	0.291	0.463	0.628	drs
beijing	2006	0.327	0.527	0.621	drs
beijing	2007	0.36	0.615	0.587	drs
beijing	2008	0.344	0.627	0.549	drs
beijing	2009	0.352	0.642	0.549	drs
beijing	2010	0.381	0.727	0.523	drs
beijing	2011	0.367	0.745	0.492	drs
beijing	2012	0.363	0.789	0.461	drs
beijing	2013	0.362	0.81	0.447	drs
beijing	2014	0.374	0.862	0.434	drs
beijing	2015	0.43	0.909	0.473	drs
beijing	2016	0.461	0.986	0.468	drs
beijing	2017	0.458	1	0.458	drs
Shanghai	2002	0.324	0.479	0.677	drs
Shanghai	2003	0.352	0.505	0.698	drs
Shanghai	2004	0.382	0.552	0.692	drs
Shanghai	2005	0.424	0.602	0.704	drs
Shanghai	2006	0.42	0.645	0.652	drs
Shanghai	2007	0.434	0.708	0.613	drs
Shanghai	2008	0.443	0.75	0.591	drs
Shanghai	2009	0.436	0.754	0.579	drs
Shanghai	2010	0.357	0.738	0.484	drs
Shanghai	2011	0.414	0.813	0.509	drs
Shanghai	2012	0.419	0.833	0.502	drs
Shanghai	2013	0.418	0.881	0.475	drs
Shanghai	2014	0.435	0.898	0.484	drs
Shanghai	2015	0.535	0.94	0.569	drs
Shanghai	2016	0.571	1	0.571	drs

Guangzhou	2002	0.361	0.374	0.968	drs
Guangzhou	2003	0.377	0.39	0.968	drs
Guangzhou	2004	0.393	0.404	0.973	drs
Guangzhou	2005	0.454	0.457	0.994	drs
Guangzhou	2006	0.446	0.477	0.933	drs
Guangzhou	2007	0.444	0.539	0.824	drs
Guangzhou	2008	0.459	0.58	0.791	drs
Guangzhou	2009	0.468	0.614	0.763	drs
Guangzhou	2010	0.421	0.616	0.683	drs
Guangzhou	2011	0.432	0.678	0.637	drs
Guangzhou	2012	0.467	0.731	0.639	drs
Guangzhou	2013	0.518	0.81	0.639	drs
Guangzhou	2014	0.49	0.819	0.598	drs
Guangzhou	2015	0.517	0.88	0.587	drs
Guangzhou	2016	0.882	1	0.882	drs
Shenzhen	2005	1	1	1	crs
Shenzhen	2007	0.986	0.986	1	crs
Shenzhen	2008	1	1	1	crs
Shenzhen	2009	0.961	0.972	0.988	drs
Shenzhen	2010	1	1	1	crs
Shenzhen	2011	0.675	0.993	0.679	drs
Shenzhen	2012	0.639	0.977	0.654	drs
Shenzhen	2013	0.678	0.968	0.7	drs
Shenzhen	2014	0.706	0.985	0.716	drs
Shenzhen	2015	0.825	1	0.825	drs
Shenzhen	2016	1	1	1	crs
Tianjin	2005	0.367	0.401	0.916	drs
Tianjin	2006	0.372	0.419	0.888	drs
Tianjin	2007	0.394	0.459	0.858	drs
Tianjin	2008	0.456	0.548	0.832	drs
Tianjin	2009	0.532	0.63	0.844	drs
Tianjin	2010	0.602	0.724	0.83	drs
Tianjin	2011	0.735	0.854	0.86	drs

Tianjin	2012	0.676	0.832	0.811	drs
Tianjin	2013	0.777	0.889	0.874	drs
Tianjin	2014	0.864	0.957	0.903	drs
Tianjin	2015	0.957	1	0.957	drs
Tianjin	2016	0.902	1	0.902	drs
Nanjing	2005	0.569	1	0.569	irs
Nanjing	2006	0.419	0.472	0.888	irs
Nanjing	2007	0.459	0.481	0.954	irs
Nanjing	2008	0.495	0.515	0.962	irs
Nanjing	2009	0.526	0.545	0.964	irs
Nanjing	2010	0.458	0.466	0.984	drs
Nanjing	2011	0.471	0.501	0.942	drs
Nanjing	2012	0.526	0.555	0.947	drs
Nanjing	2013	0.575	0.603	0.954	drs
Nanjing	2014	0.513	0.575	0.892	drs
Nanjing	2015	0.433	0.555	0.78	drs
Nanjing	2016	0.451	0.585	0.771	drs
Nanjing	2017	0.439	0.616	0.713	drs
Suzhou	2012	1	1	1	crs
Suzhou	2013	1	1	1	crs
Suzhou	2014	0.941	0.994	0.947	drs
Suzhou	2015	0.949	1	0.949	drs
Wuxi	2014	0.933	1	0.933	irs
Wuxi	2015	0.847	0.856	0.989	irs
Chongqing	2004	1	1	1	crs
Chongqing	2005	0.453	0.467	0.97	drs
Chongqing	2006	0.428	0.501	0.855	drs
Chongqing	2007	0.48	0.597	0.805	drs
Chongqing	2008	0.635	0.767	0.828	drs
Chongqing	2009	0.625	0.876	0.714	drs
Chongqing	2010	0.616	1	0.616	drs
Chongqing	2011	0.603	1	0.603	drs
Chongqing	2012	0.624	1	0.624	drs

Chongqing	2013	0.582	0.902	0.645	drs
Chongqing	2014	0.577	0.878	0.656	drs
Chongqing	2015	0.648	0.979	0.662	drs
Chongqing	2016	0.665	1	0.665	drs
Changchun	2002	0.4	1	0.4	irs
Changchun	2003	0.272	1	0.272	irs
Changchun	2004	0.291	0.916	0.317	irs
Changchun	2005	0.304	0.79	0.385	irs
Changchun	2006	0.301	0.375	0.802	irs
Changchun	2007	0.296	0.296	0.999	crs
Changchun	2008	0.335	0.336	0.998	irs
Changchun	2009	0.357	0.358	0.996	irs
Changchun	2010	0.375	0.38	0.987	irs
Changchun	2011	0.423	0.426	0.991	irs
Changchun	2012	0.41	0.414	0.99	irs
Changchun	2013	0.444	0.446	0.995	irs
Changchun	2014	0.467	0.47	0.994	irs
Changchun	2015	0.47	0.48	0.978	drs
Changchun	2016	0.496	0.501	0.99	drs
Wuhan	2004	1	1	1	crs
Wuhan	2005	1	1	1	crs
Wuhan	2006	0.391	0.391	0.999	drs
Wuhan	2007	0.407	0.408	0.998	drs
Wuhan	2008	0.475	0.477	0.996	irs
Wuhan	2009	0.535	0.535	1	crs
Wuhan	2010	0.533	0.534	0.998	irs
Wuhan	2011	0.598	0.625	0.958	drs
Wuhan	2012	0.632	0.652	0.969	drs
Wuhan	2013	0.61	0.654	0.933	drs
Wuhan	2014	0.595	0.68	0.875	drs
Wuhan	2015	0.568	0.699	0.812	drs
Wuhan	2016	0.497	0.664	0.749	drs
Dalian	2002	0.327	1	0.327	irs

Dalian	2003	0.323	0.715	0.451	irs
Dalian	2004	0.353	0.435	0.811	irs
Dalian	2005	0.365	0.406	0.899	irs
Dalian	2006	0.437	0.948	0.461	irs
Dalian	2007	0.494	0.72	0.685	irs
Dalian	2008	0.59	1	0.59	irs
Dalian	2009	0.635	0.954	0.666	irs
Dalian	2010	0.575	0.592	0.973	drs
Dalian	2011	0.669	0.687	0.974	drs
Dalian	2012	0.762	0.787	0.969	drs
Dalian	2013	0.896	0.907	0.988	drs
Dalian	2014	0.814	0.848	0.959	drs
Dalian	2015	0.575	0.644	0.893	drs
Dalian	2016	0.468	0.543	0.861	drs
Shenyang	2010	0.62	0.748	0.829	irs
Shenyang	2011	0.619	0.628	0.987	irs
Shenyang	2012	0.589	0.598	0.986	drs
Shenyang	2013	0.593	0.647	0.916	drs
Shenyang	2014	0.591	0.65	0.909	drs
Shenyang	2015	0.556	0.616	0.903	drs
Shenyang	2016	1	1	1	crs
Chengdu	2010	0.499	0.679	0.735	drs
Chengdu	2011	0.477	0.677	0.705	drs
Chengdu	2012	0.5	0.68	0.735	drs
Chengdu	2013	0.514	0.691	0.744	drs
Chengdu	2014	0.542	0.739	0.733	drs
Chengdu	2015	0.526	0.753	0.698	drs
Chengdu	2016	0.49	0.776	0.632	drs
Xi'an	2011	0.546	0.597	0.914	irs
Xi'an	2012	0.504	0.509	0.991	drs
Xi'an	2013	0.466	0.482	0.967	drs
Xi'an	2014	0.502	0.526	0.953	drs
Xi'an	2015	0.524	0.543	0.966	drs

Xi'an	2016	0.455	0.494	0.922	drs
Hangzhou	2012	0.866	0.888	0.975	irs
Hangzhou	2013	0.674	0.682	0.988	drs
Hangzhou	2014	0.692	0.692	0.999	crs
Hangzhou	2015	0.683	0.705	0.969	drs
Hangzhou	2016	0.728	0.758	0.961	drs
Ningbo	2014	0.878	1	0.878	irs
Ningbo	2015	0.816	0.828	0.985	irs
Ningbo	2016	0.718	0.765	0.938	drs
Kunming	2013	0.676	1	0.676	irs
Kunming	2014	0.494	0.499	0.989	drs
Kunming	2015	0.495	0.504	0.981	drs
Kunming	2016	0.535	0.549	0.975	drs
Qingdao	2015	1	1	1	crs
Qingdao	2016	0.939	0.963	0.975	drs
Zhengzhou	2014	0.636	0.655	0.971	drs
Zhengzhou	2015	0.672	0.705	0.954	drs
Zhengzhou	2016	0.656	0.682	0.962	drs
Changsha	2014	0.917	1	0.917	irs
Changsha	2015	0.907	0.96	0.945	irs
Changsha	2016	0.795	0.804	0.988	irs
Harbin	2013	0.554	0.598	0.926	drs
Harbin	2014	0.568	0.604	0.94	drs
Harbin	2015	0.638	0.664	0.961	drs
Harbin	2016	0.657	0.681	0.965	drs
Nanning	2016	0.54	0.736	0.734	irs
Nanchang	2016	0.659	1	0.659	irs

A.3.3

City	year	Overall	Technical	Scale	Return to Scale
beijing	2002	0.307	0.766	0.4	drs
beijing	2003	0.271	0.774	0.35	drs
beijing	2004	0.298	0.782	0.381	drs

beijing	2005	0.341	0.793	0.43	drs
beijing	2006	0.402	0.814	0.493	drs
beijing	2007	0.481	0.842	0.571	drs
beijing	2008	0.487	0.873	0.558	drs
beijing	2009	0.507	0.903	0.562	drs
beijing	2010	0.554	0.944	0.587	drs
beijing	2011	0.561	0.944	0.595	drs
beijing	2012	0.602	0.952	0.632	drs
beijing	2013	0.617	0.956	0.646	drs
beijing	2014	0.654	0.962	0.68	drs
beijing	2015	0.776	0.97	0.8	drs
beijing	2016	0.844	0.997	0.847	drs
beijing	2017	0.847	1	0.847	drs
Shanghai	2002	0.315	0.786	0.401	drs
Shanghai	2003	0.355	0.805	0.44	drs
Shanghai	2004	0.404	0.829	0.487	drs
Shanghai	2005	0.451	0.85	0.531	drs
Shanghai	2006	0.45	0.877	0.513	drs
Shanghai	2007	0.493	0.911	0.541	drs
Shanghai	2008	0.491	0.947	0.518	drs
Shanghai	2009	0.536	0.966	0.555	drs
Shanghai	2010	0.484	0.969	0.499	drs
Shanghai	2011	0.548	0.983	0.557	drs
Shanghai	2012	0.579	0.989	0.585	drs
Shanghai	2013	0.608	1	0.608	drs
Shanghai	2014	0.609	0.999	0.609	drs
Shanghai	2015	0.76	1	0.76	drs
Shanghai	2016	0.821	1	0.821	drs
Guangzhou	2002	0.699	0.85	0.822	drs
Guangzhou	2003	1	1	1	crs
Guangzhou	2004	0.496	0.808	0.613	drs
Guangzhou	2005	0.483	0.781	0.618	drs
Guangzhou	2006	0.418	0.804	0.519	drs
Guangzhou	2007	0.387	0.835	0.464	drs
Guangzhou	2008	0.401	0.871	0.461	drs
Guangzhou	2009	0.427	0.913	0.468	drs
Guangzhou	2010	0.41	0.96	0.427	drs
Guangzhou	2011	0.39	0.952	0.41	drs
Guangzhou	2012	0.425	0.949	0.447	drs
Guangzhou	2013	0.482	0.944	0.51	drs

Guangzhou	2014	0.491	0.941	0.521	drs
Guangzhou	2015	0.516	0.963	0.535	drs
Guangzhou	2016	1	1	1	crs
Tianjin	2005	0.495	0.682	0.726	drs
Tianjin	2006	0.41	0.695	0.59	drs
Tianjin	2007	0.371	0.713	0.52	drs
Tianjin	2008	0.434	0.744	0.583	drs
Tianjin	2009	0.53	0.773	0.686	drs
Tianjin	2010	0.602	0.822	0.733	drs
Tianjin	2011	0.743	0.873	0.851	drs
Tianjin	2012	0.74	0.899	0.823	drs
Tianjin	2013	0.813	0.942	0.863	drs
Tianjin	2014	0.899	0.975	0.922	drs
Tianjin	2015	0.993	1	0.993	drs
Tianjin	2016	1	1	1	crs
Nanjing	2005	1	1	1	crs
Nanjing	2006	0.676	0.777	0.87	drs
Nanjing	2007	0.676	0.783	0.864	drs
Nanjing	2008	0.677	0.789	0.858	drs
Nanjing	2009	0.677	0.793	0.853	drs
Nanjing	2010	0.4	0.795	0.503	drs
Nanjing	2011	0.409	0.792	0.516	drs
Nanjing	2012	0.477	0.792	0.602	drs
Nanjing	2013	0.537	0.788	0.682	drs
Nanjing	2014	0.47	0.779	0.603	drs
Nanjing	2015	0.376	0.773	0.486	drs
Nanjing	2016	0.404	0.766	0.527	drs
Nanjing	2017	0.424	0.75	0.565	drs
Suzhou	2012	1	1	1	crs
Suzhou	2013	1	1	1	crs
Suzhou	2014	0.875	0.998	0.877	drs
Suzhou	2015	0.879	1	0.879	drs
Wuxi	2014	0.916	0.916	1	crs
Wuxi	2015	0.762	0.883	0.863	drs
Chongqing	2004	1	1	1	crs
Chongqing	2005	0.479	0.715	0.67	drs
Chongqing	2006	0.449	0.679	0.661	drs
Chongqing	2007	0.503	0.673	0.747	drs
Chongqing	2008	0.665	0.774	0.859	drs
Chongqing	2009	0.647	0.876	0.738	drs
Chongqing	2010	0.631	1	0.631	drs
Chongqing	2011	0.612	1	0.612	drs
Chongqing	2012	0.647	1	0.647	drs

Chongqing	2013	0.6	0.902	0.665	drs
Chongqing	2014	0.601	0.878	0.684	drs
Chongqing	2015	0.668	0.979	0.682	drs
Chongqing	2016	0.691	1	0.691	drs
Changchun	2002	0.848	0.859	0.987	drs
Changchun	2003	0.822	0.856	0.961	drs
Changchun	2004	0.818	0.854	0.957	drs
Changchun	2005	0.812	0.852	0.953	drs
Changchun	2006	0.711	0.79	0.9	drs
Changchun	2007	0.458	0.649	0.705	drs
Changchun	2008	0.463	0.649	0.714	drs
Changchun	2009	0.455	0.648	0.703	drs
Changchun	2010	0.408	0.642	0.635	drs
Changchun	2011	0.408	0.64	0.637	drs
Changchun	2012	0.396	0.636	0.622	drs
Changchun	2013	0.437	0.634	0.69	drs
Changchun	2014	0.466	0.633	0.736	drs
Changchun	2015	0.489	0.639	0.765	drs
Changchun	2016	0.502	0.64	0.784	drs
Wuhan	2004	1	1	1	crs
Wuhan	2005	1	1	1	crs
Wuhan	2006	0.769	0.83	0.926	drs
Wuhan	2007	0.764	0.829	0.921	drs
Wuhan	2008	0.765	0.828	0.925	drs
Wuhan	2009	0.789	0.836	0.944	drs
Wuhan	2010	0.607	0.731	0.83	drs
Wuhan	2011	0.584	0.749	0.78	drs
Wuhan	2012	0.631	0.758	0.832	drs
Wuhan	2013	0.621	0.769	0.807	drs
Wuhan	2014	0.61	0.768	0.794	drs
Wuhan	2015	0.615	0.785	0.784	drs
Wuhan	2016	0.521	0.789	0.661	drs
Dalian	2002	0.666	0.715	0.931	drs
Dalian	2003	0.61	0.704	0.866	drs
Dalian	2004	0.572	0.676	0.845	drs
Dalian	2005	0.54	0.674	0.801	drs
Dalian	2006	0.642	0.719	0.892	drs
Dalian	2007	0.63	0.7	0.9	drs
Dalian	2008	0.692	0.725	0.955	drs
Dalian	2009	0.667	0.7	0.953	drs
Dalian	2010	0.527	0.673	0.783	drs
Dalian	2011	0.63	0.705	0.893	drs
Dalian	2012	0.74	0.791	0.936	drs

Dalian	2013	0.896	0.915	0.98	drs
Dalian	2014	0.794	0.853	0.932	drs
Dalian	2015	0.509	0.687	0.74	drs
Dalian	2016	0.436	0.661	0.66	drs
Shenyang	2010	0.871	0.889	0.98	drs
Shenyang	2011	0.57	0.724	0.787	drs
Shenyang	2012	0.534	0.719	0.744	drs
Shenyang	2013	0.565	0.735	0.769	drs
Shenyang	2014	0.573	0.738	0.776	drs
Shenyang	2015	0.525	0.717	0.732	drs
Shenyang	2016	1	1	1	crs
Chengdu	2010	0.627	0.957	0.656	drs
Chengdu	2011	0.548	0.751	0.73	drs
Chengdu	2012	0.495	0.757	0.654	drs
Chengdu	2013	0.513	0.748	0.686	drs
Chengdu	2014	0.568	0.754	0.753	drs
Chengdu	2015	0.588	0.756	0.778	drs
Chengdu	2016	0.547	0.776	0.706	drs
Xi'an	2011	0.827	0.86	0.962	drs
Xi'an	2012	0.592	0.688	0.861	drs
Xi'an	2013	0.515	0.677	0.762	drs
Xi'an	2014	0.516	0.674	0.766	drs
Xi'an	2015	0.56	0.687	0.815	drs
Xi'an	2016	0.549	0.682	0.805	drs
Hangzhou	2012	0.994	1	0.994	drs
Hangzhou	2013	0.645	0.78	0.828	drs
Hangzhou	2014	0.704	0.777	0.905	drs
Hangzhou	2015	0.673	0.79	0.852	drs
Hangzhou	2016	0.747	0.831	0.898	drs
Ningbo	2014	0.919	0.995	0.923	drs
Ningbo	2015	0.956	1	0.956	drs
Ningbo	2016	0.769	0.89	0.864	drs
Kunming	2013	0.91	0.941	0.967	drs
Kunming	2014	0.462	0.787	0.587	drs
Kunming	2015	0.464	0.784	0.592	drs
Kunming	2016	0.51	0.784	0.651	drs
Qingdao	2015	1	1	1	crs
Qingdao	2016	0.969	0.988	0.981	drs
Zhengzhou	2014	0.582	0.773	0.753	drs
Zhengzhou	2015	0.634	0.797	0.796	drs
Zhengzhou	2016	0.649	0.794	0.816	drs
Changsha	2014	0.906	0.907	0.999	irs
Changsha	2015	0.907	0.91	0.996	drs

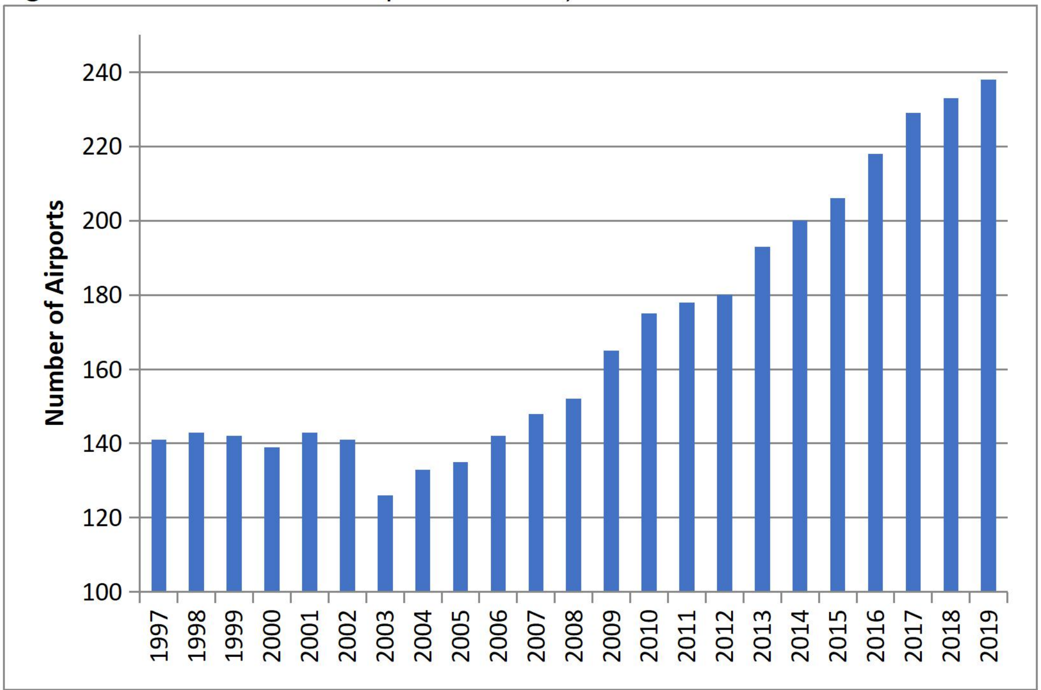
Changsha	2016	0.789	0.833	0.948	drs
Harbin	2013	0.706	0.786	0.897	drs
Harbin	2014	0.666	0.725	0.92	drs
Harbin	2015	0.696	0.741	0.939	drs
Harbin	2016	0.661	0.735	0.899	drs

Chapter 4 The Impact of Civil Airports on Sectoral Employment

Section 4.1 Introduction

China has experienced enormous economic growth in the last 40 years, creating in turn demand for rapid transportation approaches. Figure 4.1 presents the growth in airports from 1997 to 2019. Over this period, the no. of airports increased from 141 to 238 according to the Civil Aviation Administration of China (CAAC). Meanwhile, freight and passenger volume grew by more than 5 times (2.5 to 17.1 million tons) and by 12 times (111 to 1351.6 million persons) in the same period.

Figure 4.1 Number of Civil Airports in China, 1997 – 2019



Source: CAAC (http://www.caac.gov.cn/)

In spite of this rapid development, according to CAAC statistics, most small and medium-sized airports experience operating losses. As a crucial transportation mode, airports improve the accessibility of commodities (Button and Yuan, 2013) and passengers (Forsyth *et al.*, 2014; Bråthen and Halpern, 2012). In spite of suffering loss and carrying pressure on the debt, having an airport inevitably brings benefits to the local economy, both on the supply side and demand side. Having both a large number of benefits and costs, any decision to construct an airport should be taken with prudence. This becomes the first research question of this chapter that whether the benefits overweigh the costs.

In the last 2 decades, the construction of airports has mainly been financed by local and central government. For example, the budget for Bazhong Airport (designed with a capacity of 900,000 persons) was around 1.5 billion RMB (National Development and Reform Commission, 2015). The central government and civil development fund contributed 55% of this figure, while the provincial and local government carried the rest of the burden. Beijing Daxing Airport (designed with a capacity of 100 million) cost around 80 billion RMB (National Development and Reform Commission, 2014). These figures reveal that the most of the cost is covered by the public fund, though the private capital is permitted to invest in such projects for a relative small proportion. If the actual expenditure exceeds budget, central government would cover the shortage. As mentioned in the last paragraph, most civil airports in small and medium cities (SMC) generally suffer loss and most of the cost is financed from the taxpayers. It is very important to examine the benefits from having an airport.

Infrastructure is generally a merit public investment with large positive externalities, so is the airport. Many studies investigate that airports have significantly positive impacts on regional economic activities (Sudjic, 1992; Bruegmann, 1996; Glaeser, 2008; Sellner and Nagl, 2010). Improved air accessibility attracts new investment to regions and also generates GDP growth (Sellner and Nagl, 2010). Glaeser (2008) support the idea that whether there is an airport is an important factor when firms are choosing locations. Studies have argued that a new airport changes the economic structure of the local region in the USA, turning it gradually into a newly prosperous business centre (Bruegmann, 1996; Sudjic, 1992).

As the airport could flourish the regional economy and even change the local economic structure. The second question is asked that which industries are influenced most by opening a civil airport. The traditional hypothesis held that the air accessibility mainly affects hotels and the related tertiary sector and distribution centres and warehouse relying heavily on the air cargo in many European countries

(Bowen 2008; Leinbach and Bowen 2004; Sivitanidou, 1996). However, it could not explain what was happening in the USA. From the mid-1990s, the USA generally had a relatively diversified economy where airports located. Instead of warehousing companies and specific factories, airports are surrounded by retail, wholesale and accommodation businesses, transforming the neighbouring region into business centres to some extent (Freestone and Baker, 2011). Appold and Kasarda (2013) and Appold (2015) provide empirical evidence that the advantage of city expansion is a direct result of airport transportation after the construction of an airport. They also argue that airports significantly change the distribution of employment from other districts to regions adjacent to airports. In Australia, Sonnenburg and Braun (2017) point out that regions near to the airports of Sydney and Melbourne are dominated by the transport and warehousing companies, while non-traditional employment has grown significantly in Perth's and Brisbane's aviation zones. In these papers, airports could significantly boost the economy of surrounding region in some cities and even make it to regional business centre. This attracts my interest, as many local governments in China also plans or have built 'New Aviation District'[28] to develop economies. This chapter would investigate which sectors' employment would be significantly and positively affected by the Chinese airports, like European cities in traditional papers or like some American and Australian cities mentioned in this paragraph. In other words, it would like to examine if it is necessary to build an airport and encourage the 'New Aviation District'. In addition, the influenced area is another interesting focus of this chapter. Does the airport affect mainly on the airport surrounding region?

The effects of the airport in China are also examined by a number of researchers. Most of the literatures are in case study on a specific airport such as Wan *et.al* (2020), however, few have exploited the impacts of opening new airports incorporating a large number of airports. Gibbons and Wu (2020) examine local productivity improvements from opening a new airport in China by implementing the DID methodology. They find that substantial investment in aviation infrastructure in the 21st century led to a significant growth in firms' productivity and industrial output. To the best of my knowledge, however, no research has

[28] In Chinese, this specific zone is called Hangkong Xincheng

concentrated on the heterogeneous impacts of opening an airport on each specific industries, although it is generally believed that investment in infrastructure promotes overall GDP. This chapter seeks to fill this gap by offering an empirical study of which sectors' employment benefit the most from the construction of a new airport. According to specific assessments on each sector, this chapter also aims to generate new insights into local government to ascertain whether overall employment is improved by the opening of a new airport. Thus, the finding might provide some suggestions for local government that whether to treat opening an airport as an 'economic booster'.

As commonly known, the extent and nature of each sector's dependence on the air transport differs. For example, agriculture might rely little on either transporting commodity or passengers by air. Thus, opening an airport would have a relatively little influence on the employment in agriculture. As the significance of air transportation for specific industries varies, the influence of airports on each sector might be heterogeneous. This chapter primarily hypothesized that airports could bring more employment to these sectors highly depending on the air transport.

This chapter includes 19 specific industries at the prefecture level from 2003 to 2018. In addition, some city level economic indicators are included as control variables referring to Dong (2018). A DID estimation is adopted and presents the differential impacts across sectors. Increasing air accessibility causes an increase in employment in the wholesale and retail and transport and warehousing industries. Rather unexpectedly, the hotel and restaurant sector did not experience growth after a new air traffic connection was built. The total employment at the prefecture level was not significantly affected by the opening of a new airport.

To address the endogenous problems of the correlation between the airports and unobserved variables, the chapter constructs an instrument variable (IV) by using two quasi-exogenous variables, the distance to the hub airports and whether there is a military airport in that city. These two variables are either historical or geographical, which are not affected by the current economic factors. The 2SLS regression generates the similar conclusion with the baseline model that only two sectors are significantly improved by the opening a new airport.

The chapter is designed as follows. The next section gives the background to the development of the civil aviation industry in China. Section 4.3 discusses the relevant literature which either estimates the airport effect or similar infrastructure investment. A DID estimation is also included in this section. The following two sections describe the data collection and empirical methodology. Section 4.6 lays out the employment results of opening an airport in each sector. Section 4.7 draws some conclusions and implications for local projects applicant.

Section 4.2 Institution and Background

Section 4.2.1 Stages of Civil Air Development

This sub-section introduces the four stages of civil air development. In the stages, it tries to tell the readers the change of authorisation, management, financing source and the qualification to operate the civil services.

In Stage 1 (before 1978), the CAAC was founded in 1954 as a subordinate bureau controlled by the Military Commission. In the era of the 'Cold War', the aviation network served mainly for military and defence purposes, and most military airports were built during this era. As a historical factor, the location of military airports makes variable exogenous to the current employment level and other economic variables. The relatively little amount of civil use was responsible for the needs of transporting officers and urgent supplies. According to the statistics, 66% of the total flight hours were accounted for by agriculture and forestry use between 1952 and 1985 (An analysis of the historical development of general navigation of China in the past 60 years, 2011). In that era, airports did not primarily intend to improve air accessibility for firms and passengers.

Stage 2 (1978-1987) saw the introduction and early years of the reform and opening up policy. In line with other sectors, civil aviation experienced gradual development and liberalisation. In 1980, the CAAC was separated from control by the Military Commission and began to employ enterprise-style management. The CAAC set up 6 regional administration branches in Beijing, Shanghai, Guangzhou, Chengdu, Lanzhou and Shenyang. In this era, the civil services are provided by the military airports. There were still no dedicated civil airports and only a limited number of air routes connected the major cities.

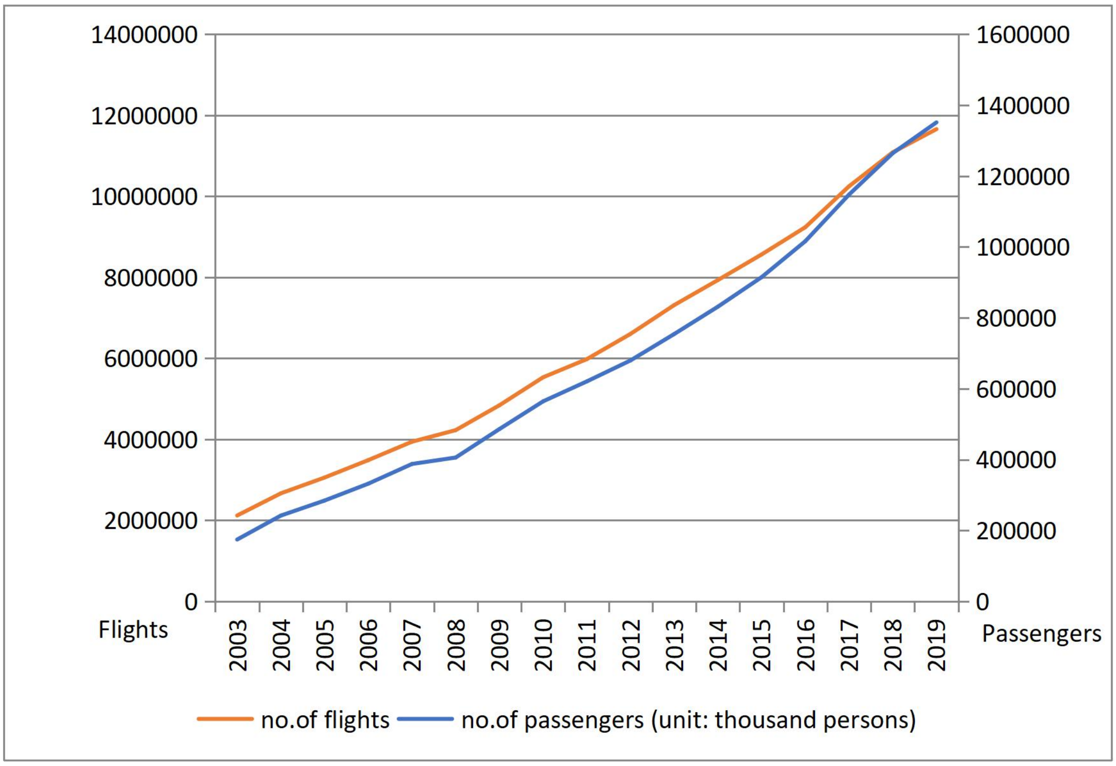
In Stage 3 (1987-2002), market-oriented reforms continued apace, and 6 state-owned enterprises catering to market demand appeared in 1988: China Airlines, Eastern Airlines, Southern Airlines, Southeastern Airlines, Northwestern Airlines and Northern Airlines[29]. State legislation introduced the Civil Aviation Act in 1995, authorising the CAAC to regulate airline services and set standards for airport facilities. Due to the lack of the dedicated civil airports, a large proportion of flights were still operated at military airports, especially in SMC. For example, Suzhou and Wuxi both utilised military airports, Guangfu airport and Shuofang airport, respectively. This means military airports are strongly correlated with the civil airport variable in this study's estimation, making it an appropriate instrument variable. Although air travel was not the main mode of transport for most members of the public as late as the 1990s and early 2000s, the growing economy and rapid urbanisation stimulated the government and the private sector to construct new airports. In this rapid expansion of the air network, nearly all the airports were still controlled by state-owned enterprises, and no private airline was permitted. Private financing only constituted to a significantly small proportion into the public-private parternership.

In Stage 4 (2002-the present), the civil aviation system reform programme (2002) offered more authorisation for the CAAC to control and develop the civil airport and airlines. First, it imposed requirements for military airport to continue to conduct civil air business. This explains why the number of operating airports fell from 141 to 126 in 2003 (see Figure 4.1), as many military airports exited the market. In order to improve the efficiency of investments, the CAAC devised a national airport construction plan (CAAC, 2007). Up to 2011, more than 40 new airports were constructed and financed at a cost of over 300 billion RMB, with the funds coming from both the central and local fiscal budget. At the same time, the CAAC gradually allowed private capital to enter both airport and airline operations. The civil air

[29] Southeastern Airlines, Northwestern Airlines and Northern Airlines continuously suffered losses in the 1990s and were merged with the other three airlines after 2002.

industry boomed rapidly in this stage. Figure 4.2 illustrates the booming market for air transport, with the number of passengers and flights increasing by approximately 7 and 5 times, respectively.

Figure 4.2 Development Trend of Passengers and Flights Airports in China, 2003 – 2019



Source: CAAC (http://www.caac.gov.cn/)

The structural change explains the special status of the military airports. Due to its location and civil-military dual-use in special historic period, the military airports have obvious advantages to be the instrument variable of the civil airport. The development illustrates the market and private fund gradually liberalized after 2002. Hence, measuring the economic effects after it would be an appropriate time range selection.

Section 4.2.2 Institutions of Airport Application

The current legislation on airport construction and management[30] was regulated by the Ministry of Transportation in 2016 and slightly revised in 2019. It provides detailed requirements for the site selection and application processes. The first phase of the application is the analysis of the site selection. Considering the natural conditions and the economic effects, any proposal had to be permitted by the military authority to confirm it would not disturb military planes. The feasibility analysis enacted by the local government was firstly submitted to the Regional Aviation Administration Bureau and then reported to the CAAC. After the approval of the application, the applicant is required to hand in more detailed information, including the future airport operating plan. With the permission of other departments, such as military defence, weather, earthquake forecasting, etc, the relevant organisations authorised by the government can prepare a budget proposal to the CAAC, after which construction can begin.

Despite the gradual privatisation, the main source of funds remained different levels of the state. The aim was to provide better market supervision and more effective allocation of resources. Regulation imposes strict controls on the use of funds. For example, the budget for the construction of Bazhong Airport can be seen in Table 4.1. Less than 20% of the investment was allocated to social capital, while more than half was funded by the central government. According to airport management regulations, the actual cost should not exceed the budget if central funds are involved, and a re-application of the feasibility report is required if the amount exceeds 10%. Due to the strict control of budget and supervision mechanism, the local governors should have a serious consideration that if the economic benefit of opening a new airport overweighs the costs and risks.

[30] Available at CAAC Website: http://www.caac.gov.cn/XXGK/XXGK/MHGZ/201606/t20160622_38637.html

Table 4.1 The source of budget of Bazhong airport

Source	Amount (million yuan)	Percentage
Central budgetary investment	289	19.4%
Civil Aviation Development Fund[31]	582	39.0%
Provincial fiscal expense	300	20.1%
The rest follows to the local government and other capital	320	21.5%
Total	1491	100%

Source: National Development and Reform Commission, 2014. Available at https://www.ndrc.gov.cn/xxgk/zcfb/tz/201605/t20160519_963381.html

The regulation also indicates that if the passenger capacity is 50% less than the expected amount, the airport is recommended to be closed. Based on the strict requirement on location, complicated application process, tight budget control and probability of closing, the decision makers must make a serious consideration on whether they should build an airport to achieve economic progress. If the incentive of economic growth is not considerable, the waste of fiscal expenditure might be accounted by the central government at some extent. Thus, the results of this chapter could give the local governors a general idea that whether there are sufficient economic benefits of applying airports.

Section 4.2.3 The Classification of Civil Airports

Classification[32] was done by CAAC in 2013, mainly focusing on two factors. The first was the length of runway, with a ranking from 1 to 4. The second is related to the width of the runway, categorised A to F (see Table 4.2). Most airports in provincial capitals and municipal cities are in the class of 4E and 4F. And nearly all airports had

[31] The fund is collected from all the air passengers per time and administrated by the CAAC. It can be regarded as a central allocated expense.
[32] The standard is available at: http://www.caac.gov.cn/XXGK/XXGK/BZGF/HYBZ/201511/t20151102_7849.html

runway lengths in class 3 or 4. Besides the professional classification, CAAC devised another general standard: passenger flow and volume of freight. This standard has 5 classes, from 'small' to 'mega'. A small airport has a passenger capacity of less than 100 thousand persons and/or 2 thousand tons of cargo, while a mega airport handles more than 10 million passengers and/or 500 thousand tons in freight. Using this categorisation, only 39 airports in 2019 were counted as mega, fewer than 20% of all civil airports in China. Most new airports opened after 2004 were small to medium, or below category 3C. As using instrument variable has to exclude most of the large airports, the final result of this chapter manly investigates the economic effects of building a non-mega airport. In addition, most of the loss-making airports aren non-mega airports, as a consequence, discussing the external economic benefit of airports in SMC is more academically and practically significant.

Table 4.2 Standard of the Categorization

Length of runway		Width of runway		
Class number	Length(metres)	Class Letter	Maximum wingspan (metres)	Distance between the main driving wheel (metres)
1	<800	A	<15	<4.5
2	[800,1200)	B	[15,24)	[4.5,6)
3	[1200,1800)	C	[24,36)	[6,9)
4	≥1800	D	[36,52)	[9,14)
		E	[52,65)	[9,14)
		F	≥65	≥14

Source: CAAC (http://www.caac.gov.cn/)

Section 4.3 Literature Review

The mechanism for improving the economy through transport infrastructure follows 2 theories. The first holds that increased accessibility and cost reductions introduce more commodities into the local market. The second contends that the agglomeration effect from market integration could further boost the economy. The economic effects of land transport infrastructure projects have been researched in developed economies (Baum-Snow, 2007; Duranton et al., 2014; Banerjee et al., 2019; Gibbons et al., 2019). Baum-Snow (2007) finds that highways decentralised the centralised populations to the suburbs between 1950 and 1990. Duranton et al. (2014) posit that highway connections bring a greater volume of exports but not a greater value. Gibbons et al. (2019) present that new road connections improve workers' productivity not only in transport intensive firms but also in non-relevant firms. Similar effects for roads and railroads in developing countries, including China, have also been examined by scholars. Banerjee et al (2020) point out that access to highways has a positive impact on GDP per capita. Baum-Snow et al. (2017) conclude that highways have augmented decentralization in China. Faber (2014) conducts least cost spanning tree networks to make an instrumental variable and finds that peripheral counties suffer GDP reduction in network connections. Qin (2017) derives a similar result to Faber (2014) using railroad data. Zheng and Kahn (2013) are the first to discuss the effects of China's high-speed railway system. As the highways and the railways are mainly planned by the central government, the local governors are not the leading applicants and participants. This dissertation intends to research the original purpose for the local government, thus highways and railways are not the most appropriate projects to investigate.

Research on airports has mainly been done in developed countries, in particular the USA. The lack of relevant researches might be attributed to the endogeneity problem of the non-random selection of airport location. The prevailing method is to focus only on hub airports, which are assumed to be quasi-exogenous to the other control factors. Button et.al (1999) and Green (2007) implement this assumption and research empirical data from the USA. Employing the airport size and location as instrument variables based on historical plans, Sheard (2014) finds that airport size has a significant positive effect on employment in tradable sectors, but an insignificant impact on non-tradable ones in the USA.

Generally speaking, these studies have considered the economic impacts on the economy or employment in the USA. In contrast, scant research has looked at the airport effects in developing countries. To the best of my knowledge, among this literature, most studies are qualitative or case studies. For example, Liu (2009) uses an input and output model to analyse the economic influence of Beijing Capital Airport. Gibbons and Wu (2020) firstly introduced the DID methodology into research on the economic impact of opening a new airport in China. By dividing industries into a directly affected category and a moderately-affected category by having a new airport, Gibbons and Wu (2020) conclude that new air accessibility improves industrial productivity and manufacturing GDP, while the impacts on the tertiary sector are still unclear. However, no previous studies have focused on employment in individual sectors. As dependence on airports in each industry might be heterogeneous, the effects could also differ. Investigating overall employment might be too general and lack detailed findings. This chapter concentrates on the specific impacts of 19 specific industries and seeks to identify which industries are most influenced by the construction of a new airport.

Excluding Gibbons and Wu (2020), no studies provide clear insights into economic effects using China's airports. This motivates the author to conduct an empirical research into the impacts of introducing a new airport in China by including most civil airports across the country rather than doing a series of case studies on one or two specific airports.

Similar work on China's the high-speed railway system was conducted by Dong (2018), who used the DID method to ascertain the impacts on the employment in 19 specific sectors at the prefecture level when they are connected to the rail system. Dong (2018) finds that the wholesale and retail industry and the hotel industry were positively affected by new railway projects. The mechanism was more connected to drawing economic benefits from neighbouring areas/cities than to creating new economic capacities. This chapter uses a similar DID estimation referring to Dong (2018) and considers which sectors are affected by the introduction of a new airport. It also compares the extent to which the results are similar to the effects of introducing the high-speed railway system.

Although the DID method has been widely applied in economic research and in other social sciences, few have adopted this quantitative technique to explore the outcomes of opening new airports. The only two examples are Tveter (2017), who investigated regional airport projects in Norway, and, as noted above, Gibbons and Wu (2020). Opening a new airport is like introducing an event into a treatment group. Therefore, the DID method is an appropriate method for estimating the effects of a new airport.

Section 4.4 Data

Data set is collected from a wide range of sources. The dependent variables are the employment data in 19 specific sectors in prefecture level. This data is collected from the China City Statistical Year Book from 2004 to 2019, which corresponds to the statistics from 2003 to 2018. Table 4.3 presents the summary of the 19 sectors. The first 3 columns of table 4.3 are the statistics of the city-governed district, or called Shixiaqu in statistical yearbook. And the next 3 column data is for the whole prefecture level including the records in suburb region and the counties. Dong (2018) believed that suburb region economic structure does not function as a city according to a large proportion of employment in agricultural sector. This chapter is not sure whether the economic structure changes mainly in the surrounding affected by the new airport. As many airports locate in the suburban area, I use the employment data of city-governed region (similar to urban area) and the overall prefecture region. As a large proportion of airports locate in the non-city-governed region. It could boldly imply that the surrounding area are the mainly influenced zone if the overall prefecture employment are significantly influenced but the city-governed district are not. 292 cities are researched in the sample, the autonomous prefectures, such as Enshi, are not included as the economy of them are relatively less developed and the statistics is incomplete in the yearbook. As there are 292 cities within 16 years included in the datasets, the full observations should be 4672 for each sector.

Table 4.3 Descriptive Statistics of the Employment Data (unit: persons)

Sectors	No.obs	mean	s.d	No.obs	mean	s.d
Agriculture	4,220	2541.4	8401.7	4,561	10931.8	35644.4
Mining	3,277	14180.0	27258.1	4,290	19009.2	30988.7
Manufacture	4,564	92866.3	200643.1	4,602	140822.6	239262.8
Power	4,547	6179.0	8722.4	4,598	10650.7	16793.2
Construction	4,558	38264.1	77620.4	4,602	62127.4	120779.8
Transportation	4,566	17484.8	48505.7	4,602	22708.2	53786.5
Information	4,531	7656.7	35697.3	4,598	9050.8	37398.0
Retail & wholesale	4,565	17487.0	55520.4	4,602	25654.7	73032.7
Hotel & resteraunt	4,526	6963.2	23737.7	4,597	9429.0	33952.4
Finance	4,562	12727.0	29473.0	4,595	19121.7	167789.6
Real estate	4,529	7680.3	27565.2	4,596	9586.6	29333.0
Rental	4,206	9707.6	47742.0	4,600	12067.8	50358.1
Scientific	4,552	8967.3	35210.7	4,601	10902.5	37692.6
Environment	4,561	4477.5	8262.0	4,602	7398.0	9062.8

The main explanatory variables, open year of each airport and the operation capacity, are collected from the 'Annual Report of Civil Airport Production Statistics' from 2002 to 2018. These data report the new airport open year, annual number of flights and passengers. In this report, the data is recorded for each specific airport. In order to generate the prefecture level of data, the cities with more than one airport, such as Beijing and Shanghai, accumulate the volume of all airports within the region. I treat dummy airport to 1 when the airport opens this year and 0, otherwise. In order to explicitly examine the effect of the airport open, the dummy variable is revised to 0, if the airport opens less than 3 months of this year. Other control variables in the regression, such as GDP, population, capacity of other transports and urbanization rate are collected from the China City Statistical Yearbook. And the connection to HSR of a city is manually collected from the reports from the China department of Transportation. This dummy variable equals 1 when connects to a HSR system, otherwise 0.

In order to address endogeneity, 36 hub airports are chosen to create an instrument variable. This contains all provincial capitals, municipalities and 5 other airports of sub-provincial cities[33]. All the hub cities had airports prior to 2003, going back even to the era of the centrally planned economy. Therefore, the founding of these airports was based on historical and political reasons rather than economic reason. The location of each city's centre and the geographic coordinates of the hub cities are manually collected from the National Platform for Common Geospatial Information Service. Straight line distances from the other cities to these hub cities are then calculated using geographic coordinates. The nearest one is Jinzhong, 13.66km from Taiyuan's airport. Jinzhong lacks an airport until now. The longest distance to a hub airport is Hulunbeir, 631km from the capital of Inner Mongolia's airport. Unsurprisingly, Hulunbeir had airport much before 2003, as cities far from hub airports tend to build their own airports. The list of distances to hub airports is shown in Appendix A.4.1.

The list of military airports in China is taken from Wikipedia (34), created and edited mainly by the Federation of American Scientists. Wikipedia uses the Annual Report of Military Power of the People's Republic of China (U.S. Department of Defense) and satellite photos to build the list of 173 military airports in China. By checking the geographic coordinates, these airports were found to be located in 115 cities. As most of these airports were built during the 'Cold War' era not for economic purposes, they are treated as quasi-exogenous.

[33] 5 other airports are in Dalian, Qingdao, Ningbo, Xiamen and Shenzhen.
[34] Available at https://en.wikipedia.org/wiki/List_of_People%27s_Liberation_Army_Air_Force_airbases#Citations

Section 4.5 Methodology

Section 4.5.1 Baseline DID Estimation

In the first step, the chapter uses a DID specification as the baseline model to estimate the effects on the employment by sectors in prefecture level as a result of opening a new airport. The model (4.1) is shown as follows:

$$E_{ct} = \alpha_0 + \beta D_{ct} + \theta X_{ct} + \gamma_c + \delta_t + \varphi_c t + \varepsilon_{ct} \tag{4.1}$$

E_{ct} is the logarithm value of the employment. A total of 19 industries are included in this chapter, which means model would run 19 times (once for each different industries). D_{ct} is the dummy variable for the airport open time which equals 1 when the airport began to operate, and 0 otherwise. Hence, the sign and coefficient of β are the treatment effects this chapter focuses. X_{ct} is the vector of control variables which might affect the employment. Referring to Dong (2018), it contains GDP, population, fiscal expenditure, fiscal revenue, urbanization rate, road freight capacity and HSR connection dummy. These control variables are all general factors affecting the magnitude of employment.

The model implements γ_c and δ_t to represent the fixed effects of cities and years. γ_c describes the specific geographic or historical factors of each city, while δ_t controls the specific national-wide macroeconomic or political shocks in one year. $\varphi_c t$ captures a dynamic and specific city time trend which might influence the construction of the airport and the employment structure. For example, one city might hold a very important exhibition event in a specific year, which might affect its employment. The standard error clustering is in city level same as Dong (2018).

The model might have endogenous issues as the decision of constructing the airport is not random and correlated to some unobserved factors. These correlations might introduce a biased estimation of β. This is why the chapter brings instrument variable to test the baseline model in the steps set below.

Section 4.5.2 Similar Pre-trend Test and Robustness Check

The design of DID allows difference between control and treatment groups and this difference changes after the treatment. This paper also conducts an event study to test the validity of the DID specification, which requires a similar pre-trend of the dependent variables for the two groups. This method is used by Card and Krueger (2000) to test the effects on employment when a new legislation of increased minimum wage was implemented. The regression is designed as follows:

$$E_{ct} = \alpha_0 + \sum_{\sigma=2}^{m} \beta_{-\sigma} D_{c,t-\sigma} + \sum_{\sigma=0}^{n} \beta_{\sigma} D_{c,t+\sigma} + \theta X_{ct} + \gamma_c + \delta_t + \varphi_c t + \varepsilon_{ct} \qquad (4.2)$$

In model (4.2), m and n represent the years before or after the open year of the airport, which would test the specific effects before and after the event. For example, $D_{c,t-2}$ equals 1 for two years earlier than the open of airport. And as the one year before the airport open is not included in the model (4.2), all the coefficient estimates the different effects on employment compared to the year before the treatment. The observations in early years help to indicate that the employment of the control and treatment groups has the similar trend before the airport open. The chapter uses 4 years before the airport open to test the pre-trend effects. In order to test the robustness, the other number of m=3 also used to check.

After testing the validity of the baseline model 3.1, this chapter uses the value of the passenger capacity and flight numbers of each airport to represent the airport dummy to do a robustness check. This presents the effects more explicitly by introducing the intensity factor rather than a dummy factor. In model (4.3), I_{ct} represents the intensity factor of the logarithm value of passenger volume or the total flights. The other variables are as same as in model (4.1).

$$E_{ct} = \alpha_0 + \beta I_{ct} + \theta X_{ct} + \gamma_c + \delta_t + \varphi_c t + \varepsilon_{ct} \qquad (4.3)$$

Section 4.5.3 Instrument Variable (IV)

Intuitively, economically prosperous and populated cities are more likely to have airport. This concern raises the endogenous problem that the DID estimation does not estimate an unbiased causal effect of the air traffic connection due to the mutual effects between the airports and other economic indicators both included and not included. In addition, some unobservable economic factors (omitted variables), might also cause biasness on the coefficients of the airport effects. To address the endogenous concerns, this chapter conducts the probability of having airports as an IV. The probability is estimated mainly by two quasi-exogenous variables, the distance to the nearest hub airports and whether the city has military airports. The first variable is geographic, while the other is historical mentioned in the above sections. Both of the variables are quasi-exogenous to the economic variables and the omitted variables, which could more accurately depict the magnitude of the new airport open. The chapter employs the Probit model to estimate the probability of having an airport for each city in the first stage of 2SLS, shown in model (4.4).

$$Prob(Airport)_{ct} = \alpha_0 + \beta_1 dist_{ct} + \beta_2 mili_{ct} + \theta X_{ct} + \gamma_c + \delta_t + \varphi_c t + \varepsilon_{ct} \quad (4.4)$$

$dist_c$ measures the distance of city c to the nearest hub airports and $mili_c$ is a dummy variable taking value of 1 if the city c has military airports.

Intuitively speaking, the shorter distance to the hub airport leads to lower needs for a SMC to have its own airport. For example, Shaoxing is only 30km from Hangzhou airport and does not have airport until now. The sign β_1 is expected to be positive. As the distance to the hub airports increases, the city tends to have its own airport. However, the major cities[35] themselves do not follow that hypothesis. As the hub airports located in the mega cities, the airport dummy is always equal to 1 in spite of the short distance to their own airports. This has no practical implication for estimating the probability of having airports in those 36 mega cities as they all have airports more than 40 years and mainly and primarily built for political reasons. Therefore, model (4.4) drops the observations in the major cities due to the theoretical and practical reasons.

The correlation between military airport and civil airport in a city is also positive. The first reason for this is that having a military airport indicates that the city is

[35] The major cities are the 36 cities mentioned above in 4.4.

either politically or economically important. This is also a reason for opening a a civil airport in this city. Second, having a military airport means the city has the natural conditions to build a civil airport to some extent. Third, some airports for are dual use - military and civil - such as Wuxi's Shuofang Airport. Before 2003, more than 40% of civil flights were operated in military airports. Therefore, the correlation between a military airport and a civil airport is practically and significantly positive. This assumes that sign of β_2 is positive.

As the two variables are time-invariant, the chapter introduces the number of the airports in that year to convert the variables to time-variant. The number of airports measures the dynamic development trend of the aviation industry. It describes the development index of the civil airports and attitude of the government to construct airport. Higher the number of airports in national level means the individual city has a higher probability to have the airport. Using the distance and military variables multiplied by the number of airports does not affect the sign of β_1 and β_2. Hence, the Equation (4.5) and Equation (4.6) presents the adjustment of the distance and military airport variable.

$$Dist_{ct} = dist_c * No.of\ airport_t \tag{4.5}$$

$$Mili_{ct} = Mili_c * No.of\ airport_t \tag{4.6}$$

After generating the estimated probability from model 4.4, This would proxy the dummy variable-airport. Then, this chapter would run the model 4.1 again to generate the unbiased estimator of the effects of the airports.

Section 4.6 Results

Section 4.6.1 Baseline Estimation Results

The empirical results generated from the DID estimation are presented in this sub-section. Table 4.4 shows the effects on each industry based on the regression of model (4.1) for the city-governed region, including city, year and city-year effects. This regression used the data of employment in city-governed regions. As shown, no sectors are significantly affected by the opening of an airport in city-governed regions. In fact, most airports are built far from city centres, even in neighbouring counties. Around 40% of the airports were not located in a city-governed district but rather in a neighbouring county in 2010. This might mean that the airport does not influence the area far from it. As the effects in city-governed districts are not significant, the chapter uses employment data from the whole prefecture region in the following sections.

Table 4.4 Baseline Results for the Employment in City-governed Region(Shixiaqu)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Agricu	Mining	Manu	Power	Constr	Trans& ware
Airport	0.028	-0.029	-0.091	0.041	0.025	-0.002
	(0.076)	(0.103)	(0.058)	(0.052)	(0.094)	(0.048)
Control variables	Included	Included	Included	Included	Included	Included
City FE	YES	YES	YES	YES	YES	YES
Time effects	YES	YES	YES	YES	YES	YES
City Trend	YES	YES	YES	YES	YES	YES
Obs	3870	2999	4179	4164	4172	4181
R-square	0.5552	0.4794	0.5302	0.4558	0.7387	0.5352

(7)	(8)	(9)	(10）	(11）	(12）	(13）
Infor	Whole &retail	Hotel	Finance	Real Estate	Rental	Sci
0.0176	0.048	-0.055	-0.066	-0.061	0.075	0.017
(0.087)	(0.048)	(0.052)	(0.22)	(0.068)	(0.089)	(0.042)
Included	Included	Included	Included	Included	Included	Included
YES	YES	YES	YES	YES	YES	YES
YES	YES	YES	YES	YES	YES	YES
YES	YES	YES	YES	YES	YES	YES
4147	4181	4143	4176	4146	3828	4166
0.6304	0.6118	0.5047	7186	0.7233	0.5653	0.5560

(14）	(15）	(16）	(17）	(18）	(19）
Envir	House service	Edu	Health	Leisure	Public admin
0.010	-0.024	-0.011	0.017	0.000	-0.027
(0.041)	(0.133)	(0.013)	(0.017)	(0.042)	(0.021)
Included	Included	Included	Included	Included	Included
YES	YES	YES	YES	YES	YES
YES	YES	YES	YES	YES	YES
YES	YES	YES	YES	YES	YES
4177	3732	4182	4182	4171	4182
0.4955	0.4600	0.6236	0.8112	0.4256	0.7365

Note: All the regressions are estimated based on model (1), including the constant and standard error clustered in city level. The sign *, ** and *** represents the significance level of 10%, 5% and 1%, respectively. The dependent variables are the logarithm form of the employees in each industry.

The empirical results of effects on employment in the whole prefecture region are presented in Table 4.5. Airport opening has a positive significant impact on two sectors - transport and warehousing and wholesale and retail - at 10% and 5% significance level respectively. The coefficients are 0.055 and 0.099, which indicates that introducing an airport to the region brings a 5.5% and 9.9% increase in employment in these two industries, respectively. These significant effects can be easily explained. The increase traffic accessibility of some new commodities and passengers or the cost reduction of transportation could both stimulate the growth of direct logistic businesses and the related warehousing industry. These two advantages could also bring new opportunities to the retail and wholesale industries. For example, some inland cities could export high value-added agricultural goods to distant regions by air transport. In previous times, these perishable goods could only be consumed locally. It is somewhat surprising to note that an airport opening does not have a significant influence on tourism employment. This result contrasts with the finding of Dong (2018) that high-speed trains had a significant positive effect on tourism employment. The effects on regional tourism revenue and the number of tourists need to be further investigated. This result is consistent with Bowen (2008) and Freestone and Baker (2011) at some extent.

Table 4.5 Baseline Results for the Employment in the Prefecture Level

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Agricu	Mining	Manu	Power	Constr	Trans& ware
Airport	0.052 (0.051)	-0.071 (0.074)	-0.050 (0.040)	0.041 (0.030)	0.013 (0.060)	0.055* (0.030)
Control Variables	Included	Included	Included	Included	Included	Included
City FE	YES	YES	YES	YES	YES	YES
Time effects	YES	YES	YES	YES	YES	YES
City Trend	YES	YES	YES	YES	YES	YES
Obs	4168	3921	4203	4200	4203	4203
R-square	0.6727	0.5219	0.7463	0.4714	0.8260	0.6202

(7)	(8)	(9)	(10）	(11）	(12）	(13）
Infor	Whole & retail	Hotel	Finance	Real estate	Rental	Sci
0.075 (0.050)	0.099** (0.040)	-0.045 (0.047)	-0.016 (0.019)	0.004 (0.050)	0.035 (0.065)	0.028 (0.036)
Included	Included	Included	Included	Included	Included	Included
YES	YES	YES	YES	YES	YES	YES
YES	YES	YES	YES	YES	YES	YES
YES	YES	YES	YES	YES	YES	YES
4200	4203	4199	4199	4198	4201	4202
0.6378	0.6170	0.5684	0.6526	0.7942	0.5917	0.6623

(14）	(15）	(16）	(17）	(18）	(19）	
Envir	House service	Edu	Health	Leisure	Public admin	
0.037 (0.041)	-0.000 (0.021)	0.005 (0.010)	0.003 (0.010)	0.003 (0.028)	-0.021 (0.014)	
Included	Included	Included	Included	Included	Included	
YES	YES	YES	YES	YES	YES	
YES	YES	YES	YES	YES	YES	
YES	YES	YES	YES	YES	YES	
4203	4075	4203	4203	4202	4203	
0.6620	0.4893	0.6505	0.9150	0.4619	0.8054	

Note: All the regressions are estimated based on model (1), including the constant and standard error clustered in city level. The sign *, ** and *** represents the significance level of 10%, 5% and 1%, respectively. The dependent variables are the logarithm form of the employees in each industry.

Section 4.6.2 Effects on Total Employment

As known, the wholesale and retail and transport and warehousing industries generally do not generate a large number of job opportunities. From the statistics, the average percentage contributions of these two industries to total employment are only 4.1% and 3.8%, respectively. Therefore, the effects on total employment are quite ambiguous. This section uses the DID model 4.1 to examine if the introduction of a new airport has a strong impact on total employment at the prefecture level. Table 4.6 shows that the coefficient is quite close to 0, and insignificant. Hence, it could be concluded that the opening of a new airport does not generally improve the overall employment level of a city. As airports bring little benefits to total employment, it suggests the local governors to be prudent to apply or operate airports.

Table 4.6 DID Estimation of Airport Effects on the Overall Employment

Variables	(1) Log value of total employment
Airport	-0.003
	(0.015)
Control variables	Included
City FE	YES
Time effects	YES
City Trend	YES
Obs	3831
R-square	0.7340

Section 4.6.3 The Validity of DID Estimation and Robustness Check by Intensity Factor

The DID specification relies on the similar trend before the event between the control and treatment group. The chapter implements model (4.2) to present the effects before the treatment. Table 4.7 presents the results of the two significant sectors by showing 4 years impacts before the airport open by the row of 'year_-4'to 'year_-2'. Column (1) and (3) reports the results for the three significant sectors in last section by controlling year, city and the city-time fixed effects. Column (2) and (4) only controls the city and year fixed effects. All the coefficients before the airport open in column (1) to (4) are insignificant in the wholesale & retail and transport & warehousing industry. This supports the DID specification that none of pre-trend effects are significantly different compared to one year before the airport open. To test the robustness of the pre-trend test, the chapter also uses other year lags (m=3). The results are similar.

Table 4.7 Pre-trend and post-trend Test

Variables	(1) Trans&ware	(2) Trans&ware	(3) Whole &retail	(4) Whole &retail
Year_-4	-0.026	-0.030	0.029	0.014
	(0.030)	(0.035)	(0.037)	(0.038)
Year_-3	-0.047	-0.049	0.014	0.007
	(0.030)	(0.034)	(0.039)	(0.034)
Year_-2	-0.024	-0.004	0.020	0.025
	(0.029)	(0.037)	(0.043)	(0.040)
Year_0	0.018	0.026	0.088**	0.057**
	(0.032)	(0.036)	(0.039)	(0.025)
Year_+1	0.020	0.050*	0.099*	0.85***
	(0.027)	(0.026)	(0.045)	(0.027)
Year_+2	0.069*	0.092**	0.140**	0.111**
	(0.038)	(0.042)	(0.061)	(0.045)
Year≥+3	0.085*	0.084*	0.175**	0.064*
	(0.046)	(0.050)	(0.066)	(0.035)
Control Variables	Included	Included	Included	Included
City FE	YES	YES	YES	YES
Time Effects	YES	YES	YES	YES
City Trend	YES	NO	YES	No
Obs	4203	4203	4203	4203
R-square	0.6213	0.5168	0.6184	0.5393

Note: The sign *,**,*** represents the significance level of 10%, 5% and 1%, respectively. The dependent variables are the logarithm form of the employees in 3 sectors. The errors are clustered in city level.

To check the robustness, the chapter adopts the log values of the number of flights and the passenger capacity representing the dummy variable ‘airport’ in model (4.3). These two variables are advantageous, as they measure the operating intensity of the airports rather than giving a simple binary value of 1 or 0. Table 4.8

describes the results for these two independent variables. Column (1) and (2) present effects of number of flights on two sectors, and the other two columns present the coefficients of the passenger capacity. All the coefficients are significant and positive. It implies that 1% increase in the number of the passengers causes a 0.004% and 0.0076% increase in the transport & warehousing and wholesale & retail industry employment. This is consistent with our DID estimation in above.

Table 4.8 Results of Model 4.3

Variables	(1) Transport & warehousing	(2) Wholesale & Retail	Variables	(3) Transport & warehousing	(4) Wholesale & Retail
Log_flightno	0.0055*	0.0130***	Log_passenger	0.0040*	0.0076**
	(0.0033)	(0.0046)		(0.0023)	(0.0031)
Control Variables	included	included	Control Variables	included	included
City FE	YES	YES	City FE	YES	YES
Time FE	YES	YES	Time FE	YES	YES
Obs	4203	4203	Obs	4203	4203
R-square	0.6202	0.6178	R-square	0.6202	0.6170

Note: The sign *,**,*** represents the significance level of 10%, 5% and 1%, respectively. The dependent variables are the logarithm form of the number of flights and the passengers.

Section 4.6.4 Addressing the Endogeneity

Table 4.9 presents the results of the Probit-regression of model (4.4) as the first stage of 2SLS regression. As note, in methodology section 4.5.3, 36 hub cities are not included in the datasets, as it affects the estimation of the variable distance. The coefficients of the distance and military airport are both significantly positive in 1% level. It implies that the city far from the hub airport is more likely to build its own airport. And the cities with military airports also tend to have civil airports as well. The Wald Chi square test supports the significance of the explanatory variables.

Table 4.9 Results of Model 4.4

Variables Dependet variable:airport	coefficients	p-value
Distance	0.0471*** (0.0104)	0.000
Military airport dummy	0.0048*** (0.0025)	0.000
Time Effects	YES	
Observation	3680	
Log Likelihood	-592.10	
Wald Chi-square test	481.43	0.000

Note: The sign *,**,*** represents the significance level of 10%, 5% and 1%, respectively. The province effects are 31 different provincial dummy variables taking the value of 1 when the city belongs to that province and 0 otherwise. The observations are from year 2002 to 2018. The errors are clustered in city level.

After having this instrument variable to proxy the airport dummy, Table 4.10 demonstrates the second stage results putting this IV into model 4.1. The coefficients of wholesale & retail and transport & warehousing are 0.115 and 0.074, significant at 1% and 10% level respectively. The coefficients are slightly higher than the baseline model (results in Table 4.5). As the sample selection is not the same for the two regressions, this result indicates that either the baseline model (4.1) underestimates the effects of opening an airport on these two sectors or the cities with no political priority have relative higher impacts. Appendix A.4.2 reports the results of model (4.1) without the major cities observations, the coefficients are 0.054 and 0.084, still lower than the coefficients in the 2SLS model. This implies that the original regression underestimates the effects of the airport. The 2SLS model suggests that a new airport brings 11.5% and 7.4% increase in the employment of these two sectors. The coefficient of hotel is still insignificant in 2SLS model. This means that the airport does not bring more working opportunities in this sector to the region. As shown in Table 4.10, the instrument variable pass through the underidentification test (Kleibergen-Paap rk LM statistic) at 99% level and weak identification test (Cragg-Donald Wald F staistics) as the Stock-Yogo weak ID test critical value at 10% is 16.38. Hansen J statistics is 5.700, which also reject the hypothesis of overidentification.

Table 4.10 Results of 2SLS Regression

Dependent Variables	(1) Wholesale & retail	(2) Transport & warehousing	(4) Hotel
Airport	0.115***	0.074*	0.034
	(0.044)	(0.039)	(0.071)
Control variables	included	included	included
City FE	YES	YES	YES
Time effects	YES	YES	YES
City Trend	YES	YES	YES
Obs	3679	3679	3675
Kleibergen-Paap rk LM statistic (p-value)	27.93 (0.0000)	27.93 (0.0000)	27.93 (0.0000)
Cragg-Donald Wald F staistics	17.310	17.310	17.310
Hansen J statistics	5.700	5.700	5.700
(p-value)	(0.017)	(0.017)	(0.017)

Section 4.7 Conclusion

This chapter has examined the economic impacts of the opening of a new airport on employment in 19 industries. The baseline DID model indicates that only the wholesale and retail and transport and warehousing sectors are significantly affected by a new airport. The reasons for this may be either an increase in the transport of new commodities by air or a reduction in transport costs for existing goods and/or passengers. All other industries do not experience an increase in employment. The insignificant coefficient for the hotel industry implies that there may not be growth in the tourism market, but this needs to be further investigated. As the wholesale and retail sector and transport and warehousing sector do not constitute a large proportion of the job market, it could imply that opening a new airport does not have a large impact on overall employment. The empirical results also prove this conclusion. The difference magnitude of impacts could be attributed to heterogeneous dependence on transport of each sector. Apparently, wholesale & retail and transport & warehousing sectors rely heavily on transport.

Comparing the effects on urban employment and overall employment at the prefecture level, it can be concluded that a new airport does not have significant impacts on the city-governed region. This finding may be attributed to the geographic location of the airport, as most logistics-related businesses, such as warehouses, are located close to airports, which are generally not directly in the city-governed district but further away from the city in the county.

In order to address the endogeneity, this chapter introduces the 2SLS method to re-estimate the effects. The TSLS results confirms that it has significant impact on the employment of wholesale & retail and transport & warehousing sectors but no significant impact on total employment in prefecture level and other specific sectors. The magnitude of the influence on those two sectors is larger in the 2SLS regression, which is to say that the original model under estimate the effects. Additionally, it finds that the magnitude is larger excluding the 36 major cities' data. This is to say that the airports in those cities have less effects of improving employment.

In the draft of the 14th Five Year Plan of Civil Aviation (2021-2025), the CAAC plans to have more than 300 civil airports and permit many major cities to build second even third airports. In the interest of allocating financial resources efficiently, this chapter provides some empirical evidence to local governments that opening new airports only encourages employment in 2 sectors, neither of which contributes large gains to total employment. The first suggestion is that local governments should not treat the airports as an employment booming tool if the economy of those cities does not depend heavily on wholesale & retail and transport & warehousing sectors. As the employment of several sectors in the surrounding area are mainly improved, for the cities with airports , this helps the idea of building 'New Aviation District' or 'Logistics Industrial Zone' at some extent.

Section 4.8 Bibliography of Chapter 3

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Section 4.9 Appendix for Chapter 3

A.4.1 The distance to the hub airports for each city (km)

City	distance	City	distance	City	distance	City	distance
Tangshan	79.86	Liaoyuan	121.95	Anqing	160.79	Ezhou	79.17
Qinhuangdao	201.62	Tonghua	203.92	Huangshan	189.58	Jingmen	194.69
Handan	187.60	Baishan	236.39	Chuzhou	83.46	Xiaogan	129.12
Xingtai	137.92	Songyuan	123.06	Fuyang	150.68	Jingzhou	195.28
Baoding	93.01	Baicheng	267.48	Suzhou	184.12	Huanggang	74.04
Zhangjiakou	167.32	Qiqihar	258.16	Chaohu	92.02	Xianning	101.55
Chengde	150.82	Jixi	371.25	Lu'an	54.19	Suizhou	127.75
Cangzhou	99.72	Hegang	364.23	Bozhou	193.89	Zhuzhou	39.55
Langfang	61.67	Shuangyashan	396.84	Chizhou	151.96	Xiangtan	45.99
Hengshui	109.27	Daqing	142.16	Xuancheng	26.21	Hengyang	155.34
Datong	150.08	Yichun	310.72	Putian	86.26	Shaoyang	200.16
Yangquan	83.81	Jiamusi	343.49	Sanming	193.89	Yueyang	132.10
Changzhi	179.41	Qitaihe	357.16	Quanzhou	62.61	Changde	177.53
Jincheng	144.35	Mudanjiang	285.61	Zhangzhou	78.86	Zhangjiajie	286.93
Shuozhou	176.38	Heihe	519.95	Nanping	169.75	Yiyang	98.40
Jinzhong	13.66	Suihua	126.01	Longyan	129.75	Chenzhou	266.06
Yuncheng	213.18	Xuzhou	254.76	Ningde	80.50	Yongzhou	268.40
Xinzhou	74.76	Changzhou	56.06	Nanchang	267.61	Huaihua	330.03
Linfen	211.22	Suzhou	26.50	Jingdezhen	296.81	Loudi	134.33
Lvliang	132.71	Nantong	87.58	Pingxiang	89.82	Shaoguan	163.61
Baotou	156.29	Lianyungang	216.20	Jiujiang	207.19	Zhuhai	48.05
Wuhai	154.20	Huaian	196.80	Xinyu	172.58	Shantou	194.30
Chifeng	310.56	Yancheng	210.99	Yingtan	365.22	Zhongwei	139.58
Tongliao	242.11	Yangzhou	89.09	Ganzhou	308.89	Qinzhou	84.78
Erdos	221.54	Zhenjiang	74.58	Jian	209.32	Guigang	157.50
Hulunbeier	631.02	Taizhou	121.20	Yichun	121.68	Yulin	202.30
Bayannaoer	283.81	Suqian	251.52	Fuzhou	307.62	Baise	214.51
Wulanchabu	112.80	Wenzhou	216.35	Shangrao	309.04	Hezhou	208.69
Anshan	78.35	Jiaxing	66.95	Zibo	75.72	Hechi	231.94
Fushun	54.60	Huzhou	76.05	Zaozhuang	224.07	Laibin	167.96
Benxi	42.99	Shaoxing	28.94	Dongying	132.13	Chongzuo	85.16
Dandong	183.55	Jinhua	145.63	Yantai	160.98	Sanya	211.16
Jinzhou	203.21	Quzhou	205.73	Weifang	120.82	Dànzhou	103.36
Yingkou	155.09	Zhoushan	74.09	Jining	173.11	Zigong	159.12
Fuxin	157.49	Taizhou	129.78	Taian	75.52	Panzhihua	204.50
Liaoyang	47.76	Lishui	204.23	Weihai	169.94	Luzhou	151.13

Panjin	131.51	Wuhu	64.68	Rizhao	125.05	Deyang	73.30
Tieling	81.44	Bengbu	111.48	*(DC)Laiwu*	84.91	Mianyang	124.79
Chaoyang	255.42	Huainan	72.10	Linyi	225.53	Guangyuan	274.50
Huludao	202.90	Maanshan	41.48	Dezhou	104.66	Suining	135.46
Jilin	72.41	Huaibei	222.77	Liaocheng	119.49	Neijiang	152.01
Siping	140.39	Tongling	133.95	Binzhou	91.98	Leshan	114.39
Heze	169.55	Foshan	42.57	Guangan	84.37	Nanchong	134.10
Kaifeng	55.47	Jiangmen	77.26	Dazhou	184.00	Meishan	55.68
Luoyang	130.06	Zhanjiang	148.27	Yaan	115.73	Yibin	107.32
Pingdingshan	99.34	Maoming	198.14	Bazhong	237.46	Karamay	455.63
Anyang	181.36	Zhaoqing	95.74	Ziyang	76.11	Xianyang	10.10
Hebi	156.07	Huizhou	78.39	Liupanshui	197.42	Weinan	69.21
Xinxiang	87.71	Meizhou	205.45	Zunyi	129.06	Yanan	247.58
Jiaozuo	98.58	Shanwei	161.55	Anshun	93.53	Hanzhong	166.38
Puyang	168.00	Heyuan	145.87	Bijie	173.24	Yulin	257.92
Xuchang	55.48	Yangjiang	210.80	Tongren	272.88	Ankang	195.39
Luohe	107.70	Qingyuan	45.05	Qujing	98.62	Shangluo	125.18
Sanmenxia	226.33	Dongguan	44.80	Yuxi	91.96	Jiayuguan	487.80
Nanyang	206.84	Zhongshan	46.24	Baoshan	377.94	Jinchang	221.81
Shangqiu	166.40	Chaozhou	179.85	Zhaotong	141.55	Baiyin	47.42
Xinyang	149.75	Jieyang	211.71	Lijiang	331.69	Tianshui	281.60
Zhoukou	122.62	Yunfu	140.62	Puer	295.52	Wuwei	164.99
Zhumadian	171.55	Liuzhou	228.22	Lincang	315.47	Zhangye	301.05
Huangshi	106.58	Guilin	366.37	Xigaze	203.30	Pingliang	222.89
Shiyan	274.89	Wuzhou	200.58	Xian	26.82	Jiuquan	470.35
Yichang	278.62	Beihai	157.80	Tongchuan	78.49	Qingyang	192.69
Xiangyang	240.28	Fangchenggang	103.19	Baoji	147.44	Dingxi	135.70
Haidong	6.22	Shizuishan	79.74	Wuzhong	40.14	Longnan	327.01
Guyuan	245.84						

A.4.2 Results of model (1) without major cities

Variables	(1) Transport & warehousing	(2) Wholesale & Retail
Airport	0.055*	0.084**
	(0.0030)	(0.034)
City FE	YES	YES
Time FE	YES	YES
City Interaction Effects	YES	YES
Obs	3679	3679
R-square	0.6157	0.5406