Highway Infrastructure and Firm Investment — Microeconomic Evidence from China

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Abstract

China experienced rapid highway expansion following the two major highway infrastructure projects by the Chinese government, that is, the National Trunk Highway System project in 1992 and the National Expressway Network project in 2004. This thesis explores how firms' investments are affected by the rapid expansion of China's highway network, using a geo-coded firm-level panel dataset for Chinese manufacturing firms in the period from 1998 to 2007. To identify the causal effect, two types of endogeneity concerns arising from the non-random distribution of highways and the endogenous location of firms are addressed using a range of time-varying instruments and samples. Empirically, three main findings are discovered in this thesis. First, better access to highways encourages firms to reduce their input and total inventories. Firms' input inventories are more affected by highways through the direct channel of reduction in transportation cost and transit time, whereas firms' output inventories are more affected by the demand channel. Second, better highway proximity promotes firms' fixed investment, supporting the crowding-in effect of public investment. Highway proximity is found to stimulate corporate investment through at least three mechanisms, that is, by reducing firms' financial constraints, releasing additional internal funds via inventory reduction, and mitigating the negative impact of uncertainties. Third, better highway proximity stimulates the allocative efficiency of capital and reduces the dispersion of marginal revenue product of capital (MRPK). Specifically, there are four mechanisms through which highway infrastructure reduces MRPK dispersion, that is, by reducing both productivity volatility and markup dispersion and by inducing heterogeneous effects on MRPK dispersion through financial constraints and policy distortion.

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Declaration

I declare that, except where explicit reference is made to the contribution of others, this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

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Chapter 1

Introduction

A noticeable expansion of China's highway infrastructure has been accompanied by rapid urbanization and economic growth over the past three decades. According to China Statistical Yearbooks, the total length of highways (expressways) has extended from 100 kilometres in 1988 when the first highway was completed, to 53,900 kilometres in 2007, ranking second only to the United States. Many academic studies about the impact of transportation investment on its economic development emerged (Banerjee et al., 2012; Faber, 2014) after the Chinese Government began expanding investments in China's National Trunk Highway System in 1992. From the regional level, some studies show that highway infrastructure contributes to economic growth from different aspects, such as spatial agglomeration (Yu et al., 2016), regional productivity (Zhang and Ji, 2019), GDP growth (Banerjee et al., 2012), trade integration (Faber, 2014) and economic geography (Baum-Snow et al., 2018; Xu and Nakajima, 2017). There is also an increase in studies about the economic efficiency of transportation infrastructure explored from the firm level. For example, academics have explored the effects of road transportation on firms' activities and performance, such as innovation (Wang et al., 2018), exportation (Liu et al., 2022), and productivity (Li and Arreola-Risa, 2017; Wang et al., 2020).

However, much less is known about how highway infrastructure affects firms' investment decisions. This thesis plans to fill this research gap by investigating the causal effects of highway development on manufacturing firms' inventory management, fixed investment, and capital allocative efficiency, using a geo-coded firm-level panel dataset for Chinese manufacturing firms in the period from 1998 to 2007.

This focus on highway infrastructure can be justified in two ways. First, road infrastructure in general, and highway infrastructure in particular, plays an important role in freight transport in China. From 1998 to 2007, approximately 75% of freight was transported by roads, whereas high-speed railways and airlines mainly transferred people. When compared with other types of roads, highways with travel speeds up to 100-120 km/hour serve as an ideal option for firms engaging in cross-city/province business because of the time and cost-saving effects. Thus, highways are expected to have a direct and significant impact on the inventory management and fixed investment of manufacturing firms. Secondly, highways experienced a rapid expansion in China over the sample period. Following the two major highway infrastructure projects by the Chinese government, that is, the National Trunk Highway System project in 1992 and the National Expressway Network project in 2004, the length of highways expanded from 8,700 kilometres in 1998 to 53,900 kilometres in 2007 in China. By contrast, the development of high-speed railways and airline networks mainly began after 2008, and is, therefore, less relevant to understanding the inventory and fixed investment decisions of manufacturing firms over the period 1998-2007.

This thesis contributes in three ways. First, instead of using regional transportation infrastructure investment as a proxy for public investment (see, for instance, Aiello et al., 2012; Li and Li, 2013), a set of highway accessibility variables based on a firm's distance to the nearest highway are constructed. With these firm-level measures, it is possible to control for unobserved industry- and region-specific time-varying factors, such as government policies, thus alleviating potential omitted variable bias.

Second, there are at least two types of endogeneity concerns in the analysis. Firstly, highway construction is endogenous, that is, the distribution of highways is not random. Governments develop highways to link large cities where firms have high investments. Secondly, the location of firms can be endogenous. New firms may choose to locate close to highways in order to benefit from the cost-saving effect of highway infrastructure, and existing firms may relocate their location by moving closer to highways (Holl, 2016). In order to control for the first type of endogeneity, this thesis constructs a number of time-varying instruments, namely, the least cost paths and straight lines constructed based on the targeted city points outlined in the national highway construction projects, and historical instruments based on the Ming dynasty' courier routes and the Qing dynasty's historical routes. To deal with the second type of endogeneity, this research excludes both new firms that opened during the sample period and relocating firms that switched their locations during the sample period.

Third, this thesis contributes to the literature on highway infrastructure from the perspective of corporate finance. Current literature about how highway infrastructure affects firms' investment and capital allocation efficiency is limited. This thesis builds on existing literature, e.g., Shirley and Winston (2004) and Li and Li (2013) in terms of inventory, Aiello et al. (2012) in terms of fixed investment, andAsker et al. (2014) and David and Venkateswaran (2019) regarding capital misallocation, and provide a deeper discussion on these topics.

Chapter 4 examines how highway infrastructure affects firms' inventory management in China, which would be a channel towards productivity enhancement. If a firm lowers its inventory storage without decreasing its market size (or sales), the firm must develop a higher operating efficiency or productivity (Capkun et al., 2009). Using a panel of 492,490 manufacturing firms (with 1,856,417 observations) over the period from 1998 to 2007, the estimation results indicate robust causal effects of highway proximity on firms' input inventory and output inventory. The result of input inventory is consistent with the theoretical intuition on the basis of the (S, s) model. That is, if a firm's demand is controlled, the improvement in highways will directly encourage firms to lower their input inventory level as the transportation cost and lead time are decreased. In addition, the cost-saving benefits of input inventories are unevenly distributed across firms, sectors and regions. However, the output inventory is less affected by the improvement of highways as finished goods are more connected with the level of sales and expected demand rather than the transportation cost. In addition, the estimation of the demand mechanism indicates that highways can affect firms' total inventories, input inventories and output inventories indirectly through the channel of demand proxies (sales and sales surprise). Furthermore, it is concluded that each dollar of highway spending in China during the period from 1998 to 2007 reduced the input inventory stock by about 3.910-10.010 cents and the total inventory stock by around 6.730-25.523 cents.

Chapter 5 investigates whether, and how, highway infrastructure affects firms' fixed investment. This research is motivated by the following two factors. First, inventory can serve as an additional financial supply of fixed investment (Bo, 2004), especially for firms facing financial constraints. Motivated by the estimation results in Chapter 4, highway infrastructure may affect corporate investment through, at least, the channel of inventory reduction. When access to highways becomes much easier, the decrease in average inventory stock induced by highways will release additional cash flow, which finally stimulates the investment of fixed assets. Secondly, this research fills the gap in understanding whether public investment in highway infrastructure crowds in or crowds out private investment from the perspective of corporate finance.

Using the large panel dataset for Chinese manufacturing firms, the two-stage least square estimation with different types of instruments confirms the positive causal effect of highway accessibility on corporate investment, supporting the view of the crowding-in effect of public transportation investment.

For possibly the first time in the relevant literature, this chapter explores the possible mechanisms through which highways affect corporate investment from the perspective of corporate finance. First, highway proximity stimulates corporate investment by reducing firms' financial constraints. Better highway accessibility reduces the potential difficulties associated with long-distance investment deals as it alleviates information asymmetries, improves the accessibility and quality of mediated information, and facilitates more efficient identification of investment opportunities (Bernstein et al., 2016; Duan et al., 2020). Thus, firms have many opportunities to secure external finance from, not only nearby banks or financial institutions but also from far-off and distant institutions. Secondly, better highway accessibility can reduce firms' inventory stock, thus releasing additional funds for fixed investment. Inventory can be served as an additional financial supply of fixed asset investment (Fazzari and Petersen, 1993). The lower average inventory stock caused by highway improvement frees up additional cash flow, which ultimately stimulates the investment of fixed assets. Thirdly, highway accessibility increases corporate investment by mitigating uncertainties. An improved highway network offers flexible supply chains and facilitates market integration, which significantly reduces the uncertainties faced by firms from both the demand and supply sides, thus encouraging investment. In addition, further estimation result shows that better highway infrastructure increases both the quantity and quality of corporate investment by allocating more investment to firms with higher marginal returns.

Chapter 6 further explores whether better highway infrastructure promotes the allocative efficiency of capital at a more aggregate level. A marginal return of capital (MRPK) dispersion is applied to capture the inefficiency of capital allocation (capital misallocation). The estimation result shows that better highway proximity reduces the dispersion of MRPK. Specifically, the baseline estimation results indicate that a 0.1 unit increase in highway proximity over the sample period can lead to a 0.03-0.04 unit decrease in MRPK dispersion. The causal effect of highway proximity on

MRPK dispersion is robust, by using either the standard deviation of MRPK or the interquartile range (IQR) of MRPK; either unweighted or weighted average highway proximity; either 4-digit industry-province level estimation or 4-digit industry level estimation; or by applying alternative measures to estimate MRPK.

Specifically, there are four channels through which highway infrastructure influences MRPK dispersion, that is, by reducing both productivity volatility and markup dispersion or by inducing heterogeneous effects on MRPK dispersion through financial constraints and policy distortion. First, better highway proximity can affect revenue-based productivity volatility, which captures uncertainties from both the supply side and demand side. By reducing productivity volatility, highway infrastructure will result in lower dispersion in the static measure of MRPK dispersion as the new capital level in the next period is less likely to be dramatically different from the optimal level. Secondly, better highway access reduces markup dispersion by imposing heterogeneous effects on firm-level markups, i.e., those with higher markup levels reduce more than those with lower markup levels. Thirdly, industries with higher financial constraints can benefit from better transportation networks and can increase their capital allocative efficiency, since better highway proximity helps constrained firms to increase the availability of external and internal finance (evidence supported in Chapter 5). Fourthly, industries with lower policy interventions (i.e., with lower state-owned and foreign-owned capital shares or lower subsidy levels) tend to largely reduce the dispersion of MRPK, implying a better allocative efficiency of capital, whereas insignificant effects are found on industries with high policy interventions.

The remainder of this thesis is structured as follows. Chapter 2 presents the background information on China's highway development and Chapter 3 illustrates data and key variable construction which are used in the following three chapters. Chapter 4 discusses the effect of highway access on firms' inventory investment in China. Chapter 5 investigates how better highway accessibility affects corporate investment and Chapter 6 explores the impacts of highway infrastructure on capital misallocation. Chapter 7 offers a conclusion and policy implications.

Chapter 2

The Background to Highway Development in China

2.1 Stylized facts

The stylized facts of China's transportation development are discussed to support the research motivation and why there is a focus on highway infrastructure rather than other types of transportation infrastructure in the sample period from 1998 to 2007.

First, compared with other kinds of transportation such as the railway, waterways and civil aviation, road infrastructure is the most important for freight transport. As shown in Figure 2.1, approximately an average of 75% of freights is transported by road infrastructure, although it shows a slight downward trend, with 77.01% in 1998 and 72.04% in 2007. Although the share of freight volume transported by railways and waterways shows a slightly increasing trend, railways and waterways still remain less important. The average proportion of freight volume transported by railways is approximately 14%, and the average proportion transported by waterways is approximately 10%. Civil aviation and pipelines are the least important infrastructure in terms of freight traffic, as their average proportions are 0.01% and 1.50% respectively.

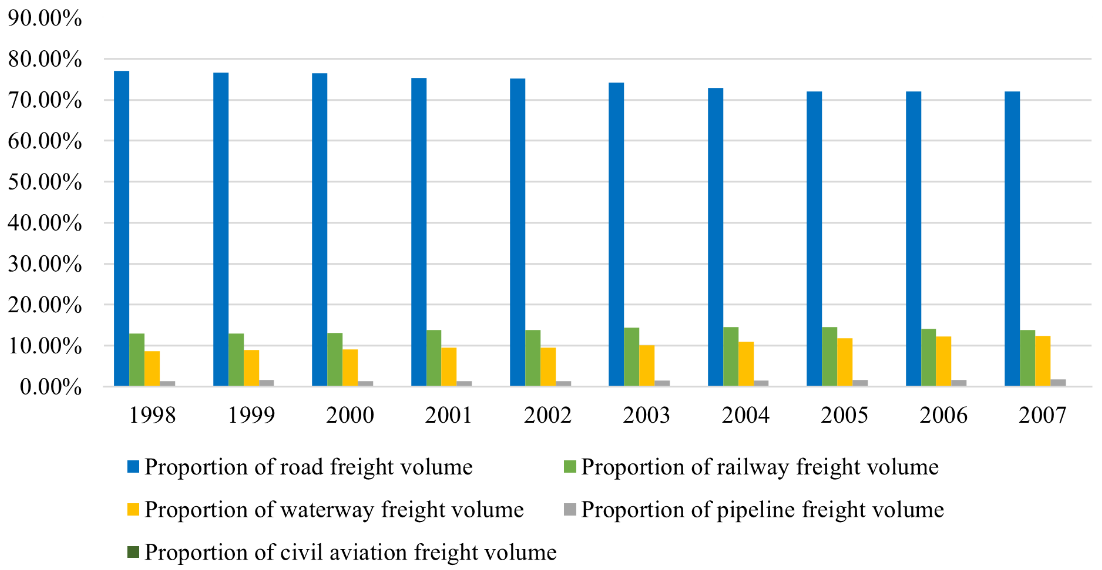


Figure 2.1: The proportion of freight volume between different transportation infrastructures

Source: China Statistical Yearbooks from 1988 to 2018

Secondly, over the past three decades, China has undergone not only rapid urbanization and economic growth but also a remarkable expansion of its transportation infrastructure. During the sample period, the rapid development of the expressway transportation system was the most impressive part.

Table 2.1 shows the average annual growth rate of different transport infrastructures over the last thirty years. The expressway network has been fast-growing since the opening of the first expressway, the Shanghai-Jiading Expressway, in mainland China in 1988. Compared with other transportation, expressways have displayed the largest growth rate from 1988 to 2013, although other transportation such as railways and regular civil aviation routes started to be focused on from 2008. As shown in Table 2.2 with regard to the average annual growth rate of different roads by technical classification, the high growth rate of the expressway is also the most striking part.

Table 2.1: Average annual growth rate of the length of different transportation

Year	Railways	Roads	Expressway	Navigable Inland Waterways	Regular Civil Aviation Routes	Petroleum and Gas Pipelines
1988-1993	0.83%	1.62%	61.54%	0.15%	20.78%	2.78%
1993-1998	2.53%	3.37%	51.23%	0.02%	9.40%	7.09%
1998-2003	1.91%	7.20%	27.83%	2.37%	3.05%	7.13%
2003-2008	1.77%	15.56%	15.22%	-0.20%	7.07%	12.35%
2008-2013	5.30%	3.15%	11.61%	0.50%	10.77%	11.03%
2013-2018	5.01%	2.16%	6.43%	0.20%	15.34%	4.43%

Note: The average annual growth rate is calculated based on the data from the China Statistical Yearbook.

Table 2.2: Average annual growth rate of different road lengths

Year	Total	Expressway, Class I to Class IV roads					Substandard Roads
		Subtotal	Expressway	Class I	Class II	Class III &IV	
1988-1993	1.62%	3.35%	61.54%	22.03%	13.98%	2.59%	-2.87%
1993-1998	3.37%	5.40%	51.23%	27.17%	14.61%	4.08%	-4.35%
1998-2003	7.20%	6.12%	27.83%	14.34%	11.10%	4.87%	12.15%
2003-2008	15.56%	14.07%	15.22%	12.63%	6.12%	15.30%	20.72%
2008-2013	3.15%	6.21%	11.60%	7.96%	3.61%	6.32%	-8.79%
2013-2018	2.16%	3.53%	6.43%	7.04%	2.94%	3.39%	-8.72%

Note: The average annual growth rate is calculated based on the data from the China Statistical Yearbooks from 1988 to 2019.

Based on the *Technical Standard of Highway Engineering (JTG B01 2003)*, the road infrastructure can be classified into two major categories or six minor ones: standard

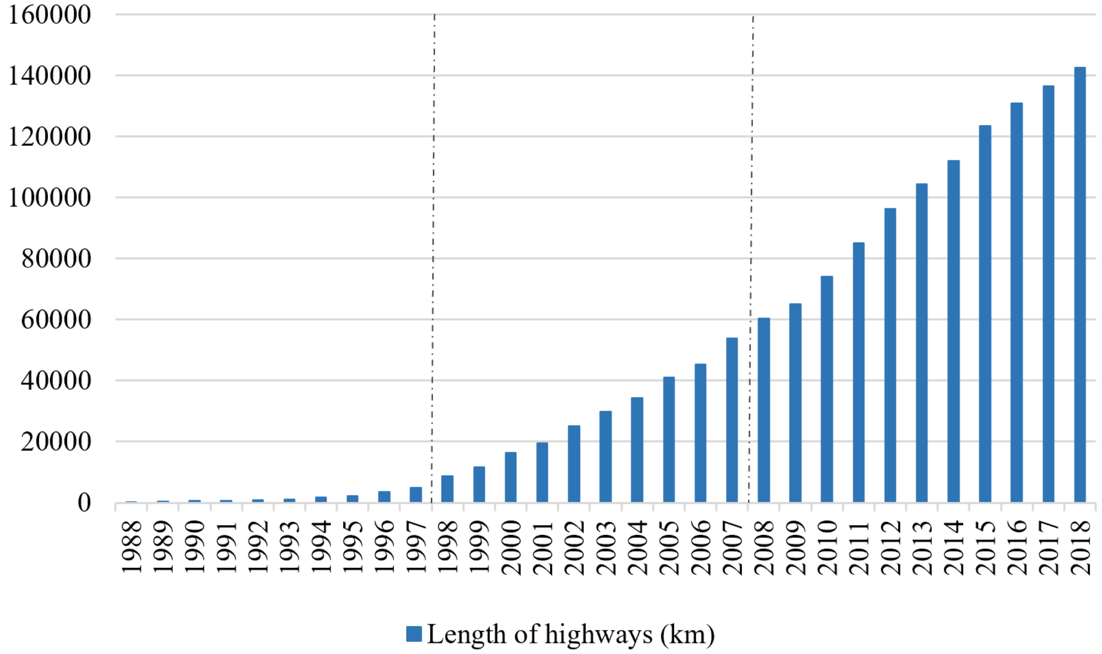


Figure 2.2: Length of highways (km)

Source: China Statistical Yearbooks

roads, including expressways, first-class roads, second-class roads, third class roads and fourth class roads; and substandard roads. Among them, the expressway allows the highest carrying capacity and traffic speed. In a broad sense, the term "highway" in China means standard roads that include expressways and class I to class IV roads. In this research, the highway is defined as the expressway only in the narrow sense. Technically, highway routes are four-lane, six-lane, or eight-lane toll roads with high-speed limited access. Nearly all highways are designed for a limited driving speed of up to 100 km/hour or 120 km/hour, depending on the geological conditions or types of vehicles.

Thirdly, the choice of the sample period is reasonable. As shown in Figure 2.2, the total length of highways in China has increased dramatically. According to the China Statistic Yearbooks from 1988 to 2019, the length of highways started from 100 kilometres in 1988 when the first highway was completed, to 8,700 kilometres in 1998, 53,900 kilometres in 2007, and 142,600 kilometres in 2018. Compared with other roads, the biggest advantage of using highways is to significantly shorten the transit time and reduce transit uncertainty. From 1998 to 2007, the highway stock had reached a certain level and grew rapidly. This would encourage firms to use the highway as much as possible, as it helps them to reduce transportation costs

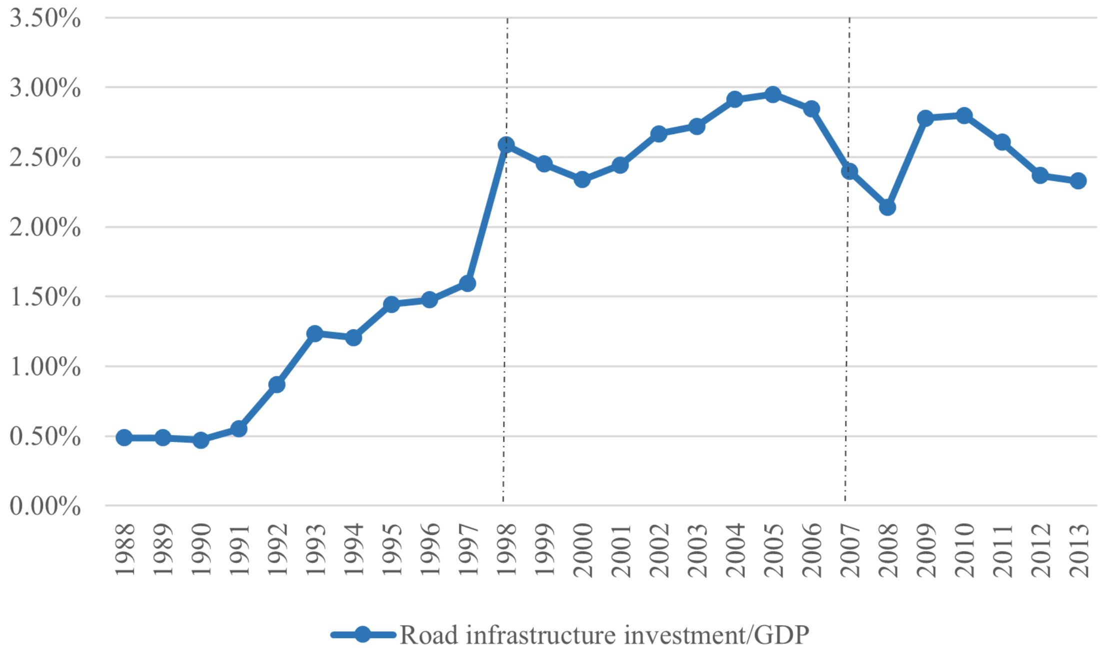


Figure 2.3: Road infrastructure investment/GDP

Source: China Statistical Yearbooks

and lead time. However, before 1998, the stock of highways might be too small to attract firms to adjust their inventory decisions. However, after 2007, the highway stock reached a higher level and grew further, as most of the firms were beginning to make good use of highways and the effect in decreasing the transportation cost and lead time would be much lower than before. Moreover, the sample period is also characterized by a relatively high level of public road investment. As shown in Figure 2.3, China increased its road infrastructure investments from about 0.5% of GDP in 1990 to approximately 3% by 2005 and 2006. In response to the Asian financial crisis, China implemented a positive fiscal policy to speed up road infrastructure construction in 1998. From 1998 to 2007, the Government invested approximately $40 billion a year on average in road construction, about 40% of which goes directly to the development of the highway network (World Bank, 2007).

2.2 National Trunk Highway Projects

The rapid development of highway infrastructure is mainly a result of huge investments together with national programmes and policy support. There were two

Table 2.3: The '5-7' NTHS plan

7 east-west lines			5 north-south lines		
Code	Name	Start city -end city	Code	Name	Start city -end city
GZ10	Tongsan Highway	Tongjiang-Sanya	GZ15	Suiman Highway	Suifenhe-Manzhou
GZ20	Jingfu Highway	Beijing-Fuzhou	GZ25	Danla Highway	Dandong-Lhasa
GZ30	Jingzhu Highway	Beijing-Zhuhai	GZ35	Qingyin Highway	QingdaoYinchuan
GZ40	Erhe Highway	Erenhot-Hekou	GZ45	Lianhuo Highway	Lianyungang-Horgos
GZ50	Yuzhan Highway	Chongqing-Zhanjiang	GZ55	Hurong Highway	Shanghai-Chengdu
			GZ65	HuRui Highway	Shanghai-Ruili
			GZ75	Hengkun Highway	Hengyang-Kunming

Note: Collected from the official document *National Trunk Highway System Planning.*

important national trunk highway projects promoting the rapid construction of highways during the sample period: the National Trunk Highway System (NTHS) project and the National Expressway Network (NEN) project.

2.2.1 The National Trunk Highway System (NTHS)

The National Trunk Highway System (NTHS) was approved in 1992 (Faber, 2014), in order to alleviate the main contradictions existing in China's road traffic, including overloading of main arterial roads, severe mixed traffic, low vehicle speed, high fuel consumption, and a high accident rate. The NTHS plan was aimed at constructing seven east-west and five north-south routes, and is summarized in Table 2.3.

The NTHS was almost completed in 2007, realizing the stated goal to connect all the provincial capitals, municipalities, and all other cities with above one million urban registered population and 93% of cities with a population above 500,000 (Li and Shum, 2001), by a network of high-speed highways. According to the NTHS plan, 114 cities were targeted to be connected, among the total of 434 cities in 1992.

2.2.2 The National Expressway Network (NEN)

In 2004, the Ministry of Transportation implemented the "7-9-18" plan, as an extension of the original "5-vertical 7-horizontal" NTHS. The "7-9-18" plan is also called the National Expressway Network (NEN), and was aimed at constructing a highway network of seven capital radial, nine north-south vertical and eighteen east-west

Table 2.4: The '7-9-18' NEN plan

7 capital radial lines			9 north-south vertical lines			18 east-west horizontal lines		
No.	Start city and end city	Mileage	No.	Start city and end city	Mileage	No.	Start city and end city	Mileage
1	Beijing-Shanghai	1245	1	Hegang-Dalian	1390	1	Suifenhe-Manzhouli	1520
2	Beijing-Taibei	2030	2	Shenyang-Haikou	3710	2	Hunchun-Huhehaote	885
3	Beijing-Hong Kong and Macau	2285	3	Changchun-Shenzhen	3580	3	Dandong-Xilinhot	960
4	Beijing-Kunming	3710	4	Jinan-Guangzhou	2110	4	Rongcheng-Wuhai	1820
5	Beijing-Lhasa	2540	5	Daqing-Guangzhou	3550	5	Qingdao-Yinchuan	1600
6	Beijing-Urumqi	1280	6	Erenhot-Guangzhou	2685	6	Qingdao-Lanzhou	1795
7	Beijing-Harbin		7	Baotou-Maoming	3130	7	Lianyunganag-Huoerguosi	4280
			8	Lanzhou-Haikou	2570	8	Nanjing-Luoyang	710
			9	Chongqing-Kunming	838	9	Shanghai-Xi'an	1490
						10	Shanghai-Chengdu	1960
						11	Shanghai-Chongqing	1900
						12	Hangzhou-Ruili	3405
						13	Shanghai-Kunming	2370
						14	Fuzhou-Yinchuan	2485
						15	Quanzhou-Nanning	1635
						16	Xiamen-Chengdu	2295
						17	Shantou-Kunming	1710
						18	Guangzhou-Kunming	1610

Note: Collected from the official document *National Highway Network Planning*.

horizontal lines, with a planned total length of 85,000 km. Table 2.4 summarizes the layout of this "7-9-18" plan. As the economy came to rely increasingly on road transportation, it was targeted to connect provincial capitals and all cities with a population of over 200,000, with five planning goals: (1) connect provincial capital cities to form a national security network; (2) connect major economic zones to form an inter-provincial expressway network; (3) connect large and medium-sized cities to form an intercity expressway network; (4) connect neighbouring countries to form an international expressway passage; and (5) connect transportation hubs to form a road network with high-speed collection and distribution. According to the NEN plan, 323 cities were targeted to be connected, among a total of 662 cities in 2004. Thus, approximately, 50% of cities share around 90% of the urban population and 96% of trade sales.

According to the *National Highway Network Planning*, the planning of the national expressway network is targeted to help accelerate the construction of a unified national market and promote the free flow and full competition of commodities and various factors across the country. At the same time, the construction of the national highway network also plays an important role in narrowing regional differences, increasing employment and promoting the development of related industries. In the long run, the construction of the national expressway network is expected to maintain its development potential and achieve long-term sustainable development.

The construction system of highways in China is mainly based on local governments and is regulated by the central government. The central government will provide financial support if some provinces, especially in Western and Central regions, need financial support to implement their highway project. To realize the national highway network planning, an investment of approximately 2.2 trillion yuan is required, of which 430 billion yuan is in the Eastern region, 570 billion yuan is in the Central region, and 1.2 trillion yuan is in the Western region. The national highway network is aimed to develop rapidly before 2020. According to the *National Highway Network Planning*, it is estimated that the average annual investment scale will be approximately 140-160 billion yuan before 2010, and the reasonable finance demand scale will be around 70-80 billion yuan each year. In order to ensure the sustained and healthy development of the national highway construction, and considering the insufficient local financial resources and weak project financing capabilities in the Central and Western regions, the Central Government investment scale is around 50-60 billion yuan per year.

In short, the highway project provides detailed guidance about the layout of highways, the purposes of highway extension, investment demand, and cooperation between central and local governments.

2.3 The National Highway Network Plan (2013-2030)

In addition to the NTHS plan and the NEN plan, the Chinese Government implemented another road transportation project called The National Highway Network Plan (2013-2030), which is targeted at guiding the development of ordinary national highways[1] and national expressways over the period from 2013 to 2023. This project is built on the foundation of the NTHS plan and the NEN plan to further improve the efficiency of the national highway network.

[1]The term 'ordinary national highways' in this section denotes standard roads mainly including first-class roads and second-class roads, and excluding expressways.

By the end of 2011, the country's total highway mileage reached 4.106 million kilometres, including 106,000 kilometres of ordinary national highways and 64,000 kilometres of expressways[2]. Although there was a rapid construction rate in China's highway(expressway) network because of the implementation of the NTHS plan and the NEN plan, the government highlighted the following three reasons regarding the necessity of further highway network improvement. First, the coverage of the highway network needed to be increased. Until 2011, there were more than 900 counties, eighteen new cities with an urban population of more than 200,000, and twenty-nine prefecture-level administrative centres that were not connected to national highways. Secondly, transportation capacity is insufficient. Some expressway corridors had tight capacity and serious congestion, and could not adapt to the rapid growth of traffic volume. Thirdly, the network efficiency should be further improved. Ordinary national highway routes were discontinuous and incomplete. Specifically, the connection and coordination between national highways and other modes of transportation, and between ordinary national highways and national expressways should be further improved to achieve network efficiency.

Therefore, the National Highway Network Plan (2013-2030) guided the construction of two types of roads, namely, the ordinary national highway network and the expressway network. First, the planned ordinary national highway network includes 12 capital radial lines, 47 north-south longitudinal lines, 60 east-west horizontal lines, and 81 tie lines, with a total length of 265,000 kilometres. Around 97% of the planned network is based on the existing ordinary national highways, provincial highways, and lower-class roads, and 60% of those existing roads need to be upgraded to first-class roads or second-class roads to meet the standard of ordinary national highways, and approximately 3% of the total length should be newly constructed. Figure 2.4 provides the layout map of the planned ordinary national highway network.

Secondly, the guided expressway network ('7-11-18' network) consists of 7 capital radial lines, 11 north-south longitudinal lines and 18 east-west horizontal lines and regional ring lines. A total length of 118,000 kilometres of expressways is planned, of which 71,000 kilometres have been completed, 22,000 kilometres are being con-

[2]The target scale of the 2004 NEN plan is a total length of 85,000 km of expressways.

structed, and 25,000 kilometres are scheduled to be built. These account for 60%, 19%, and 21%, respectively. Figure 2.5 displays the layout map of the planned expressway network.

Figure 2.4: The layout map of the ordinary national highway network

Source: The National Highway Network Plan (2013-2030)

Figure 2.5: The layout map of the expressway network

Source: The National Highway Network Plan (2013-2030)

Chapter 3

Data and Key Variable Construction

3.1 Data

In the following three chapters, a number of datasets covering the sample period from 1998 to 2007 are used in the estimation, including geo-referenced highway routes, firm-level production data and a series of geographic information data.

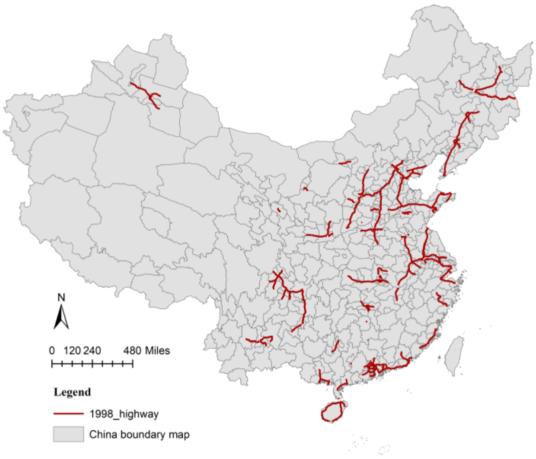
3.1.1 Geo-referenced highway routes

The original geo-referenced highway routes are obtained from the ACASIAN Data Centre at Griffith University in Brisbane. As the highway network in 1999, 2001, 2004, and 2006 are not included in this dataset, the geo-referenced highway routes are updated to a 10-year panel by checking the information from the published China Road Atlas. Specifically, road atlases published by China Atlas Press or China Communications Press in 2000, 2002, 2005, and 2007 have been used to digitize highway routes. Figure 3.1 shows the time-changing highway maps from 1998 to 2007, denoting the fast-growing highway infrastructure.

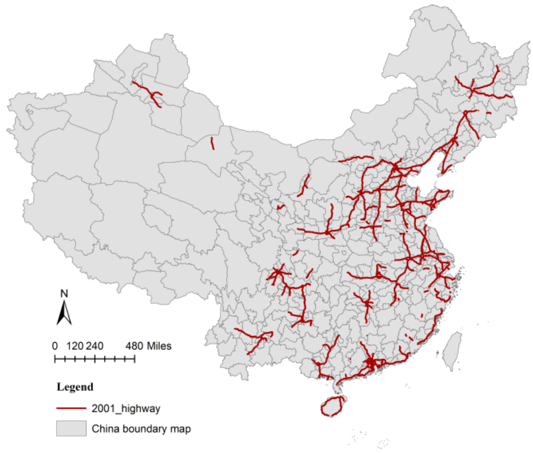
3.1.2 Firm-level production data

Firm-level data are from the Annual Survey of Industrial Firms (ASIF) database over the period from 1998 to 2007, which are collected by the National Bureau of Statistics of China. All state-owned enterprises (SOEs) and other types of enterprises with annual sales above RMB 5 million (about $0.65 million) are covered in the surveys. These firms operate in the manufacturing sector[1] and are located in all 31 Chinese provinces or province-equivalent municipalities. Their overall production accounts for more than 85% of China's industrial output (Jefferson et al., 2008). In addition to the financial information, this dataset also provides firms' detailed location information, which can be used to digitize firms' geographic locations. The annual data are matched into a panel strictly following the user manual of Brandt

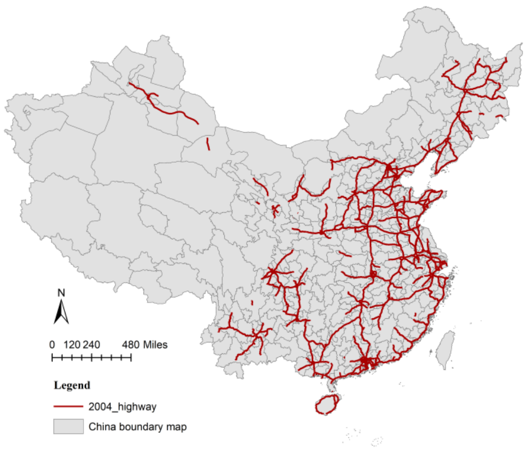
[1]Since this thesis only focuses on the manufacturing firms, some observations belonging to the mining industry and electric, heating, gas and water industries are dropped.



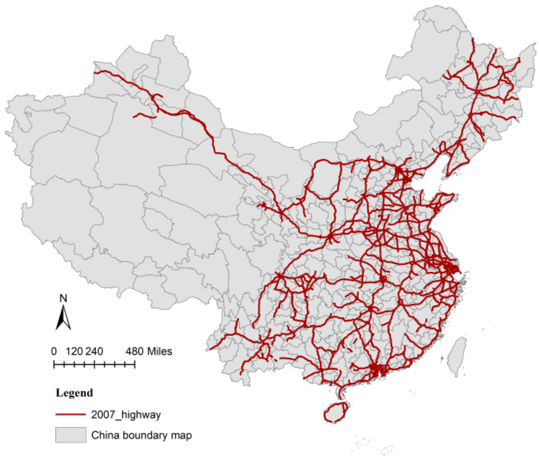
(a) Year=1998



(b) Year=2001



(c) Year=2004



(d) Year=2007

Figure 3.1: Time changing highway maps

et al. (2012).

Before matching firms over time, I standardized variable names and dropped duplicate observations in terms of ten variables, allowing the existence of the same legal representative code but different firms. The observation for every year, after deleting duplicate data, ranges from 162,033 (in 1999) to 336,766 (in 2007), as shown in Table 3.1.

The ASIF data are then merged into a ten-year panel dataset in two stages. The first stage is to match any two consecutive years by the following steps (see Table 3.2 for matched proportions). The first step is matching firm observations with firm ID. The remaining unmatched observations are then matched by firm name, legal representative of the firm, and phone number (with city code), respectively. After this, those remaining unmatched observations are matched simultaneously by the firm's founding year, industry code, geographic code, name of town, and the firm's main product. Then, all the unmatched and matched firms are merged to create a file over two consecutive years.

The second stage is to match any three consecutive years. First, a three-year balanced panel dataset is generated on the basis of the matching result of the first stage. The remaining firm observations are matched with the $t-1$ and $t+1$ observations by firm ID and firm name. Then a three-year unbalanced panel dataset is created by merging all the matched and unmatched firms. Finally, these three steps are repeated to merge the whole ASIF dataset into a ten-year panel dataset.

Table 3.1: NBS data observations

Year	Original Observations	Cleaned Observations	Geocoding Observations
1998	179,114	165,118	165,050
1999	172,208	162,033	161,895
2000	167,163	162,883	162,715
2001	179,587	169,031	169,030
2002	190,419	181,557	181,516
2003	208,438	196,222	196,072
2004	279,092	279,089	278,996
2005	271,845	271,835	271,813
2006	301,961	301,961	301,947
2007	336,766	336,766	336,701

Table 3.2: Fraction of observations matched to previous year observations

Year	Matched by ID	Matched by other information	Total matched
1999	82.39%	3.60%	86.00%
2000	82.05%	0.38%	82.43%
2001	71.11%	16.64%	87.75%
2002	78.98%	8.05%	87.03%
2003	76.46%	5.28%	81.74%
2004	51.77%	32.56%	84.33%
2005	84.76%	6.90%	91.66%
2006	81.14%	10.50%	91.64%
2007	81.11%	1.06%	82.17%

Firms' detailed location information is used in identifying firms' geographic location. The internationally used geocentric coordinate system is called the World Geodetic System-1984 (WGS84), which is built for use by the global positioning system (GPS). However, in China, for reasons of national secrecy, WGS84 is not allowed in any Chinese Map. The commonly used system in China is GCJ-02 (G for Guojia/state, C for Cehui/surveying and mapping, J for Ju/ bureau), developed by the State Bureau of Surveying and Mapping of China[2]. The locations of firms are geocoded by the Application Program Interface (API) from Gaode map on the basis of the Local Space Viewer software. This software is used as it provides the function of geocoding two forms of latitude and longitude coordinates, with GCJ-02 and WGS84, based on the location information of ASIF data. As the China expressway GIS data from the ACASIAN data centre are normally distributed in WGS84, the latitude and longitude coordinates of WGS84 are chosen for their accuracy in calculating distance indicators.

Most of the latitude and longitude information is accurate to the specific address of enterprises, and a small part is accurate to the street or village. The specific geocoding process is as follows: First, the latitude and longitude information by city and detailed address (with company name) were extracted. More than 99% of firms every year (except 2006 and 2007, for about 97%-98%) can be geocoded in this step. Secondly, I extracted the latitude and longitude information by city and company name for those that couldn't be successfully geocoded in the first step.

[2]It is a coordinate system encrypted by adding random deviation based on WGS84. Gaode Map, Tencent Map, and Google China Map all use the GCJ-02. There are also some other geographic coordinate systems used in China, which are generally obtained by adding a migration algorithm on GCJ-02. For instance, BD-09 is used by Baidu Map.

Thirdly, the longitudes and latitudes information was extracted by city and village/ street/ neighbourhood committee to ensure accuracy in villages/ streets.

In the end, only a few observations could not be geo-coded successfully, as shown in the third column of Table 3.2. The geocoded location information is then imported into GIS. By combining firms' digitized location information and the time-varying highway network, each firm's distance to the nearest highway can be calculated using the GIS software. Finally, firms' distance-related information was merged with the cleaned ASIF data.

3.1.3 Other datasets

In addition to the geo-referenced highway routes and firm-level production data, a series of geographical information data for the construction of instruments and a set of province-level data for control variables are used. Because of the endogeneity issue of highway infrastructure[3], several data sources are used in the construction of instruments, namely, the historical Ming dynasty and Qing dynasty's courier routes obtained from the Harvard WorldMap Project, the Digital Elevation Model (DEM) downloaded from China's Geo-spatial Data Cloud, and the remote sensing land cover data downloaded from the Climate Change Initiative-Land Cover (CCI-LC) database.

3.2 Highway Proximity and Its Endogeneity

3.2.1 Measurement of highway proximity

As outlined in the introduction, this thesis investigates whether, and how, better highway proximity affects firms' inventory (Chapter 4) and investment decisions (Chapter 5), and the allocative efficiency of capital (Chapter 6).

[3]This will be discussed in the following section

In Chapters 4 and 5, the key variable - highway proximity - is measured using three methods[4]. I use the inverse of a firm's distance to the nearest highway (unit: km), as the main highway proximity measure. The distance between each firm's location and its closest highway is measured using a geographical information system (GIS) on the basis of the annual geo-referenced highway maps and the firm's geographical coordinates. Each firm's distances vary over time as the distances are calculated based on the construction of the highway network. Using the inverse of a highway distance, the larger the highway proximity, the better the firms' access to highway infrastructure. Following Holl (2016), the logarithm of the distance to the nearest highway (unit: m) (Ln (highway distance)) is used as an alternative measure of highway proximity in the additional robustness check. The shorter the distance, the better the highway proximity.

However, the first two highway proxies only consider firms' absolute highway accesses. To additionally test whether the empirical results are robust by using different highway measures, I construct a new measure of firms' relative highway accessibility, inspired by Amiti and Khandelwal (2013) and Ding et al. (2016b). As shown in equation (3.1), the relative highway proximity ($RHP_{i,t}$) captures firms' highway accessibility relative to their competitors in the same industry and province.

$$RHP_{i,t} = \frac{min_{i\in j,k,t}(lnhighway(m)_{i,t})}{lnhighway(m)_{i,t}} \tag{3.1}$$

where $min_{i\in j,k,t}(lnhighway(m)_{i,t})$ is the minimum distance value among firms in the industry j and province k at time t, which captures the best access to the highway in a given industry, province, and year. $lnhighway(m)_{i,t}$ is the firm i's distance to the nearest highway at time t. In this case, $RHP_{i,t} \in (0,\ 1]$. For varieties close to the best highway proximity, $RHP_{i,t}$ is close to 1, while for varieties far from the best highway proximity, $RHP_{i,t}$ is close to 0. Thus, the higher the RHP value, the

[4]Existing literature generally quantifies road transportation infrastructure at the regional level, e.g., using the logarithm of road length in a province or municipality (e.g., in Li and Li, 2013; Lin et al., 2019b) or the logarithm of the density of roads in a province (Zhang et al., 2018) or a smaller area (Liu et al., 2022). The downside of those measures is that they ignore the heterogeneity of road/highway access at the firm level within the specific region (province). For instance, using province-level proxies, all firms located in the same province should share the same highway access. To overcome the above drawback, I construct three alternative proxies to measure firm-level highway proximity based on the geo-coded location of each firm and highway network over the period of 1998-2007.

better the firm's relative advantage in highway accessibility.

In Chapter 6, the analysis of highway proximity and capital allocative efficiency is on the industry-province level. Thus the key variable of highway proximity is calculated as follows the inverse of the unweighted average distance to the nearest highway among firms in the 4-digit industry j and province p at year t:

$$Highway_{jpt} = \frac{1}{\sum_{i=1}^{n} distance_{i\in j,p,t}/n} \tag{3.2}$$

where $distance_{i\in j,p,t}$ is firm i's distance to the nearest highway at year t. n is the number of firms within the 4-digit industry j and province p at year t. A larger value of $Highway_{jpt}$ indicates better average highway accessibility.

With the concern that the size of firms may matter in measuring industry-level highway proximity, i.e., more output within the industry j and province p is produced with higher or lower highway accessibility. For the robustness test, Chapter 6 also applies an additional highway proximity measure, which is calculated as the inverse of the weighted average distance to the nearest highway among firms within the 4-digit industry j and province p at year t:

$$Highway_{jpt} = \frac{1}{\sum_{i=1}^{n} distance_{it\in j,p} * s_{it\in j,p}} \tag{3.3}$$

where $distance_{it\in j,p}$ is firm i's distance to the nearest highway at year t. $s_{it\in j,p}$ is firm i's employment share within the 4-digit industry j and province p at year t. A larger value of $Highway_{jpt}$ indicates better highway accessibility.

3.2.2 Endogeneity of highway construction

When investigating the effect of highway proximity, it is essential to carefully examine the endogeneity issue. As documented in Chapter 2, the distribution of highways is not random. Governments tend to develop highways to link large cities where firms may have high investment or better inventory management efficiency. In addition, there is concern that planners targeted economically and politically important regions along the way between the network's nodal cities (Faber, 2014). Moreover, in the empirical estimation, it is likely to have omitted variables explaining both highway proximity and the dependent variables.

In order to control this type of endogeneity, a number of time-varying instruments are constructed, namely, the least cost paths and straight lines constructed based on the targeted city points outlined in the national highway construction projects, and historical instruments based on the Ming dynasty's courier routes and the Qing dynasty's historical routes.

3.3 Construction of Time-varying Instruments

Recent research on transportation infrastructure has developed alternative instruments designed to reduce the potential endogeneity, for instance, instruments based on historical roads, least cost paths, minimum spanning trees or straight lines. To establish a causal relationship between Spain's highways and firm-level productivity, Holl (2012) constructs a historical IV by digitizing the historical 1760 postal routes and calculating the distance from each firm's location to the nearest historical route. Focusing on the regional impacts of China's highway development, Faber (2014) proposes two instrumental variables based on the construction of the Euclidean minimum spanning tree network and the least cost path spanning tree network, respectively. Studying the impact of railroad access on Prussia's urban population growth, Hornung (2015) develops the straight-line corridor instrument and least cost paths instrument to address the possible endogeneity. Ghani et al. (2016), when highlighting India's approach, also applies a straight-line IV framework to investigate the causal relationship between highway infrastructure and the efficiency of manufacturing activity.

Historical roads are frequently used to address the endogenous issue in infrastructure-related literature. One reason is that the factors shaping the historical road in the distant past are not related to the factors affecting firms' current financial decisions or productivity shocks (Holl, 2012). In addition, historical roads are mostly constructed in flat places that are easy to travel to and with lower costs, which are correlated with highway construction.

Although the construction of the straight-line instrument is rough, it has its reasonability. The objective of *China's National Trunk Highway System* is to connect all provincial capitals, municipalities, and all other cities with over one million urban registered population and 93% of cities with a population above 500,000 (Li and Shum, 2001), using a network of high-speed limited access roads. Taking only the construction costs into account, infrastructure roads are mostly built linearly to reduce the costs, except for the geographical obstacles such as hills and lakes (Hornung, 2015). The possible geographical obstacles problem could be addressed by creating a buffer of a certain width. In this case, the straight-line buffer areas are able to gain access to the highway by chance, while highways deviating from the straight-line buffer could be explained by potentially endogenous factors.

The least cost paths instrument is the strictest method for considering more accurate geographical cost information, while the historical roads and straight lines are comparatively rough methods. Based on the land slope and remote sensing land cover data, the cost surface could be calculated and then the least cost paths can be generated. This method is also commonly used in real life such as road construction analysis or site suitability analysis.

In this thesis, alternative instrumental maps are applied to jointly address the possible endogeneity, namely, historical routes based on the Ming dynasty's courier routes and Qing dynasty's courier routes, straight lines based on the NEN plan, and least-cost paths based on both the NTHS plan and NEN plan.

Since the empirical test is based on ten-year panel data, it is important to construct time-varying instrumental maps for the calculation of panel instruments. Holl (2012) generates a historical time-varying instrument by interacting the local length of historical routes with Spain's national highway construction rates over the sample period. This was designed to interact the underlying instrumental routes with the national construction rates (overlapping with the buffer area). As a first step, the buffer area around the highways built in time t will be created, then the overlap between the underlying instrument routes and the buffer area will be extracted, and

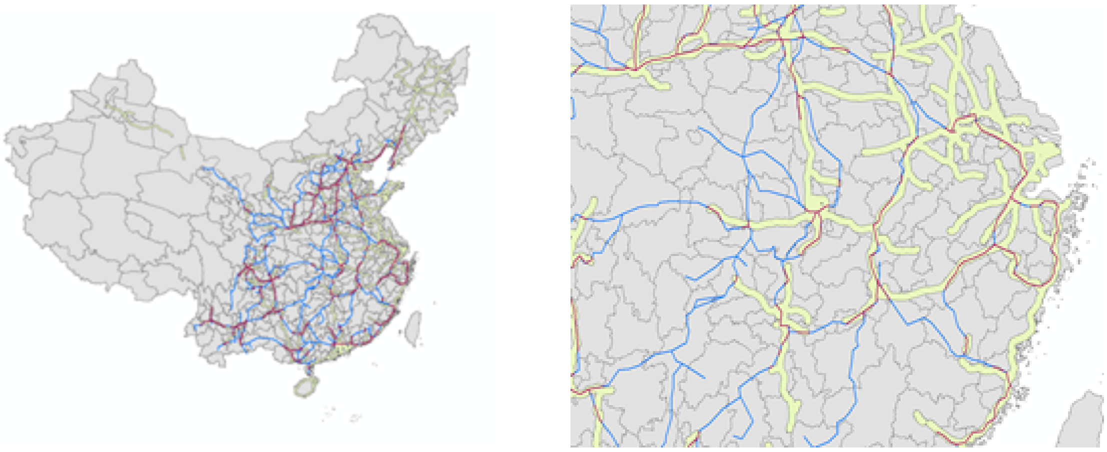


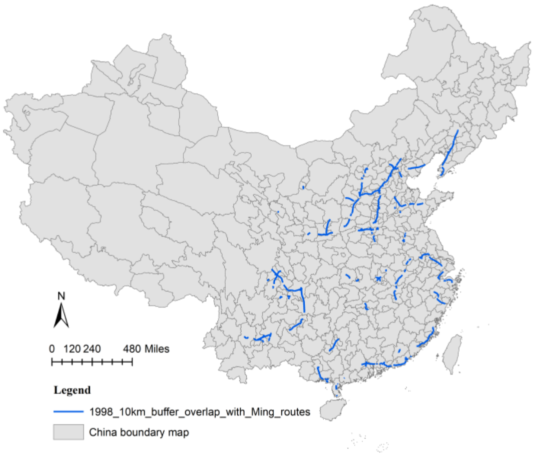
Figure 3.2: Construction example

thirdly the shortest distance between the company's location and those overlapped routes will be calculated.

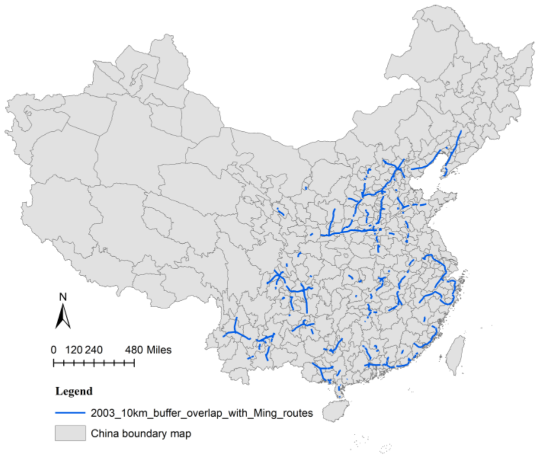
3.3.1 Historical IV construction

The courier routes in Ming dynasty (Berman and Zhang, 2017) are used to construct a historical IV. Figure 3.2, taking the IV construction for the year 2003 as an example, shows the way to interact the underlying instrumental routes with the national construction rates. The 10km-width yellow buffer area is generated based on the highway routes that were built before 2003. The blue lines are a part of Ming's courier routes that are located outside the buffer areas, while the red lines are overlaps between Ming's courier routes and buffer areas. The read lines located inside the buffer areas are extracted as the proxy routes in 2003. Then the distance between each firm and the nearest proxy route is calculated. This approach is repeated to generate time-varying historical maps and distance IV.

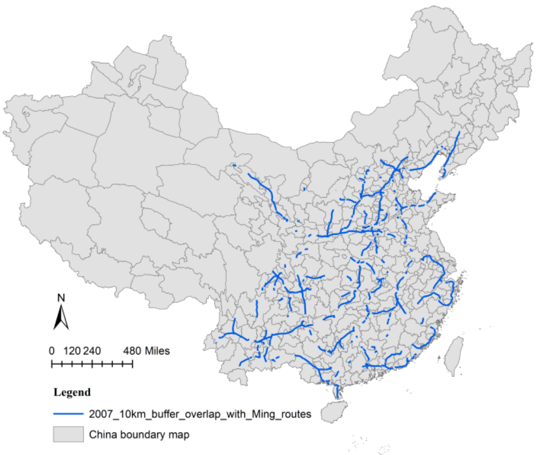
Figure 3.3 shows time-changing historical maps based on the courier routes in the Ming dynasty. 3.3a, 3.3b, and 3.3c represent the historical proxy routes in 1998, 2003, and 2007, respectively. 3.3d is the overall map of Ming's courier routes. The panel instrument for highway proximity is calculated as the firm's distance to the nearest time-varying Ming dynasty courier routes. Compared with figure 3.1, the time-changing highway maps, it is easy to see that the Ming's historical routes are not sufficient for IV construction. The main consideration is that the historical



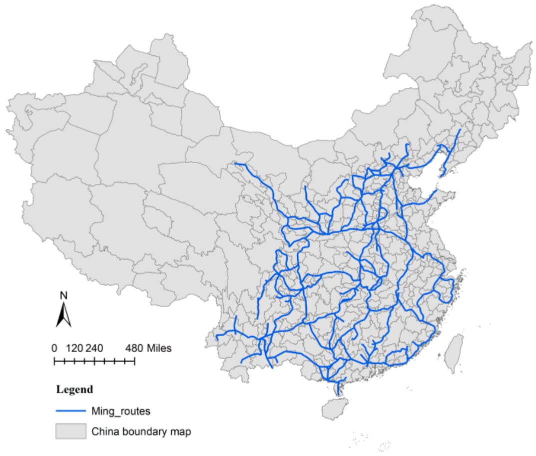
(a) Year=1998



(b) Year=2003



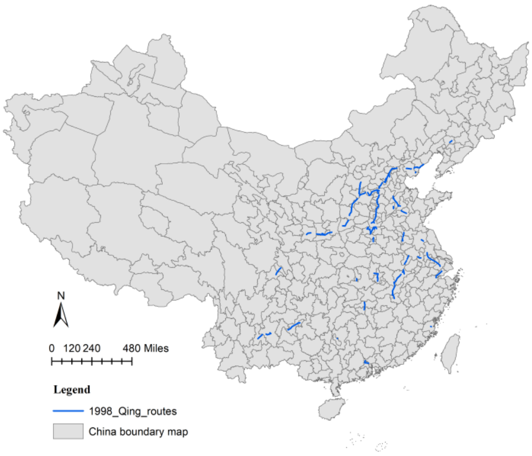
(c) Year=2007



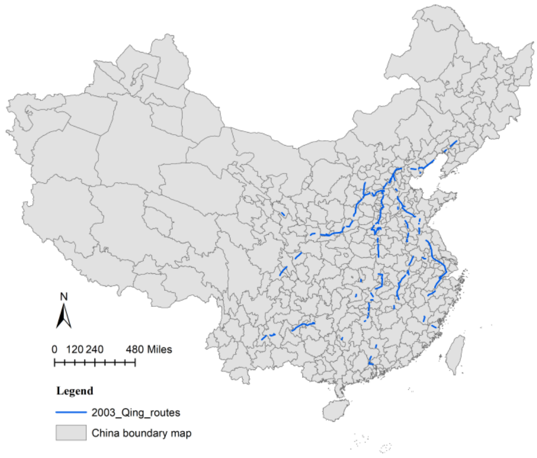
(d) Courier routes in the Ming dynasty

Figure 3.3: Time-varying routes of the Ming dynasty

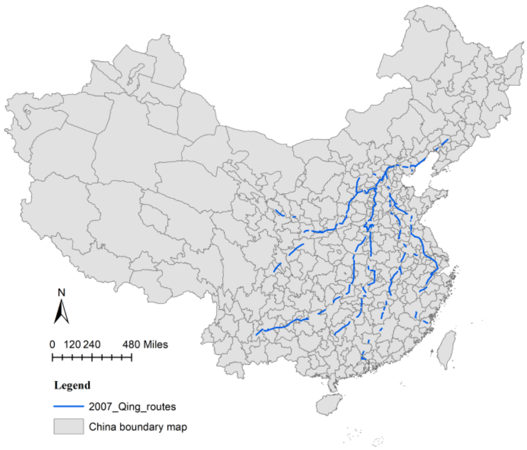
Note: Figure 3.3 shows time-varying historical routes based on the Ming dynasty courier routes. The network in blue in subfigure (d) depicts courier routes in the Ming Dynasty. The time-varying courier routes are constructed by overlapping buffer zones of highways with courier routes in the Ming dynasty. The panel instrument for highway proximity is calculated as the firm's distance to the nearest time-varying Ming dynasty courier routes.



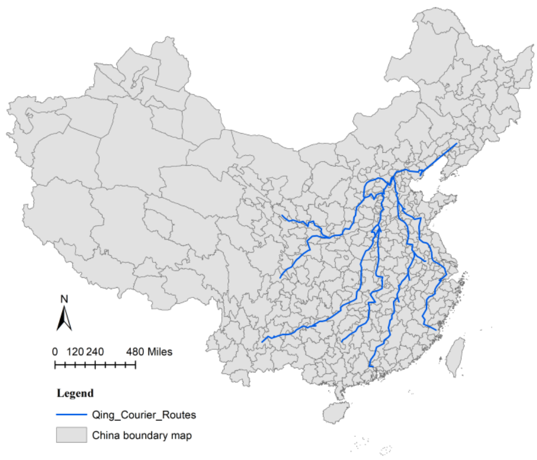
(a) Year=1998



(b) Year=2003



(c) Year=2007



(d) Courier routes in the Qing dynasty

Figure 3.4: Time-varying routes of the Qing dynasty

Note: The time-varying historical routes depicted in Figure 3.4 are based on Qing dynasty courier routes. The blue network in subfigure (d) depicts courier routes in the Qing Dynasty. The time-varying courier routes are formed by overlapping highway buffer zones with courier routes in the Qing dynasty. The panel instrument for highway proximity is calculated as the firm's distance to the nearest time-varying Qing dynasty courier routes.

routes do not reach some provinces including Jilin, Heilongjiang, Hainan, Qinghai, Inner Mongolia, Tibet, and Xinjiang. In the robustness tests, this issue will be addressed by dropping firm observations of these seven provinces and rerunning the historical instrument regression.

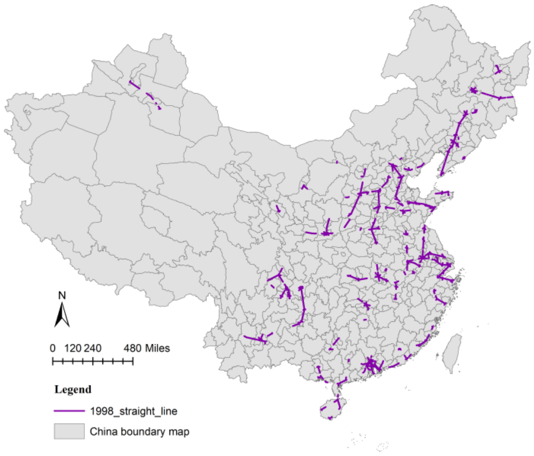
Moreover, to ensure the robustness of using historical instruments, the courier routes of the Qing dynasty (Skinner et al., 2008) are also used to construct the additional historical IV. The time-changing routes of the Qing dynasty and the combination with Ming courier routes would be used as additional historical instruments in the robustness tests. The time-changing maps of the Qing dynasty are shown in Figure 3.4.

3.3.2 Straight-line IV construction

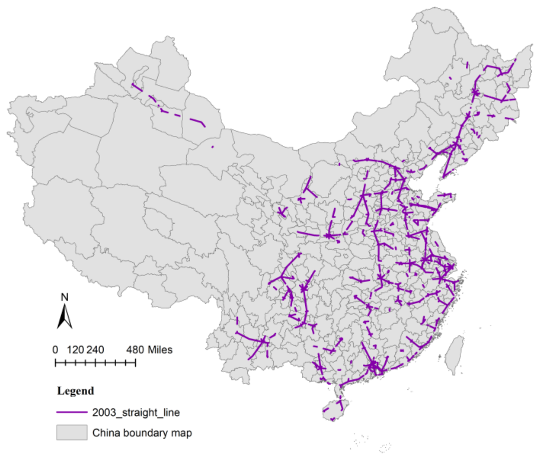
A straight-line network based on the "7-9-18" NEN project was constructed as it specifies the detailed routes of "7-9-18" connecting targeted cities. In this research, the highway network considers not only the "5-7" network but also the extension of the "7-9-18" network. So, the targeted city destinations (323 cities) include provincial capitals and all medium and large cities with populations of more than 200,000. According to the official document, the National Expressway Network Planning, I geocode the targeted city points and connect the "7-9-18" routes by straight lines using ArcGIS software. Figure 3.5 shows the time-varying straight-line maps, by interacting the straight lines with the national construction rates (10 km buffer).

3.3.3 Least-cost paths construction

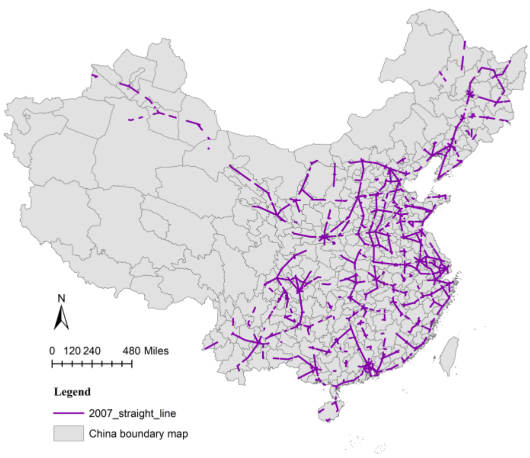
As already outlined, the highways which were constructed between 1998 and 2007 are based on both the "5-7" NTHS network and the extension of the "7-9-18" NEN network. Since these two projects provided detailed connecting city points, this allows the construction of the least cost paths by connecting all target cities with the minimal spanning tree network based upon Kruskal (1956)'s algorithm, i.e., to find the best solution using one single network to connect targeted points with a



(a) Year=1998



(b) Year=2003



(c) Year=2007

(d) Straight lines based on the NEN plan

Figure 3.5: Time-varying straight lines based on the NEN plan

Note: Figure 3.5 displays the time-vary straight line network based on the "7-9-18" NEN project. The black dots in subfigure (d) are targeted cities according to the NEN plan. According to the detailed routes outlined in this project, I connect targeted cities with straight lines using ArcGIS software. The time-varying straight-line networks are then generated by interacting the straight lines in subfigure (d) with the national highway construction rates (10 km buffer). Subfigures (a), (b) and (c) depict straight-line networks in 1998, 2003, and 2007, respectively. The panel instrument for highway proximity is calculated as the firm's distance to the nearest time-varying straight-line network.

least total cost. Unlike Faber (2014) who only constructed the least cost paths according to the "5-7" NTHS project, this research constructs two kinds of least-cost paths using GIS: the first one is based on the "7-9-18" NEN project (Figure 3.6) and the second one is based on the "5-7" NTHS project (Figure 3.7). Although two least-cost paths are constructed, it can be argued that the one based on the NEN plan is better as it has a similar density to the actually constructed highways. Thus, the LCP_NEN instrument is used as the main instrument of this research.

Since the construction of least cost paths relates to the issue of which routes central planners would have probably built if the only policy purpose was to link all intended destinations to a single network while minimising overall construction costs (Faber, 2014), this can help to address the concern that planners targeted economically and politically important regions along the way between the network's nodal cities. With land cover and elevation data, the least-cost path network predicts routes between bilateral connections on an all-China minimum spanning tree with high accuracy[5].

There are four steps in the construction of least-cost paths. The first step is to select the targeted cities (nodes) to be connected and geocode the nodes' information using ESRI's ArcGIS software. According to the 1992 NTHS plan, 114 cities, including provincial capitals, important ports, and big cities with populations of more than 500,000, were selected for the construction of LCP_NTHS instrument. While 323 cities were selected to construct the LCP_NEN instrument based on the criteria of the NEN plan which consisted of provincial capitals and all large and medium cities with populations of more than 200,000.

The second step is to construct a cost surface which gives each 1km$\times$1km land raster a weighted land cost. As in transport engineering literature (Jong and Schonfeld, 2003) and even in real-life applications, the most important factors for planning the best path are the land use and terrain such as the slope and relief. The generation

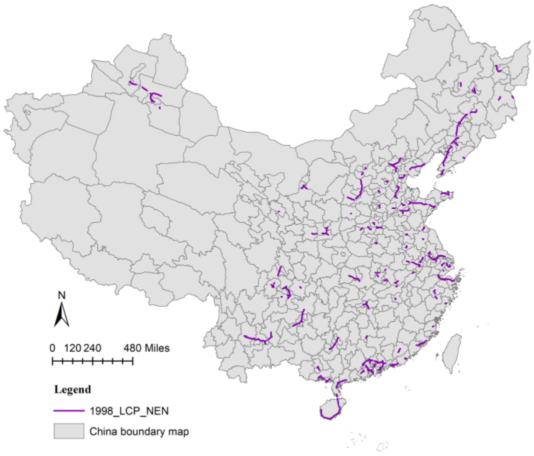
[5] For the construction of both straight lines and the least-cost paths, one may argue that the least-cost paths and straight lines cannot fully address the endogenous issue as the targeted city points were endogenously chosen by government planners. To further control this issue, additional robustness tests will be conducted in the following chapters by excluding the observations located in the targeted cities.

of the cost surface is based on the following construction cost function form:

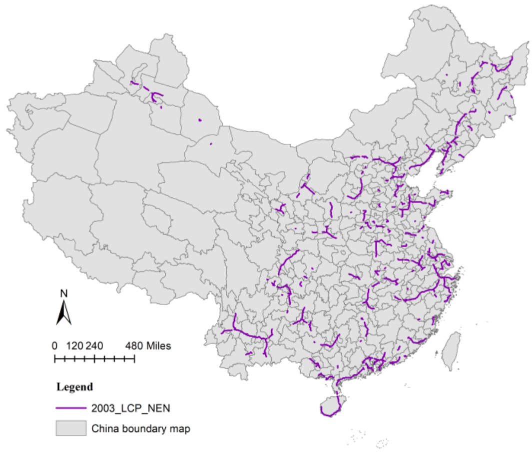
$$Cost_i = 0.6 * Reclass\_slop_i + 0.4 * Reclass\_relief_i + 20 * Reclass\_landuse_i \quad (3.4)$$

where $Cost_i$ is the cost of crossing a pixel (1km $\times$ 1km) of land i. $Reclass_slop_i$ is a reclassed slop information ranging from 0 to 20. $Reclass_relief_i$ is a re-classed terrain relief information ranging also from 0 to 20. The original relief here means the difference between the altitude of the highest point and the altitude of the lowest point in a certain area. Lands with steeper slopes and higher reliefs are given higher land costs and, therefore, are less likely to have a route. $Reclass_landuse_i$ is a dummy variable which equals 1 if the pixel of land is either covered by built structures, water, wetland, permanent snow and ice, or bare areas. Thus, the total cost of each raster ranges from 0-40. Specifically, the information on slop and terrain relief is extracted from the Digital Elevation Model (DEM) and re-classed using ArcGIS tools. The land use information is extracted from the remote sensing land cover data downloaded from the Climate Change Initiative-Land Cover (CCI-LC) database.

The third step is to find the least cost paths that connect all the targeted nodes with the minimal spanning tree network based upon Kruskal (1956)'s algorithm, i.e., to find the best solution using one single network to connect the targeted points with a least total cost. In the last step, the time-changing least-cost paths are generated by interacting the least-cost paths with the 10 km buffer area of the highway during the sample period.



(a) Year=1998



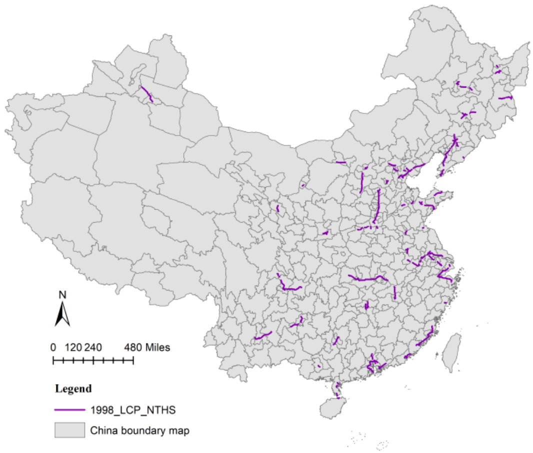
(b) Year=2003

(c) Year=2007

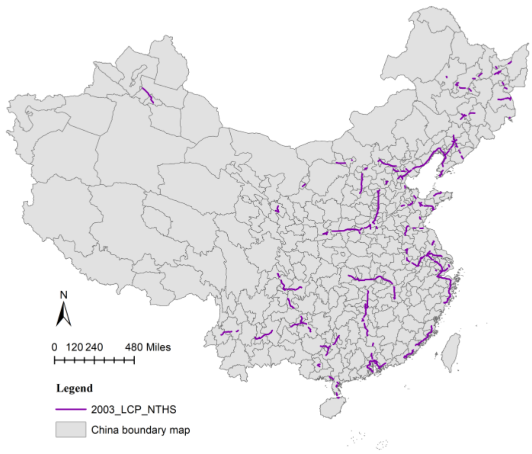
(d) Least-cost paths based on the NEN plan

Figure 3.6: Time-varying least-cost paths (LCP) based on the NEN plan

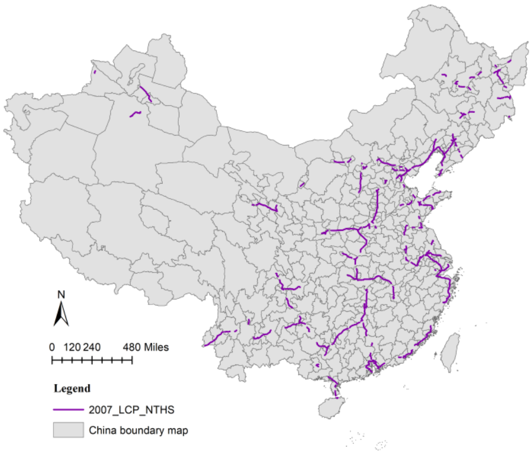
Note: Figure 3.6 depicts time-varying least-cost paths based on the "7-9-18" NEN project. The black dots in subfigure (d) are targeted cities according to the NEN plan. The least cost path spanning tree network in subfigure (d) connects all targeted cities using a single network with the least total construction costs based upon Kruskal (1956)'s algorithm of minimal spanning tree network. The time-varying least-cost paths are generated by interacting the constructed least-cost paths (in Subfigure d) with the 10 km buffer zones of highways during the sample period. Subfigures (a), (b) and (c) depict the least-cost paths in 1998, 2003, and 2007. The panel instrument for highway proximity is calculated as the firm's distance to the nearest time-varying least-cost path.



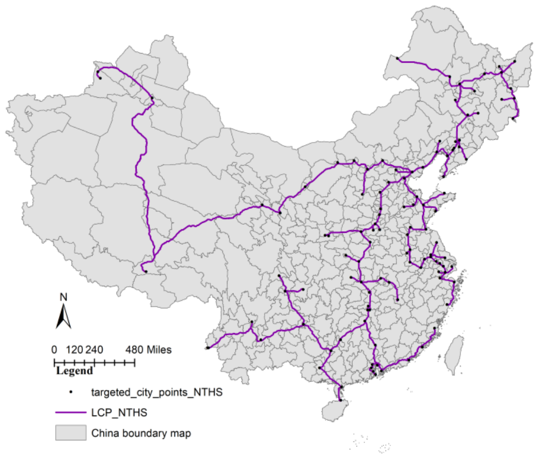
(a) Year=1998



(b) Year=2003



(c) Year=2007



(d) Least-cost paths based on the NTHS plan

Figure 3.7: Time-varying least-cost paths (LCP) based on the NTHS plan

Note: Figure 3.7 depicts time-varying least cost paths based on the "5-7" NTHS project. The black dots in subfigure (d) are targeted cities according to the NTHS plan. The least-cost path spanning tree network in subfigure (d) connects all targeted cities using a single network with the least total construction costs based upon Kruskal (1956)'s algorithm of minimal spanning tree network. The time-varying least-cost paths are generated by interacting the constructed least-cost paths (in Subfigure d) with the 10 km buffer zones of highways during the sample period. Subfigures (a), (b) and (c) depict the least-cost paths in 1998, 2003, and 2007, respectively. The panel instrument for highway proximity is calculated as the firm's distance to the nearest time-varying least cost path.

Chapter 4

The Effect of Highway Access on Firms' Inventory Investment in China

4.1 Introduction

Over the past three decades, China has undergone the process of rapid urbanization and economic growth but also a remarkable expansion of its transportation infrastructure. Between 1998 and 2007, the rapid development of the expressway transportation system was the most impressive part. According to China Statistical Yearbooks, the total length of highways (expressways) extended from 100 kilometres in 1988 when the first highway was completed, to 53,900 kilometres in 2007, ranking second only to the United States. China's transportation infrastructure has attracted the attention of many academics. This was especially true when the Chinese Government began to increase the investment in China's National Trunk Highway System in 1992, and many academic studies about the impact of transport investment on China's economic development emerged (Banerjee et al., 2012; Faber, 2014). At the regional level, some studies show that highway infrastructure contributes to economic growth from different aspects, such as spatial agglomeration (Yu et al., 2016), regional productivity (Zhang and Ji, 2019), GDP growth (Banerjee et al., 2012), trade integration (Faber, 2014) and economic geography (Baum-Snow et al., 2018; Xu and Nakajima, 2017). There is also an increase in the number of studies about the economic efficiency of transportation infrastructure explored from the firm level. For example, some academics have explored the effects of road transportation on firms' activities and performance, such as innovation (Wang et al., 2018), exportation (Liu et al., 2022), and productivity (Li and Arreola-Risa, 2017; Wang et al., 2020).

However, much less is known about how highway infrastructure affects firms' inventory investment decisions in China, which would be a channel towards productivity enhancement. Evidence about the association between inventory (primary working-in-progress) reduction and productivity growth, for example, in the Japanese automotive industry, is highlighted by Lieberman and Asaba (1997) and Lieberman and Demeester (1999). The reduction of actual input inventories reduces the costs of inventory carrying and related activities such as warehouse management and materials management, thereby making a potential contribution to productivity (Lieberman and Demeester, 1999). Based on the financial information of manufacturing firms in the US from 1980 to 2005, the empirical results of Capkun et al. (2009) indicate that a firm's inventory performance is positively correlated with its financial performance at both the operating and gross levels. This suggests that if a firm lowers its inventory storage without decreasing its market size (or sales), the firm must come with a higher operating efficiency or productivity.

According to China Statistical Yearbooks, approximately 75% of freight was transported by road infrastructure between 1998-2007, which confirms the important role of road infrastructure in freight transport. The improvement of highways can help firms to reduce transportation costs, transit time and transit uncertainty. This might encourage firms to reduce their inventory level, as it is more convenient to order raw materials or work in progress from their suppliers by using highways.

Only a few researchers have investigated the impact of China's transportation improvement on inventories. Li and Li (2013) investigate the substitutional relationship between provincial road infrastructure and firm-level inventory in the period of 1998-2007. Their empirical results suggest that every dollar in road investment saves about two cents in inventory costs. Cui and Li (2019) investigate the impact of the high-speed railway (HSR) on firms' inventory decisions in the period of 2007-2013. They conclude that the improvement of HSR influences inventory through the declines in transportation and communication costs and the increases in the agglomeration effect, leading to a 9.5% reduction in firms' inventory investment. Different from previous literature, Lin et al. (2019b) find that the province-level transportation infrastructure, including road and railway, does not reduce manufacturing sectors' inventory at the provincial level in the period from 2005 to 2014. The reason for this discrepancy can be partly explained by China's ongoing inland relocation of industries and expansion of regional markets has resulted in longer transportation distances and delivery times from suppliers to customers.

Although there is little literature related to the association between China's transportation improvement and firm-level inventory, what there is tends to focus on broad transportation including different kinds of roads (provincial level) and railways, or high-speed railways, rather than on the specific highway infrastructure which is more used for manufactured goods (Lin et al., 2019b). This research is targeted to fill this gap by asking: What is the impact of highway improvement on manufacturing firms' inventory behaviours and how does highway influence individual inventory investment decisions?

The contribution of this research can be seen in three dimensions. Firstly, unlike previous studies that only use the provincial road stock as the proxy of transportation development (e.g., in Li and Li, 2013; Lin et al., 2019b), I construct several measures of firm-level highway access based on the geo-coded firms' location and highway network. Using provincial road stock, all firms located in the same province should share the same highway access, which ignores the heterogeneity of highway access at the firm level within the specific province. Specifically, in this research, three measures of highway accessibility are calculated to capture the firm-variant highway access, namely, the absolute highway proximity, the distance to the nearest highway and the relative highway proximity. Those firm-level highway access measures enable us to control for the unobserved industry-time and region-time varying factors such as government policies, local labour market environment, and public services, and therefore this research is less likely to endure the criticism of omitted variable bias as the provincial road stock measures.

The second contribution is to develop a more convincing method to address the endogeneity issue. This is different from Li and Li (2013), who use a quasi-natural experiment to control the endogeneity issue by comparing companies that vary in their transportation needs because of the reach of their supplier networks, I apply the time-varying IV method in this research, which would be a new way to better handle the possible reverse causality. Specifically, I construct several instruments using GIS, such as the least cost path and straight line constructed based on the targeted city points outlined in the highway construction planning, and historical instruments based on the Ming dynasty's courier routes and the Qing dynasty's historical routes, to support the robustness of the empirical results. In addition, the potential concern about the endogeneity issue of new firms and relocation is addressed, as firms may decide to locate closer to highways.

The third contribution of this research is to provide some mechanisms through which highway infrastructure affects inventory from different aspects such as demand, ownership, highway reliance, supply chain position, inventory structure, main supplier's location, and regional difference.

Using a panel of 492,490 firms (with 1,856,417 observations) over the period from 1998 to 2007, the IV estimation results indicate a robust causal effect of highway proximity on firms' input inventory and output inventory. This result of input inventory is consistent with the theoretical intuition and hypothesis on the basis of the (S, s) model. That is, if a firm's demand is controlled, the improvement of highways will directly encourage firms to lower their input inventory level as the transportation cost and lead time are decreased. However, the output inventory is less affected by the improvement of highways as finished goods are more connected with the level of sales and expected demand rather than the transportation cost. Moreover, each dollar of highway spending in China during the period of 1998-2007 reduced the input inventory stock by about 3.910-10.010 cents and the total inventory stock by around 6.730-25.523 cents.

In addition, the estimation of the demand mechanism indicates that highways can affect firms' total inventories, input inventories and output inventories indirectly through the channel of demand proxies (sales and sales surprise). The positive effects of sales on firms' total/input/output inventories are larger for firms with improved highway proximity, and the total effect of sales surprise on total inventories and input inventories would be larger if the firm had better access to the highway infrastructure. However, the indirect channel effect is limited as highway proximity would not influence firms' inventory level through the channel of sales growth or excess sales growth.

A variety of additional estimation results is presented, inspired by the testable implications of various mechanisms: (1) Private firms more efficiently respond to the changes in highway proximity than SOEs. (2) Firms with high infrastructure reliance would benefit more from the increase in highway proximity than those with low infrastructure reliance. (3) Supply chain position also matters, as the results indicate that firms in a relative upstream position enjoy a higher direct cost-saving effect from better access to highways. (4) Firms' major suppliers' location is another important aspect. As the highway provides a higher transport speed, the time-saving and cost-saving effects are more prominent for firms whose major suppliers are located in different provinces. (5) It is also the expectation that firms with a higher share of input inventory are more responsive to the increase in highway accessibility.

(6) From the perspective of location heterogeneity, the result indicates that firms in the more developed coastal area benefit more from the inventory cost-saving effect.

The rest of this chapter is structured as follows. Section 2 introduces the literature review from both empirical and theoretical perspectives and then accordingly develops our theoretical intuition and hypothesis. Section 3 presents the baseline specification, data and summary statistics, and section 4 reports the baseline empirical results. Section 5 discusses the endogeneity and IV estimation results. Sections 6 and 7 are the channel and mechanism discussion. Section 8 estimates the implied savings of inventory with respect to highway development. Some robustness tests regarding the instrument construction and highway measures are presented in Section 9. Section 10 concludes the chapter.

4.2 Literature Review and Theoretical Intuition

4.2.1 Theories on inventory investment

Maintaining a modest inventory level is an investment decision often faced by operators in manufacturing firms. As goods are produced or received only when needed, firms need to trade off the amount of inventory investment among the relevant factors including spoilage cost, storage cost, ordering cost, and potential demand to minimize the inventory cost (Blinder and Maccini, 1991; Grasselli and Nguyen-Huu, 2018). In this subsection, some inventory theories will be briefly introduced as background to the theoretical intuition.

There is a large body of logistics research literature focusing on inventory management modelling for solutions to inventory management, such as models through collaborative or non-collaborative inventory management approaches (see, for example, a comprehensive literature review from Williams and Tokar (2008)), or models from the perspective of microeconomics or macroeconomics (see, a review from Blinder and Maccini (1991)). For manufacturing firms' inventories of raw materials and partially finished goods, the most prominent strategy in micro firms is the economic order quantity (EOQ) model. It was first introduced in Harris (1913), based on the trade-off between ordering costs and holding costs to enable cost minimization. From then on, there are many inventory models, most of which are extensions of the traditional EOQ model.

4.2.1.1 Economic Order Quantity (EOQ) model

The original EOQ model (Harris, 1913) defines the optimal lot size for companies that minimize total costs under a relatively restricted set of assumptions. Firms face no financial restrictions and no stock-outs, with deterministic annual demand, D. The lead time (from ordering an order to receiving an order), L, is constant and known. The ordering cost, S, annual holding cost for a unit item, H, and unit cost of the item, p, are fixed, known, and independent of the lot size. Then the total annual inventory cost TC is a function of order quantity, Q.

$$TC = S\frac{D}{Q} + H\frac{Q}{2}$$

The optimal lot size Q^* is:

$$Q^* = \sqrt{\frac{2DS}{H}}$$

Although the original EOQ model is quite restrictive because of its assumptions, the EOQ model is often used in inventory management. A great deal of correlated research over the past century has been spawned based on the major foundations of the original EOQ model (Torres et al., 2014). For example, Langley (1976) suggest four alternative ways (minmax, minimin, minimax regret and Laplace criterion strategies) when an inventory manager faces uncertain conditions in the EOQ model inputs. Kuzdrall and Britney (1982) develop a total setup lot-sizing model to help managers solve the price-discount or quantity-discount problem. This approach gives managers a solution selection among the feasible EOQ, the lower break-point quantity, or the up-break point quantity, to meet the lowest-total-cost solution. In San-José et al. (2015), the deterministic EOQ model has allowed for partial backlogging, that is, during the shortage period, only a part of the demand is back-ordered. Thus, firms will suffer lost sale costs and back-order costs. This paper provides a procedure to determine the optimal lot size and minimum total cost, which is more suitable for real-life usage.

When considering the economic lot size of inventories, the transportation cost is often non-negligible. There is also some research extending the EOQ model with the incorporation of transportation costs or transportation options. Russell and Krajewski (1991) explore an extended EOQ model with assumptions of a standard less-than-truckload (LTL) freight rate structure and all-units price discounts. Subsequently, the total related cost of the lot-size decision contains four components: material costs, ordering costs, transportation costs, and inventory holding costs. The model extended by Mendoza and Ventura (2008) considers three kinds of transportation options - LTL transportation with a constant cost per unit shipped, truckload (TL) transportation with a fixed cost per truck, and a combination option of LTL and TL. Moreover, it is extended to study the all-units quantity discount situation, as quantity discount is a common phenomenon in real life. In the cost function, the greater the transportation cost, the greater the inventory cost. Madadi et al. (2010) address inventory decisions in a supplier-warehouse-retailers supply chain with transportation cost consideration, by comparing the centralized ordering model and decentralized ordering model. Moreover, the result shows that transportation costs account for a large proportion of total costs, which are often overlooked.

Baumol and Vinod (1970) present a theoretical model that integrates transportation and inventory costs. Their strategy combines three transportation elements: shipping cost, mean lead time, and variance of lead time. It has been shown that quicker and more reliable transport service merely eliminates inventories, including inventory in transit and safety stock. The mixed integer non-linear programming model explored by Mendoza and Ventura (2013) examines the impact of transportation cost on inventory management and supplier selection decisions while considering the purchasing, transportation costs, and inventory under suppliers' quality and capacity constraints. The goal of this model solution is to determine the lot size and the number of orders in each order cycle that should be assigned to each chosen supplier while minimising the average inventory cost per time unit. It is shown that including transportation costs in inventory management has an impact not only on the order quantities delivered from selected suppliers but also on the supplier selection.

4.2.1.2 (S, T) model and (S, s) model

The (S, T) model was first explained by Hadley and Whitin in 1963 (Williams and Tokar, 2008), where S refers to the order-up-to-level and T the cycle duration, or say, a pre-set review interval. It is also called a periodic review system as an order is placed to reach an up-to-level inventory position when reaching a review interval. The (S, T) model here is to characterize the frequency and the quantity of an order that directly affects the service level.

In Frenk et al. (2014), a generalized EOQ model with (S, T) inventory control policy is discussed. Their assumptions include deterministic demand, back-log cost allowed, no constraint on order quantity, and no replenishment lead time. The following notations are used to formulate this model:

λ: demand rate.

Q: order of size, where $Q = \lambda T$.

$\alpha + c(Q)$: ordering cost per order, α means a fixed order cost, $c(Q)$ means the transportation and purchasing cost a firm incurs when ordering Q lot size.

$f(x)$: holding-backlog cost rate function, when the net inventory level x is positive, $f(x)$ represents the out-of-pocket holding cost; otherwise, it refers to the backlog cost per time unit.

$rc(Q)Q^{-1}$: the opportunity cost rate with order quantity Q is a fraction of ordering cost.

$g(T, x)$: the holding-backlog-opportunity cost, which equals to$f(x) + \frac{rc(\lambda T)}{\lambda T}x$, if $x \geq 0$; otherwise, equals to$f(x)$.

Then the average inventory cost $v_c(S, T)$ including average ordering cost and average holding-backlog-opportunity cost is given by:

$$v_c(S, T) = \frac{\alpha + c(\lambda T) + \frac{rc(\lambda T)S^2}{2\lambda^2 T} + \int_0^T f(S - \lambda t)dt}{T}$$

The optimal (S, T) control policy is then a solution of minimizing the average cost

$v_c(S, T)$. In Frenk et al. (2014), the lead time is assumed to be zero. If the lead time is positive, then the order should be issued when the pocket inventories are reduced to a minimum safe inventory level, s. In this case, the model is called the (S, s) model.

In Bensoussan et al. (2010), a firm's optimal inventory level is determined by the (S, s) policy under the assumption of the limited upstream capacity, Poisson demand process, and fixed ordering cost. The lead time is positive because of the limitation of the supplier's production capacity and the limitation of transportation capacity between the upstream supplier and downstream manufacturer in a supply chain. Under the (S, s) policy, firms choose the order-up-to level, S and the reorder point, s, to minimise the average inventory costs. In this setting, inventories are depleted continually without being restocked until inventories fall behind the reorder point. As firms cannot receive their order instantaneously, the reorder point, s, should be larger than the expected demand between the time of placing an order and receiving the goods. The numerical experiments indicate that, under the (S, s) policy, the decline in lead time would reduce not only both the optimal targeted inventory order-up-to level, S, and reorder point, s, but also the average inventory cost. In this case, the improvement of highway infrastructure, which provides a better transportation choice with higher transport speed and lower transit uncertainty, would help shorten the lead time and encourage firms to reduce the inventory level and average inventory cost.

4.2.1.3 (Q, r) model

(Q, r) model is also an extension of the traditional EOQ model, where Q refers to order quantity and r means the reorder point. The procedure for this model is to first formulate an average cost function that contains order quantity Q, reorder point r, and other relevant factors, based on some assumptions. The second step is to calculate the optimal order quantity and reorder point that meets the minimum-cost criterion. However, the calculation will become complicated when considering additional factors, such as transportation cost, quantity discount and particular demand or lead-time distributions. For example, Tyworth and Ganeshan (2000) demonstrate an efficient approach to finding the optimal values of order quantity and reorder point that jointly minimizes the cost under the gamma lead-time demand condition.

Constable and Whybark (1978) argue that the interaction between the assessment of inventory parameters (order quantities and reorder points) and the selection of transportation alternatives imply that decisions should be taken simultaneously because differences in transit time fluctuations could lead to different reorder points, and differences in shipping prices would involve different order quantities. In order to examine the interaction of inventory and transport decisions, Constable and Whybark (1978) develop an exploratory (Q, r) system to jointly determine the order quantities, reorder points, and transportation options that meet the target of minimum total inventory and transportation costs. Specifically, three attributes are used to jointly describe every transportation alternative: the cost of transportation, the estimated transit time, and the uncertainty of transit time. A change in any of these aspects, for example, the improvement in highway infrastructure to lower the amount and variation of estimated transit time, would generate a new transportation alternative. Applying the model derivation to a case study, they confirm that the differences in transportation costs and the variability of lead time could lead to different order quantities and reorder points.

4.2.1.4 Economic Production Quantity (EPQ) model

As one of the first extensions to Harris' original EOQ model, the Economic Production Quantity (EPQ) model was developed by Taft in 1918. In the manufacturing sector, it is often used to help firms determine the optimal production lot size by utilizing the minimizing production-inventory cost (Pasandideh et al., 2015). The main difference between the original EOQ model and the EPQ model is that the EPQ model is only applicable to the inventory of finished products.

The basic assumptions required to formulate the EPQ model are as follows: (1) there is only one product considered; (2) annual demand is deterministic and known; (3) lead time does not vary; (4) quantity discounts are not allowed; (5) usage rate and production rate are constant and (6) usage happens continually, and production happens periodically. In the scenario of the EPQ model, the actual production of a product exceeds the amount of the product used or consumed. If the production continues, the inventory increases. In the production cycle, the rate of inventory formation is the difference between productivity and utilization. The following notations are used to formulate this model:

D: annual demand

d: demand rate, units per time

P: production rate, units per time (P>d)

K: annual cost of a production setup

H: annual inventory carrying cost

C: manufacturing cost of a product, \$ per unit

Q: batch size (units)

TC: annual inventory-production cost

Suppose a firm uses EPQ type decision, then the inventory accumulates as the production continues, with a speed of$(P-d)$ units per time, until a maximum inventory. The production restarts when the inventory runs out. Then the annual total cost of inventory as the sum of carrying cost, set up cost and manufacturing cost is:

$$TC = \frac{Q}{2P}(P-d)H + \frac{D}{Q}K + CD$$

According to the cost-minimizing logic, the optimal production lot size is:

$$Q^* = \sqrt{\frac{2DK}{(1-d/P)H}}$$

And the minimizing inventory-production cost is

$$TC^* = \sqrt{2(1-d/P)DHK} + CD$$

This is a simple and restricted version of the EPQ model. There are some extensions of this model to make it more suitable for real-life conditions. For example, Cárdenas-Barrón (2009) develops the EPQ model with back-orders and imperfect quality products that should be modified at the same run, and Taleizadeh et al. (2018) develop four EPQ models that consider the situation of non-shortage, lost sale, partial back-ordering and fullback-ordering, respectively.

4.2.1.5 ROQ model

Inventory is usually viewed as working capital or current assets in the literature on corporate finance. For a profit-maximizing firm, the objective in inventory or capital management is to maximize the return on investment (ROI), yielded by the ratio of profit to investment level. However, in the inventory management literature or operation research literature, the decision objective is often assumed to be cost-minimizing or profit-maximizing. Schroeder and Krishnan (1976) is the first to apply the ROI as a criterion for inventory model decisions. Because it has some similarities to the traditional EOQ model, the model developed by utilizing the ROI concept is called the ROQ model.

With regard to the applicability of the ROQ model, it is appropriate for most finished goods. It is especially useful for retailers and wholesalers whose investments in assets may largely be in inventories. However, this model is not suitable for raw materials and half-finished goods, because they are held to produce products and are not ultimate investments themselves. For raw materials and half-finished goods, traditional cost minimization is more reasonable.

4.2.1.6 Newsvendor Model

The newsvendor model is also a popular inventory management model, which was first introduced by Arrow et al. (1951). As is the case with newspaper vendors, they must decide on the stock of newspapers in the face of uncertain demand and given that unsold newspapers will be valueless. It is particularly useful for firms that face an uncertain demand for perishable products, such as airlines, fashion goods, and hospitality industries (Qin et al., 2011).

There are some extensions of the newsvendor problem. For example, Li and Arreola-

Risa (2017) combine the Capital Asset Pricing Model (CAPM) model and the newsvendor model to demonstrate firms' decision problem in the face of financial risk. They show that the supplier's random capacity has nothing to do with the optimal order quantity but has something to do with the firm value. By exploring the impact of capacity process improvements on firm value, they also find out when and how such improvements will make the greatest contribution to firm value.

4.2.2 Research on Highway Infrastructure

4.2.2.1 General literature

Highway infrastructure has always played a key role in many areas, such as economic impacts (Chèze and Nègre, 2017), trade integration (Coşar and Demir, 2016), agglomeration (Graham, 2007) and productivity growth (Yeaple and Golub, 2007; Holl, 2016). Both policymakers and academics are concerned about the impacts of highway infrastructure investment on economic outcomes. There has been extensive literature on the relationship between transportation infrastructure investment and regional economic growth (e.g., Lakshmanan, 2011; Ferrari et al., 2019).

In the United Kingdom, Linneker and Spence (1996) investigate the relationship between regional employment and accessibility improvements caused by the development of the M25 London orbital motorway. The improved accessibility of a region as a result of the development of a large new road has two possible implications. It can help local businesses broaden their market areas by entering more distant markets, potentially increasing jobs in the region because of the increased accessibility. Alternatively, it can encourage expansion in the opposite direction if stronger businesses from outside the region enter the area where accessibility has been comparatively improved, and thus any expansionary developmental consequences such as job growth may arise in places other than those where accessibility has been largely improved. According to the regression results, there is a negative association between accessibility and employment transition. Places with high accessibility in comparison to other regions are characterized by declining employment and vice versa.

For the US highway network, Baum-Snow (2007) evaluates the extent to which interstate highways led to a central city population decline in metropolitan areas between 1950 and 1990. Empirical estimates imply that a new highway passing through a central city decreases its population by around 18%. The counterfactual estimation indicates that if the interstate highway system had not been completed, the aggregate population of the central cities would have increased by about 8%.

Pereira and Andraz (2012b) investigates the aggregate effects of highway investment on the gross private investment, employment, and output, respectively, in the case of the US during the period of 1977-1999. Based on VAR estimates, the empirical results indicate significantly positive relationships between highway improvement and investment, employment, and output respectively at both the state and aggregate levels. Specifically, the elasticities of private investment, employment, and output with respect to highway investment are 0.130, 0.126, and 0.158, respectively. Pereira and Andraz (2012a) also consider both the direct impacts of highway improvement in the state itself and the indirect spillover influences of highway improvement in other states based on the same dataset and methodology. According to the empirical findings, the largest states are likely to be the greatest beneficiaries of highway investment, suggesting that highway investment contributed not only to regional concentration of economic activity but also to regional asymmetries in the US.

Similar results are found in He et al. (2014) for estimating the effect of highway construction on employment in the United States' industrial sector. Using panel data covering the period from 1980 to 2008 from 351 metropolitan statistical areas, the estimated results support that highway investment promotes job creation and economic growth. Specifically, a 10% increase in highway capacity is estimated to create a yearly \$326 billion increase in the U.S. GDP and roughly 1.5 million new positions for the entire country in the long term.

In the case of Italy, Percoco (2016) studies the effect of highway network construction on the structure of local economies in the setting of quasi-experiment. It has been discovered that the level of economic activity increased captured by a rise in new job positions and the number of plants following the improvement of the Italian highways system between 1951 and 2001, especially in transport-intensive sectors. Interestingly, no statistically significant increase in the rate of population growth is found, which seems to imply that the impact of the highway system may have succeeded through the creation of new jobs and an increase in labour force participation rates rather than by an expansion in city size.

Agrawal et al. (2017) is the only article to have studied the causal impact of interstate highways in the US on regional innovation. Over a five-year cycle, their research indicates that a 10% rise in a region's highway stock resulted in a 1.7% growth in regional patenting. Regarding the mechanism, empirical evidence suggests that roads foster local knowledge transfers, raising the probability that innovators can gain access to knowledge inputs from local but remote neighbours. As a result, transportation infrastructure could stimulate regional growth in addition to the more widely discussed agglomeration economies based on an inflow of new workers.

There has been other research on the impact of road transportation networks on trade, such as Duranton et al. (2014) and Duranton (2015). Duranton et al. (2014) is one of the first studies investigating the impact of interstate highways on the value and weight of bilateral trade between large cities in the case of the US. The cross-sectional analysis based on the two-step approach suggests that highways within cities have a large influence on the weight of exports, with an elasticity of around 0.5, while highways have no impact on the overall volume of exports. Following the same approach, Duranton (2015) then estimates the effect of road transportation on the composition and level of trade in Colombian cities. Different from the US case, this research finds that highway distance between cities is negatively correlated to the value and weight of bilateral trade, although the impacts of highways are greater for the value of exports. Moreover, a positive effect of intra-city roads on trade has been discovered. A 10% increase in highway stock in a city would lead to an approximately 3–5% growth in the weight and volume of exports.

There is also an increasing focus on the microeconomic analysis of transport effects on firm performance. Employing establishment-level data, Ghani et al. (2016) investigates the effect of the Golden Quadrilateral highway project on the efficiency and organization of India's manufacturing activity. Applying the straight-line instrument, the empirical evidence suggests that the Golden Quadrilateral upgrades resulted in significant growth in manufacturing activity for industries initially positioned along the Golden Quadrilateral network, which includes higher entry rates, spatial sorting adjustments of industries, productivity expansion, and improved allocative efficiency. However, there is no evidence that highways exert a significant impact on districts 10–50 kilometres away from the Golden Quadrilateral network.

Similar results are found by Gibbons et al. (2019) for the effects of road improvements in the United Kingdom on productivity-related firm outcomes and employment. Based on the firm-level panel data in the period of 1998-2008, they find a rise in employment in areas around the small road projects surveyed, with the increase stemming solely from new entrants, as opposed to incumbents who dropped employment and improved their productivity. There is also no evidence of a spatial reorganisation influence in this analysis.

Turning to the effects of highways on firm-level productivity, Holl (2012) and Holl (2016) are closely related works. Using panel data from 1991 to 2005, Holl (2012) investigates the effect of market potential, calculated based on the existing transportation network, on firm performance in the Spanish manufacturing sector. Applying alternative models and estimation techniques, Holl (2012) concludes some significant and robust productivity gains resulting from increased market potential. The implied mechanism is that improvement in transport infrastructure reduces the cost of doing business over long distances by reducing travel times, which can increase economic opportunities for businesses by offering greater market potential, and this allows companies to specialise more and to take advantage of scale economies to a larger extent. Simultaneously, transportation improvements that increase market potential decrease geographic market segmentation, which can promote substitutability in differentiated goods markets and, as a result, raise productivity through greater competition.

Holl (2016) also estimates the effects of Spain's highway accessibility on firm-level productivity using the panel data from 1997-2007. Holl (2016) argues that highways can have a direct impact on firm-level efficiency by lowering transportation costs, which leads to lower input and output costs. This can broaden the market, allowing for sales and exports to more distant markets, but it can also increase competition in the goods market. Highway improvements may also open up new avenues for new forms of production, as well as opportunities to strengthen supply chains and customer service through time savings. This would lead to increased productivity by optimising production and input/output market relationships. In line with this, the estimated results suggest a significant and robust causal effect of highways on Spain's firm-level productivity.

There is also research considering the impact of road infrastructure on firm-level fixed investment. Combining theoretical framework with the firm-level empirical examination in Italy, Aiello et al. (2012) suggest that investment in infrastructure affects corporate investment positively through two channels—adjustment costs and the component of profit (through cost and revenues). Firms adjust if the difference between the expected value and cost of adjustment under optimally adjusted capital stock is larger than the difference under the unadjusted capital stock. The adjustment cost in Aiello et al. (2012) is assumed to be a quadratic function of investment and infrastructure. They have proved that a change in infrastructure expenditure stimulates firms' investment by reducing their adjustment costs. For the second channel, infrastructure interacts with costs and revenues in shaping a firm's capital profitability. Assuming that transport costs are reduced because of the change in infrastructure, both the price of final goods and intermediate should decrease (Chirinko, 1993), and firms' current and expected variable costs and revenues (per product) will decrease accordingly. Then the change in firm value and firm investment will occur accordingly.

4.2.2.2 China specific literature

Internationally, some academics have indicated the asymmetrical effects in which transportation improvements play a larger role in developing markets than in developed markets with more advanced and denser infrastructure systems (Barzin et al., 2018; Hulten et al., 2006). As the largest developing country in the world, China's transportation infrastructure has attracted the attention of many academics and policymakers. When the Chinese Government began to increase its investment in China's National Trunk Highway System in 1992, many academic studies about the impact of transport investment on China's economic development emerged (Banerjee et al., 2012; Faber, 2014). From the regional level, some studies show that highway infrastructure contributes to economic growth from different aspects, such as spatial agglomeration (Yu et al., 2016), regional productivity (Zhang and Ji, 2019), GDP growth (Banerjee et al., 2012) and economic geography (Baum-Snow et al., 2018; Xu and Nakajima, 2017). It is known that the government has targets to stimulate the economy and promote trade integration and coordinated development of the inter-regional economy through infrastructure investment, but there is still some debate about the convergence of regional economic activities.

On the one hand, some studies show that the development of the highway system benefits under-developed inland cities. The reduction of transport costs between coastal mega-cities and inland cities stimulates the development of inland businesses from two perspectives. First, the lower cost of inputs, because of the highway improvement, delivered to the inland factories, help create a higher net revenue from their sales (World Bank, 2007). Secondly, easier access to markets and relatively low land rents in inland cities attract more new firms, creating more competition and attracting more highly skilled labourers (Limao and Venables, 2001). As a result, by linking both under-developed and developed regions, the improvement in transportation provides more opportunities for the improvement of low-income areas and converges the regional economic activities (Bouraima and Qiu, 2017).

On the other hand, some research has shown the heterogeneity of highways' regional impact. For example, as a side-effect, the large-scale National Trunk Highway System (NTHS) connects both metropolitan centres and peripheral regions. Faber (2014) tests the core-periphery theory by treating the NTHS as a natural experiment. To address the endogeneity problem, an instrumental variable based on the construction of the Euclidean spanning tree network and the least cost path spanning tree network is employed. The estimation shows that, instead of distributing production from the metropolitan to peripheral regions, the NTHS results in a decline in the industrial development and total output growth of the connected peripheral regions, compared with other non-connected ones, as economic activities would be more concentrated in core areas after the market integration.

Yu et al. (2016) explore the impact of highway networks on the development of spatial economic agglomerations, using panel data of 274 Chinese municipalities from 2000 to 2010. Their results present that the improvement of road infrastructure has a distributive effect, which would accelerate the geographic concentration of economic activities. Although a transport-oriented development strategy could reshape economic activities and increase the output as well, new motorway construction has led to negative agglomeration in China's lagging western regions, indicating that industries in these poorer areas suffer losses during the observed interval. With increased access to transport infrastructure, firms appear to further concentrate in better-developed regions in China, which would expand the spatial inequity. Similarly, by studying the relationship between China's highway construction and local economic output, Baum-Snow et al. (2018) indicate that after the road is built, the output and population of the core city increases, while the situation in edge cities is the opposite.

There are also rising studies about the economic efficiency of transportation infrastructure explored from the firm level. For example, some scholars explore firms' activities, like innovation and exportation. Using a matched database containing firm-level patent data and city-level road infrastructure information between 1998-2017, Wang et al. (2018) estimate the impact of road infrastructure on firms' innovation behaviours. By exploiting the interaction between regional variation and the export price of road construction equipment as a time-varying instrumental variable, they emphasize that the improvement of road density simulates firms' innovation through the channel of facilitating market expansion and knowledge spillover. The improvement of road infrastructure expands firms' market size and lowers their transportation costs, which in turn spurs innovation. Moreover, because of the knowledge spillover caused by road improvement, some large private firms benefit not only from their cities but also from neighbouring cities.

Liu et al. (2022) estimate the effects of highway density on firms' export behaviour in the period of 2000-2006. They argue that, through the theoretical model, firms' exports would be affected, by the lower domestic trade costs, through three channels. Firms' exports are facilitated through increased access to suppliers and savings in transport costs. Meanwhile, the increase in highway density may also impede firms' exporting behaviours through tougher competition. Thus, the overall impact is uncertain and needs an empirical examination. Consistent with the hypothetical expectations, the empirical results support that highway infrastructure can stimulate exports after controlling both industry-year and city-year fixed effects. Moreover, this positive effect is stronger for firms with lower productivity. As low-productivity firms decrease their markup, but high-productivity firms increase their profit, with easier highway access.

While more researchers pay attention to firms' productivity. Wan and Zhang (2018) estimate the impact of infrastructure on firm-level productivity by distinguishing both the direct and indirect effects. Using panel data of Chinese manufacturing firms, they exert that infrastructure affects firm productivity positively through the agglomeration channel. They also rule out that, even if the indirect effect of the agglomeration is controlled, the infrastructure, including telecommunication, cable and road infrastructure, has a significant causal relationship with firm-level productivity. Based on the data of manufacturing firms in China, Li and Arreola-Risa (2017) estimate the positive effect of road infrastructure on firm-level productivity and uncover that the overall annual rate of return from productivity gains during 1998-2007 is about 11.4%, although some inefficiency occurred in inland China in the early 2000s. Wang et al. (2020) also confirm the contribution of infrastructure on firms' productivity by documenting that, on average, productivity increases by 3.07% annually because of the improvement of transportation, and this infrastructure-productivity effect is larger in firms relying more on infrastructure.

4.2.3 Transportation infrastructure and firm inventory investment

However, much less is known about how highway infrastructure affects firms' inventory investment decisions in China, which would be a channel towards productivity. Evidence about the association between inventory (primary working-in-progress) reduction and productivity growth, for example, in the Japanese automotive industry, has been shown in Lieberman and Asaba (1997) and Lieberman and Demeester (1999). The reduction in actual input inventories reduces the costs of inventory carrying and related activities such as warehouse management and materials management, thereby making a potential contribution to productivity (Lieberman and Demeester, 1999). Based on the financial information of manufacturing firms in the US from 1980 to 2005, the empirical results of Capkun et al. (2009) indicate that a firm's inventory performance is positively correlated with its financial performance at both the operating and gross levels. This suggests that if a firm lowers its inventory storage without decreasing its market size (or sales), the firm must come with a higher operating efficiency or productivity.

There are indeed several works of empirical literature focusing on the impact of transportation improvement on firms' inventories. Internationally, Shirley and Winston (2004) is the first to analyse the impact of highway infrastructure on inventory investment. Using the data on highway infrastructure and plant-level inventory in the United States from the 1970s to the 1990s, it is found that investment in highway facilities significantly reduces firm-level raw material inventories. They also calculate the rate of returns generated by the savings on logistics costs. It is confirmed that an additional dollar invested in the highway generated about 7.0, 2.0, and 0.33 cents reduction in raw materials annually during the 1970s, 1980s, and 1990s, respectively. Based on the dataset of 4268 retail firms around 60 countries in the period from 1983 to 2004 (only retail firms are considered because these firms hold sizable inventories as a portion of their course of general business), the same substitution effect is confirmed by Lai (2011). More specifically, with a doubling of the density of roads' length, retail firms' inventories reduce by about 6%.

Focusing on India's Golden Quadrilateral highway project, which aimed to enhance the quality and width of existing highways linking the four largest cities, Datta (2012) applies the difference-in-difference estimation strategy to investigate the effect of improved highways on firm-level input inventories using data from the World Bank Enterprise Surveys for India in 2002 and 2005. The empirical evidence suggests that firms in highway-affected cities lowered their average stock of input inventories by 6 to 12 days' worth of production, whereas those in cities where highway quality did not improve demonstrated no substantial change. Moreover, the reduction in input inventories differed inversely with the distance between a firm's location and the closest city on an enhanced highway. Companies on the Golden Quadrilateral were also much more likely to have replaced the supplier who supplied their main input, implying that they saw the opportunity to re-optimize their supplier option due to the arrival of improved highways.

Following Shirley and Winston (2004), Li and Li (2013) extend the highway infrastructure into all road infrastructure and confirm the substitutional relationship between provincial road length and firms' input inventory stock, in the background of China from 1998-2007. Moreover, the numerical experiment shows that every dollar in road investment saves about two cents in inventory costs. In terms of the endogeneity issue, two approaches are used in Li and Li (2013). The first one is to add the final goods inventory to the regressions. They argue that bias due to the omitted variables such as the business cycle and inventory management technology can be reduced if the final goods variable is controlled. In the second approach, they divide two groups based on the location of firms' suppliers. Some industries rely only on local suppliers (control group), while other industries use the road link in neighbouring areas to collect raw materials from distant suppliers (treatment group). By adding the road stock of neighbouring provinces into regressions, they argue that the effect of the road in other provinces would affect only the treatment group if the road does influence the input inventory of firms.

Cui and Li (2019) consider the impact of China's high-speed rail system on firms' input inventory decisions. Based on the difference-in-differences (DID) specification, with the data of manufacturing firms from 2007-2013 and the information of high-speed railway stations, they conclude that the high-speed rail system influences inventory by declines in transportation cost and agglomeration effect, leading to a 9.5% reduction in firms' input inventories.

Different from previous literature, Lin et al. (2019b) find that transportation infrastructure, including road and railway, does not reduce manufacturing sectors' inventory at the provincial level in the period from 2005 to 2014. The reason for this discrepancy can be partly explained by China's ongoing inland relocation of industries and expansion of regional markets have resulted in longer transportation distances and delivery times from suppliers to customers. However, they also mention that adopting provincial-level data in China (both infrastructure and inventory) is one limitation, as the estimations may vary by using different methods and data sources.

4.2.4 Economic intuition and hypothesis development

The first subsection briefly introduced several influential models of inventory management. It is clear that some theories are more suitable for raw materials and intermediate goods, such as the traditional EOQ model and its extensions of (Q, r) model, (S, T) model or (S, s) model. In these models, the optimal inventory level is determined by the principle of cost-minimization based on the trade-off among, for example, the ordering cost, holding cost, holding-backlog-opportunity cost, and transportation-related costs such as the estimated transit time and shipping price. Comparatively, the EPQ model, ROQ model and newsvendor model are more suitable for the finished goods. The EPQ model is especially suitable for manufacturing firms in the production process to help determine the optimal production lot size by utilizing the minimizing production-inventory cost. While the ROQ model and newsvendor model are more appropriate and useful for retailers and wholesalers whose investment in assets may largely be in inventories, the optimal inventory quantities of which are determined by the order of profit-maximizing.

Although firms may apply different inventory management systems, some common characteristics and economic intuitions can be generated based on the theoretical discussion. Firstly, firms may treat input inventories and finished goods separately with the cost minimization principle on raw materials or intermediate goods and the profit maximization or production-inventory cost minimization on finished goods. This is a reminder to investigate not only the total inventory but also its discrete components (raw materials, intermediate goods, and finished goods) when considering the impact of highway improvement on firms' inventory decisions. Secondly, for all the inventory models, the common factor of both input inventory and output inventory-related decisions is the estimated demand or demand rate. Demand is positively correlated with the optimal ordering quantity of input inventory as it would affect, for instance, the annual ordering cost in the setting of the EOQ model. Demand and average finished goods level are also proportional as shown in the optimal lot size of the EPQ model, ROQ model, and newsvendor model. Thus, the estimated demand is an important factor regarding the decision on a firm's inventory level and, therefore, cannot be ignored in this research. Thirdly, the theoretical intuition of how highway construction could affect firms' inventory decisions can be developed based on the theories.

For input inventories in manufacturing firms, once a firm's demand is controlled or remains unchanged, the improvement of highways may directly encourage firms to lower their input inventory level as the transportation cost and lead time are decreased. Applying the (S, s) model (Shirley and Winston, 2004) into the discussion, the improvement of infrastructure saves transportation costs which reduces the cost of inventory procurement. Enterprises can reduce the maximum holding level (S) of inventory by increasing the frequency of procurement. Moreover, it reduces the uncertainty of transit time and shortens the lead time of purchasing inventory, then reducing the minimum safe inventory level (s). Thus, the improvement of the highway can significantly reduce the cost of inventory or the average input inventory levels through the path of the (S, s) model. In addition, the theoretical model presented by Baumol and Vinod (1970) combines three transportation elements: shipping cost, mean lead time, and variance of lead time. It has been shown that quicker and more reliable transport service merely eliminates inventories, including inventory in transit and safety stock.

However, comparatively, finished goods are more connected with future sales and expected demand rather than the transportation cost (Shirley and Winston, 2004; Li and Li, 2013). As this research focuses only on manufacturing firms, the EPQ model is appropriate for integration into the discussion. According to the EPQ model, the optimal batch size is positively correlated with the annual demand, demand rate and annual cost of a production setup, and negatively correlated with the production rate and annual inventory carrying cost. In this case, it is hypothesised that the output inventory would be less affected by the highway improvement, while the direct effect of highway proximity on total inventories is ambiguous as its components of input inventory and output inventory may react differently. Given that, on average, around two-thirds of total inventories are raw materials and intermediate goods, the improvement of highway proximity may result in a decline in total inventories.

In addition to the direct effect, highways may indirectly affect inventories through the channel of demand. Theoretically, the estimated demand is an important factor with regard to the decision on a firm's inventory level, no matter what kind of inventory is considered. A firm will re-evaluate its strategic decisions or competition decisions if the highway improvement helps to expand market catchment or access broader labour markets by connecting the markets not previously covered (Linneker and Spence, 1996). Large-scale highway investment promotes market integration, which may inspire companies to expand their market share by competing with other similar firms. This would result in changes in demand and then make firms dynamically adjust their inventories as inventories are positively correlated with the estimated demand.

In the empirical estimation section, the main interest is to investigate the direct effect of highway proximity on firms' inventories, namely, total inventories, input inventories and finished goods. It is hypothesised that after controlling the proxy of demand, the improvement of highway proximity would cause the decline of firms' average input inventory level, in line with the existing empirical evidence (e.g., Shirley and Winston, 2004; Datta, 2012; Li and Li, 2013) and the theoretical predictions. Whereas highway proximity is expected to have no direct effect on finished goods and may have a negative effect on total inventories. The indirect effect of the demand mechanism will be discussed subsequently in Section 6.

4.3 Empirical Specification and Data

4.3.1 Model specification

This research first considers the direct effect of highways through the channel of input sourcing cost reduction, as a combined result of transportation cost reduction, shortened lead time and uncertainty decline. As predicted in the theoretical intuition, it is hypothesised that the improvement in highway infrastructure will lead to a decrease in transportation cost, lead time, and uncertainty of ordering inventories, which would directly encourage firms to lower their input inventory holdings. However, the finished goods are more connected with the level of sales or the expected demand rather than the transportation cost. Thus, it is hypothesised that the direct impact of highway construction on finished goods is insignificant, while the effect of highway construction on total inventory is ambiguous as its components of input inventory and output inventory may react differently.

To investigate the direct effect of highway improvement on firms' inventories, the following regression equation (4.1) is considered as the baseline specification.

$$\begin{aligned} Inventory_{i,j,k,t} = \alpha_0 + \alpha_1 Highway_{i,t} + {\alpha_2}' X_{i,t} + {\alpha_3}' Z_{k,t} \\ + \varepsilon_i + \varepsilon_j + \varepsilon_k + \varepsilon_t + \varepsilon_{i,j,k,t} \end{aligned} \tag{4.1}$$

where the subscripts i, j, k, and t are the firm, industry, province, and year, respectively. As mentioned before, it is necessary to investigate not only the total inventory but also its discrete components (raw material, work-in-process, and finished goods) when considering the impact of highway improvement on firms' inventory decisions. Following the measurement of Shirley and Winston (2004) and Li and Li (2013), I use the absolute value of inventories rather than the relative value of inventories. Here $Inventory_{i,j,k,t}$ represents three alternative inventory variables: the logarithm of total inventory, the logarithm of input inventory and the logarithm of output inventory. The total inventory is the sum of raw materials, work-in-progress (intermediate goods), and finished goods. Input inventory is the sum of raw materials and intermediate goods. Output inventory, also called finished goods, is the difference between production and sales. Although alternative inventory measures are used in this research, the focus would be on the input inventory as it would be more affected by highway construction.

$Highway_{i,t}$ represents the highway access. As discussed in Chapter 3, I use highway proximity, calculated as the inverse of distance (km), as the main highway access measure. The larger the highway proximity, the better the firms' access to highway infrastructure. It is expected that the coefficient of highway proximity is negative especially when the dependent variable is input inventory. In contrast, the direct effect of highways on finished goods may be insignificant, as finished goods are more affected through the indirect demand channel. Two additional highway variables will be used to test the robustness of highways' effect, namely, the logarithm of the distance to the nearest highway and the relative highway proximity.

Some firm-level variables ($X_{i,t}$) are controlled, including firm size, firm age, leverage, export ratio and sales. Specifically, firm size is defined as the nature logarithm of the number of employees. Firm age is defined as the natural logarithm of the number of years since the firm was founded. Firms' size and age are usually controlled in corporate finance literature (for example, in Ding et al., 2013, 2018, 2019; Shan and Zhu, 2013). It is expected that the coefficients of firm size and age are positive, as larger firms and older firms are more likely to have larger market sizes and therefore higher absolute levels of inventories.

Leverage is used as a proxy for firms' financial constraints, which is calculated as the ratio of current liabilities to current assets. In corporate finance literature regarding inventory, financial constraint is an important consideration. Compared to fixed capital, inventories have lower adjustment costs and can easily be turned into cash, thus inventories can be changed downward to provide additional financial resources, especially for firms with financial constraints (Caglayan et al., 2012; Fazzari and Petersen, 1993; Bo, 2004). Moreover, using firms' leverage as one of the main proxies of financial frictions, Sangalli (2013) highlights the negative response of inventory investment to the presence of financial constraints over the period from 1991 to 2009 in the Italian manufacturing industry. It is thus expected that the coefficient of leverage is negative, as higher leverage means higher financial constraints.

The export ratio is the ratio of export value to sales. Firms conducting export-processing business may import intermediate goods or raw materials for processing and then export the final goods, which therefore hold high stocks of inventories (Ding et al., 2013). It is thus hypothesised that the coefficient of export is positive.

According to the theory discussion, firm-level demand is an important factor affecting a firm's inventory investment, no matter which kind of inventory is considered. Thus it is necessary to control the demand when investigating the effect of highway access on firm inventory decisions. Given the data constraints, it is unable to approximate a firm-level demand function and measure firms' idiosyncratic demand level as Foster et al. (2016). Although it is hard to measure demand, the nature logarithm of sales is used as the proxy of demand, following Sangalli (2013). Because the optimal lot size is proportional to the annual demand, it is expected that the coefficient between sales and inventories is positive.

Some provincial-level variables ($Z_{k,t}$) are controlled as well, including road congestion, other roads' density, waterway density and rail density. Following Li and Li (2013) and Shirley and Winston (2004), road congestion is measured by the total number of vehicles scaled by the total road length at the provincial level. It is hypothesised that the coefficient of congestion is positive as higher congestion would reduce travel speed and inspire firms to increase inventories. When investigating the effect of highway improvement on firms' inventories, it is necessary to control other transportation options which may correlate with highway infrastructure and could also affect firms' inventory decisions, as argued in Li and Li (2013). As this research only considers the highway rather than all road infrastructure, other roads' density is controlled, which is calculated by the ratio of the total length of other roads at the provincial level to the provincial area. Similarly, waterway density is defined as the total length of waterways to the provincial area, and rail density is defined as the total length of the railway to the provincial area. Other kinds of transportation such as civil aviation and pipelines are not controlled as they are less likely to be a choice in transporting inventories, as shown in Figure 2.1.

Equation (4.1) also includes five terms: firm-specific time-invariant effects (ε_i); industry-specific effects (ε_j); location-specific effects (ε_k); time specific effects (ε_t); and an idiosyncratic error ($\varepsilon_{i,j,k,t}$). The information on ordering cost, holding cost, and stockout cost for individual firms varies by geography and commodity. As these firm-level or plant-level costs are publicly unavailable, following Shirley and Winston (2004), the 2-digit industry dummy and provincial location dummies are used to capture these effects on inventory decisions, while the year dummy is used to control other time-varying unobserved influences on inventories.

Using the firm-level panel data in the period of 1998-2007, the above basic specification will be firstly estimated by the fixed-effect OLS method. The possible endogeneity issue will be considered later.

4.3.2 Data and summary statistics

In the empirical estimation, a number of datasets are used including firm-level production data, geo-referenced highway routes, a series of geographic information data for the construction of instruments and a set of province-level data for control variables.

Firm-level data is from the Annual Survey of Industrial Firms (ASIF) database over the period of 1998-2007, which is collected by the National Bureau of Statistics of China[1]. Following Ding et al. (2013) and Liu et al. (2022), I drop observations with negative total inventories, negative input inventories, negative finished goods, negative sales, negative export value, negative total tangible fixed assets, negative accumulated depreciation minus current depreciation, and unreasonable opening year. In addition, observations in the 0.5% tails of each of the firm-level variables are excluded, to control the potential influence of noisy observations. The final unbalanced panel covers 1,856,417 firm-year observations, with the number of observations ranging from a minimum of 119,771 in 1998 to a maximum of 293,901 in 2007.

The original geo-referenced highway routes are obtained from the ACASIAN Data Centre at Griffith University in Brisbane. Because the highway networks in 1999, 2001, 2004, and 2006 are not included in this dataset, I updated the geo-referenced highway routes to a 10-year panel by checking the information from the published China Road Atlas. Specifically, road atlases published by China Atlas Press or China Communications Press in 2000, 2002, 2005, and 2007 are used to digitize the highway routes. Combining firms' digitized location information and the time-varying highway network, each firm's distance to the nearest highway can be calculated using the GIS software. To construct panel instruments for highway accessibility, several data sources are used, including the historical Ming dynasty's and Qing dynasty's courier routes obtained from the Harvard WorldMap Project, the Digital Elevation Model (DEM) downloaded from China's Geo-spatial Data Cloud, and the remote sensing land cover data downloaded from the Climate Change Initiative-Land Cover (CCI-LC) database.

[1]A detailed description of the ASIF dataset is in Chapter 3.

A series of province-level data are obtained from the China Statistical Yearbooks. These include the lengths of railways, waterways, and other kinds of roads except highways, as well as the area information for each province. Moreover, the province-level Producer Price Index (PPI), published by the National Bureau of Statistics of China, is used to deflate some firm-level variables such as inventories and sales.

Table 4.1 illustrates the mean value and standard deviation (in parentheses) in performance across the 1,856,417 manufacturing firms. Moreover, the observations of SOEs, private firms, foreign firms, and collective firms are 165,199, 1,158,506, 270,229, and 177,904, respectively. For the full sample, the mean total inventory is 7.259 with a standard deviation of 2.211. Specifically, firms store more input inventories (5.953) than finished goods (5.493). Compared with their counterparts, private firms are characterized by the lowest average total inventory and input inventory level and state-owned firms are characterized by the highest input inventory level.

For the full sample, the mean highway proximity value and the distance to the nearest highway are 0.509 and 8.716, respectively. The relative highway proximity (RHP) captures a firm's relative highway access level (ranging from 0 to 1) in a given province-industry-year. The mean RHP value is 0.518, with a standard deviation of 0.115. Among the ownership groups, foreign firms have the best access to highway infrastructure, with the nearest average distance (8.195) and highest highway proximity (0.724), followed by private firms. Although SOEs have the lowest absolute highway proximity, they have the highest relative highway proximity level (0.552), indicating a relative advantage to the access of highways.

By ownership, the average leverage ratio, calculated as the ratio of current liabilities to current assets, ranges from a minimum of 88.42% for foreign firms to a maximum of 149.8% for SOEs, while the mean value of export-to-sales ratio ranges from a minimum of 4.189% for SOEs to a maximum of 49.02% for foreign firms. Private firms and foreign firms are characterized by higher sales or demand, whereas SOEs and collective firms have relatively lower sales or demand.

Table 4.1 also shows the p-value associated with the t-test for differences between SOEs and private firms by means of corresponding variables. At the 1% level, the

Table 4.1: Summary statistics

	Full sample	SOEs	Private	Foreign	Collective	Diff (SOE & private)
Ln (total inventory)	7.259	7.468	7.045	8.001	7.125	0.00***
	(2.211)	(2.452)	(2.135)	(2.252)	(2.113)	
Ln (input inventory)	5.953	6.347	5.604	7.109	5.835	0.00***
	(2.941)	(2.886)	(2.931)	(2.863)	(2.674)	
Ln (output inventory)	5.493	5.827	5.436	5.376	5.559	0.00***
	(3.102)	(3.297)	(2.966)	(3.525)	(3.000)	
Highway proximity	0.509	0.360	0.497	0.724	0.385	0.00***
	(1.393)	(1.074)	(1.388)	(1.667)	(1.135)	
Ln (highway distance)	8.716	9.156	8.742	8.153	8.994	0.00***
	(1.426)	(1.555)	(1.403)	(1.262)	(1.409)	
RHP	0.518	0.552	0.509	0.530	0.522	0.00***
	(0.115)	(0.138)	(0.111)	(0.106)	(0.120)	
Size	4.736	5.027	4.596	5.064	4.778	0.00***
	(1.093)	(1.408)	(1.014)	(1.111)	(1.031)	
Ln (age)	2.003	2.911	1.827	1.839	2.461	0.00***
	(0.886)	(0.932)	(0.834)	(0.644)	(0.799)	
Leverage (%)	105.8	149.8	103.6	88.42	104.1	0.00***
	(91.12)	(127.7)	(85.42)	(79.42)	(89.36)	
Export ratio (%)	17.02	4.189	12.64	49.02	8.208	0.00***
	(34.25)	(16.24)	(30.08)	(44.56)	(24.66)	
Ln (sales)	9.802	8.927	9.813	10.35	9.642	0.00***
	(1.271)	(1.867)	(1.111)	(1.218)	(1.135)	
Sales growth (%)	11.99	-2.819	15.92	12.25	3.596	0.00***
	(50.02)	(56.63)	(49.36)	(47.06)	(48.03)	
Excess sales growth (%)	19.70	10.89	23.33	18.25	9.976	0.00***
	(86.53)	(90.46)	(89.59)	(80.62)	(70.42)	
Sales surprise	0.997	0.938	1	1.026	0.987	0.00***
	(0.0805)	(0.123)	(0.0702)	(0.072)	(0.0735)	
Observations	1,856,417	165,199	1,158,506	270,229	177,904	

Note: The definition and calculation of sales growth, excess sales growth and sales surprise will be discussed in Section 6. For preliminary information, excess sales growth is calculated as sales growth minus the mean value of four-digit industry-level sales growth in each year. The sales surprise dummy is defined as the ratio of sales to forecast sales, while the sales surprise dummy equals 1 if the sales surprise is larger than 1.

differences are statistically significant. It is interesting to show that SOEs are quite different compared with private firms. They are characterized by the higher total inventory, input inventory, and output inventory, but lower sales value, sales growth, excess sales growth, and sales surprise, indicating a lower inventory management efficiency. Comparatively, private firms are on average closer to the highways, with a higher mean value of highway proximity and a lower mean value of highway distance. The general firm characteristics suggest that state-owned firms are larger (in size) and older (in age) than private firms. The SOEs also display a higher leverage ratio and a lower export ratio. As the differences between SOEs and private firms are distinct, it is also necessary to investigate whether different types of firms will respond differently in the face of highway improvement.

Table 4.2: Mean time trends of highway proximity and highway distance

	Mean highway proximity			Mean ln(highway distance)		
YEAR	TOTAL	SOE	PRIV	TOTAL	SOE	PRIV
1998	0.292	0.250	0.261	9.311	9.472	9.424
1999	0.313	0.252	0.284	9.268	9.531	9.352
2000	0.363	0.285	0.338	9.113	9.437	9.166
2001	0.382	0.314	0.355	9.029	9.298	9.102
2002	0.444	0.356	0.419	8.829	9.079	8.902
2003	0.454	0.382	0.420	8.797	9.017	8.887
2004	0.555	0.481	0.521	8.583	8.734	8.679
2005	0.615	0.571	0.574	8.441	8.507	8.536
2006	0.627	0.624	0.585	8.431	8.434	8.529
2007	0.639	0.653	0.594	8.396	8.370	8.495

Table 4.3: Mean time trends of inventory-sale ratios (%)

	Mean total inventory			Mean input inventory			Mean output inventory		
YEAR	TOTAL	SOE	PRIV	TOTAL	SOE	PRIV	TOTAL	SOE	PRIV
1998	47.71	98.01	31.64	24.88	51.45	16.10	22.84	46.56	15.54
1999	45.22	97.36	30.39	22.76	48.87	15.22	22.45	48.49	15.17
2000	40.71	94.78	26.86	20.70	47.69	13.54	20.01	47.09	13.32
2001	36.95	96.88	24.96	18.52	48.25	12.33	18.43	48.63	12.63
2002	33.84	100.5	23.09	16.51	46.97	11.28	17.33	53.58	11.81
2003	27.04	89.09	19.53	13.78	43.91	9.717	13.26	45.18	9.808
2004	21.99	83.14	16.83	12.42	42.62	9.325	9.572	40.52	7.503
2005	19.31	60.13	16.06	10.65	32.43	8.391	8.661	27.70	7.666
2006	18.01	63.07	15.01	9.819	31.07	7.839	8.192	32.01	7.174
2007	15.67	35.29	13.84	8.755	20.01	7.249	6.913	15.27	6.593

Table 4.2 illustrates the time trend of the mean highway proximity and log distance to the nearest highway. The figures suggest a continuous increase in highway proximity over the sample period, not only for the full sample but also for SOEs and private firms. Table 4.2 also shows a continuous decline in the mean distance to the nearest highway, indicating an increase in highway accessibility for both ownership groups.

Table 4.3 is the trend of relative inventory level, including the total inventory-to-sales ratio, input inventory-to-sales ratio, and output inventory-to-sales ratio. The total inventory-sales ratio dropped steadily from 47.71% to 15.67% in the full sample.

The output inventory-sales ratio also fell from 22.84% to 6.91% in the sample period. Similarly, the input inventory-sales ratio fell from 24.88% to 8.76% between 1998 and 2007. Although the declining processes are also true for both ownership groups, it is clear that SOEs are characterised by higher levels of alternative inventories.

4.4 Baseline results

Table 4.4 shows the baseline fixed effect regression results of equation (4.1). Beyond the firm-level and province-level controls, time-fixed effect, industry-fixed effect and regional fixed effect are included to control for the time-invariant and time-variant unobservable factors that may affect both inventories as well as highway proximity. The dependent variable in columns (1)-(3) is total inventory, input inventory, and output inventory, respectively. The inverse of highway distance (km) is used to proxy a firm's highway accessibility.

Column (1) shows that the coefficient of highway proximity is insignificant, which means the improvement in highway proximity would not affect the total inventory level, while the results in columns (2) and (3) indicate that the highway proximity is negatively and positively correlated with the input inventory level at 1% significant level and the output inventory level at 5% significant level, respectively. This indicates that with other factors remaining unchanged, every single unit increase in highway proximity is associated with a 0.6% reduction in firms' input inventory and a 0.5% increase in firms' output inventory.

Most of the control variables are significantly correlated with inventories. Inventories are also proportional to the logarithm of sales, which is in line with the theory and the empirical result of Li and Li (2013). Since larger firms and older firms are more likely to have a larger market size, their inventories should be at a higher absolute level. This is the case of China's manufacturing firms as the coefficients of firm size and age are significantly positive for all kinds of inventories. Leverage is found to have a significant and negative impact on inventories, which is consistent with the literature that a higher financial constraint is associated with a lower level of inventories (Sangalli, 2013). This is reasonable as inventories are easy to turn into cash and can be treated as a form of internal fund in relieving firms' financial pressure. Firms' export-to-sales ratio is positively correlated with all kinds of inventories. This means that firms with export behaviour are more likely to hold high stocks of inventories, and the more export shares they have, the higher the level of their inventories. Similar to the result of Shirley and Winston (2004), regional highway congestion would reduce travel speed and inspire firms to increase inventories, while other transportation infrastructures affect input inventories and output inventories differently. Other road density, river density and rail density are positively correlated with input inventories but negatively associated with finished goods.

4.5 Endogeneity and IV estimation

4.5.1 Endogeneity

The baseline result shows that highway proximity is negatively correlated with input inventory, positively correlated with finished goods and has no effect on total inventory. However, to investigate the causal effect of highway proximity, it is necessary to address the potential endogeneity issues. Specifically, there are at least two types of endogeneity concerns in the analysis, namely, endogenous highway construction and endogenous location choice.

4.5.1.1 Endogenous highway construction

The first type of endogeneity comes from endogenous highway construction, that is, the distribution of highways is not random. Governments tend to develop highways to link large cities where firms have better inventory management. In addition, there is concern that planners targeted economically and politically important regions along the way between the network's nodal cities (Faber, 2014).

This is indeed the case according to the two national trunk highway projects related

Table 4.4: FE-OLS regression result

VARIABLES	(1) Total inventory	(2) Input inventory	(3) Output inventory
Highway proximity	0.001	-0.006***	0.005**
	(0.61)	(-2.58)	(2.04)
Ln (sales)	0.271***	0.241***	0.265***
	(83.49)	(52.11)	(55.85)
Size	0.349***	0.364***	0.376***
	(87.12)	(63.89)	(63.39)
Age	0.086***	0.063***	0.136***
	(25.94)	(12.66)	(26.11)
Leverage	-0.001***	-0.001***	-0.001***
	(-48.13)	(-36.53)	(-34.04)
Export ratio	0.001***	0.001***	0.001***
	(8.92)	(9.47)	(6.79)
Congestion	0.002***	0.005***	0.001***
	(16.25)	(26.75)	(5.45)
Other roads density	-0.037***	0.063***	-0.060***
	(-2.60)	(2.99)	(-2.70)
River density	-0.281	7.723***	-5.661***
	(-0.97)	(17.98)	(-11.05)
Rail density	1.349**	4.540***	-0.601
	(2.10)	(4.75)	(-0.50)
Constant	0.609	0.299	1.274*
	(1.24)	(0.40)	(1.70)
Observations	1,856,417	1,856,417	1,856,417
R-squared	0.051	0.024	0.023
Number of firms	492,490	492,490	492,490
Company FE	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Province FE	YES	YES	YES

Note: Robust t-statistics corrected for clustering at the firm level are reported in parenthesis. Significant coefficients are indicated by ***,**,* for significance at the 1%, 5% and 10% level, respectively.

to the sample period, that is, the National Trunk Highway System (NTHS) project issued in 1992 and the National Expressway Network (NEN) project implemented in 2004. The NTHS project was the first national highway project in China, which was targeted to construct seven east-west and five north-south ("5-vertical 7-horizontal") routes by connecting all the provincial capitals, municipalities, all other cities with a population of over one million and 93% of cities with a population over 500,000 (Li and Shum, 2001). The NEN project from 2004 is an extension of the original

NTHS project, which was aimed at constructing a highway network of 7 capital radial, 9 north-south vertical and 18 east-west horizontal ("7-9-18") lines, with a planned total length of 85,000 km. As the economy comes to rely increasingly on road transportation, it was targeted to interconnect provincial capitals and all cities with a population of over 200,000.

In addition, empirically there may be some omitted variables explaining both the highway proximity and firms' inventory investment decisions. In order to control for this type of endogeneity, I construct a number of time-varying instruments, namely, the least cost paths and straight lines constructed based on the targeted city points outlined in the national highway construction projects, and historical instruments based on the Ming dynasty' courier routes and the Qing dynasty's historical routes[2].

4.5.1.2 Endogenous location choice

The second type of endogeneity comes from firms' location choices. New firms may choose to locate close to the highways in order to benefit from highway infrastructure. Existing firms may relocate their location by moving closer to highways (Holl, 2016). Thus, the effect of highway proximity on inventory investments may not only be derived from the construction of highways but also from the new firms and relocating firms closer to highways. To deal with the second type of endogeneity, This research further excludes both new firms that opened during the sample period and relocating firms that switched their locations in this analysis.

4.5.2 IV estimation result

To solve the first type of endogeneity, this subsection reports the empirical results of fixed effect two-stage least squares (FE-2SLS) estimation. The highway proximity is instrumented with the distance to the instrumental routes, which are calculated on the basis of the least cost paths of the NEN plan (referred as LCP_NEN), the least cost paths of the NTHS plan (referred as LCP_NTHS), the Ming dynasty's courier

[2] A detailed discussion on the construction of instruments are provided in Chapter 3.

Table 4.5: FE-2SLS result using total inventory as the dependent variable

VARIABLES	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Highway proximity	-0.106***	-0.402***	-0.222***	-0.085***
	(-4.58)	(-5.02)	(-6.21)	(-3.32)
size	0.349***	0.351***	0.350***	0.349***
	(87.02)	(84.64)	(86.49)	(87.04)
age	0.086***	0.087***	0.086***	0.086***
	(25.90)	(25.03)	(25.69)	(25.92)
leverage	-0.001***	-0.001***	-0.001***	-0.001***
	(-47.96)	(-46.73)	(-47.62)	(-48.00)
Export ratio	0.001***	0.001***	0.001***	0.001***
	(8.92)	(8.69)	(8.87)	(8.92)
Ln (sales)	0.270***	0.268***	0.269***	0.270***
	(83.05)	(79.55)	(82.15)	(83.11)
Congestion	0.003***	0.004***	0.003***	0.002***
	(15.62)	(10.39)	(15.01)	(14.58)
Other roads density	-0.029**	-0.005	-0.019	-0.030**
	(-1.99)	(-0.32)	(-1.32)	(-2.10)
River density	0.062	1.019**	0.437	-0.003
	(0.21)	(2.52)	(1.37)	(-0.01)
Rail density	0.913	-0.302	0.437	0.996
	(1.40)	(-0.40)	(0.65)	(1.53)
Company/Year/Industry/Province FE	YES	YES	YES	YES
Observations	1,732,900	1,732,900	1,732,900	1,732,900
R-squared	0.039	-0.022	0.024	0.041
Instruments	First-stage results: highway proximity as dependent variable			
Least cost path (2004NEN)	-0.121***			
	(-3.35)			
Least cost path (1992NTHS)		-0.193*		
		(-1.72)		
Ming courier routes			-0.233***	
			(-4.37)	
Straight line routes				-0.091**
				(-2.31)
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	1355.201	153.392	660.331	1136.150

Note: The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak-identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak-identification test is 16.38. The critical value, 16.38, is applied to the rest of the tables unless specified otherwise.

routes (referred as Ming routes), and the straight-line routes (referred as straight line).

Table 4.5 demonstrates the regression result of FE-2SLS using the total inventory as the dependent variable. Although in Table 4.4 the coefficient of highway proximity to total inventory is insignificant, the estimated coefficient of interest in Table 4.5 indicates that highway proximity has a significant negative effect on firms' total inventory level. Specifically, column (1) shows that the coefficient of highway proximity is -0.106, indicating every 0.1 unit increase in highway proximity is associated with a 1.06% reduction in the total inventory at the firm level. Although the magnitudes are different using alternative instruments, the estimated coefficients of highway proximity in columns (2)-(4) are all negative with significance.

The first-stage result shows that highway proximity is negatively correlated with the instruments on the basis of two kinds of least cost paths, historical routes, and straight lines, respectively, at 1% significance level. All instruments pass the under-identification test at 1% significant level, suggesting that all instruments are not under-identified. In columns (1)-(4), the first stage Kleibergen-Paap rk Wald F statistics are high and well above the commonly suggested threshold to be believed as a relevant instrument, indicating that the weak-instrument bias is not a problem for all instruments. Nevertheless, the LCP-NEN IV estimate is of the highest F statistic value in the weak identification test. The LCP-NEN IV is thus a most valid IV for this research. This is reasonable as it is strictly constructed on the basis of the minimum spanning tree principle and has a similar density compared with the actual highways.

Table 4.6 shows the FE-2SLS result using input inventory as the dependent variable. Similar to the FE regression, the same control variables, time-fixed effect, industry-fixed effect and regional fixed effect are all controlled. The first stage results suggest a significant correlation between highway proximity and instruments. The weak identification and under-identification tests are passed for all instruments. The LCP-NEN IV estimate is considered as the main result as column (1) has the highest F statistic value in the weak identification test. As IV regression addresses the downward bias in OLS, it is reasonable that the estimated coefficient in FE-2SLS regression is larger than the coefficient in FE regression. In column (1), the coefficient of highway proximity is -0.121 with 1% significant level, indicating that a 0.1 unit increase in highway proximity is associated with 1.21% reduction in the input inventory at the firm level. Moreover, this demonstrates that no matter which IV is used, the causal effect of highway proximity on input inventory reduction is robust. As the regression controls for the effect of sales, the negative coefficient of interest indicates the direct effect that the improvement in highway transportation encourages firms to negatively adjust their input inventories to a lower average inventory cost level, as better highway accessibility provides firms with an alternative transportation choice with lower transportation cost, shorter transit time and less uncertainty.

Table 4.7 is the FE-2SLS regression result using output inventory as the dependent variable. Although in Table 4.4 the coefficient of highway proximity to finished goods is significantly positive, the IV results show that highway proximity has no robust causal effect on finished goods. Specifically, in column (1), using the distance to the least cost paths of the NEN plan as an instrument, the coefficient of interest is insignificant, indicating that once the sales are controlled, the reduction in transportation cost and transit time because of the improvement in highways will not encourage firms to accordingly adjust their stocks of finish goods.

4.5.3 New firms and relocation

This subsection further addresses the second type of endogeneity, by considering that the endogeneity may come from not only the endogenous construction of highways but also the endogenous location of firms. There are a total of 614,785 observations of which firms have existed since 1998 and never relocated in the period of 1998-2007.

Table 4.8 shows the estimation results of highways' effect on total inventory, input inventory and output inventory. After considering firms' endogenous location issue, the first column of panel A shows that the improvement of highway proximity, instrumented by the least cost path of the NEN plan, causes the cost-saving effect of total inventory, at the 1% significant level. Moreover, this cost-saving effect is robust and significant when using the historical instrument or straight-line instrument.

Panel B also indicates a robust result using the input inventory as the dependent variable. In column (1), the coefficient of highway proximity is -0.336 with 1%

Table 4.6: FE-2SLS result using input inventory as the dependent variable

	(1)	(2)	(3)	(4)
VARIABLES	LCP_NEN	LCP_NTHS	Ming_routes	Straight_line
Highway proximity	-0.121***	-0.193*	-0.233***	-0.091**
	(-3.35)	(-1.72)	(-4.37)	(-2.31)
size	0.364***	0.365***	0.365***	0.364***
	(63.87)	(63.52)	(63.66)	(63.87)
age	0.064***	0.064***	0.064***	0.063***
	(12.67)	(12.65)	(12.65)	(12.68)
leverage	-0.001***	-0.001***	-0.001***	-0.001***
	(-36.42)	(-36.23)	(-36.25)	(-36.45)
Export ratio	0.001***	0.001***	0.001***	0.001***
	(9.47)	(9.46)	(9.45)	(9.47)
Ln (sales)	0.240***	0.240***	0.240***	0.241***
	(51.83)	(51.08)	(51.41)	(51.88)
Congestion	0.006***	0.006***	0.006***	0.006***
	(23.03)	(11.71)	(20.50)	(21.72)
Other roads density	0.072***	0.078***	0.081***	0.070***
	(3.38)	(3.39)	(3.74)	(3.27)
River density	8.091***	8.326***	8.454***	7.996***
	(18.17)	(14.73)	(18.04)	(17.82)
Rail density	4.072***	3.774***	3.611***	4.193***
	(4.21)	(3.55)	(3.66)	(4.34)
Company/Year/Industry/Province FE	YES	YES	YES	YES
Observations	1,732,900	1,732,900	1,732,900	1,732,900
R-squared	0.015	0.011	0.009	0.016
Instruments	First-stage results: highway proximity as dependent variable			
Least cost path (2004NEN)	-0.121***			
	(-3.35)			
Least cost path (1992NTHS)		-0.193*		
		(-1.72)		
Ming courier routes			-0.233***	
			(-4.37)	
Straight line routes				-0.091**
				(-2.31)
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	1355.201	153.392	660.331	1136.150

significant level, indicating that a 0.1 unit increase in highway proximity is associated with a 3.36% reduction in the input inventory at the firm level. Moreover, the significant results of columns (3) and (4) indicate that the causal effect of highway proximity on input inventory reduction is robust. In addition, the coefficients of columns (1), (3) and (4) are larger than the results of Table 10, in which new firms and relocation firms are not excluded. This suggests that the cost-saving effect

Table 4.7: FE-2SLS result using output inventory as the dependent variable

VARIABLES	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Highway proximity	-0.029	-0.440***	-0.121**	-0.045
	(-0.80)	(-3.59)	(-2.24)	(-1.10)
size	0.377***	0.379***	0.377***	0.377***
	(63.39)	(62.45)	(63.34)	(63.37)
age	0.136***	0.137***	0.136***	0.136***
	(26.11)	(25.68)	(26.10)	(26.11)
leverage	-0.001***	-0.001***	-0.001***	-0.001***
	(-34.01)	(-33.15)	(-33.89)	(-33.99)
Export ratio	0.001***	0.001***	0.001***	0.001***
	(6.79)	(6.73)	(6.80)	(6.80)
Ln (sales)	0.265***	0.262***	0.264***	0.265***
	(55.72)	(53.79)	(55.47)	(55.67)
Congestion	0.001***	0.003***	0.002***	0.002***
	(5.09)	(5.54)	(5.52)	(5.13)
Other roads density	-0.057**	-0.025	-0.050**	-0.056**
	(-2.56)	(-1.01)	(-2.21)	(-2.49)
River density	-5.550***	-4.227***	-5.254***	-5.499***
	(-10.55)	(-6.44)	(-9.68)	(-10.35)
Rail density	-0.741	-2.422*	-1.117	-0.806
	(-0.61)	(-1.82)	(-0.91)	(-0.66)
Company/Year/Industry/Province FE	YES	YES	YES	YES
Observations	1,732,900	1,732,900	1,732,900	1,732,900
R-squared	0.019	-0.013	0.016	0.019
Instruments	First-stage results: highway proximity as dependent variable			
Least cost path (2004NEN)	-0.121***			
	(-3.35)			
Least cost path (1992NTHS)		-0.193*		
		(-1.72)		
Ming courier routes			-0.233***	
			(-4.37)	
Straight line routes				-0.091**
				(-2.31)
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	1355.201	153.392	660.331	1136.150

of highway proximity would be larger if new firms and relocation firms were not considered. In short, highways' cost-saving effect on input inventory is robust, even when I take the endogenous location issue into account.

Comparatively, panel C suggests an insignificant effect of highway proximity on finished goods, which is in line with the hypothesis that finished goods are less or

Table 4.8: FE-TSLS result after controlling the possible endogeneity of new firms and relocation

VARIABLES	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Panel A: total inventory as dependent variable				
Highway proximity	-0.159***	-0.153	-0.226***	-0.090*
	(-2.79)	(-1.02)	(-3.43)	(-1.85)
Observations	614,785	614,785	614,785	614,785
R-squared	0.034	0.034	0.023	0.041
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	227.098	29.068	162.628	292.443
Panel B: input inventory as dependent variable				
Highway proximity	-0.336***	0.356	-0.219**	-0.209***
	(-3.72)	(1.56)	(-2.22)	(-2.78)
Observations	614,785	614,785	614,785	614,785
R-squared	0.000	-0.002	0.010	0.011
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	227.098	29.068	162.628 292.443	
Panel C: output inventory as dependent variable				
Highway proximity	-0.127	-0.345	-0.135	-0.048
	(-1.41)	(-1.41)	(-1.40)	(-0.62)
Observations	614,785	614,785	614,785	614,785
R-squared	0.014	-0.001	0.014	0.017
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	227.098	29.068	162.628	292.443

Note: Control variables, time fixed effect, industry fixed effect and province fixed effect are included. Control variables include firm size, age, leverage, export ratio, sales, congestion, other road density, waterway density, and railway density.

not affected by changes in highway accessibility if the proxy of demand is controlled.

4.6 The Indirect Channel of Demand

4.6.1 Estimation methodology

4.6.1.1 Proxies of firm-level demand

As discussed in the economic intuition part, demand might be a possible channel through which highways affect firms' inventory decisions. Regardless of the type of inventory being considered, the expected demand is a critical component in determining a company's inventory volume. If the highway improvement helps to increase the catchment of suppliers and retailers or reach larger labour markets by linking markets that were historically unconnected, a company's financial or competitive decisions will be re-evaluated. Large-scale highway construction promotes market integration, which will encourage companies to compete with one another for market share. This will result in a transition in demand, causing companies to dynamically modify their inventories since inventories are strongly associated with expected demand.

However, given the data constraints, it is not possible to approximate a firm-level demand function and measure firms' idiosyncratic demand level as Foster et al. (2016). In the baseline specification, I use the logarithm of sales as a proxy for firms' demand, following Sangalli (2013). In the indirect channel discussion, apart from sales, another three alternative proxies will be used to measure firm-level demand, namely, sales growth, excess sales growth, and sales surprise dummy. While these proxies may have limitations, together they can reinforce the empirical evidence.

First, sales growth is often used in the literature to approximately represent demand (Sharpe, 1994; Ding et al., 2018). In Rumyantsev and Netessine (2007) and Shan and Zhu (2013), sales growth is applied to control the demand side factor when explaining firms' inventory dynamics. Sales growth, on the one hand, can capture the taste changes of buyers from the demand side (Ding et al., 2018). On the other hand, it may represent factors unrelated to demand, for example, firms' market expansions. When the highway comes, firms may be encouraged to expand their market catchment by adopting different sales strategies to connect markets not previously covered and to gain a larger market share. Thus sales growth is highly likely to be affected by highway proximity. This research, therefore, uses the sales growth in the indirect channel discussion to test whether sales growth would be a link that connects highway proximity and firm-level inventories.

Secondly, following Ding et al. (2018), I construct a variable of excess sales growth, which captures firms' relative market share. It is calculated as sales growth minus the mean value of four-digit industry-level sales growth in each year. Compared to firms with lower excess sales growth, firms with higher excess sales growth might experience a market expansion and have a larger relative market share in the given 4-digit industry. As argued by Ding et al. (2018), through this method, it is possible to partially out some factors affecting a firm's market share from the shocks on the demand side.

Third, a sales surprise dummy is constructed as another demand proxy. Sales surprise is defined as the ratio of sales to forecast sales, while the sales surprise dummy equals 1 if the sales surprise is larger than 1. As firms' forecast information is unavailable, following Rumyantsev and Netessine (2007) and Shan and Zhu (2013), it is simulated from the available data using extrapolation of sales shown as equation (4.2). Sales surprise is larger than 1 if the realized demand is higher than the forecast. Otherwise, it would be less than 1. The sales surprise dummy is used to account for a lower-than-anticipated inventory level in the event that the demand exceeds the forecast.

$$Lnsales_{i,t} = \gamma_0 + \gamma_1 Lnsales_{i,t-1} + \varepsilon_i + \varepsilon_t + \varepsilon_{i,t} \tag{4.2}$$

$$Sales\_surprise_{i,t} = \frac{Lnsales_{i,t}}{\widehat{Lnsales}_{i,t}} \tag{4.3}$$

It should be noted that the four proxies differ from each other. The logarithm of sales captures firms' demand, while sales growth refers to the total growth of demand. Excess sales growth captures a firm's relative market share, while sales surprise represents unexpected sales shocks. Those four dimensions enable us to empirically investigate the possible indirect channel of demand, although there are limitations on the measurement of firm-level demand.

4.6.1.2 Specification

To further test the possible mechanism of demand, the basic specification (4.1) is extended by including the interaction of highway proximity and the proxy of demand.

$$\begin{aligned} Inventory_{i,j,k,t} = \gamma_0 + \gamma_1 Highway_{i,t} + \gamma_2 Highway_{i,t} * Demand_{i,t} + \\ \gamma_3 Demand_{i,t} + \gamma_4{}' \ X_{i,t} + \gamma_5{}' \ Z_{k,t} + \theta_i + \theta_j + \ \theta_k + \theta_t + \theta_{i,j,k,t} \end{aligned} \tag{4.4}$$

Similar to the basic specification, $Inventory_{i,j,k,t}$ represents the logarithm of total inventory, input inventory and output inventory, respectively. $Highway_{i,t}$ represents highway proximity. $X_{i,t}$ is the vector of firm-level controls including firm size, firm age, leverage, and export ratio. $Z_{k,t}$ is the vector of provincial-level variables, including road congestion, other roads' density, river density and rail density. The specification also consists of firm-specific time-invariant effects (ε_i), industry-specific effects (ε_j), location-specific effects (ε_k), time-specific effects (ε_t), and an idiosyncratic error ($\varepsilon_{i,j,k,t}$).

The demand proxies include the logarithm of sales, sales growth, excess sales growth and sales surprise dummy, respectively. The total influence of highway proximity on inventories depends on both the γ_1 and $\gamma_2 Demand_{i,t}$. It is expected that γ_1 is negative, which means the highway would encourage firms to lower the inventory cost due to the reduction of transportation cost and lead time. If γ_2 is positive, then for firms with higher demand, the cost reduction effect of highways would be lower compared with firms with lower demand, while the total influence of demand on inventories depends on both the γ_3 and $\gamma_2 Highway_{i,t}$. It is expected that γ_3 would be positive to coincide with the theory that inventories are proportional to demand. If γ_2 is positive, then for firms facing a higher level of highway proximity, the total effect of demand on inventories would be larger.

4.6.2 Estimation result

Table 4.9 reports the IV estimation of the channel effect of four demand proxies on total inventories, using the instrument of LCP_NEN. It is noted that no matter which demand proxy is used, the coefficient of highway proximity is significant and negative, suggesting the direct cost-saving effect on total inventories. The coefficient of demand proxies is positive and significant in all cases, which is in line with the theory that a firm's inventory level is proportional to demand. In column (1) the interaction term of highway proximity and sales is significantly positive, indicating that the effect of sales on total inventories would be larger if firms face better highway accessibility. Similarly, the positive and significant coefficient of the interaction of highway proximity and sales surprise dummy means that the total effect of sales surprise on total inventories would be larger if the firm had better access to the highway infrastructure. However, the coefficients of sales growth interaction and excess sales growth interaction are insignificant, suggesting that changes in highway proximity would not affect the total influence of sales growth or excess sales growth on total inventories.

Table 4.10 is the estimation result of input inventories regarding the demand channel effect. Using sales, sales surprise dummy, sales growth and excess sales growth as the proxy of demand respectively, the coefficient of highway proximity in columns (1)-(4) is significant and negative, suggesting the robust cost-saving effect of highway proximity on input inventories. In addition, four demand proxies are positively correlated with input inventories at 1% or 5% significance level.

The positive sign of sales is in line with the theory and existing literature such as Lovell (1964), Shirley and Winston (2004), Rumyantsev and Netessine (2007), and Caglayan et al. (2012). Moreover, the interaction term of highway proximity and sales is positive, indicating that the effect of sales on input inventory level is larger for firms with improved highway proximity. In addition, the positive coefficient of the sales surprise dummy is consistent with Rumyantsev and Netessine (2007) that, on average, inventories increase when sales increase unpredictably. Similarly, the positive sign of interaction suggests that firms facing sales surprises will react more and positively adjust their input inventories if they have better highway accessibility.

Table 4.9: The channel effect of demand on total inventory

Instrument: LCP_NEN Dep. Var.: total inventory	(1)	(2)	(3)	(4)
Highway proximity	-0.968***	-0.113***	-0.103***	-0.103***
	(-9.19)	(-4.70)	(-3.92)	(-3.92)
Proximity*ln(sales)	0.090***			
	(8.48)			
Ln(sales)	0.228***			
	(38.14)			
Proximity*SSD		0.055***		
		(3.37)		
Sales surprise dummy (SSD)		0.138***		
		(15.05)		
Proximity*SG			-0.0001	
			(-0.62)	
Sales growth (SG)			0.0002***	
			(3.42)	
Proximity*ESG				-0.0001
				(-0.81)
Excess sales growth (ESG)				0.0002***
				(3.65)
Observations	1,732,900	1,732,900	1,287,712	1,287,712
R-squared	0.036	0.032	0.026	0.026
Under identification test	0.000***	0.000***	0.000***	0.000***
weak identification test	546.694	660.322	491.971	491.647
Control variables	YES	YES	YES	YES
Firm/Time/Industry/Province FE	YES	YES	YES	YES

Note: control variables include firm size, age, leverage, export ratio, sales, congestion, other road density, waterway density, and railway density. The critical value to pass the weak-identification test is 7.03.

The coefficients of sales growth and excess sales growth are significantly positive. In contrast to the empirical result of Rumyantsev and Netessine (2007) that inventories decrease on average with higher overall sales growth, this estimation suggests that firms react immediately by increasing inventories as demand increases. The coefficients of sales growth interaction and excess sales growth interaction, on the other hand, are insignificant, implying that shifts in highway proximity have little effect on the overall impact of sales growth or excess sales growth on input inventories.

Table 4.11 exhibits the estimated effect of the demand channel on final goods. In contrast to the empirical results of Table 4.9 and Table 4.10, the negative coefficient of highway proximity is only significant in column (1), when the interaction of highway proximity and sales is controlled. The coefficient of interaction in column (1)

Table 4.10: The channel effect of demand on input inventory

Instrument: LCP_NEN Dep. Var.: input inventory	(1)	(2)	(3)	(4)
Highway proximity	-0.894***	-0.130***	-0.112***	-0.113***
	(-5.75)	(-3.53)	(-2.66)	(-2.68)
Proximity*ln(sales)	0.081***			
	(5.06)			
Ln(sales)	0.203***			
	(22.93)			
Proximity*SSD		0.060**		
		(2.33)		
Sales surprise dummy (SSD)		0.102***		
		(7.09)		
Proximity*SG			-0.0000	
			(-0.27)	
Sales growth (SG)			0.0002***	
			(2.58)	
Proximity*ESG				-0.0000
				(-0.25)
Excess sales growth (ESG)				0.0002**
				(2.57)
Observations	1,732,900	1,732,900	1,287,712	1,287,712
R-squared	0.014	0.013	0.011	0.011
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	546.694	660.322	491.971	491.647
Control variables	YES	YES	YES	YES
Firm/Time/Industry/Province FE	YES	YES	YES	YES

Note: control variables include firm size, age, leverage, export ratio, sales, congestion, other road density, waterway density, and railway density. The critical value to pass the weak-identification test is 7.03.

is positive and significant. This documents that whether the total effect of highway proximity on final goods is positive or negative depends on the value of sales. Column (1) also indicates that highways can affect firms' level of final goods through the channel of sales. However, the coefficients of interaction term are insignificant in columns (2)-(4), suggesting that highway will not affect firms' final goods levels through the channel of sales surprise, sales growth and excess sales growth.

Overall, the estimation indicates that highways can affect firms' total inventories and input inventories indirectly through the channel of demand proxies (sales and sales surprise), while highways can only affect output inventories through the channel of sales. In sum, the improvement of highways not only has direct cost-saving effects on firms' input inventories and total inventories but also indirectly affects firms' input

Table 4.11: The channel effect of demand on output inventory

Instrument: LCP_NEN Dep. Var.: output inventory	(1)	(2)	(3)	(4)
Highway proximity	-0.656***	-0.020	-0.045	-0.046
	(-4.23)	(-0.54)	(-1.08)	(-1.09)
Proximity*ln(sales)	0.065***			
	(4.08)			
Ln(sales)	0.234***			
	(26.90)			
Proximity*SSD		-0.001		
		(-0.03)		
Sales surprise dummy (SSD)		0.175***		
		(12.39)		
Proximity*SG			-0.0001	
			(-0.96)	
Sales growth (SG)			0.0001	
			(1.41)	
Proximity*ESG				-0.0002
				(-1.08)
Excess sales growth (ESG)				0.0001
				(1.57)
Observations	1,732,900	1,732,900	1,287,712	1,287,712
R-squared	0.018	0.016	0.013	0.013
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	546.694	660.322	491.971	491.647
Control variables	YES	YES	YES	YES
Firm/Time/Industry/Province FE	YES	YES	YES	YES

Note: control variables include firm size, age, leverage, export ratio, sales, congestion, other road density, waterway density, and railway density. The critical value to pass the weak-identification test is 7.03.

inventories through the channel of demand. However, the finished goods are more connected with the level of sales or expected demand rather than the transportation cost. Thus, the impact of highway construction on finished goods is more subject to the channel of sales.

4.7 Further Mechanism Analysis

Firms may react differently in response to the improvement in highway accessibility, thus the argument that highway construction can affect firm-level inventory decisions can be extended to investigate heterogeneous patterns through different firms, industries and locations. This section presents a variety of additional estimation results, inspired by the testable implications of various mechanisms, including the heterogeneity effects of ownership, transportation reliance, supply chain position, supplier's location, inventory structure and spatial difference. Based on ownership, SOEs and private firms are sub-grouped. The highway reliance and supply chain position are calculated based on the Input-Output table of 1997, 2002, and 2007. The highway reliance, supply chain position, and inventory structure are all sub-grouped according to the medium value. Observations are also sub-grouped by whether the first two major suppliers' locations are located in other provinces or not at the 2-digit industry level. East and inland groups are divided by regional differences. As previous empirical results indicate that input inventories are more robustly affected by highway improvements through the channel of transportation cost and demand, the following heterogeneity tests are all on the basis of input inventories.

4.7.1 The ownership

In summary statistics, it is obvious that SOEs are quite different from private firms in many ways such as inventory management efficiency and financial health. SOEs are more likely to experience less efficient corporate governance and higher inventory ratios, as they have social and political objectives other than just profit maximization. In addition to a lack of motivation to optimize benefits in general, the loose inventory management of SOEs can also reflect its advantage in financial accessibility, as they are more likely to be favoured by state-owned banks (Ding et al., 2013; Hsieh and Klenow, 2009). Comparatively, facing higher capital costs and extreme budget restrictions, private firms are more reactive to alternative ways of reducing their inventory cost, as the active adjustment of inventory can be used as internal finance to smooth firms' fixed investment (Bo, 2004). In addition, in Li and Li (2013), the input inventory level of SOEs is unresponsive to the change in provincial road investment. In Cui and Li (2019), the effect of high-speed railways connection on SOEs' input inventories is statistically insignificant.

To uncover the possible difference, Table 4.12 compares the heterogeneous effect of highway proximity on input inventory between SOEs and private firms. The rela-

Table 4.12: Heterogeneity test by ownership

Dep. Var.: ln (input inventory)	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Panel A: SOEs				
Highway proximity	0.271***	0.530***	0.168	0.143
	(2.84)	(2.89)	(1.52)	(1.47)
Observations	154,763	154,763	154,763	154,763
R-squared	0.010	-0.022	0.016	0.018
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	374.965	130.349	226.441	331.775
Panel B: private firms				
Highway proximity	-0.181***	-0.653***	-0.276***	-0.109**
	(-3.84)	(-3.72)	(-4.16)	(-1.98)
Observations	1,075,124	1,075,124	1,075,124	1,075,124
R-squared	0.011	-0.043	0.005	0.013
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	796.753	72.614	402.836	573.768
Control variables	Y	Y	Y	Y
Company/Year/Industry/Province FE	Y	Y	Y	Y
Instruments				
Least cost path (2004NEN)	Y			
Least cost path (1992NTHS)		Y		
Ming courier routes			Y	
Straight line routes				Y
Empirical p-value	0.005***	0.000***	0.065*	0.145

Note: Control variables include sales, firm size, age, leverage, export ratio, congestion, other road density, river density, and rail density. The same control variables are applied to the rest of the regression tables unless specified otherwise. The empirical p-value is to test the significance of the difference in the coefficient of highway proximity between groups, which is obtained by 200 times bootstrap.

tionship between highway proximity and SOEs' input inventories is quite different compared with the private firms. In panel A, the results in columns (1) and (2) indicate that SOEs increase inventories in the face of highway improvement. While the coefficients of interest in columns (3) and (4) are insignificantly positive. In panel B, the estimated coefficient of highway proximity is significantly negative no matter which instrument is used. Column (1) indicates that a 0.1 increase in highway proximity, is associated with a 1.81% decrease in input inventory in private firms, but a 2.71% increase in input inventory in SOEs. The empirical p-value provides evidence regarding whether the difference in the coefficient of highway proximity between two ownership groups is significant. This is especially useful when the coefficients of interest in the two groups are both significant. The p-values in column (1) and column (2) indicate that the coefficient difference of highway proximity is significant at 1% significance level. The results indicate that private firms are more efficiently responsive to the changes in highway proximity, which is consistent with the estimation result of Li and Li (2013) and Cui and Li (2019).

4.7.2 Infrastructure reliance

Industries that rely more on transportation infrastructure may be affected more by highway improvement. The industry-level of transportation infrastructure reliance can be calculated as the share of the value of transportation infrastructure investment as an intermediate input in an industry to the total intermediate input value of that industry (Wang et al., 2020). The higher the transportation reliance, the more the industry uses transportation inputs in the production phase through total input-output linkages. It is then hypothesised that firms with high transportation infrastructure reliance would benefit more from the increase in highway proximity than those with low infrastructure reliance. The industry heterogeneity can be tested by sub-grouping low transportation reliance and high transportation reliance based on the medium value.

The National Bureau of Statistics provides the 42-sector Input-Output (I-O) Table (2-digit) every two or three years and a more detailed I-O Table (5-digit) every five years, such as the 124-sector I-O Table in 1997, 122-sector I-O Table in 2002, and 135 I-O Table in 2007. Each 5-digit I-O sector corresponds to one or more 3-digit Chinese Industry Classification (CIC) sectors. For example, in Table 17, I-O code 40084 stands for the 3-digit CIC code 404, while I-O code 41089 combines two 3-digit CIC codes (419 and 415). To calculate a more detailed infrastructure reliance, I calculate the 5-digit I-O sector's infrastructure reliance, i.e., the 3-digit CIC industry-specific ones. Specifically, this research uses the 1997's 124-sector I-O table to calculate transportation reliance for observations from 1998 to 2001, the 2002's 122-sector I-O table for observations from 2002 to 2004, and the 2007's 135-sector I-O table for samples from 2005 to 2007.

Table 4.13: The twenty lowest and highest infrastructure-reliant manufacturing industries

I-O sector code	I-O sector name	CIC industry code (3-digit)	infrastructure reliance
	10 lowest infrastructure reliance		
40084	Electronic computer	404	0.00887
33062	Nonferrous metal pressing	335	0.01456
37075	Ship building	375	0.01476
41079	Wire, cable, optical cable, and electrical equipment	393	0.01505
41089	Cultural and office equipment	419;415	0.01564
17026	Woolen textiles	172	0.01599
40087	Other electronic equipment	409	0.01670
40085	Electronic element and device	405;406	0.01739
13015	Slaughtering and meat processing	135	0.01760
17027	Hemp textiles	173;174	0.01768
	10 highest infrastructure reliance		
26045	Chemical products for daily use	267	0.04866
15023	Soft drinks and refined tea processing	153	0.05007
13014	Sugar manufacturing	134	0.05061
31052	Brick, stone, and other building materials	313	0.05408
31051	Cement and gypsum products	312	0.05779
31054	Pottery, china and earthenware	315	0.05990
31056	Graphite and other nonmetallic mineral products	319	0.06106
15022	Alcohol and drinking alcohol	151;152	0.06475
25038	Coking	252	0.07427
31055	Fireproof materials	316	0.08327

Using the calculations on the basis of 2007's 135-sector I-O Table as an example, among the 135 sectors, 81 I-O sectors belong to manufacturing industries. As shown in Table 4.13, only the twenty lowest and highest infrastructure-reliant manufacturing industries are reported, with the sector name and code, the corresponding 3-digit CIC industry codes, and the infrastructure reliance indicator. In the 81 manufacturing industries, electronic computers and nonferrous metal pressing are characterized by the lowest infrastructure reliance, while coking and fireproof materials have the highest infrastructure reliance.

The full sample is sub-grouped according to the medium value of transportation infrastructure reliance. Table 4.14 is the heterogeneous test of industry-specific infrastructure reliance. The robust results in panel A show that firms relying more on transportation infrastructure would greatly benefit from the highway improvement, while firms with low infrastructure reliance have no robust highway effect, as shown in panel B. In column (3), using the historical routes as an instrument, the significant coefficients of highway proximity suggest that for every 0.1 increase in highway proximity, firms with higher infrastructure reliance will lower their input inventory level by 2.36%, whereas firms with lower transportation reliance would reduce their input inventories by 1.89%, all other things being equal. The empirical p-value of 0.070 indicates that the difference in cost-saving effect between these two groups is significant. This is in line with the expectation that through the channel of transportation cost reduction, firms relying more on transportation would more actively adjust their inventory level, while firms relying less on transportation may have less motivation to adjust their inventory level.

Table 4.14: Heterogeneity test by infrastructure reliance

Dep. Var.: ln (input inventory)	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Panel A: high infrastructure reliance				
Highway proximity	-0.110**	-0.446***	-0.236***	-0.085*
	(-2.36)	(-2.72)	(-3.33)	(-1.70)
Observations	828,754	828,754	828,754	828,754
R-squared	0.011	-0.015	0.005	0.012
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	851.664	82.676	350.424	719.243
Panel B: low infrastructure reliance				
Highway proximity	-0.094	-0.152	-0.189**	-0.091
	(-1.48)	(-0.75)	(-2.10)	(-1.30)
Observations	841,080	841,080	841,080	841,080
R-squared	0.017	0.015	0.013	0.017
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	494.300	52.637	275.479	428.327
Control variables	Y	Y	Y	Y
Company/Year/Industry/Province FE	Y	Y	Y	Y
Instruments				
Least cost path (2004NEN)	Y			
Least cost path (1992NTHS)		Y		
Ming courier routes			Y	
Straight line routes				Y
Empirical p-value	0.130	0.015**	0.070*	0.270

4.7.3 Upstreamness

An industry's production line position is eventually regarded relative to households, governments, and investors (HGIs) (Miller and Temurshoev, 2017). Producers sell final output (goods or services) to HGIs. Some companies are closer to HGIs in the production supply chain because they sell a large portion of their output products directly to final customers, whereas others are further away because substantial portions of their outputs are heavily used as intermediate inputs by other firms. Antràs et al. (2012) developed an indicator called "upstreamness" of industries that quantifies this relative positioning (or say, the average distance from final use). According to the measure of upstreamness, industries are in a more upstream position if their output is more used by other producers as intermediate inputs (a higher upstreamness value), whereas industries with smaller average distances to final use are regarded as positioning in more downstream (less upstream).

Chor et al. (2021) use matched firm-level manufacturing survey data and customs data in the period from 1992 to 2014, together with the measurement of upstreamness following the methodology of Antràs et al. (2012) based on Input-output tables for China, to investigate how Chinese firms position themselves in global production lines and how this evolves over the firm's lifecycle. According to their research, there are two notable characteristics. On the one hand, Chinese imports are continually more upstream than exports, which signifies the tendency that China-based firms use imported inputs to produce goods and then export their final goods to foreign markets, in line with (but not entirely driven by) China's important role in processing trade. Secondly, the average upstreamness of China's exports declined slightly from 3.29 to 3.21 during the sample period, whereas Chinese imports grew noticeably more upstream, rising from 3.57 to 4.02. Chor et al. (2021) further argued that the latter rise was not simply driven by the rising imports in mineral commodities and agriculture, but also in manufacturing. They further considered only manufacturing industries and confirmed the similar characteristics of imports and exports.

Based on Chor et al. (2021)'s research, it would be interesting to test whether firms in different production line positions react differently. One possible hypothesis is that more downstream firms in China may purchase input inventories not only from domestic upstream firms but also from international companies, while more upstream firms are less likely to use imported inputs, given their original high production line position. In this case, when the highway comes, the cost-saving effects in downstream firms would be weaker compared with more upstream firms, as they rely not only on domestic highways but also on international transportation.

If the hypothesis is correct, then downstream firms are possibly indirectly affected by highways through the supply chain network. A firm's inventory level is positively correlated with the lead time, which depends on the supplier's production capacity and the transportation capacity (Bensoussan et al., 2010). If the firm's supplier is affected by the improvement in highways, resulting in better inventory management, this should somehow benefit the firm's inventory management. The changes in highway proximity would affect upstream firms' input inventories and then might affect the supplier production capacity relative to the downstream firms. Upstream firms with better highway accessibility are associated with shorter lead times and lower lead time uncertainties. Thus, it is easier to order inputs, maintain product availability and reduce the possibility of stock-outs, which is good for the relative downstream firms to order inputs from those upstream firms. In this case, the downstream firms may be affected by highways through the supply chain network.

To test this possible heterogeneous effect, this research calculated the 5-digit-I-O-industry-specific upstreamness on the basis of the detailed Input-Output Table in 1997, 2002 and 2007, following the methodology of Antràs et al. (2012). Similarly, this research uses the estimated upstreamness indicator calculated based on 1997's 124-sector I-O table for observations from 1998-2001, based on the 2002's 122-sector I-O table for observations from 2002 to 2004, and 2007's 135-sector I-O table for samples from 2005-2007.

Taking the upstreamness calculation on the basis of 2007's 135 I-O sectors as an example, the measure of upstreamness ranges from a minimum of 1 (Social welfare industry) to a maximum of 6.09075 (Non-ferrous metal ore mining industry), with a mean value of 3.16742. If considering only the 81 I-O manufacturing industries, the upstreamness ranges from a minimum of 1.24495 (Convenience food manufacturing) to a maximum of 5.50584 (Basic chemicals), with a mean value of 3.28159. Table

4.15 exhibits the twenty least and most upstreamness of Chinese manufacturing industries, where a higher value of upstreamness means a more upstream position. Convenience food manufacturing, other food manufacturing, and liquid milk and dairy products are among the most downstream industries, with most of their output going directly to the end-user. In contrast, basic chemicals and chemical fibres are the most upstream industries which are involved in processing raw materials.

Table 4.15: The twenty least and most upstreamness of China manufacturing industries

I-O sector code	I-O sector name	CIC industry code (3-digit)	upstreamness
	10 lowest upstreamness		
14018	Convenience food manufacturing	143	1.24495
14021	Other food manufacturing	141;142;145;149	1.51117
14019	Liquid milk and dairy products	144	1.57487
36072	Other special industrial equipment	363; 364;365; 366;368;369	1.79667
14020	Seasoning, fermentation products	146	1.84615
13017	Other food processing	137;139	1.96885
35066	Crane transportation equipment	353	1.97876
36071	Agriculture, forestry, animal husbandry and fishing machinery	367	1.98323
40086	Radio, television, and communication	407	1.99966
40082	Telecommunication equipment	401	2.00288
	10 highest upstreamness		
32060	Alloy iron smelting	324	4.78575
17029	Knitted and crocheted fabrics and articles	176	4.79766
17025	Cotton textiles	171	4.81375
32057	Iron-smelting	321	4.88227
26044	Special chemical products	266	5.02258
33061	Nonferrous metal smelting and alloy	331;332;333;334	5.03056
25038	Coking	252	5.18688
43091	Scrap and waste	430;431;432	5.19773
28047	Chemical fibers	280;281;282	5.31606
26039	Basic chemicals	261	5.50584

The full sample is sub-grouped according to the medium value of upstreamness. Table 4.16 is the heterogeneous test of upstream and downstream supply chains. The robust results in panel A show that the cost-saving effect of highways is more prominent for firms in an upstream position, while firms in a downstream position have a lower cost-saving effect, as shown in panel B. The empirical p-values of columns (1)-(4) all suggest that heterogeneity between upstream firms and downstream firms

Table 4.16: Heterogeneity test by supply chains

Dep. Var.: ln (input inventory)	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Panel A: upstream				
Highway proximity	-0.172***	-0.328*	-0.242***	-0.142**
	(-2.99)	(-1.94)	(-3.02)	(-2.32)
Observations	877,914	877,914	877,914	877,914
R-squared	0.012	0.000	0.007	0.013
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	620.270	79.828	345.133	542.993
Panel B: downstream				
Highway proximity	-0.107**	-0.133	-0.171**	-0.060
	(-2.18)	(-0.80)	(-2.36)	(-1.11)
Observations	811,962	811,962	811,962	811,962
R-squared	0.014	0.013	0.011	0.015
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	681.208	68.197	334.057	564.256
Control variables	Y	Y	Y	Y
Company/Year/Industry/Province FE	Y	Y	Y	Y
Instruments				
Least cost path (2004NEN)	Y			
Least cost path (1992NTHS)		Y		
Ming courier routes			Y	
Straight line routes				Y
Empirical p-value	0.045**	0.075*	0.045**	0.020**

is significant. This empirical result is in line with the hypothesis that upstream firms are more affected by the improvement of highways. However, the argument that downstream firms can be indirectly affected by the improvement of highways through the supply chain network is not significant based on the empirical result.

4.7.4 Supplier's location

Administrative monopolies in China generate severe local protectionism and trade barriers, resulting in regional market segmentation (Liu and Ye, 2019). Although China's economic reform has effectively encouraged international free trade, it has not reduced trade barriers or impediments between provinces. Prior to the late 1970s market economic reform, China had retained a closed and planned economy that prioritised planning autonomy and regional self-sufficiency (Poncet, 2005; Ke, 2015). Despite the market-oriented reforms leading to a growing involvement of the Chinese economy in the global economy, achievements in integration in the domestic market are less evident, and even researchers have continued to raise concerns about Chinese provinces having a large degree of market fragmentation, especially over the first 20 years of market-oriented reforms (Liu and Ye, 2019).

Table 4.17: Supplier distribution by 2-digit industry

Category	Industry	Percentage
Treatment group	Transportation equipment	87
	Fabricated metal products	67
	Electronic equipment	64
	Primary nonferrous metal products	57
	Industry machinery	51
	Communications equipment	40
	Construction materials	37
	Chemicals and allied products	31
	Coal products	26
	Stationary products	25
	Primary ferrous metal products	24
	Plastic and rubber products	20
	Pharmaceutical products	17
	Textile mill products	14
	Chemical fibers	9
Control group	Beverages	0
	Tobacco products	0
	Apparel and other finished products of fabrics	0
	Leather products	0
	Lumber and wood products (No Furniture)	0
	Furniture	0
	Papers & Allied Products	0
	Printing and publishing	0

Note: Treatment group includes industries whose major suppliers may locate in a different province. The control group includes industries whose major suppliers are in the same province. The percentage figure is the share of firms in a 2-digit industry whose major suppliers are in a different province. Source: Li and Li (2013), originally from CASS Survey of Enterprises (1994–1999).

Moreover, insufficient transportation infrastructure and poor geographic conditions also contribute to market fragmentation (Zhao and Ni, 2018). Under the presumption that declining trade costs foster both national growth and the diffusion of economic activity to peripheral regions, investments in transportation infrastructure have long been a prominent policy instrument for influencing the degree of regional

Table 4.18: Heterogeneity test by main supplier's location

Dep. Var.: ln (input inventory)	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Panel A: suppliers outside the province				
Highway proximity	-0.133***	-0.173	-0.231***	-0.078*
	(-3.39)	(-1.56)	(-4.00)	(-1.77)
Observations	1,431,164	1,431,164	1,431,164	1,431,164
R-squared	0.015	0.013	0.009	0.016
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	1138.233	162.199	557.233	896.566
Panel B: suppliers within the province				
Highway proximity	-0.002	-0.088	-0.201	-0.143
	(-0.03)	(-0.15)	(-1.40)	(-1.63)
Observations	296,135	296,135	296,135	296,135
R-squared	0.014	0.013	0.009	0.012
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	196.045	4.881	95.980	244.066
Control variables	Y	Y	Y	Y
Company/Year/Industry/Province FE	Y	Y	Y	Y
Instruments				
Least cost path (2004NEN)	Y			
Least cost path (1992NTHS)		Y		
Ming courier routes			Y	
Straight line routes				Y
Empirical p-value	0.345	0.290	0.150	0.055*

trade integration (Faber, 2014). Although existing evidence suggests that large-scale inter-regional highway infrastructure contributes to the concentration of economic activities in core areas rather than the diffusion to peripheral regions (e.g., Faber, 2014), the market integration with lower trade costs benefits firms, especially those whose suppliers are in another province. If a firm's major suppliers are in other provinces, then the transit of raw materials and intermediate goods should be cross-province. As the highway provides a higher transport speed, it is hypothesised that the time-saving and cost-saving effects would be more prominent for firms whose major suppliers may be located in a different province, which in turn may further promote within-country trade integration.

The Chinese Academy of Social Sciences (CASS) survey on manufacturing firms during the period of 1994 to 1999 is used to identify whether the main suppliers are in a different province at the 2-digit industry level. Although the CASS survey is not a large-scale investigation, it provides information on each firm's top two suppliers. According to the information on each firm's suppliers, it is possible to categorize industries based on their propensity to use non-local suppliers, as shown in Table 4.17. Following the information of Li and Li (2013) regarding suppliers' distribution, the full sample is divided into two sub-groups: group 1 with firms whose major suppliers may locate in a different province, and group 2 with firms whose major suppliers are in the same province. The subgroup IV regression is estimated, and the result of Table 4.18 shows that for firms whose major suppliers are likely to locate in other provinces, the inventory reduction caused by highway proximity is more significant which is consistent with the expectation.

4.7.5 Inventory structure

Given that input inventories are more affected by the improvement in highways, it is interesting to test whether the inventory cost-saving effect would be more prominent in firms with a greater share of input inventories. The inventory structure is calculated by the ratio of input inventories to output inventories, following the method of Shirley and Winston (2004). One related concept is "just-in-time"(JIT) manufacturing or "lean" manufacturing, which was widely implemented in Japan and North America from the late 1960s (Lieberman and Asaba, 1997) and 1980s (Gao, 2018), respectively. Lean manufacturing began in China in the automotive industry in the late 1970s, even earlier than it did in the United States and Europe. Some non-automotive companies in China have also adopted lean manufacturing principles in order to cut costs and waste and to maintain competitiveness (Taj, 2008). Rossiter Hofer et al. (2011) compare the existing state of adoption of lean manufacturing methods in China and the United States. Their results are based on a review of survey data from samples of Chinese and American industrial executives, and the findings indicate that the degree of lean production adoption in China is comparable to, if not greater than, that of the United States.

JIT inventory practises allow firms to minimise waste associated with overproduction, material waiting, and excess inventory in the manufacturing process and enable firms to better detect product quality during the manufacturing process. In compar-

Table 4.19: Heterogeneity test by inventory structure

Dep. Var.: ln (input inventory)	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Panel A: high input inventory ratio				
Highway proximity	-0.112***	-0.287***	-0.141***	-0.071***
	(-5.20)	(-3.34)	(-4.42)	(-3.15)
Observations	634,276	634,276	634,276	634,276
R-squared	0.094	-0.008	0.084	0.105
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	506.422	42.591	250.436	443.287
Panel B: low input inventory ratio				
Highway proximity	-0.074	-0.087	-0.023	0.056
	(-1.22)	(-0.42)	(-0.28)	(0.78)
Observations	625,043	625,043	625,043	625,043
R-squared	0.010	0.010	0.011	0.010
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	637.520	62.744	310.307	489.301
Control variables	Y	Y	Y	Y
Company/Year/Industry/Province FE	Y	Y	Y	Y
Instruments				
Least cost path (2004NEN)	Y			
Least cost path (1992NTHS)		Y		
Ming courier routes			Y	
Straight line routes				Y
Empirical p-value	0.170	0.030**	0.055*	0.040**

ison to systems that transfer batches into and through production in pre-determined amounts, orders are placed only when stocks are depleted under the JIT method. Firms that have implemented JIT should have lower input inventories than their less-diligent counterparts (Shirley and Winston, 2004). It is hypothesised that firms with a low share of input inventories would be less affected by the improvement of highway accessibility than firms with high input inventory shares. On the one hand, firms with lean input inventories may adopt the JIT inventory policy and already utilize their inventories to a minimizing level, thus the effect of highway improvement would be weak. On the other hand, firms with low inventory structures may have no motivation to adjust their input inventories as the absolute cost saving is low and less attractive.

In Table 4.19, panel A is the regression of the subgroup firms whose inventory structure is above the medium value, while panel B is the estimation of the subgroup with a lower level of input inventory share. It is the expectation that firms with a higher share of input inventory are more responsive to the increase in highway accessibility. If the majority of a firm's inventories are input inventory, then it is more attractive for the firm to negatively adjust its input inventory level as a result of the reduction in transportation costs. However, if the firm stocks more finished goods rather than raw materials or work-in-process, then it would be less attractive to adjust the input inventory, as it only accounts for a small proportion of its total inventories.

4.7.6 Coastal and inland regions

China's regional economies are categorized according to economic growth by the central government into eastern regions (or coastal areas), central regions, and western regions. Industrial economics in eastern regions developed earlier and more compared with the central and western areas (Liu et al., 2019b). Moreover, highways are more developed in the eastern area. According to the sample data, the mean value of highway proximity (firm-level) in the eastern area is 0.557, in contrast to 0.374 in inland areas (central regions and western regions). In addition, about 73% of firms are located in eastern areas, with higher agglomeration and higher highway improvement. Given the difference between coastal areas and inland areas, it is interesting to investigate whether the firms in inland areas behave differently from firms in coastal areas. It is expected that firms in coastal areas would benefit more from the cost savings of input inventory as the generally higher accessibility of highways provides a faster and more convenient transportation condition.

Table 4.20 is the result of considering the location difference. In line with the expectation, the estimation result indicates that firms in the more developed coastal area benefit more from the cost-saving effect. Although the coefficients of highway proximity in column (2) are insignificant for both groups, the empirical p-value suggests that the coefficient difference is significant. Moreover, it is believed that the LCP_NEN instrument is better than the LCP_NTHS, as the least cost paths on the basis of NEN plan have similar density compared with highways. In addition, the values of the weak identification test in both groups of column (1) are larger compared with column (2). Specifically, column (1) suggests that every 0.1 increase in highway accessibility would encourage coastal firms to reduce their input inventories by 1.5% on average, but it has no significant effect on inland firms.

Table 4.20: Heterogeneity test by spatial difference

Dep. Var.: ln (input inventory)	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Panel A: coastal areas				
Highway proximity	-0.150***	-0.361	-0.442***	-0.150***
	(-3.29)	(-1.36)	(-5.35)	(-2.91)
Observations	1,274,821	1,274,821	1,274,821	1,274,821
R-squared	0.014	-0.004	-0.015	0.014
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	677.964	22.689	242.421	527.383
Panel B: inland areas				
Highway proximity	-0.070	0.061	0.010	0.006
	(-1.25)	(0.62)	(0.14)	(0.10)
Observations	458,071	458,071	458,071	458,071
R-squared	0.017	0.017	0.018	0.018
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	827.955	403.104	606.533	885.606
Control variables	Y	Y	Y	Y
Company/Year/Industry/Province FE	Y	Y	Y	Y
Instruments				
Least cost path (2004NEN)	Y			
Least cost path (1992NTHS)		Y		
Ming courier routes			Y	
Straight line routes				Y
Empirical p-value	0.065*	0.015**	0.000***	0.005***

4.8 The implied savings of inventory

Following the methods of Shirley and Winston (2004) and Li and Li (2013), the implied savings of total inventory and input inventory are calculated on the basis of the IV regression result of Table 4.5 and Table 4.6. Using the least cost path generated on the basis of the NEN plan as the instrument, the coefficient between highway proximity and total inventory is -0.106, and the coefficient between highway proximity and input inventory is -0.121.

First, the implied inventory savings from the improvement of highway proximity can be estimated for each firm per year. As the dependent variable is the logarithm of input inventory, the percentage reduction of input inventory caused by the highway access can be calculated by multiplying the estimated coefficient of highway proximity and the change in firm-level highway proximity. Multiplying this percentage change of input inventory by the total stock of input inventory of a firm in the same year gives the firm-level input inventory saving. Similarly, the firm-level total inventory saving can be calculated. As shown in Table 4.21, the average firm-level saving rate of input inventory and total inventory is 0.455% and 0.399%, respectively. On average, in the period of 1998-2007, firms will annually benefit from the highway access by saving RMB 21.464 thousand in the input inventory and RMB 30.203 thousand in the total inventory.

Table 4.21: Implied savings of inventory

Variable	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming routes	(4) Straight line	(5) Observations
Firm level					
Annual changes in highway proximity	0.038	0.038	0.038	0.038	1,325,516
Annual saving rate of input inventory	0.455%	0.726%	0.877%	0.342%	1,325,516
Annual saving rate of total inventory	0.399%	1.513%	0.835%	0.320%	1,325,516
Annual input inventory saving	21.464	34.235	41.331	16.142	1,325,516
Annual total inventory saving	30.203	114.542	63.255	24.219	1,325,516
National level					
Annual saving rate of input inventory	0.486%	0.776%	0.937%	0.366%	9
Annual saving rate of total inventory	0.406%	1.540%	0.850%	0.326%	9
Input inventory saving/highway investment	2.079%	3.317%	4.004%	1.564%	1
Total inventory saving/highway investment	2.926%	11.097%	6.128%	2.346%	1
Adjusted national level					
Input inventory saving/highway investment	5.198%	8.293%	10.010%	3.910%	1
Total inventory saving/highway investment	6.730%	25.523%	14.094%	12.389%	1

Note: Table 4.21 reports the mean value of each variable. Columns (1)-(4) are calculated based on the estimation of Table 4.5 and Table 4.6.

Secondly, following Li and Li (2013), I sum up the input inventory saving across firms each year to obtain the national input inventory saving. Dividing this national input inventory saving by the gross input inventory of the same year gives the percentage of reduction nationwide, and it is necessary to repeat this method for the nationwide total inventory saving rate. The average annual reduction rate of input inventory is 0.486%, and the average annual reduction rate of total inventory is 0.406%.

Thirdly, the implied savings of input inventory and total inventory are calculated. According to the World Bank (2007), the average percentage of the road investment used in trunk highways was around 40% between 2000 and 2004. As the data on annual highway investment are unavailable, I calculate the proximate highway investment by multiplying the average share of highway investment, assumed as 40%, and the annual amount of road investment downloaded from the National Bureau of Statistics. Dividing the gross savings of inventory by the proximate national highway spending during the sample period suggests that each dollar of highway spending in China reduced the total inventory stock by around 2.926 cents and the input inventory stock by 2.079 cents, as shown in Table 4.21. The magnitude is similar to the result of Li and Li (2013), in which the input inventories decreased by 2 cents per dollar of road investment during 1998-2007.

However, the results are underestimated as the calculated national inventory saving only contains the manufacturing firms with annual sales above RMB 5 million. As argued in Shirley and Winston (2004), these estimates should be inflated to obtain national inventory cost savings. According to the data of inventories of the industrial firms (including firms in the manufacturing industry, mining industry, and electric, heating, gas and water industry) from the National Bureau of Statistics, the total inventory of the entire industry is approximately 2.3 times the total inventory of our sample data, and the input inventory of the entire industry is approximately 2.5 times the input inventory of the sample data. If the magnitudes of the inventory cost savings are adjusted, then it can be concluded that every dollar of highway spending in China reduced the total inventory stock by around 6.730 cents and the input inventory stock by 5.198 cents.

Repeating the same approach, I also apply the estimation results of columns (2)-(4) in Table 4.5 and Table 4.6 to estimate the implied savings of input inventory and total inventory, respectively. As shown in Table 4.21, column (2) is calculated based on the estimation result using the least cost path of the NTHS plan. Column (3) is estimated on the basis of the estimation with the historical instrument of Ming routes. Column (4) is the result according to the estimation of using the straight-line instrument.

At the firm level, the average annual saving rate of input inventory ranges from

0.342% to 0.877%, while the average annual saving rate of total inventory varies from 0.320% to 1.513%. Moreover, on average, in the period between 1998 and 2007, firms will annually benefit from the highway access by saving around 16.142-41.331 thousand RMB in the input inventory and around 24.219-114.542 thousand RMB in the total inventory. At the aggregate level, this exercise indicates that the improvement in highway proximity caused the input inventory level to decline by 0.366%-0.937% annually, and the total inventory level to decline by 0.326%-1.540% annually. At the adjusted national level, each dollar of highway spending in China during the period of 1998-2007 reduced the input inventory stock by about 3.910-10.010 cents and the total inventory stock by around 6.730-25.523 cents.

4.9 Additional Robustness Tests

4.9.1 Further control of the endogenous issue of targeted cities

It is possible to argue that the least cost paths and straight lines cannot fully address the endogenous issue as the targeted city points were endogenously chosen by government planners. To further control this issue, the observations located in the targeted cities of the NTHS plan are excluded. This is reasonable as the cities outlined in the NTHS plan are provincial capitals or big cities with more developed economies. Once observations in these targeted areas are dropped, the remaining firm observations all have access to highways by chance. It is worth mentioning that the principle is not on the basis of the targeted cities in the NEN plan, as the 323 targeted cities include not only large cities but also medium cities, which share 90% of the urban population and 96% of trade sales. Moreover, more than 90% of these firms are located in the NEN-targeted cities, which might encourage the problem of selection bias if the majority of the observations are excluded. Table 4.22 shows the IV regression result excluding observations located in the targeted NTHS cities. The coefficient of highway proximity is significantly negative no matter which instruments are used. Specifically, in column (1), the result indicates that a 0.1 increase in highway proximity is associated with a 1.9% reduction in firms' input inventories.

Table 4.22: Drop observations located in the targeted NTHS cities

Dep. Var.: ln (input inventory)	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Highway proximity	-0.190***	-0.239***	-0.224***	-0.081*
	(-3.79)	(-2.94)	(-4.30)	(-1.81)
Observations	615,546	615,546	615,546	615,546
R-squared	0.011	0.009	0.010	0.014
Company/Year/Industry/Province FE	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Instruments	First-stage results: highway proximity as dependent variable			
Least cost path (2004NEN)	-0.125***			
	(-25.60)			
Least cost path (1992NTHS)		-0.115***		
		(-13.08)		
Ming courier routes			-0.112***	
			(-19.51)	
Straight line routes				-0.120***
				(-27.62)
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	912.921	238.185	530.522	1062.932

4.9.2 Historical IVs

It is also possible to argue that the historical instrument of the Ming dynasty is not perfect as the Ming's courier routes did not reach seven provinces (Jilin, Heilongjiang, Hainan, Qinghai, Inner Mongolia, Tibet, and Xinjiang). It should also be highlighted that the Ming routes may not have a similar road density as the actual highways. To make sure these issues would not change the consistency of our main results, Table 4.23 shows the IV estimation of using the time-changing routes of the Qing dynasty and its combination with Ming's routes. In panel A of the full sample regression, the coefficients of highway proximity in columns (1)-(3) are all significantly negative, suggesting that the result is robust no matter whether using Ming's routes, Qing's routes, or their combination. The results are also robust if the observations located in these seven provinces are excluded in the IV regression, as shown in panel B. The weak identification and under-identification tests are all passed in columns (1)-(3). In column (3), since the estimation contains more instruments than endogenous variables, the Hanson J statistic is used for the overidentification test of all instruments. The p-value of panel A (0.218) and panel B (0.071) are larger than

Table 4.23: Additional IV result using different historical instruments

Dep. Var.: ln (input inventory)	(1) Ming	(2) Qing	(3) Ming&Qing
Panel A: full sample			
Highway proximity	-0.233***	-0.405**	-0.203***
	(-4.37)	(-2.35)	(-4.20)
Observations	1,732,900	1,732,900	1,732,900
R-squared	0.009	-0.008	0.011
Under identification test	0.000***	0.000***	0.000***
Weak identification test	660.331	96.418	337.580
Overidentification test	-	-	0.218
Panel B: drop 7 provinces			
Highway proximity	-0.249***	-0.516***	-0.204***
	(-4.62)	(-2.79)	(-4.20)
Observations	1,680,944	1,680,944	1,680,944
R-squared	0.007	-0.024	0.011
Under identification test	0.000***	0.000***	0.000***
Weak identification test	651.894	86.051	334.629
Overidentification test	-	-	0.071
Control variables	Y	Y	Y
Company/Year/Industry/Province FE	Y	Y	Y
Instruments			
Ming courier routes	Y		Y
Qing courier routes		Y	Y

Note: The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak-identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak-identification test is 16.38 in column (1)-(2) and 19.93 in column (3). The overidentification test reports the p-value of Hanson J statistic. The critical p-value to pass the overidentification test is more than 0.05.

the critical value, indicating that the combination of the two historical instruments is valid and exogenous.

4.9.3 Using different highway measures

To give additional robust evidence that firms will lower their input inventory level when they have better access to the highway, two other highway access measures are used. Table 4.24 shows the results of using the log of highway distance as a highway access variable. The smaller the log distance, the better the highway access. As hypothesised, the coefficient of the log distance is significantly positive, no matter which method and instrument are used, and whether observations located in the NTHS cities are excluded.

Table 4.24: Using the log distance as highway variable

Dep. Var.: ln (input inventory)	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Panel A: full sample				
Ln (highway distance)	0.021***	0.016*	0.034***	0.014**
	(3.36)	(1.74)	(4.43)	(2.32)
Observations	1,732,900	1,732,900	1,732,900	1,732,900
R-squared	0.017	0.017	0.017	0.017
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	5.5e+04	1.9e+04	3.4e+04	4.5e+04
Panel B: drop observations located in the targeted NTHS cities				
Ln (highway distance)	0.035***	0.055***	0.046***	0.015*
	(3.81)	(3.01)	(4.37)	(1.81)
Observations	615,546	615,546	615,546	615,546
R-squared	0.014	0.014	0.014	0.014
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	3.3e+04	5929.895	2.3e+04	3.5e+04
Control variables	Y	Y	Y	Y
Company/Year/Industry/Province FE	Y	Y	Y	Y
Instruments				
Least cost path (2004NEN)	Y			
Least cost path (1992NTHS)		Y		
Ming courier routes			Y	
Straight line routes				Y

Table 4.25 uses the relative highway proximity (RHP) as a highway variable. A higher RHP means better highway access. The results are also robust, indicating the inventory cost-saving effect of highway improvement.

4.9.4 Different buffer (5km)

The time-varying instrument routes are all calculated by interacting the 10 km buffer of actual highways with instrument routes. In this part, it is shown that the results are also robust by using different buffers (5km, for example) to compute time-varying

Table 4.25: Using the relative highway proximity as highway variable

Dep. Var.: ln (input inventory)	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Panel A: full sample				
RHP	-0.396***	-0.330*	-0.650***	-0.272**
	(-3.36)	(-1.74)	(-4.43)	(-2.32)
Observations	1,732,900	1,732,900	1,732,900	1,732,900
R-squared	0.017	0.017	0.016	0.017
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	2.1e+04	7592.971	1.5e+04	2.0e+04
Panel B: drop observations located in the targeted NTHS cities				
RHP	-0.720***	-1.120***	-0.872***	-0.289*
	(-3.81)	(-3.01)	(-4.37)	(-1.81)
Observations	615,546	615,546	615,546	615,546
R-squared	0.014	0.013	0.014	0.014
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	1.0e+04	2124.520	8936.221	1.4e+04
Control variables	Y	Y	Y	Y
Company/Year/Industry/Province FE	Y	Y	Y	Y
Instruments				
Least cost path (2004NEN)	Y			
Least cost path (1992NTHS)		Y		
Ming courier routes			Y	
Straight line routes				Y

IVs. Table 4.26 shows the robust results of using alternative highway accessibility measures.

Table 4.26: IVs calculated by 5km buffer & observations located in the NTHS targeted cities dropped

Dep. Var.: ln (input inventory)	(1) LCP_NEN	(2) LCP_NTHS	(3) Ming_routes	(4) Straight_line
Panel A: highway proximity as highway variable				
Highway proximity	-0.156***	-0.141**	-0.228***	-0.123***
	(-3.53)	(-2.09)	(-5.15)	(-3.20)
Observations	615,546	615,546	615,546	615,546
R-squared	0.012	0.012	0.009	0.013
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	1043.096	308.993	636.172	1272.641
Panel B: highway distance as highway variable				
Ln (highway distance)	0.032***	0.037**	0.053***	0.025***
	(3.54)	(2.11)	(5.25)	(3.22)
Observations	615,546	615,546	615,546	615,546
R-squared	0.014	0.014	0.014	0.014
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	4.2e+04	7796.665	2.8e+04	4.1e+04
Panel C: relative highway proximity as highway variable				
RHP	-0.637***	-0.748**	-0.983***	-0.491***
	(-3.54)	(-2.11)	(-5.25)	(-3.22)
Observations	615,546	615,546	615,546	615,546
R-squared	0.014	0.014	0.014	0.014
Under identification test	0.000***	0.000***	0.000***	0.000***
Weak identification test	1.2e+04	2523.466	1.0e+04	1.6e+04
Control variables	Y	Y	Y	Y
Company/Year/Industry/Province FE	Y	Y	Y	Y
Instruments				
Least cost path (2004NEN)	Y			
Least cost path (1992NTHS)		Y		
Ming courier routes			Y	
Straight line routes				Y

4.10 Conclusion

This research has investigated the causal effect of highway accessibility on firms' inventory decisions, using a geo-coded firm-level panel dataset for Chinese manufacturing firms in the period between 1998 to 2007 and GIS to calculate the highway distance and proximity that vary over time based on the highway network and firms' exact locations. To identify the causal relationship, two possible endogeneity issues are considered, namely, the endogenous construction of highways and the endogenous location of firms. To address the endogeneity issue of highway construction, four time-varying instruments are used to support the robustness of the causal relationship, on the basis of least-cost paths and straight lines constructed based on the targeted city points outlined in the highway construction planning, and historical routes of Ming and Qing dynasty. In addition, this research has considered the possible drawbacks of the instruments such as the possible endogenous issue of targeted cities, the coverage area and density of historical routes, and the robustness of using different buffer areas in the robustness test. Considering the possibility of firms' endogenous location choice, the endogeneity is further controlled by only including firms that existed since 1998 and never switched their locations during the sample period.

These estimates indicate a robust causal effect of highway proximity on the reduction in firm-level total inventories and input inventories. After controlling the demand proxy such as sales or sales surprise, the estimation result shows that better access to highways could encourage firms to lower their input inventories and total inventories. Moreover, this estimation indicates that highways can affect firms' total inventories, input inventories, and finished goods indirectly through the channel of demand proxies (sales and sales surprise). The positive effects of sales on firms' total/input/output inventories are larger for firms with improved highway proximity, and the total effect of sales surprise on total inventories and input inventories would be larger if the firm had better access to the highway infrastructure. However, the indirect channel effect is limited as highway proximity would not influence firms' inventory level through the channel of sales growth or excess sales growth.

In addition, the cost-saving effects on input inventories are heterogeneous: Private firms more efficiently respond to changes in highway proximity, while SOEs respond little to highway improvement. Firms with high infrastructure reliance would benefit more from the increase in highway proximity than those with low infrastructure reliance. Compared with downstream firms, enterprises in a relatively upstream position enjoy a higher direct cost-saving effect from better access to highways. The cost-saving effects are more prominent for firms whose major suppliers are more likely to locate in a different province. Firms with higher shares of input inventory are more responsive to the increase in highway accessibility, and firms in the more developed coastal area benefit more from the inventory cost-saving effect compared with those in the inland area.

Highway investment in China has indeed contributed to the decline of firm-level inventories. Specifically, from 1998 to 2007, an additional dollar of highway spending in China reduced, on average, the input inventory stock by about 3.910-10.010 cents and the total inventory stock by around 6.730-25.523 cents. The magnitude is higher than the result in Li and Li (2013) that the input inventories decreased by 2 cents per dollar of road investment during 1998-2007. This is reasonable as this research only considers highways, with the highest transport speed compared with other kinds of roads, rather than all kinds of roads. Moreover, this result should be more accurate as firm-level highway access measures enable us to control for the unobserved industry-time and region-time varying factors such as government policies, local labour market environment, and public services, and therefore our research is less likely to endure the criticism of omitted variable bias as the provincial road stock measures.

This research contributes to the literature in estimating the causal effect of transportation infrastructure on the economy by providing empirical evidence that highways affect firms' inventory decisions. This study implies that the rapid development in highway infrastructure conducted by China's government indeed benefits individual firms and thus facilitates the development of China's economy.

This research also relates to the literature on inter-regional trade integration. The improvement of highway proximity encourages firms to expand or compete in the market catchment area by connecting the markets not previously covered, which leads to a larger market size and a more efficient business environment. Moreover, market integration with lower trade costs also benefits firms, especially those whose suppliers are in another province. Therefore, this research also provides evidence related to the argument that highway infrastructure stimulates the economy by promoting trade integration.

Despite the support for highway development, there are some policy implications as well. First, SOEs are less efficient compared with private firms, which thus suggests the importance of further market reform and source reallocation to the private sector, in order to benefit more from the construction of highway infrastructure. Second, in coastal areas, firms benefit more from the cost-saving effect as the generally higher accessibility of highways provides a faster and more convenient transportation condition, whereas a significant cost-saving effect in the inland area is not observed. This might suggest a direction of further developing highway accessibility in the inland area. Thirdly, infrastructure development is essential to reducing market segmentation and eliminating local protectionism in order to achieve a unified national market.

Chapter 5

The Effect of Highway Accessibility on Corporate Investment in China

5.1 Introduction

The economic impact of government investment has long been a focus of attention in fiscal policy debates. A central question in the debate over public investment is whether it crowds out or crowds in private investment. The theoretical literature suggests that there are two countervailing effects between public and private investment. On the one hand, government investment can squeeze private investment by decreasing the availability of funds to private firms, increasing the cost of borrowing from banks and, thus, impeding the private sector from investing (Aschauer, 1989a). On the other hand, public investment, especially infrastructure investment, allows firms to have broader access to their potential markets (Cavallo and Daude, 2011), a reduction in firms' cost of production (Akkina and Celebi, 2002) and the adjustment cost associated with investment (Turnovsky, 1996; Ott and Soretz, 2006), and an increase on the marginal productivity of capital (Aschauer, 1989a), which crowds in private investment. Existing empirical literature has provided mixed evidence, either supporting the overall crowding-in effect (Pereira and Andraz, 2012a; Pereira and Sagales, 1999; Saidi and Hammami, 2017; Aiello et al., 2012) or crowding-out effect (Wang, 2005; Mitra, 2006; Dash, 2016).

Despite extensive research on the relationship between public and private investment, most studies are based on aggregate data which ignores various components of public spending and heterogeneous channels. The limited firm-level studies, for instance, Aiello et al. (2012) for Italy, and Ru (2018) and Huang et al. (2020) for China, consider the aggregate infrastructure or government credit rather than the specific transportation infrastructure. Moreover, the current research on the link between transportation proximity and investment focuses mainly on the airline networks in the US (Giroud, 2013; Bernstein et al., 2016) or high-speed railways in China (Lin et al., 2019a; Duan et al., 2020). Thus, this research fills in the gap in the literature by examining the impact of highway accessibility on corporate investment using a comprehensive dataset of more than 360,000 manufacturing firms over the period from 1998 to 2007.

This focus on highway infrastructure can be justified in two ways. First, road infrastructure in general, and highway infrastructure in particular, plays an important role in freight transport in China. During 1998-2007, about 75% of freight was transported by roads, whereas high-speed railways and airlines mainly transfer people. When compared with other types of roads, highways with travel speeds up to 100-120 km/hour serve as an ideal option for firms engaging in cross-city/province business because of the time- and cost-saving effects. Thus, highways are expected to have a direct and significant impact on the investment of manufacturing firms. Secondly, highways experienced a rapid expansion in China over the sample period. Following the two major highway infrastructure projects by the Chinese Government, that is, the National Trunk Highway System project in 1992 and the National Expressway Network project in 2004, the length of highways expanded from 8,700 kilometres in 1998 to 53,900 kilometres in 2007 in China. By contrast, the development of high-speed railways and airline networks mainly began after 2008, which is thus less relevant in understanding the investment decisions of manufacturing firms over the sample period.

This research contributes in three ways. First, instead of using regional infrastructure investment as a proxy for public investment (see, for instance, Aiello et al., 2012), three firm-level highway accessibility measures are constructed based on the geo-coded firms' location and highway network, including the absolute highway proximity, the distance to the nearest highway and the relative highway proximity. These disaggregate and novel measures enable us to control for the unobserved industry-time and region-time varying factors such as the government policies, local labour market environment and public services, thus alleviating potential omitted variable bias associated with the regional-level measures.

Second, there are at least two types of endogeneity concerns in the analysis. Firstly, highway construction is endogenous, that is, the distribution of highways is not random. Governments develop highways to link large cities where firms have high investments. Secondly, the location of firms can be endogenous. New firms may choose to locate close to highways in order to benefit from the cost-saving effect of highway infrastructure. Existing firms may relocate their location by moving closer to highways (Holl, 2016). In order to control for the first type of endogeneity, this research constructs a number of time-varying instruments, namely, the least cost paths and straight lines constructed based on the targeted city points outlined in the national highway construction projects, and historical instruments based on the Ming dynasty' courier routes and the Qing dynasty's historical routes. To deal with the second type of endogeneity, this research excludes both new firms that opened during the sample period and relocating firms that switched their locations during the sample period. The results based on the two-stage least square estimation confirm the causal effect of highway accessibility in enhancing firm investment in China, thus supporting the crowd-in effect of public investment on private investment.

Third, for the first time in the literature, this chapter explores the possible mechanisms through which highways affect corporate investment from the perspective of corporate finance. Firstly, highway proximity stimulates corporate investment by reducing firms' financial constraints. Better highway accessibility reduces the potential difficulties associated with long-distance investment deals as it alleviates information asymmetries, improves the accessibility and quality of mediated information, and facilitates more efficient identification of investment opportunities (Bernstein et al., 2016; Duan et al., 2020). Thus, firms have opportunities to secure external finance from not only nearby banks or financial institutions but also from far-off-distant ones. Secondly, better highway accessibility can reduce firms' inventory stock, thus releasing additional funds for fixed investment. Inventory can be served as an additional financial supply of fixed asset investment (Fazzari and Petersen, 1993). The lower average inventory stock caused by highway improvement frees up additional cash flow, which ultimately stimulates the investment of fixed assets. Thirdly, highway accessibility increases corporate investment by mitigating uncertainties. Improved highway network offers flexible supply chains and facilitates market integration, which significantly reduces the uncertainties faced by firms from both the demand and supply sides, thus encouraging investment.

In addition, it is found that better highway infrastructure not only stimulates the quantity of corporate investment but also improves the quality of investment by allocating more investment to firms with higher marginal returns of capital.

The remainder of this chapter is structured as follows. Section 2 presents a literature review on the nexus between public and private investment as well as corporate investment. Section 3 illustrates the empirical specification and identification problem. Section 4 reports summary statistics and empirical results of baseline models.

Section 5 explores three mechanisms through which highway proximity stimulates corporate investment and Section 6 provides evidence regarding whether highway infrastructure improves the quality of investment. Section 7 provides extensive robustness checks. Section 8 concludes the chapter.

5.2 Literature Review

5.2.1 Review of public investment and private investment

5.2.1.1 Theories

The relationship between government spending and private investment has long been a focus of attention in fiscal policy debates, although much research has contributed useful insights into the matter. Aschauer (1989a) argues that there are two countervailing effects, the crowding-out effect and crowding-in effect, between public investment and private investment along neo-classical lines. On the one hand, higher governmental capital accumulation increases the national investment rate above the level selected by rational agents. As individuals strive to restore an optimal intertemporal resource allocation, the public capital investment may therefore crowd out private capital accumulation on an ex-ante basis. On the other hand, public investment, especially infrastructure investment, such as highways, railways, and airports, allows firms to have broader access to their potential markets (Cavallo and Daude, 2011) and a reduction in firms' cost of production (Akkina and Celebi, 2002), which is expected to increase the marginal productivity of private capital (Aschauer, 1989a). In this case, an increase in the marginal productivity of private capital crowds in private investment because individuals respond by deferring consumption, increasing saving, and, in equilibrium, boosting capital accumulation to greater marginal returns on future production. Therefore, the overall effect is ambiguous which depends on the comparative strength between these two opposing effects.

It has been reasoned that government investment may crowd out private investment either by ex-post or ex-ante. Within the demand-orientated Keynesian model, government spending supported by borrowing decreases the number of loanable funds available for private investment, increasing real interest rates and then bringing an ex-post crowding out effect on private capital investment (Mitra, 2006). However, in the Keynesian type models, the private investment may not have to be crowded out by government expenditure as output might increase to make available for higher levels of private investment and public spending (Aschauer, 1989a). The possibility of an ex-ante crowding out effect of government expenditure is emphasized in David and Scadding (1974). Typically, it is argued that households autonomously perceive government bond issues as public investment and treat investment initiatives in the public and private sectors interchangeably. Thus bond-financed government expenditure is hypothesized to squeeze private capital accumulation. In contrast, an increase in tax-financed government expenditure crowds out an equivalent amount of private consumption since tax-financing is regarded as public consumption. As a result, fiscal policy is thought to have little impact on aggregate demand.

Since Barro (1990), government expenditure has been introduced in the production function as an input to reveal its theoretical influence on the economy's productive potential in the endogenous growth context (Ott and Soretz, 2006; Turnovsky, 1996, 1999). Without considering the congestion effect of public capital and the adjustment cost of capital investment, it has been argued that productive government expenditure on infrastructure services can have a direct influence on the production conditions and can increase the productivity of private capital (Barro, 1990; Futagami et al., 1993). Barro (1990) incorporates tax-financed public services into a traditional endogenous-growth AK model with the assumption of constant return to capital. In this theoretical framework, growth and saving rates increase initially with productive infrastructure services but subsequently decrease, suggesting a threshold effect. While the two rates fall with a rise in government consumption, as a greater government consumption spending share has no direct influence on private sector productivity, this does result in a higher income tax rate. Individuals then have less motivation to invest since they keep a lesser portion of their investment returns, and the economy grows at a slower rate.

Fisher and Turnovsky (1998) argue that it is the accumulated stock of productive government investment such as education and roads that contributes to productive capacity rather than the current flow as in Barro (1990). The theoretical framework developed by Fisher and Turnovsky (1998) investigates the effect of the stock of public capital on private capital accumulation with the incorporation of congestion which is naturally linked to public capital. It is highlighted that there is an important trade-off in evaluating the influence of public investment on private capital investment between the substitutability of public and private capital in production and the degree of congestion. In the long run, the crowd-in effect will dominate in the absence of congestion. Larger public capital stock will enhance the level of public services, thereby raising the marginal productivity of private capital and stimulating long-run private capital accumulation. However, when it comes to public capital that is subjected to proportional congestion, such as road infrastructure, the crowding-in effect will prevail if and only if the elasticity of substitution of public and private capital in production outweighs the portion of output attributable to labour. In the short run, the initial response of private investment to an expansion in public capital is ambiguous and is dependent on two balancing effects. First, to the degree that public capital leads to long-run accumulation of private capital, private investment is boosted in the short term, albeit the fact that public capital grows slowly initially weakens this beneficial influence on private investment. Second, a higher rate of return on public capital tends to reduce private investment in the short term because it increases wealth, causing the private sector to substitute consumption for savings and capital accumulation. As the positive output benefits of the government capital stock start functioning over time, the expansion effect will prevail, and public investment will enhance private capital stocks.

Although some models presume that output can be transferred into private capital without incurring further adjustment costs, the literature on investment theories such as the Tobin q theory, Euler Equation model, and Direct Forecasting models, focus on the adjustment costs (Chirinko, 1993). Adjustment cost is a necessary consideration when considering fixed investment, as in the real world, private investment is always lumpy (Bachmann and Ma, 2016). Firms make adjustments if the difference between the expected value and cost of adjustment under optimally adjusted capital stock is larger than the difference under the unadjusted capital stock. The one-sector endogenous growth model developed by Turnovsky (1996), with an application of Hayashi (1982)'s convex adjustment cost framework incurred by capital investment, is the first to investigate how the ability of government expenditure to influence adjustment costs has a significant impact on fiscal policy's overall effectiveness. This paper argues that aside from enhancing the productivity of private capital, the second role of public expenditure is to reduce the adjustment costs associated with fixed investment and thus accelerate the accumulation of new capital.

Following Turnovsky (1996), Ott and Soretz (2006) investigate how a firm decides on fixed-asset investment within a dynamic model where the associated adjustment costs are a function of the firm's investment and governmental expenditure on infrastructure. The public infrastructure has a two-fold effect on the model's dynamics: as a complementary input in the production process, it boosts private capital productivity and results in a production effect on the growth rate. In addition, the amount of available public infrastructure reduces adjustment costs, thus imposing an adjustment cost effect. Using comparative dynamics, this shows that a stronger regional infrastructure endowment unambiguously stimulates capital investment through two channels: production effect and adjustment costs effect. They further consider the congestion effects of infrastructure which in contrast have an ambiguous effect: reducing congestion decreases adjustment costs, which encourages private capital growth. However, because of increased individual availability, the marginal productivity of public spending rises, resulting in a crowding out of private investment. It is argued that the extent of both is determined by the degree of congestion.

Aiello et al. (2012) extend the standard q model to analyse firms' fixed investment behaviour to regional infrastructure expenditure, including transportation, communication, hydraulic and electric infrastructure. Combining theoretical framework with the firm-level empirical examination in Italy, Aiello et al. (2012) argue that investment in regional infrastructure affects private investment positively through two channels—adjustment costs and the component of profit (through cost and revenues). The adjustment cost in Aiello et al. (2012) is assumed to be a quadratic function of investment and infrastructure, following Turnovsky (1996) and Ott and Soretz (2006). It is concluded that public infrastructure investment stimulates firms' fixed investment by reducing their adjustment costs. One example is that the improved infrastructure, such as transportation and communication, allows firms to lower the diseconomies of scale associated with the instalment of new capital goods, which in turn affects firms' value and investment. In addition to the adjustment cost channel, the authors also demonstrate that regional infrastructure interacts with costs and revenues in shaping a firm's capital profitability. It can be argued that, given a perfectly competitive market, if the transport costs are reduced because of the improvement in transportation infrastructure, both the price of final goods and intermediate goods should decrease, resulting in changes in firms' current and expected variable costs and revenues. Then the changes in firm value and firm investment will occur accordingly. In this channel, firms' investment may be stimulated (impeded) due to an increase (decrease) in profits caused by the relative changes in costs and revenues.

5.2.1.2 Empirical evidence

In response to the theoretical arguments, the existing empirical literature has extensively investigated the linkage between public investment and private investment. For instance, looking at 39 developed and developing countries from 1975 to 1984, Hamed and Miller (2000) find that government investment in transport and communication crowds in private investment only for developing countries, while public expenditure on social security and welfare squeezes private investment in both developed and developing countries. On a similar theme, Erden and Holcombe (2005), using a panel of nineteen developing countries and twelve developed countries, concludes that public investment has a beneficial influence on private investment only in developing economies but not in industrial countries. In contrast, using the system GMM approach with a panel of 116 developing countries over the period from 1980 to 2006, Cavallo and Daude (2011) claim that the crowding-out effect dominates on average. Moreover, the authors demonstrate that better institutions and access to international trade and financial flows can break up this negative connection by either increasing private capital's marginal productivity or alleviating financial constraints.

For country-specific investigation, existing empirical studies also offer inconsistent findings, with a large proportion of studies showing that government investment promotes private investment and others claiming that government investment squeezes private investment.

Using data from the United States, the extent to which the behaviour of output, productivity, and private investment can be explained by government capital accumulation and consumption from the neoclassical perspective has been extensively investigated. In the research of Aschauer (1990), it is empirically observed that public investment in infrastructure such as transportation, electrical and gas facilities, etc., has a considerably larger effect on output than does public consumption or military investment. Aschauer (1990) interprets this by emphasizing the expansionary effect of public non-military capital accumulation on private capital investment by enhancing the marginal productivity of private capital. Focusing on the period from 1949 to 1985, Aschauer (1989b) explores the impact of government expenditure on aggregate productivity by discriminating between government consumption and public sector capital accumulation. Estimates indicate a strong positive association between nonmilitary public capital stock and productivity, while military capital and government consumption have little impact on productivity. Moreover, the author offers supporting evidence by distinguishing between nonmilitary infrastructures and equipment. It is claimed that a core infrastructure of highways, airports, and water systems, for example, is of primary importance to productivity.

Aschauer (1989a) estimates the impact of government expenditure in the US on domestic private investment and the rate of return to private capital over the sample period of 1953 to 1986. Similarly, this paper distinguishes between public consumption, public military investment and nonmilitary public investment. The empirical findings are strikingly consistent with the predictions of the neoclassical theories of fiscal policy analysis. Controlling for the separate influence of public capital on the return to private capital, an increase in non-military public capital accumulation results in a dollar-for-dollar reduction in private capital stock, showing a complete crowding-out effect. Evidence also shows that the nonmilitary public capital stock has a significant positive effect in affecting the rate of return on private capital, which in turn crowds in private capital investment. In addition, public consumption and public military capital have no quantitative or statistical significance in explaining private investment and the rate of return on private capital. Finally, the empirical findings indicate that the net effect of public investment is negligible since the negative effect is compensated over time by the positive influence of the return on capital.

Although Aschauer's work contributes much by emphasising the importance of public investment and incorporating public capital into the traditional production function, Munnell (1992) questions his work regarding the estimation of using aggregate time series and the interpretation of the results. Munnell (1992) further estimates the effect of public capital at the state level and finds that public capital has positive effects on state-level economic performance, including output, investment, and employment growth, while the magnitudes are noticeably smaller than those discovered at the national level. In particular, the two opposing forces of public investment on private investment, as discussed in Aschauer (1989a), are confirmed, although public investment encourages private investment on balance.

Employing a VAR approach, Pereira (2000) analyses the influence of different types of non-military government investment on the private sector's performance in the United States over the period from 1956 to 1997. They find evidence that aggregate public capital accumulation contributes to the performance of the private sector, including output, investment, and employment. Moreover, shocks to various forms of government investment all have positive effects on output and private investment. Specifically, although the improvement of highways and streets squeezes out private employment, output, and private investment respond positively to public investment in highways and streets with an elasticity of 0.0055 and 0.0115, respectively.

Pereira and Andraz (2012a) investigates the aggregate effects of highway investment on the gross private investment, employment, and output, respectively, in the case of the US during the period from 1977 to 1999. Based on VAR estimates, the empirical results indicate significant positive relationships between highway improvement and investment, employment, and output respectively at both the state and aggregate levels. Specifically, the elasticities of private investment, employment, and output with respect to highway investment are 0.130, 0.126, and 0.158, respectively. Pereira and Andraz (2012a) also consider both the direct impacts of highway improvement in the state itself and the indirect spillover influences of highway improvement in other states based on the same dataset and methodology. According to the empirical findings, the largest states are likely to be the greatest beneficiaries of highway investments, suggesting that highway investment contributed not only to regional concentration of economic activity but also to regional asymmetries in the US.

In the case of Spain, Pereira and Sagales (1999) conclude that public capital in transportation has been a powerful instrument for the promotion of private-sector performance at both aggregate and regional levels for 1970-1989. According to the empirical findings of VAR estimation, the marginal product of private investment relative to public investment is 10.2, and one million euros in transportation-related investment generates 129 jobs in the long run. In addition, regions that gained the most from public investment are among the most populous in the country and have the highest GDP per capita. It is therefore argued that, while public investment is vital for overall economic growth, it is also a cause of growing regional disparities.

In the Portuguese context, Pereira and Andraz (2005) also justify the long-run effects of public investment in transportation infrastructure for the period from 1976 to 1998 both from a long-run development point of view and a long-term public budgetary standpoint. They find that similar to the result of Pereira (2000), public investment in transportation bears significant and positive effects on private investment, employment, and output in the long run. Considering different types of transportation infrastructure, they conclude that all types of public investment enhance the performance of the private sector. With regard to marginal products, government investment in ports, airports, and national roads bears the highest effect on private investment. Public investment in ports, municipal roads, and national roads shows the largest effects on employment. With regard to the effect on output, the dominant effect comes from the development of ports, followed by national roads, municipal roads, airports, and railroads. Specifically, they argue that the magnitudes of the marginal effects of transportation improvement on private investment for Portugal are much larger than the estimates of Pereira (2000) in the US case and Pereira and Sagales (1999) in the case of Spain.

With regard to Pakistan, Saeed et al. (2006) study the impact of public capital on private capital by distinguishing between different sectors (agriculture and manufacturing) and confirm the existence of the crowding-in effect in the agriculture sector and the crowding-out effect in the manufacturing sector.

In the Tunisian economy from 1975 to 2014, Saidi and Hammami (2017) indicate that both physical infrastructure (e.g., transportation and communications) and social infrastructure (e.g., education and health) are conducive to private investment.

Shankar and Trivedi (2021) apply the Autoregressive Distributed Lag (ARDL) cointegration estimation method to evaluate the long-run and short-run relationship between government investment and private investment in India. Their empirical results reveal that, from 1981 to 2019, public investment and private capital investment are complementary both in the short run, and the long run, at the aggregate level. Furthermore, in the long run, public capital accumulation crowds in private investment both at the sectoral (non-infrastructure, infrastructure, and service sectors) and industrial level, while government investment in the industries of financial service and construction squeezes private investment in the short run.

There are also studies which balance the scale with contrasting findings. For instance, Wang (2005) focuses on the effects of different types of public expenditure on private capital accumulation in Canada using annual data which covers the period from 1961 to 2000. The empirical result shows that public expenditure on health and education crowds in private investment whereas government investment in infrastructure and capital bears a crowding-out effect on private capital accumulation.

Mitra (2006) applies a structural vector autoregression (SVAR) model to Indian government investment, private investment, and gross domestic product, over a sample period between 1969 and 2005. Although there is no evidence of a significant and positive correlation between government investment and GDP, a significant short-run crowding-out effect of government investment on private investment is uncovered. Specifically, a 1% increase in government investment is accompanied by a 0.738% reduction in private investment. However, in the medium to long run, the crowding-out effect is not present based on the impulse response function of private investment. The author argues that it is in line with the theoretical argument that public investment such as in infrastructure may enhance the marginal productivity of private capital and, thus, complement private investment.

Mallick (2019) also employs the SVAR method to evaluate the impact of increasing government investment in infrastructure and non-infrastructure between 1960 and 2018 and concludes with a crowding-out effect on private investment in the short run. Moreover, the results supplemented by using quarterly data of aggregated governmental investment from 1996-2018 confirm a negative relationship between public and private investment for a few quarters, although the relationship turns positive afterwards. According to this research, the major reason for this is that more public investment leads to increased government spending, which causes the fiscal deficit to grow. In the Indian economy, the budget deficit is mostly funded by domestic borrowing from the private sector. As a result, the availability of capital for private investors is reduced. In contrast, Dash (2016) finds that India's public investment crowded out private investment no matter in the short run or long run. However, public road infrastructure investment crowds in private investment in the short run.

The utilization of data at the country, regional, or industry level is a feature shared by all that research. As a rule, empirical results are much more likely to be mixed as it is hard to disentangle the impacts of different components of public spending at the aggregate level, as well as the channels by which they act. Aiello et al. (2012) argue that, due to the heterogeneity of firms, a study based on microdata would provide more accurate information about the microeconomic relationship between infrastructure provision and the nature of the production process, and limit bias from data aggregation. The authors apply the GMM method to test the link between regional infrastructure and firm investment using a panel of Italian manufacturing firms from 1995 to 2000. Consistent with the theory, the empirical findings indicate that core infrastructure stimulates firms' investment both by increasing the firm's marginal profitability of capital and by decreasing adjustment costs. Moreover, these impacts vary by sector and area. Regional infrastructure boosts private investment in Italy as a whole, but the benefit is larger in the South than in the Centre-North. Infrastructure spending, from this vantage point, helps to close the economic gap between Italian regions. In addition, the effect acts mostly via firm revenues and costs in the North, and primarily through adjustment costs in the South. Finally, they document that certain industries gain more than others from infrastructure investment.

5.2.1.3 China-specific evidence

In terms of China-specific literature, Xu and Yan (2014) investigate the impact of government investment from 1980 to 2011 on private investment using the SVAR method. According to the findings, government investment in public goods considerably stimulates private investment, whereas public investment in private goods, mostly by SOEs, squeezes private investment.

In a more detailed perspective, Ru (2018) explores the impacts of government credit on firms' activities between 1998 and 2013 based on the province-industry-level loan data from China Development Bank (CDB) and Chinese Industry Census (CIC) data. Countervailing effects have been observed in the theoretical literature related to government credit. In one respect, government credit that supports infrastructure projects with high social returns can have positive spillover effects (Stiglitz, 1993). Government credit might, in contrast, squeeze more productive private investments (King and Levine, 1993b,a). Ru (2018) in his research examines how government credit operates at different levels of the supply chain to identify countervailing channels. Moreover, as the largest policy bank in China, the CDB lends primarily to SOEs in strategic industries and to local governments to develop infrastructure, which allows the author to separate the SOE loans and infrastructure loans. Using the interactions of dummies representing the predetermined focal industry in each city and its predicted turnover cycle as instruments for province-industry loan amounts, the author applies the two-stage least squares (2SLS) method and suggests two main findings. First, CDB lending to SOEs crowds out private firms in the same industry as is demonstrated by decreases in asset investment, employment, and sales, but it crowds in private firms in downstream industries. Private companies in downstream industries that are more efficient can benefit substantially more from CDB loans to upstream SOEs. Second, CDB loans to local governments' infrastructure projects can stimulate private-sector activities.

More recently, Huang et al. (2020) investigate the crowding-out effect of local public debt on private investment in the period between 2006 and 2013 by highlighting the channel that local public debt tightens funding constraints on private firms. They argue that the issuance of local government debt is finally absorbed by local banks due to the regional segmentation of the credit market, and this does not cause a rise in local interest rates and hence a response of local savings because of interest rate ceilings. Moreover, if banks optimise profit, the credit to riskier debtors such as those with lower guarantees and greater monitoring expenses would be tightened. If banks, on the other hand, prioritise politically linked borrowers, such as state-owned businesses, enterprises with no political ties would be rationed more severely. Their hypotheses are well supported by the city-level and firm-level estimations using a novel database on public debt of China's prefecture-level cities and a database of industrial firms. They provide evidence that local public debt squeezes private firms' investment, especially for private firms located at a distance from banks in other cities or more dependent on external finance. Furthermore, they find that local government debt increases the cash-flow investment sensitivity for private firms rather than state-owned firms, for small firms rather than large firms, and for financially constrained firms rather than unconstrained firms.

5.2.1.4 Transportation proximity and investment

Relevantly, several studies have focused on the positive role of transportation proximity, proxied by new airlines or high-speed rail (HSR) network, at plant-level or firm-level investment and capital mobility, by arguing that transportation network facilitates face-to-face communication between far-off cities.

Giroud (2013) firstly investigates whether the improvement of headquarters' proximity to plants, proxied by the introduction of new airline routes, has positive effects on plant-level investment and productivity applying plant-level data and airline information from the U.S. Department and Transportation. It is argued that new airlines help reduce the travel time between headquarters and plants, thus improving the ease of monitoring and acquiring information. An increase in monitoring by the headquarters could motivate managers and workers at the plant to work harder, improving productivity and marginal return on investment. In addition, a greater investment budget may be assigned to plants because of the headquarters' ability to evaluate local projects. This hypothesis is confirmed by the difference-in-difference estimation results that new airline routes lead to an increase of 8% to 9% in investment at the plant level and an increase from 1.3% to 1.4% in the plants' total factor productivity.

Bernstein et al. (2016) demonstrates that the engagement of venture capitalists (VCs) is sensitive to the advent of direct flights which shorten VCs' travel duration to their current portfolio firms in the U.S. context. According to a large-scale poll of venture capitalists, over 90% believe that direct flights improve their connection with their portfolio businesses and management and assist them in better comprehending the operations of the companies. The difference-in-difference analysis also shows that VCs' on-site participation with their portfolio firms increases both innovation and the chance of a successful exit.

Using the staggered growth of the HSR network as plausible exogenous shocks to the ease of travel between cities, Lin et al. (2019a) investigate how transportation infrastructure development promotes inter-regional flows of private capital by arguing that HSR connection improves remote investors' monitoring capacities. Using a unique dataset of Chinese business registrations, they show that establishing a direct HSR link between two cities improves cross-city investment by 38% and increases the number of investors between city pairs by 8%.

Duan et al. (2020) analyze the impacts of transportation networks on capital mobility over the period from 2008 to 2016 applying the detailed information of venture capital investment events, airline networks, and high-speed rail networks in China, and show that a 1% decrease in travel time leads to a 0.02 increase in VC investment transactions between city-pairs.

5.2.1.5 Research gap

Although there is a vast literature with respect to the effects of highway expansion on economic development in terms of spatial agglomeration (Yu et al., 2016; Baum-Snow et al., 2018; Baum-Snow, 2007), market integration (Faber, 2014), productivity (Zhang and Ji, 2019; Wan and Zhang, 2018; Li and Arreola-Risa, 2017; Holl, 2012, 2016), employment (Linneker and Spence, 1996; Pereira and Andraz, 2012a; He et al., 2014) exports (Volpe Martincus et al., 2017; Liu et al., 2022) and inventory (Shirley and Winston, 2004; Datta, 2012; Li and Li, 2013), much less is known about the role of highway infrastructure on firms' investment decisions, especially in the case of China.

Despite the extensive research regarding whether public investment crowds out or crowds in private investment, most of which are on the aggregate level rather than firm-level specific. The empirical results of those studies are likely to be controversial since it is difficult to pinpoint the impacts of different components of public spending at the aggregate level, as well as their interaction channels. To the best of my knowledge, existing firm-level studies, including Aiello et al. (2012) for the case of Italy, and Ru (2018) and Huang et al. (2020) for the case of China, consider the aggregate perspective of infrastructure or government credit rather than the specific highway infrastructure. Moreover, there is a lack of literature on transportation proximity and investment besides airline networks (Giroud, 2013; Bernstein et al., 2016) for the U.S. and the HSR network (Lin et al., 2019a; Duan et al., 2020) for China.

According to the China Statistic Yearbooks, the rapid expansion of the HSR network and new airlines began mainly in 2008, while the period of our focus between 1998 and 2007 witnessed an explosion in highway construction. Compared to other types of roads, highways with limited driving speeds up to 100 km/hour or 120 km/hour serve as an ideal option for lower transportation costs and shorter travel time for firms engaging in cross-city trade and communication. It is thus worthwhile to fill the gap of whether the expansion of the highway network in 1998-2007 crowds in the firm-level investment in China and the potential mechanisms at work.

5.2.2 Review of corporate finance literature

5.2.2.1 Investment and financial constraints

Prior research shows that market imperfections together with the absence of investor protection lead to a divergence in costs between external and internal financing, which limits the ability of firms to finance investment projects externally (Khurana et al., 2006). In order to finance potentially profitable projects, constrained firms are forced to manage their cash flows. A stream of research has attempted to formulate empirical and theoretical predictions regarding the impact of financial frictions on firms' financial policies such as investment and cash holding. Yet no consensus appears to exist regarding how financial constraints can and should be quantified, nor whether cash flow sensitivities are reliable indicators of financial constraints (D'Espallier et al., 2008).

Fazzari et al. (1988) pioneered an indirect measure of financial constraints by introducing investment to cash-flow sensitivity (ICFS). The rationale is that when a firm has difficulty getting external finances, its investment should be sensitive to internal funding availability. When facing a positive cash flow shock, firms with financial constraints will display an excess sensitivity of ICFS and adjust their capital stock to a higher level. However, financially unconstrained firms should not exhibit such systematic relationships as they can easily obtain external finance for their investments. The authors classify financially constrained and unconstrained firms a priori based on firms' dividend policy. It is assumed that financially constrained firms will pay lower dividends and hold onto most of their low-cost internal funds to finance their investment. Based on a sample of 422 USA companies over the period of 1970-84, ICFS was found to be higher in low-dividend firms than in high-dividend ones, suggesting that ICFS could be useful in evaluating financial constraints.

Since Fazzari et al. (1988), a number of influential studies have focused on the use of ICFS to identify firms' financial constraints, including Chapman et al. (1996) for Australia; Fazzari and Petersen (1993) and Hadlock (1998) for the US; Audretsch and Elston (2002) for Germany; Guariglia (2008) for the UK, and Bond et al. (2003) for cross countries.

However, as summarized in Silva and Carreira (2012), there are three main critiques of Fazzari et al. (1988) regarding the classification and ICFS. For instance, Kaplan and Zingales (1997) stress that the categorization method employed by Fazzari et al. (1988) is faulty as the dividend policy may represent an incorrect sorting variable resulting from cautious savings and hazardous unfavourable management. Meanwhile, some specific assumptions made regarding the curvature of the cost function of external finances (e.g., positive third derivatives) may not be verified.

Moreover, some researchers argue that the cash flow sensitivity of investment does not increase monotonically with the degree of financing constraints, which is one of the criticisms by Silva and Carreira (2012). Kaplan and Zingales (1997) construct a static model about investment-cash flow sensitivities with no adjustment cost. In this model, all firms face financial constraints (costly external finance), and the cost premium rises with the use of external finance. By using the costly external funds, the required return on fixed investment should be higher or at least equal to the cost rates. For firms relying on external funds, a positive cash flow shock will increase access to low-cost internal finance and then lead to the higher optimal capital stock, as it lowers the required rate of return. This is especially true, for firms that face lower-cost premiums of external finance, as the sensitivity of fixed investment to such "windfall" cash flow shocks is higher. Kaplan and Zingales (1997) then classify the forty-nine low-dividend firms from the sample of Fazzari et al. (1988) into five groups based on cash stocks, unused lines of credit and leverage, and empirically show that ICFS do not increase monotonically with the degree of financing constraints. In addition, the non-monotonic ICFS relationship is supported by some authors such as Cleary (1999) and Lyandres (2007).

However, the classification of constraint degree from Kaplan and Zingales (1997) is questioned by Fazzari et al. (2000). Moreover, the model in Kaplan and Zingales (1997) does not consider the important role of adjustment cost, which shows a departure from reality. Bond and Söderbom (2013) modify this to a dynamic investment model with quadratic adjustment costs. In the case of using new equity finance with an increasing cost premium, the excess sensitivity of investment to positive cash flow shocks increases monotonically with the premium cost of issuing new equity. The result does not change conditional on the marginal q by introducing debt (with an increased borrowing cost) as do the other external funds.

Another criticism of ICFS is that cash flow might also include information about investment opportunities, especially for companies facing high levels of uncertainty, such as startups and growing firms (Alti, 2003). Indeed, Alti (2003) considers a benchmark case where financing is frictionless and finds that investment is sensitive to cash flow even after controlling for Tobin's q. Additionally, the sensitivity is considerably higher for young, small-scale firms with high growth rates and low dividend payout ratios. It is argued that if q is not a proper control for the investment opportunity set, higher sensitivities may be obtained simply for the reason that cash flow reveals information about investment opportunities.

Almeida et al. (2004) argue that using cash flow sensitivity of cash works better than that of ICFS to test for financial frictions. In contrast to the criticism of ICFS that cash flow includes information about investment opportunities, it is difficult to claim that cash flow's explanatory power over cash policies may be attributed to its capacity to foresee future investment demand. Changes in cash holdings for unconstrained enterprises should not be based on current cash flows or future investment opportunities, hence there should be no systematic patterns in cash policy in the absence of financial restrictions. In contrast, financially constrained firms with distorted investment policies must consider the cost of having cash available for future investments and balance the profitability of current and future investments. The theoretical model developed by Almeida et al. (2004) to reveal the impact of financial constraints suggests that financially constrained firms exhibit positive cash-to-cash flow sensitivity (CCFS), whereas there is no systematic relation between cash savings and cash flows for firms without financial constraints. Using a sample of manufacturing enterprises between 1971 and 2000, the authors then empirically assess whether cash flow sensitivity of cash offers a valid measure of financial constraints. Firms are divided into constraint and unconstraint subsamples based on five forms of financial constraint criteria respectively, namely, payout policy, asset size, bond ratings, commercial paper ratings, and the "KZ index" from Kaplan and Zingales (1997). Except for the KZ index classification scheme, the subgroup of financially constrained firms based on the first four classifications shows a significant and positive CCFS whereas, under the group of unconstraint firms, the CCFS is not significantly different from zero, suggesting that CCFS can be an empirically useful measure of financial frictions.

However, there seems to be no consensus about the best measure of financial constraints. Acharya et al. (2007) point out that the future funding capacity of financially constrained firms to take on new investment opportunities can increase by saving cash or reducing current debt. Specifically, their theoretical and empirical discussion shows that firms with limited access to external finance prefer higher cash levels over lower debt if they have strong hedging needs to protect future investment from revenue shortfalls, but lower debt over higher cash in the case of low hedging needs. Riddick and Whited (2009) present theoretical evidence that optimal savings are determined by the trade-off between external financing cost and interest income taxation, along with empirical evidence that savings are negatively associated with cash flow when controlling for Tobin's Q, as constrained firms reduce their cash savings to invest after experiencing favourable cash-flow shocks. Empirically, Bao et al. (2012) examine a sample of manufacturing firms spanning 1972 to 2006 and argue that cash is asymmetrically sensitive to cash flow. In specific, the CCFS is negative in a positive cash flow environment, supporting Riddick and Whited (2009), but positive in a negative cash flow environment.

Both ICFS and CCFS are commonly estimated by subsample regression, with the grouping based on a priori classifier representing the vulnerability to imperfect capital markets, such as pay-out policy, firm size, age, and ownership. The pay-out policy is usually used in literature such as Fazzari et al. (1988) and Almeida et al. (2004), by assuming that financially constrained firms will pay lower dividends and hold onto most of their low-cost internal funds to finance their future investment. Firm size and firm age can be proxies for the extent of asymmetric information. Smaller firms and younger firms may have more difficult access to external funds because of the adverse selection problems, whereas larger and older firms are more diversified and find it easier to raise external capital (Ding et al., 2012; Hovakimian, 2011; Ek and Wu, 2018). In China, government intervention as an institutional feature can work from ownership. For instance, state-owned enterprises, even with low profitability, can obtain large amounts of loans with low-interest rates from the state-owned banking system because of their economic and political functions (Ding et al., 2012). Foreign-owned firms can enjoy special investment tax deductions and subsidies when introducing foreign direct investment (Wu, 2018). However, private companies are considered to be the most restricted, as they are often discriminated against by the formal financial system, and they must rely mainly on relatively low-cost internal funds to finance investments (Ding et al., 2013).

In addition to the prior classification scheme, the other method is to estimate firm-level cash flow sensitivity. For instance, D'Espallier et al. (2008) estimate the firm-level cash flow sensitivities of cash and investment by using the maximum-entropy (GME) estimator advanced by Golan et al. (1996) and then define ex-post sensitivity classes based on the distribution of firm-specific parameter estimates. This approach allows for direct evaluation of the measures of interest instead of ex-ante classification. Further, Hovakimian and Hovakimian (2009) introduce a CFS indicator to represent the sensitivity of investment to changes in cash flows at the firm level. It is measured by comparing the annual average of investment weighted by cash flow to the basic average of investment. As a result, investment in years with higher cash flow obtains a higher weight, implying that if a company invest more (less) in years with higher cash flow, the CFS indicator will be positive (negative).

5.2.2.2 Investment and inventory (working capital)

In the modelling of investment literature, there are two kinds of assumptions regarding adjustment cost: one is convex cost, such as a quadratic function (Bond et al., 2007; Holly and Turner, 2001); the other is the non-convex cost which is always accompanied by irreversibility (Cooper and Haltiwanger, 2006). By studying the nature of capital adjustment cost, Cooper and Haltiwanger (2006) suggest that a combination of non-convex and convex adjustment costs suits the plant-level data best. Irreversibility and non-convexity play an important role in investment, as firms' fixed investment is at least partially irreversible. There are several reasons, such as a shortage of secondary market for fixed capital (Speight and Thompson, 2006), especially for industry-specific or highly specialized capital goods (Ding et al., 2013), or a lemon's problem occurred in reselling capital because of the asymmetric information of quality (Akerlof, 1970). Irreversibility is a non-negligible issue especially when firms want to reverse their implemented investment decisions. Compared with reversible investment, irreversibility does reduce the value of a firm, although it does not affect Tobin's q (Abel and Eberly, 1997). In this case, firms are less likely to pay a high cost for changing the level of fixed investment and more likely to maintain a stable fixed investment (Fazzari and Petersen, 1993).

Comparatively, inventory, as an important part of working capital, is more reversible than fixed investment. One reason is that inventory investment has fewer adjustment costs, for example, the fixed cost of ordering. That is, firms will suffer fewer sunk costs by adjusting the stock of inventories rather than fixed asset stock. Easy of turning it into cash is also another advantage for inventory investment (Caglayan et al., 2012), as inventory serves as a part of current assets which can be changed downward to provide additional financial resources. Inventory variability is also a concern when understanding the business cycle. According to Christiano (1988), inventory variability is about half the size of the variability shown in the Gross National Product, although the percentage of inventory on the GNP is quite small (only 0.6% in the US).

In the micro-perspective literature that considers firms' investment decisions, the relationship between fixed investment and working capital (or inventory) is generally considered under the premise of financing constraints.

Fazzari and Petersen (1993) were almost the first to underline the essential but often neglected role of working capital in the investigation of financial constraints on fixed investment, by using the US manufacturing firm panel data. For firms facing financial constraints or negative cash flow shocks, working capital will serve as a source of internal funds to smooth fixed asset investment. However, the extent of the smoothing effect depends on the initial stockpile of working capital. Firms with a higher stock of working capital will face a lower marginal value of working capital and then a higher tendency to forgo the working capital investment in response to the negative shocks of cash flow. By using a large sample of manufacturing firms in China throughout 2000—2007, Ding et al. (2013) also support the view that the active adjustment of working capital can be used as internal finance to smooth firms' fixed investment, especially in the context of financial constraints.

Bo (2004) explores the interaction between inventory and fixed investment through both theoretical modelling and an empirical test using Dutch-listed firms from 1985 to 2000. Because of the limited fund pool, firms should manage the adjustment of fixed asset investment and inventory investment together, and it is important for firms to allocate funds to the most productive uses. His paper uncovers a substitutional relation and suggests that the inventory stock is used not only as a buffer in response to demand uncertainty but also as an alternative to the additional financial supply of fixed asset investment.

Aktas et al. (2015) use a sizable sample of US firms in the period between 1982 and 2011 to explore the relationship between working capital management and firm performance. They rule out the existence of an optimal working capital level and an inverted U-shaped relationship between working capital and firm performance. This means that, for firms with too much working capital, the release of cash over-invested in working capital will come with a superior firm performance, which implies an increase in firms' financial flexibility and then a greater ability to invest in higher-value uses such as fixed asset projects. However, for firms with low-level working capital, the working capital cannot be offset as it is essential for firms in operation and production.

Relying on the panel data of Polish firms, Mielcarz et al. (2018) also confirm that the substitution relationship between capital expenditures and working capital is more likely to exist in financially constrained firms. In particular, working capital is found to be positively related to the availability of external funds and negatively related to the extent of financing limitations. Because of the nature of the fixed investment, which is costly to adjust, illiquid and at least partly irreversible, working capital may be taped as a complementary resource of internal funding to keep away from the more expensive external capital, especially when encountering a cash flow shortage.

5.2.2.3 Investment and uncertainty

The uncertainty-investment relationship is controversial in investment theories. The relationship between uncertainty and investment could be positive, negative, or even ambiguous depending on different assumptions or focuses. A first line of research argues that greater uncertainty is associated with higher levels of investment in risk-neutral competitive firms with adjustment costs. According to Hartman (1972) and Abel (1983), with the assumption of constant returns to scale in production and the marginal value of capital being a convex function of uncertain prices and costs, greater uncertainties can lead to an increase in the value of the marginal unit of capital by Jensen inequality, which will drive more investment (Guiso and Parigi, 1999). As the stream of profits is a convex function of the stochastic variables, the expected present value of future profits generated by the marginal unit of capital can also be increased by Jensen's inequality (Pindyck, 1993).

Pindyck (1982) constructs a dynamic model to study the impact of uncertainties over future demand and cost on a firm's behaviours. It indicates that firms' adjustment costs are critical in determining the effects of such uncertainties. Specifically, the targeted capital stock and production level will increase (decrease) in response to demand uncertainty if marginal adjustment costs rise at a growing (declining) rate. Risk-averse firms whose marginal adjustment costs are increasing at an increasing or constant rate will increase their capital stock and output in the face of demand uncertainty. Similarly, variations in factor costs affect the firm's behaviour in the same way as fluctuations in demand do.

A second set of literature, in contrast, highlights the role of irreversibility and the negative effects of uncertainty on firms' investment decisions. Because of the characteristic of irreversibility or partial irreversibility, it is valuable to postpone investment when the future is uncertain (Dixit and Pindyck, 1994). Uncertainties create opportunity costs associated with immediate investments. Thus, the total cost of investing in a marginal unit of capital rises, which lowers investment. Pindyck (1993)'s two-period investment example demonstrates how industry-wide uncertainty can negatively affect investments that are irreversible even if companies are completely competitive and with constant returns on scale. According to Bernanke (1983)'s theory of irreversible investment choice under uncertainty, agents need to make investment timing decisions trading off the benefits of additional information gained from waiting against those gained by early commitment.

It has been acknowledged that the real option's 'now or latter' method treats uncertainty better than the Net Present Value (NPV) approach's static 'now or never' rule, as it recognises flexibility in investment appraisal decision (Dixit and Pindyck, 1994). The real option theory treats investment as the exercising of options. By waiting for the uncertainty to be resolved before deciding to invest in the irreversible capital, managers can prevent potentially substantial losses by abandoning the irreversible investment if the outcome is unfavourable. As a result, the real option theory applies to irreversible investments: the higher the uncertainty in an investment's predicted future cash flows, the more valuable the option to defer the investment (Bulan, 2005).

Although irreversibility is an important element in determining the negative sign of the uncertainty-investment relationship, other relevant assumptions such as imperfect competition should be required. For instance, Caballero (1991) presents a model with a generic cost of adjustment mechanism that takes symmetric convexity and irreversibility as both special cases into consideration to demonstrate the investment-uncertainty relationship. It is claimed that price uncertainty and capital investment do not exhibit a robust relationship under risk neutrality. The existence of asymmetric adjustment costs (i.e., irreversibility) is not sufficient to render the negative relationship between investment and uncertainty. It is also essential that imperfect competition exists. In addition, Abel and Eberly (1993)'s general framework emphasizing adjustment costs and irreversibility suggests that investment is a non-decreasing function of the output price uncertainty if the firm is in a competitive market.

In the theoretical model of Boyle and Guthrie (2003), the dynamic investment for a company with endogenous financing constraints is analyzed. Their research indicates that firms are encouraged to accelerate investments beyond the 'first-best optimal level' when potential funding shortfalls lurk in the future. While increased uncertainty about project value raises the value of delaying investments, increased uncertainty regarding firm liquidity has the contrary effect. Increased unpredictability in the firm's future cash flow distribution increases risks of future financing deficits, thereby decreasing the value of waiting and boosting present investment.

It is worth saying that there is also some research arguing a nonlinear relationship (see French and Sichel, 1993; Abel and Eberly, 1999; Sarkar, 2000). According to French and Sichel (1993), negative and positive shocks are treated asymmetrically by firms. Because negative shocks are frequently linked with high levels of uncertainty, a negative effect of uncertainty predominates if it has a high level of uncertainty, whereas a positive effect may occur when uncertainty is at a low level. The study by Sarkar (2000) demonstrates that it is not always accurate to assume a negative relationship between uncertainty and investment. For instance, in the case of a low-risk and low-growth firm, a slight increase in uncertainty might enhance the probability of investing, thus stimulating investment.

The topic of uncertainty and investment has been extensively studied not only from the theoretical side but also from an empirical perspective. Although uncertainty itself can take many forms, including micro-level uncertainties such as price uncertainty, demand uncertainty, and profit uncertainty, and macro-level uncertainties such as macroeconomic uncertainty and policy uncertainty, a large proportion of evidence suggests a negative relationship between uncertainty and investment.

The empirical research of Leahy and Whited (1996), using a panel of U.S. firms, demonstrates that uncertainty, measured as the expected variance of the daily return on the stock market, has a significant negative impact on investment, as irreversible investment theories predict. Guiso and Parigi (1999) also explore the impacts of demand uncertainty on the investment decisions of Italian manufacturing enterprises, utilising information on the firms' subjective probability distribution of future demand. The findings support the idea that uncertainty dampens investment's reaction to demand, hence reducing capital accumulation. Moreover, the effect of uncertainty on investment is higher for enterprises that cannot readily reverse investment decisions and for those with strong market power. Ghosal and Loungani (2000) empirically investigate the influence of profit uncertainty on investment and whether this impact differs in sectors dominated by small enterprises versus industries dominated by bigger enterprises, using a panel data of 4-digit industrial level. Their results again confirm a negative sign of investment-uncertainty connection and a larger quantitative negative impact in small-firm-dominated industries. Focusing on a panel of Swedish manufacturing firms over the period of 1979-1994, Carlsson (2007) documents that firm-level uncertainty, motivated by the neoclassical investment model with time to build, has a significant and negative effect on capital accumulation no matter in the short run or long run.

Bloom et al. (2007) establish a theoretical model about the relationship between uncertainty and fixed asset investment and then apply it numerically and empirically by using both simulated data and a panel of manufacturing firms from the UK. They illustrate that, by considering (partial) irreversibility, time-varying uncertainty, and alternative forms of revenue function together, firms' sensitivity of investment to demand fluctuations reduces in line with the higher uncertainty. Their theoretical and empirical findings also support the real options theory, that is, if individual investment projects are irreversible to some extent, firms should trade off the benefits of current investment against the possible returns of waiting for future investment with lower uncertainty (Bernanke, 1983). Because the increase of real option value induced by uncertainty makes firms more cautious about investment or divestment, in the short run, the adjustment of fixed investment caused by demand uncertainty should be limited.

A study of Dutch non-financial firms over the period from 1984 to 1996, Bo and Lensin (2005) demonstrate that investment and uncertainty are related in an inverted U-shape. According to the GMM estimations, increasing uncertainty has a positive influence on investment for low levels of uncertainty, while increasing uncertainty has an adverse effect on investment for high levels of uncertainty. This is in line with the theoretical findings of French and Sichel (1993).

More recently, Chen et al. (2019a) apply the GMM method to examine the connection between investment and economic policy uncertainty (EPU) using U.S. firm-level panel data from 1999 to 2013. When faced with greater economic policy uncertainty, firms reduce short-term, long-term, and total investments. They also investigate the non-linear investment-uncertainty relationship and conclude with a U-shaped connection. Suh and Yang (2021) employ eleven measures of global uncertainty, including EPU using firm-level data from thirty-six countries over the period from 1997 to 2016. Their empirical results demonstrate a significant and negative effect of global EPU on corporate investment and a positive effect of non-EPU global uncertainty on investment. Focusing on the time-varying effects of financial uncertainty in the U.S., Haque et al. (2021) also support the negative sign of an uncertainty-investment relationship, which is consistent with the wait-and-see behaviour demonstrated by Bloom (2009).

5.3 Empirical Specification and Identification Problem

5.3.1 Baseline model specification

To investigate the overall effect of highway improvement on firms' fixed investment, the following regression equation (5.1) is considered as the baseline specification.

$$\begin{aligned} Investment_{i,j,k,t} &= \alpha_0 + \alpha_1 Highway_{i,t} + \alpha_2{}' X_{i,t} + \alpha_3{}' Z_{k,t} \\ &+ \mu_i + \mu_j + \mu_k + \mu_t + \mu_{i,j,k,t} \end{aligned} \tag{5.1}$$

where the subscripts i, j, k, and t indicate firm, industry, province, and year, respectively. The dependent variable $Investment_{i,j,k,t}$ signifies the investment ratio, which is measured as the real value of fixed investment scaled by real capital stock. This research strictly follows Brandt et al. (2012) in calculating the real capital stock by the perpetual inventory method. Detailed information is documented in the Appendix.

$Highway_{i,t}$ represents the highway access. As shown in Chapter 3, this research uses highway proximity, calculated as the inverse of distance (km), as the main highway access measure. The larger the highway proximity, the better the firms' access to highway infrastructure. It is expected that the coefficient of highway proximity is positive if the baseline result is in line with the hypothesis that the improvement in highway infrastructure encourages firms to increase their fixed investment. Two additional highway variables will be used to test the robustness of highways' effect, namely, the logarithm of the distance to the nearest highway and the relative highway proximity.

A vector of firm-specific variables ($X_{i,t}$) is controlled, including firm size, cash flow, sales growth, tangibility, and leverage.

Firms' size is usually controlled in corporate finance literature (e.g., Ding et al., 2012, 2018; Shan and Zhu, 2013), which is measured as the logarithm of the number of workers (e.g., Ding et al., 2012). It is expected that the coefficient of firm size is positive as a firm's size may provide an inverse indicator of informational asymmetry between its insiders and outside financiers. Smaller firms may have more difficult access to external funds because of the adverse selection problems, whereas larger firms are more diversified and find it easier to raise external capital (Ding et al., 2012; Hovakimian, 2011).

Cash flow is measured as the sum of the firm's net profit and the accumulative depreciation of fixed assets, divided by capital stock. The coefficient of the cash flow ratio is expected to be positive, for two possible reasons. On the one hand, existing literature shows that firms exhibit positive cash-flow sensitivity of investment when facing financial constraints (Fazzari et al., 1988; Guariglia, 2008), although the coefficient may not necessarily raise monotonically with the degree of financing constraints (Kaplan and Zingales, 1997; Lyandres, 2007). On the other hand, cash flow might also include information about investment opportunities, especially for companies facing high levels of uncertainty, such as startups and growing firms (Alti, 2003).

Sales growth is also controlled, and the coefficient of sales growth is expected to be positive. Sales growth is used as a proxy of demand growth (Bloom et al., 2007), growth opportunities (Ding et al., 2013), or demand-side investment opportunities (Ding et al., 2018), and a positive relationship between sales growth and investment is observed in these studies. The empirical results of Aiello et al. (2012) also suggest that a firm increases its investment when it observes an increase in profits due to either an increase in revenues or a reduction in variable costs.

Tangibility is defined as the ratio of tangible fixed assets to total assets. Ding et al. (2018) and Hovakimian (2009) highlight a negative relationship between tangibility and investment supporting that firms with higher tangible fixed assets ratios tend to operate with lower growth potential. However, tangibility can be used as a proxy for firms' ability to raise external finance. When accessing capital markets or external funds, firms can pledge their tangible fixed assets such as buildings or equipment as collateral. In this case, firms with higher tangibility may encourage firms to increase their fixed investment.

Leverage defined as the ratio of current liabilities to current assets is a critical determining factor of external financing decisions (Ding et al., 2012). Firms with higher leverage are defined as financial constraints, as they have more financial obligations outstanding in the short term and less freedom in raising additional external capital or managing cash flows (Manova and Yu, 2016). It is then expected that the coefficient of leverage is negative.

Some provincial-level variables ($Z_{k,t}$) are controlled as well, including other roads' density, waterway density, and rail density. μ_i, μ_j, μ_k and μ_t denote the firm, industry, province and year fixed effects, respectively. Finally, $\mu_{i,j,k,t}$ is the random error term.

5.3.2 Identification problem

As mentioned in Chapter 4, to investigate the causal effect of highway proximity, it is necessary to address the potential endogeneity issues. Specifically, there are two types of endogeneity concerns in the analysis, namely, endogenous highway construction and endogenous location choice.

The first type of endogeneity comes from endogenous highway construction. Governments tend to develop highways to link large cities where firms have better inventory management. In addition, there is concern that planners targeted economically and politically important regions along the way between the network's nodal cities (Faber, 2014) and there may be some omitted variables explaining both the highway proximity and the firm's inventory investment decisions. In order to control for this type of endogeneity, a number of time-varying instruments are constructed, namely, the least cost paths and straight lines based on the targeted city points outlined in the national highway construction projects, and historical instruments based on the Ming dynasty' courier routes and the Qing dynasty's historical routes[1].

The second type of endogeneity comes from firms' location choices. New firms may choose to locate close to the highways in order to benefit from highway infrastructure. Existing firms may relocate their location by moving closer to highways (Holl, 2016). Thus, the effect of highway proximity on inventory investments may not only

[1]A detailed discussion on the construction of instruments are provided in Chapter 3.

be derived from the construction of highways but also from the new firms and relocating firms closer to highways. To deal with the second type of endogeneity, this research will further exclude both new firms that opened during the sample period and relocating firms that switched their locations during this analysis.

5.4 Statistics and Basic Empirical Results

5.4.1 Stylized facts

Fixed investment increased significantly both at the national and firm levels during the analysing period. As shown in figure 5.1, the growth rate of fixed asset investment in society as a whole rose sharply from 5.1% in 1999 to 20.2% in 2007. Given the fact that infrastructure investment is typically made by state-owned companies with funds from both central and local governments (Qin, 2016; Xu and Yan, 2014; Wu et al., 2021), the aggregate private investment is measured as the difference between total fixed asset investment in the whole society and fixed investment by state-owned enterprises, following Xu and Yan (2014). The growth patterns of both absolute volume and growth rate of private investment at the national level are also evident in figure 5.1. Moreover, the growth rates of private investment over the period are comparatively much higher than the growth rates of total investment, showing the possibility of an overall crowding-in effect of public investment on private investment.

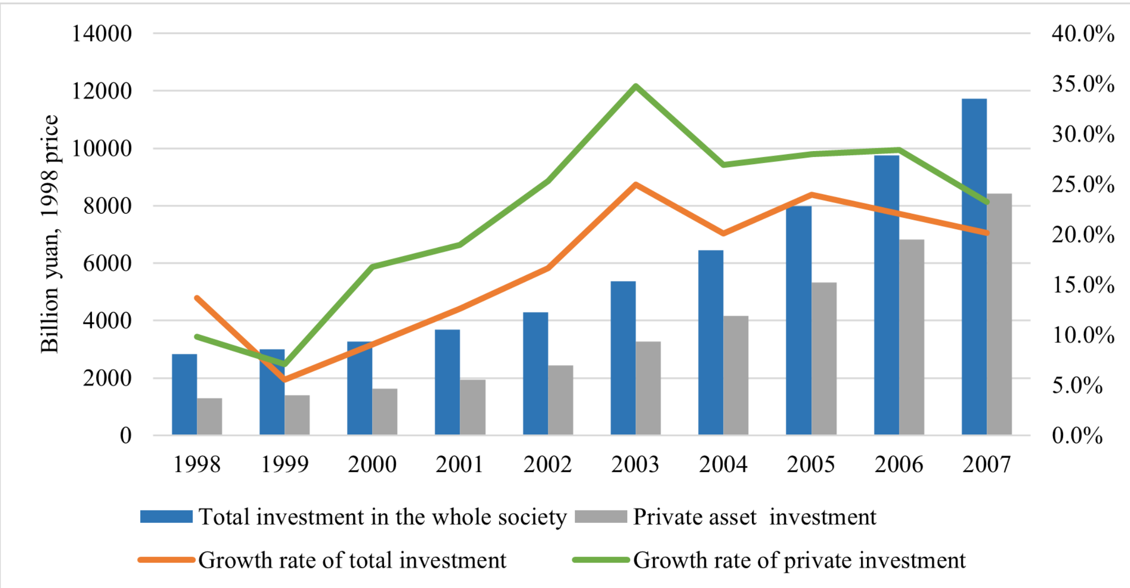


Figure 5.1: Total investment and private investment at national level

Source: China Statistical Yearbooks

The sample period also witnesses an overall growing trend of fixed investment in manufacturing firms. Table 5.1 provides the mean value of the fixed investment

Table 5.1: Time trend of the mean fixed investment at firm level

Year	Full sample	By ownership		By location	
		Private firms	SOEs	Coastal area	Inland area
1999	8.917%	11.95%	2.226%	9.699%	7.162%
2000	7.818%	10.59%	0.858%	8.863%	5.644%
2001	8.426%	11.08%	0.712%	9.642%	5.639%
2002	10.06%	12.84%	0.723%	11.49%	6.437%
2003	11.93%	14.58%	1.774%	13.13%	8.692%
2004	13.81%	15.74%	2.916%	14.53%	11.58%
2005	16.49%	18.14%	4.423%	17.27%	13.89%
2006	15.28%	16.38%	4.771%	15.94%	13.14%
2007	15.04%	15.92%	6.289%	15.24%	14.41%
Total	12.86%	15.21%	2.193%	13.79%	10.23%
Average annual growth rate	7.461%	4.172%	28.022%	6.380%	10.667%
Observation	1,682,956	1,077,436	131,894	1,247,739	435,217

Notes:

1. Data source: the Annual Survey of Industrial Firms (ASIF).

2. Only manufacturing firms are included.

3. 0.5% of outlier observations in terms of investment are excluded.

to capital stock ratio over time. In the full sample of manufacturing firms, the mean fixed investment ratio rose from 8.917% in 1999 to 15.04% in 2007, with an average annual growth rate of 7.461%. Classified by ownership, it is notable that the average investment level of private enterprises (15.21%) is much higher than that of state-owned enterprises (2.193%), which is in line with the growth pattern of national-level investment. In addition, when compared to firms located inland, those located in coastal areas are more likely to have higher investment levels.

5.4.2 Summary statistics

This research uses a number of datasets including geo-referenced highway routes obtained from the ACASIAN Data Centre and Road Atlas, firm-level production data from the Annual Survey of Industrial Firms (ASIF) database, a series of geographic information data for the construction of instruments and a set of province-level data for control variables, which are the same as in Chapter 4.

Following Ding et al. (2013) and Liu et al. (2022), observations with missing records

Table 5.2: Summary statistics for firm-level variables used in baseline estimation

	Full sample	Private	SOEs	MeanDiff
Investment (I/K, %)	13.29	15.73	2.055	0.00***
	(24.71)	(26.10)	(18.04)	
Highway proximity	0.529	0.512	0.383	0.00***
	(1.443)	(1.436)	(1.136)	
Ln (highway distance)	8.667	8.705	9.092	0.00***
	(1.415)	(1.392)	(1.550)	
Relative highway proximity (RHP)	0.524	0.514	0.560	0.00***
	(0.119)	(0.114)	(0.143)	
Cash flow (CF/K, %)	32.71	35.91	5.688	0.00***
	(63.41)	(63.16)	(33.87)	
Size	4.872	4.733	5.169	0.00***
	(1.087)	(1.013)	(1.379)	
Sales growth (%)	12.14	15.89	-2.365	0.00***
	(48.75)	(48.25)	(54.25)	
Tangibility (%)	35.19	35.17	41.61	0.00***
	(20.46)	(20.40)	(21.05)	
Leverage (%)	104.9	103.3	149.5	0.00***
	(87.67)	(81.64)	(125.2)	
Observation	1,334,772	820,461	116,499	

on the main regression variables are eliminated. Since investment and sales growth are used in the main regression, observations in the year 1998 are lost. In addition, observations in the 0.5 percent tails of each of the firm-level variables are excluded, to control for the potential influence of noisy observations. The final unbalanced panel covers 1,334,772 firm-year observations, with the number of observations ranging from a minimum of 105,248 in 1999 to a maximum of 234,856 in 2007.

Table 5.2 reports the mean value and standard deviation (in parentheses) in performance across the 1,334,772 manufacturing firms, and the p-value associated with the t-test for differences between SOEs and private firms by means of corresponding variables. Private enterprises and state-owned enterprises (SOEs) have 820,461 and 116,499 observations, respectively.

For the full sample, the mean investment ratio is 13.29% with a standard deviation of 24.71. The average investment in private firms is much higher than in SOEs, with a significant difference of 13.68%. Overall, the mean highway proximity value and the distance to the nearest highway are 0.529 and 8.667, respectively. The relative highway proximity (RHP) captures a firm's relative highway access level (ranging from 0 to 1) in a given province-industry-year. The mean RHP value is 0.524, with a standard deviation of 0.119. Private firms, on average, have better absolute highway accessibility (0.512 in highway proximity and 8.705 in highway distance) but lower relative highway proximity (0.514) compared with SOEs. This indicates that SOEs have a relative advantage over access to highways. In terms of other firm characteristics, there are also significant differences between SOEs and private firms. SOEs are on average larger than private firms, and they have lower sales growth, higher tangibility and higher leverage than private firms.

5.4.3 Baseline results

Table 5.3 shows the baseline regression results of equation (5.1). In addition to the firm-level and provincial-level controls, time-fixed effect, industry-fixed effect and province-fixed effect are included to control for the time-invariant and time-variant unobservable factors that may affect investment. The inverse of highway distance (km) is used to proxy highway proximity.

Column (1) shows the estimation result of fixed effect OLS regression. The estimation indicates that there is no significant correlation between highway proximity and firms' investment. However, it is too early to conclude that improving highway proximity would not affect firms' investment, as the variable of highway proximity is endogenous and there are possibly omitted variables explaining both highway proximity and fixed investment, although some fixed effects are controlled. It is, therefore, necessary to use fixed effect two-stage least squares (FE-2SLS) estimation with alternative instrumental variables to verify whether there is a significant causal relationship between highway proximity and fixed investment.

Columns (2)-(5) demonstrate the empirical results of fixed effect two-stage least squares (FE-2SLS) estimation. The highway proximity is instrumented with the distance to the time-varying instrumental routes, which are calculated on the basis of the least-cost paths of the NEN plan, the least-cost paths of the NTHS plan, the straight-line routes, and the Ming dynasty's courier routes, respectively. Although

Table 5.3: Baseline estimation result

Dep. Var.: investment	(1)	(2)	(3)	(4)	(5)
	FE estimation	FE-2SLS estimation			
		Second-stage results: investment as dependent variable			
Highway proximity	-0.034	1.359***	5.240**	1.844***	3.601***
	(-1.30)	(3.38)	(2.41)	(4.02)	(4.81)
Size	3.024***	3.020***	3.010***	3.019***	3.014***
	(45.69)	(45.53)	(44.02)	(45.43)	(44.89)
Sales growth (%)	0.056***	0.056***	0.056***	0.056***	0.056***
	(100.63)	(100.56)	(99.19)	(100.49)	(100.03)
Cash flow (%)	0.008***	0.008***	0.008***	0.008***	0.008***
	(11.54)	(11.65)	(11.59)	(11.69)	(11.76)
Tangibility (%)	0.462***	0.461***	0.461***	0.461***	0.461***
	(175.44)	(175.14)	(171.27)	(174.90)	(173.63)
Leverage (%)	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(-1.99)	(-2.06)	(-2.20)	(-2.08)	(-2.15)
Density of other roads	-0.030***	-0.029***	-0.028***	-0.029***	-0.028***
	(-12.16)	(-11.95)	(-10.86)	(-11.87)	(-11.51)
River density	-0.197***	-0.250***	-0.399***	-0.269***	-0.336***
	(-3.98)	(-4.82)	(-4.04)	(-5.08)	(-5.74)
Railway density	0.943***	1.076***	1.444***	1.122***	1.288***
	(5.56)	(6.16)	(5.31)	(6.36)	(6.85)
Constant	-42.087***				
	(-16.48)				
Observations	1,334,772	1,251,590	1,251,590	1,251,590	1,251,590
R-squared	0.081	0.069	0.033	0.067	0.053
Number of firms	364,077	280,895	280,895	280,895	280,895
Company/year/industry/province FE	YES	YES	YES	YES	YES
		First-stage results: highway proximity as dependent variable			
Least cost path (2004NEN)		-0.102***			
		(-27.51)			
Least cost path (1992NTHS)			-0.016***		
			(-5.76)		
Straight line routes				-0.070***	
				(-23.89)	
Ming courier routes					-0.045***
					(-15.85)
Under identification test		0.000	0.000	0.000	0.000
Weak identification test		1040.533	45.608	784.767	345.243

Note: Robust Z-statistics corrected for clustering at the firm level are reported in parenthesis. Significant coefficients are indicated by ***, **, * for significance at the 1%, 5% and 10% level, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak-identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 16.38.

in column (1) the coefficient of highway proximity is insignificant, the estimated coefficient of interest in columns (2)-(5) indicates that highway proximity has a significant positive effect on firms' fixed investment. Specifically, column (2) shows that the coefficient of highway proximity is 1.359, indicating that every 1 unit increase in highway proximity is associated with a 1.359% increase in fixed investment ratio at the firm level. Although the magnitudes differ when using alternative instruments, the estimated coefficients of highway proximity in columns (3)-(5) are all positive with significance. The estimation result reinforces the theoretical view of the crowding-in effect that public investment in transportation infrastructure crowds in private investment.

The first-stage result shows that highway proximity is negatively correlated with the instruments on the basis of two kinds of least-cost paths, historical routes, and straight lines, respectively, at 1% significance level. All instruments pass the under-identification test at 1% significant level, suggesting that all instruments are not under-identified. In columns (2)-(5), the first stage Kleibergen-Paap rk Wald F statistics are well above the commonly suggested threshold to be believed as a relevant instrument, indicating that the weak-instrument bias is not a problem for all instruments.

Most of the control variables are significantly correlated with fixed investment. The coefficient of firm size is positive, in line with Ding et al. (2012) that larger firms are more diversified and find it easier to raise external finance for investment. Sales growth is positively correlated with investment, supporting the findings of Aiello et al. (2012) that firms tend to increase investment when an increase in profit is observed due to either an increase in revenues or a reduction in variable costs. There is a positive correlation between cash flow and investment, indicating that China's manufacturing firms are sensitive to cash flow shocks in general, which is consistent with existing literature such as Ding et al. (2018). The positive coefficient of tangibility indicates that tangibility can serve as a proxy of firms' ability to raise external finance, as firms can pledge their tangible fixed assets such as buildings or equipment as collateral when accessing capital markets or external funds. The negative coefficient of leverage is consistent with the estimation of Manova and Yu (2016). Firms with higher leverage face more constraints to raise external finance, as they have more financial obligations outstanding in the short term and less freedom in raising additional external capital or managing cash flows (Manova and Yu, 2016). Fixed investment is positively correlated with railway density but negatively correlated with river density and the density of other roads.

5.4.4 The endogeneity of new firms and relocation

Table 5.4: FE-TSLS result after excluding new firms and relocation

Dep. Var.: Investment	(1) LCP_NEN	(2) LCP_NTHS	(3) Straight_line	(4) Ming_routes
Second-stage results: investment as dependent variable				
Highway proximity	1.159*	2.022	1.128**	5.415***
	(1.83)	(0.70)	(1.96)	(4.16)
Control variables	YES	YES	YES	YES
Company/Year/Industry/Province FE	YES	YES	YES	YES
Observations	672,021	672,021	672,021	672,021
R-squared	0.062	0.057	0.062	0.015
First-stage results: highway proximity as dependent variable				
Least cost path (2004NEN)	-0.093***			
	(-15.89)			
Least cost path (1992NTHS)		-0.018***		
		(-3.52)		
Straight line routes			-0.083***	
			(-16.96)	
Ming courier routes				-0.043***
				(-8.36)
Under identification test	0.000	0.000	0.000	0.000
Week identification test	338.285	16.635	385.399	93.683

Note: Control variables include firm size, sales growth, cash flow, tangibility, leverage, the density of other roads, river density and railway density.

There is some concern about the possibility that the endogeneity may come from not only the endogenous construction of highways but also the endogenous location of firms. To further control the second type of endogeneity, I exclude new firms that opened during the sample period and relocating firms that switched their locations during the sample period. There is a total of 672,021 observations of firms that have existed since 1999 and never changed their location during the period 1999-2007. Table 5.4 reports the estimation results using instruments on the basis of the least-cost paths of the NEN plan, the least-cost paths of the NTHS plan, the straight-line routes, and the Ming dynasty's courier routes, respectively. The coefficients of interest are significantly positive in three of them. In column (1), the coefficient of highway proximity is 1.159 with a 10% confidence level, indicating that a 1 unit increase in highway proximity is associated with an increase of 1.159 in the fixed investment to capital ratio. Possibly because of a lower density of the least-cost paths of the NTHS plan, the coefficient of highway proximity is insignificant in column (2). Column (3) and column (4) support the robustness, suggesting that the positive causal effect of highway proximity on private investment is robust even after excluding new firms and firms that changed locations during the sample period.

5.5 Mechanisms

It is hypothesized that there are at least three mechanisms through which highway proximity stimulates corporate investment, that is, by reducing firms' financial constraints, releasing additional internal funds via inventory reduction, and mitigating the negative impact of uncertainties.

5.5.1 Financial constraints: access to external finance

5.5.1.1 Hypothesis

The significant tendency of investors to hold investments that are geographically local in both within-country and cross-country settings (French and Poterba, 1991; Coval and Moskowitz, 2001; Ivković and Weisbenner, 2005; Lin et al., 2019a) demonstrates the importance of distance when it comes to investment decisions. For instance, the evidence discovered in Coval and Moskowitz (2001) that fund managers gain considerable abnormal returns in nearby investments is argued as the result of monitoring capabilities and informational advantage to geographically proximate firms. In addition, information asymmetries caused by geographical distance are likely to impede long-distance investment (Wright and Robbie, 1998). Using investment data of U.S. individual investors from 1991 to 1996, Ivković and Weisbenner (2005) document that individuals exhibit a strong preference and superiority for local investments relative to non-local investments. They also find strong evidence that such locality bias is caused largely by individual investors' ability to exploit asymmetric information about local investments.

It is important to highlight that transport network expansion contributes greatly to inter-city commuting and information transmission, which plays an important role in reshaping the spatial distribution of economic geography and fostering the development of economic activities (Duan et al., 2020). Moreover, transportation accessibility reduces the potential difficulties associated with long-distance investment deals since it improves the accessibility and quality of mediated information, alleviates information asymmetries and allows more efficient identification of investment opportunities (Giroud, 2013; Bernstein et al., 2016; Duan et al., 2020). Thus, the improved highway network may stimulate the incentives of bankers, professional money managers, and individuals to engage with long-distance investments.

Does improving highway infrastructure influence firms' fixed investment via the mechanism of financial constraints? This is intuitively plausible. When bankers lend money to nearby firms, for instance, they may feel confident in their ability to easily monitor the firm's performance, but if the bank is far away from the firm, it can be difficult to monitor the firm's performance. A better highway connection will, however, allow banks access to far-off-distant businesses with better monitoring. Firms, therefore, have opportunities to attract external finance not only from nearby banks but also from banks in other cities. With the improvement in highways, firms may have a higher probability of getting external finance, and they will find it possible to get external finance with lower costs because they can compare different banks. As a result, the increase in highway accessibility may promote private investment by reducing firms' financial constraints.

Hypothesis 1: The improvement of highway proximity reduces financial constraints and therefore increases private investment.

5.5.1.2 Estimation method

Existing literature usually uses investment to cash flow sensitivity to identify financial constraints (e.g., Fazzari et al., 1988; Fazzari and Petersen, 1993; Audretsch and

Elston, 2002; Guariglia, 2008), whereas it is still controversial whether investment to cash flow sensitivity is monotonic with the degree of financing constraints (Kaplan and Zingales, 1997; Lyandres, 2007; Cleary, 1999). Moreover, cash flow might also include information about investment opportunities (Alti, 2003), thus higher sensitivities may be obtained simply for the reason that cash flow reveals information about investment opportunities.

Although it is difficult to directly measure financial constraints, an easier way to test the financial constraint mechanism is to consider whether highway accessibility promotes firms' overall external borrowing. Since firms have better access to both local and distant banks and therefore a higher probability of getting external finance, the overall debt is supposed to increase, although it is unavailable to identify whether the borrowing is from the local banks or distant banks. As shown in equation (5.2), this research uses firms' overall debt-to-capital ratio as the dependent variable, to test whether highway accessibility promotes firms' overall external borrowing.

$$Debt_{i,j,k,t} = \beta_0 + \beta_1 Highway_{i,t} + \beta_2{}' X_{i,t} + \beta_3{}' Z_{k,t} + \varepsilon_i + \varepsilon_j + \varepsilon_k + \varepsilon_t + \varepsilon_{i,j,k,t} \quad (5.2)$$

where the subscripts i, j, k, and t indicate firm, industry, province, and year, respectively. The dependent variable $Debt_{i,j,k,t}$ represents the overall debt-to-capital ratio at the firm level. $Highway_{i,t}$ is highway proximity, calculated as the inverse of distance (km). $X_{i,t}$ specifies a vector of firm-specific variables, including the logarithm of total assets, sales growth, cash flow and age. $Z_{k,t}$ include some provincial-level variables including other roads' density, waterway density, and rail density. ε_i, ε_j, ε_k and ε_t denote the firm-, industry-, province- and year- fixed effects, respectively. And $\varepsilon_{i,j,k,t}$ is the random error term. If the estimation result is consistent with the hypothesis, then it is expected that the coefficient of highway proximity is significantly positive.

Furthermore, this research will indirectly test the mechanism of financial constraints via subgroup regression based on ownership and firm age. Researchers often use an exogenous sample separation rule to separate the sample into constrained versus unconstrained firms and test whether investment to cash flow sensitivity is significantly positive in the constrained group. Although there is concern that financial constraints may not be the only difference between private firms and state-owned companies, there is much consensus that ownership can be a good criterion to separate constraint and non-constraint firms (Ding et al., 2012, 2013; Ek and Wu, 2018; Huang et al., 2020; Guariglia et al., 2011). Especially in China, it is natural to use state-owned versus private firms for such a sample split, as state-owned companies often get preferential treatment from banks and are thus less likely to be financially constrained (Guariglia et al., 2011; Huang et al., 2020). Private companies are considered to be credit-constrained, as they face stricter investigations by the formal financial system and higher risk premiums. Therefore, this research will split the sample into state-owned ownership and private ownership, and test the heterogeneity effect of highway improvement on firm-level investment. If the hypothesis that the increase in highway accessibility promotes corporate investment by reducing firms' financial constraints is correct, then it should be seen that the positive effect of highway proximity on corporate investment would be larger in private firms.

In addition to ownership, this research also follows Ek and Wu (2018) in splitting the sample into two categories based on the median age in the annual age distribution of all firms: young firms (more likely to be constrained) and old firms (less likely to suffer financial constraints). Firm age is often used as a proxy for financial constraints (Oliner and Rudebusch, 1992), since younger firms may face difficult access to external funds because of the asymmetric information problems, whereas older firms may find it easier to raise external capital (Ding et al., 2012; Hovakimian, 2011). Similarly, it is expected that the effect of highway proximity should be larger among younger firms if our hypothesis is correct.

5.5.1.3 Estimation result

Table 5.5 is the estimation result supporting that highway accessibility promotes firms' overall external borrowing. Columns (1)-(4) show the estimation result of using least-cost path IV constructed based on the 2004NEN plan, least-cost path IV based on the 1992NTHS plan, straight-line IV based on the 2004NEN plan, and historical IV based on the Ming dynasty's courier routes, respectively. The estimation result indicates that the coefficient of highway proximity is significantly

Table 5.5: The effect of highway proximity on firms' overall debt

Dep. Var.: Debt to capital ratio	(1) LCP_NEN	(2) LCP_NTHS	(3) Straight_line	(4) Ming_routes
Second-stage results: debt to capital ratio as dependent variable				
Highway proximity	13.880**	85.492**	13.075**	4.699
	(2.32)	(2.13)	(2.16)	(0.28)
Control variables	YES	YES	YES	YES
Company/Year/Industry/Province FE	YES	YES	YES	YES
Observations	1,251,590	1,251,590	1,251,590	1,251,590
R-squared	0.030	-0.015	0.030	0.031
First-stage results: highway proximity as dependent variable				
Least cost path (2004NEN)	-0.102***			
	(-27.55)			
Least cost path (1992NTHS)		-0.016***		
		(-5.76)		
Straight line routes			-0.069***	
			(-23.90)	
Ming courier routes				-0.045***
				(-15.86)
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	1043.455	45.683	785.267	346.029

Note: Robust Z-statistics corrected for clustering at the firm level are reported in parenthesis. Significant coefficients are indicated by ***, **, *, for significance at the 1%, 5% and 10% levels, respectively. Control variables include the logarithm of total assets, sales growth, age, cash flow, other road density, river density, and rail density. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak-identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 16.38.

positive in three of them. Specifically, the coefficient of highway proximity is 13.88 with a 5% confidence level when the main instrument least cost path (2004NEN) is applied. This suggests that every 1 unit increase in highway proximity is associated with a 13.88% increase in debt-to-capital ratio at the firm level. It is not surprising to have an insignificant coefficient with the Ming dynasty's historical routes because of the limitation that Ming courier routes have lower road density than the actual highways and 7 provinces are not covered by historical routes.

Overall, there is evidence that improved highway accessibility stimulates firms' overall external borrowing with ease of financial constraints since they have easier access to local banks as well as distant banks and therefore have a higher probability of accessing external funds.

Table 5.6: Financial constraint channel by ownership and firm age

Dep. Var.: investment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LCP (2004NEN)		LCP (1992NTHS)		Straight lines		Ming routes	
Panel A: ownership	Private	SOEs	Private	SOEs	Private	SOEs	Private	SOEs
Highway proximity	1.637***	-0.424	8.589**	-0.729	1.949***	0.599	2.949***	0.507
	(2.90)	(-0.48)	(2.12)	(-0.40)	(2.81)	(0.61)	(2.99)	(0.43)
Observations	765,270	109,588	765,270	109,588	765,270	109,588	765,270	109,588
R-squared	0.080	0.048	-0.002	0.047	0.078	0.047	0.073	0.047
Under identification test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification test	608.837	262.181	17.346	70.131	384.091	208.405	211.481	120.284
Coefficient difference	2.061**		9.318**		1.350		2.443	
	(1.96)		(2.10)		(1.13)		(1.60)	
Panel B: firm age	Young	Old	Young	Old	Young	Old	Young	Old
Highway proximity	3.141***	0.570	8.050**	1.337	4.264***	0.695	4.389**	3.271***
	(4.03)	(1.20)	(2.04)	(0.61)	(4.57)	(1.32)	(2.53)	(4.02)
Observations	523,970	676,298	523,970	676,298	523,970	676,298	523,970	676,298
R-squared	0.079	0.064	0.024	0.062	0.071	0.064	0.070	0.047
Under identification test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification test	433.531	598.657	21.561	34.652	300.584	523.010	115.256	241.984
Coefficient difference	2.571***		6.713		3.569***		1.118	
	(2.82)		(1.49)		(3.34)		(0.58)	
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Robust Z-statistics corrected for clustering at the firm level are reported in parenthesis. Significant coefficients are indicated by ***, **, *, for significance at the 1%, 5% and 10% levels, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak-identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 16.38. Coefficient difference reports the significance of the difference in coefficient of highway proximity between private firms and SOEs, and between young firms and old firms, with the following statistic (Almeida et al., 2021): $Z = \frac{\beta_{constrained} - \beta_{unconstrained}}{\sqrt{SE(\beta_{constrained})^2 + SE(\beta_{unconstrained})^2}}$.

Furthermore, Table 5.6 shows the subgroup FE-2SLS estimation by ownership and firm age. Four different instruments are used respectively: least-cost path IV constructed based on the 2004NEN plan (columns 1-2) and the 1992NTHS plan (columns 3-4), straight-line IV based on the 2004NEN plan (columns 5-6), and historical IV based on the Ming dynasty's courier routes (columns 7-8).

Panel A reports the second-stage estimation of IV regression for private firms and SOEs. No matter which instrument is used, the results demonstrate a positive and robust causal effect of highway proximity on private firms' investment, but an insignificant effect on SOEs. This suggests that private firms respond more sensitively to highway improvements which is in line with the expectation.

The heterogeneity between private firms and SOEs is reasonable. Note that in the summary statistics, the average investment level of SOEs is much lower than that of private firms and SOEs perform less efficiently than private firms. SOEs are more likely to experience less efficient corporate governance as they have social and political objectives other than profit maximization. Even with low profitability and poor financial health, SOEs are more likely to obtain large amounts of loans with low-interest rates from the state-owned banking system due to their economic and political functions (Ding et al., 2013; Hsieh and Klenow, 2009). This helps to explain the insignificant effect of highway proximity as SOEs care little about the benefits of highway accessibility, such as access to external finance.

In contrast, private firms are sensitive to the benefits of highways, which provides supporting evidence for the hypothesis regarding the financial constraint channel. Unlike SOEs, which have government backing and therefore have lower risk premiums for borrowing, private firms are highly likely to be financially constrained as they face stricter investigations by the formal financial system and higher risk premiums. If a better highway connection allows banks to have easier access to distant businesses with the ability to monitor them more closely, private firms may be able to access external finance not only from nearby banks but also from banks in other cities. As a result, the increase in highway accessibility promotes corporate investment possibly by reducing private firms' financial constraints.

Panel B shows the estimation results based on firm age. The coefficient of highway proximity is always positive and significant in the group of young firms that are more likely to be credit-constrained. Although in columns (7)-(8) the coefficients of highway proximity in both old and young firms are significantly positive with insignificant coefficient differences, the coefficient of interest among old firms is insignificantly different from zero in columns (2), (4) and (6). Overall, to some extent, highway proximity has a greater effect on constrained firms than on unconstrained firms, which is consistent with the hypothesis regarding the financial constraint mechanism.

5.5.2 Inventory: access to internal finance

5.5.2.1 Hypothesis

Theoretically, the improvement in highway transportation has two main effects on inventory in manufacturing firms based on the (S, s) model (Shirley and Winston, 2004). First, the improvement in infrastructure saves transportation costs which reduce the cost of inventory procurement. Enterprises can reduce the maximum holding level (S) of inventory by increasing the frequency of procurement. Second, it reduces the uncertainty and time of cargo transportation and shortens the lead time of purchasing inventory, and then reduces the minimum safe inventory level (s). Thus, the improvement in the highway can significantly reduce the cost of inventory through the path of the (S, s) model.

Empirically, there are several works of literature focusing on the impact of transportation improvement on firms' inventories. For instance, Shirley and Winston (2004) analyse the impact of highway infrastructure on inventory investment. Using the data on highway infrastructure and plant-level inventory in the United States from the 1970s to the 1990s, it is found that investment in highway facilities significantly reduces firm-level inventories. Following Shirley and Winston (2004), Li and Li (2013) extend the highway infrastructure into all road infrastructure and confirm the substitutional relationship between road infrastructure and micro inventory, in the background of China from 1998-2007. Moreover, Chapter 4 concludes that better access to highways encourages firms to lower their inventories, and each dollar of highway spending in China during the period of 1998-2007 reduced the input inventory stock by about 3.910-10.010 cents and the total inventory stock by around 6.730-25.523 cents.

In this case, inventory can be a possible channel through which highway stimulates firms' fixed investment. Inventory and fixed investment are substituted as they are competing in a limited funding pool. In addition, inventory can serve as an additional financial supply of fixed asset investment (Bo, 2004), especially for firms facing financial constraints. When access to highways becomes much easier, the decrease in average inventory stock induced by highways (Shirley and Winston,

2004) will release additional cash flow, which finally stimulates the investment of fixed assets. The possible inventory channel can be convincing because of the high pace of highway infrastructure construction in China as well as the fact that most Chinese manufacturing firms (Ding et al., 2012), face financial constraints.

However, as argued in Fazzari and Petersen (1993), the extent of the smoothing effect depends on the initial stockpile of working capital. Firms with a higher stock of working capital will face a lower marginal value of working capital and then a higher tendency to forgo the working capital investment in response to the negative shocks of cash flow. Aktas et al. (2015), using a sizable sample of US firms in the period between 1982 and 2011, echo the view of Fazzari and Petersen (1993) by arguing an inverted U-shaped relation between working capital and firm performance. Specifically, for firms with too much working capital, the release of cash over-invested in working capital will come with a superior firm performance, which implies an increase in firms' financial flexibility and then a greater ability to invest in higher value uses such as fixed asset projects. However, for firms with low-level working capital, the working capital cannot be offset as it is essential for firms in operation and production. Therefore, it is further expected that the positive effect of highway improvement on fixed investment would be larger for firms with higher levels of inventory.

Hypothesis 2: Better highway proximity stimulates fixed investment through the mechanism of inventory. The decrease in average inventory stock caused by highway improvement frees up additional cash flow, ultimately stimulating the investment of fixed assets. Furthermore, the positive effect of improved highways would be greater for firms with more inventories.

5.5.2.2 Estimation method

To test the inventory mechanism, the basic specification is extended by including the interaction of highway proximity and channel variables.

$$
\begin{aligned}
Investment_{i,j,k,t} = \gamma_0 + \gamma_1 Highway_{i,t} + \gamma_2 Inventory_{i,t} * Highway_{i,t} \\
+ \gamma_3 Inventory_{i,t} + \gamma_4{}' X_{i,t} + \gamma_5{}' Z_{k,t} + \mu_i + \mu_j + \mu_k + \mu_t + \mu_{i,j,k,t}
\end{aligned}
\tag{5.3}
$$

where the subscripts i, j, k, and t indicate firm, industry, province, and year, respectively. As shown in the baseline specification, the dependent variable $Investment_{i,j,k,t}$ represents the investment ratio in time t. $Highway_{i,t}$ is highway proximity, calculated as the inverse of distance (km). $X_{i,t}$ specifies a vector of firm-specific variables, including firm size, sales growth, cash flow, tangibility, and leverage. $Z_{k,t}$ include some provincial-level variables, such as other roads' density, waterway density, and rail density. μ_i, μ_j, μ_k and μ_t denote the firm, industry, province and year fixed effects, respectively. And $\mu_{i,j,k,t}$ is the random error term.

$Inventory_{i,t}$ indicates the inventory variable, which is measured as the real value of inventories divided by the real value of the capital stock, following Bo (2004) in which he provides a theoretical and empirical link between inventory stock and fixed investment. Specifically, two measures of inventories are used, including the total inventory-to-capital stock ratio, and input inventory-to-capital ratio. Where the total inventory is the sum of raw materials (or materials and supplies), work-in-progress (intermediate goods), and finished goods. Input inventory is the sum of raw materials and intermediate goods.

Although Bo (2004) merely considers total inventories, this research argues that it is important to investigate not only the total inventory but also its discrete components, as highways might have different effects on firms' inventory decisions. In transportation-related inventory research, input inventory is often used not only in empirical research (Shirley and Winston, 2004; Li and Li, 2013) but also in most classical inventory models. Input inventories are more subject to the highway infrastructure in terms of delivery cost and lead time.

Even though different types of inventories are considered, the coefficient of inventory to capital ratio is expected to be negative, as inventories (part of working capital) can serve as a complementary resource of internal funding to smooth fixed asset investment when firms face financial constraints or negative cash flow shocks (Fazzari and Petersen, 1993; Ding et al., 2013; Mielcarz et al., 2018). With the characteristics of liquidity and reversibility, inventory stock is used not only as a buffer in response to demand uncertainty but also as an alternative to the financial supply of fixed asset investment (Bo, 2004), especially for firms facing financial constraints.

The interaction term between the inventory variable and highway proximity is hypothesised to be positive if the result is in line with the hypothesis. On the one hand, in Chapter 4, the empirical results support that the improvement in highway infrastructure will lead to a decrease in transportation cost, lead time, and uncertainty in ordering inventories, which would directly encourage firms to lower their input inventory holdings. If highway improvement encourages firms to reduce their average inventory stock, the positive cash flow shock will stimulate the investment of fixed assets, according to the theoretical intuition of Bond and Söderbom (2013). In this case, it is reasonable to expect that the interaction term's coefficient is positive, demonstrating that the positive effect of highway proximity on fixed investment is greater for firms with larger inventory stock.

On the other hand, inspired by Fazzari and Petersen (1993) and Aktas et al. (2015), inventories are less likely to be reduced if firms are characterised by low inventory stock, as they are essential for firms in production and operation. Those firms may already utilize their inventories to a minimised level and may have less motivation to reduce their inventories. This provides further rationale for the positive coefficient of the interaction term, i.e., the channel effect of highway development through the inventory mechanism should be larger for firms with higher inventory stock.

Table 5.7: Summary statistics for inventory variables

	Observation	Mean	Min	Max	Std.Dev.
Inventory to capital ratio (IWK, %)	1,334,772	84.58	0	2,476	144.1
Input inventory to capital ratio (IIWK, %)	1,334,772	47.73	0	1,527	103.7

Table 5.7 shows the summary statistics for the inventory variables.

5.5.2.3 Estimation result

Table 5.8 shows how highway proximity affects corporate investment via the channel of inventories. Without interaction terms, the positive and significant effect of highway proximity still holds when adding the control of inventories. The negative coefficient of the total inventory to capital stock ratio in column (1) shows that every 10 percent decrease in total inventory is associated with a 0.1 percent increase in fixed investment. The substitution effect between total inventory and fixed investment is in line with the empirical result of Bo (2004). This implies that the decrease in the average inventory-to-capital ratio will release additional cash flow and then stimulate the investment of fixed assets. Similar results are found in column (3) using input inventories.

Columns (2) and (4) are estimations with interaction terms. The interaction term of highway proximity and inventories is always with a significant and positive coefficient no matter which inventory variable is used, revealing that the crowding-in effect of highway development on corporate investment would be larger for firms with a higher level of inventories. This is in line with the hypothesis that the improvement of highway accessibility affects private investment through the channel of inventories. Indeed, highway development will encourage firms to reduce their inventories, especially input inventories (Shirley and Winston, 2004), as highway improvement is associated with a decrease in transportation cost, lead time, and uncertainty in ordering inventories. Therefore, firms with originally high levels of inventory are more likely to improve their inventory management efficiency by reducing the average inventory level to reach a lower inventory cost. And the released cash flow will serve as an additional low-cost financial supply of fixed-asset investment. Moreover, if firms face investment opportunities caused by highway development, they can easily forgo inventories for more low-cost internal funds. Whereas for firms with low levels of inventories, the cost-saving effect of inventories caused by highways is limited (one of the findings in Chapter 4), and inventories cannot be actively offset for funds of fixed investment (Aktas et al., 2015) as inventories are essential for firms in operation and production.

Specifically, using the total inventory to capital ratio, column (2) implies that the

Table 5.8: Inventory channel: interaction term

Dep. Var.: investment	(1)	(2)	(3)	(4)
Highway proximity	1.491***	1.134***	1.490***	1.361***
	(3.90)	(2.91)	(3.90)	(3.53)
Inventory to capital ratio (IWK)	-0.010***	-0.012***		
	(-27.79)	(-13.29)		
IWK*proximity		0.004***		
		(3.21)		
Input inventory to capital ratio (IIWK)			-0.008***	-0.010***
			(-20.15)	(-8.78)
IIWK*proximity				0.003**
				(2.00)
Observations	1,251,590	1,251,590	1,251,590	1,251,590
R-squared	0.070	0.068	0.069	0.069
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	644.242	315.533	644.211	320.218
Over identification test	0.192	0.291	0.193	0.436
Control variables	YES	YES	YES	YES
Company FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES

Note: Control variables include firm size, sales growth, cash flow, tangibility, leverage, the density of other roads, river density and railway density. The same control variables are applied to the rest of the regression tables unless specified otherwise. Instrument variables for columns (1) and (3) are least cost path (2004NEN plan) and straight-line instruments; instrument variables for columns (2) and (4) are least cost path (2004NEN), straight line instruments, channel variable interacted with Ming courier routes and channel variable interacted with the straight line instrument. The Kleibergen-Paap rk Wald F statistic values are well above the corresponding critical value to pass the weak-identification test. The overidentification test reports the Hansen J statistic p-value, which is well above the critical value for the overidentification test (0.05).

average marginal effect of highway proximity on fixed investment is 1.47 ($1.134 + 0.004 \times 84.58$), i.e., a 1 unit increase in highway proximity is associated with a 1.47% increase in fixed investment to capital ratio. Instead of using the mean of the total inventory ratio to compute the average marginal effect, the interval of the marginal effect is from 1.134 to 11.04, calculated using both the minimum and maximum value of the total inventory ratio. Using the input inventory to capital ratio in column (4), the corresponding marginal effect ranges from 1.361 to 5.942, with an average marginal effect of 1.50.

Table 5.9: Further test of the inventory channel

Dep. Var.: investment	(1)	(2)
Highway proximity	1.383***	1.411***
	(3.09)	(3.16)
Inventory to capital ratio (IWK)	-0.012***	
	(-29.11)	
IWK*proximity	0.0003***	
	(2.63)	
Input inventory to capital ratio (IIWK)		-0.010***
		(-20.43)
IIWK*proximity		0.0004***
		(2.87)
Observations	922,877	922,877
R-squared	0.072	0.071
Under identification test	0.000	0.000
Weak identification test	192.050	191.972
Over identification test	0.934	0.951
Control variables	YES	YES
Company FE	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
Province FE	YES	YES

Note: Standard errors are clustered at the firm level. Instrument variables for columns (1) and (2) are least cost path (2004NEN), straight line instrument, twice-lagged inventory variable interacted with Ming courier routes and twice-lagged inventory variable interacted with least cost path (1992NTHS). The Kleibergen-Paap rk Wald F statistic values are well above the corresponding critical value to pass the weak-identification test. The overidentification test reports the Hansen J statistic p-value, which is well above the critical value for the overidentification test (0.05).

In the discussion regarding the inventory channel, it is possible to argue that inventory is likely to be endogenous. Some literature has used lagged variables as instruments in the research, e.g., Fazzari and Petersen (1993) and Almeida et al. (2004). Although far from being perfect, using lagged variables indeed helps to mitigate the possible endogeneity problem. To mitigate the endogeneity issue of inventory, this research further uses the twice-lagged inventory variable interacted with Ming courier routes and the twice-lagged inventory variable interacted with the least cost path (1992NTHS) as the instruments of the interaction term. Table

5.9 reports the robustness of the inventory mechanism where firms with a higher level of inventories respond with higher sensitivities to highway proximity as firms can reduce inventory level (with better efficiency) to have more internal funds for fixed investment.

5.5.3 Uncertainties: incentive to invest

5.5.3.1 Hypothesis

Firms' investment motivation can be affected by uncertainties. The uncertainty-investment relationship is controversial in investment theories, which can be positive (e.g., Abel, 1983; Guiso and Parigi, 1999), negative (e.g., Dixit and Pindyck, 1994; Bernanke, 1983), or even ambiguous (e.g., Abel and Eberly, 1999; Sarkar, 2000) depending on different assumptions or focuses. Although uncertainty itself can take on many forms, including micro-level uncertainties such as stock return uncertainty (e.g., Leahy and Whited, 1996), demand uncertainty (e.g., Guiso and Parigi, 1999), profit uncertainty (e.g., Ghosal and Loungani, 2000), and macro-level uncertainties such macroeconomic uncertainty (e.g., Bloom, 2009), policy uncertainty (e.g., Chen et al., 2019b; Suh and Yang, 2021), most of the empirical evidence suggests a negative relationship between uncertainty and investment, supporting the real options theory; that is, if investment projects are irreversible to some extent, firms should trade off the benefits of current investment against the possible returns of waiting for future investment with lower uncertainty (Bernanke, 1983; Dixit and Pindyck, 1994).

The improvement of highway accessibility is likely to affect firms' fixed investment through the mechanism of uncertainties. Specifically, it is argued that highway expansion may mitigate the negative impact of uncertainties from both the micro-level and the aggregate level on firms' investment.

Micro-level: The improvement of highway proximity is beneficial for firms to effectively cope with micro-level uncertainties, for instance, demand uncertainties. On the one hand, a better highway network with lower trade costs and travel time allows firms to have an easier connection with upstream suppliers and downstream partners, and achieve better inventory management efficiency. On the other hand, market integration improved by highway network (Faber, 2014) also helps firms identify cheaper suppliers and diversify their supply chains. Thus, firms can better absorb demand uncertainties through flexible supply chains and better inventory management.

Moreover, market integration promoted by large-scale highway investments may inspire manufacturing firms to expand their market share by competing with other homogeneous enterprises. Both the price of final goods and intermediate goods may decrease (Aiello et al., 2012) because of reduced input and output costs, lower delivery uncertainties and active market competition. In terms of fixed investment, firms have options to invest, delay, abandon or expand with the trade-off between benefits and costs associated with uncertainties. If firms have the motivation to expand their production and market share given successful investment, then the net present value (with the possibility of good status and bad status) under the option to expand would be larger, therefore encouraging the incentive to invest.

Aggregate level: As discussed in Chapter 2, the rapid development in highway infrastructure is mainly due to huge investments together with national programmes and policy supports, including the National Trunk Highway System approved in 1992 and the National Expressway Network implemented in 2004. The national highway projects, with clear goals announced by the government, provide certain anticipation of future highway networks with lower economic policy uncertainty. Manufacturing firms may actively anticipate a positive future development with the expansion of highway infrastructure. Thus highway construction may mitigate firms' concerns about macro uncertainty and encourage firms to increase investment and expand their production.

Hypothesis 3: The improvement of highway networks stimulates firms' investment incentives by mitigating firms' concerns about uncertainties.

5.5.3.2 Estimation method

By including the interaction term of highway proximity and uncertainty variables, the uncertainty channel is tested in a similar manner to the specification in the inventory mechanism. Specifically, three types of uncertainty are considered, namely, firm-level uncertainty, industry-level uncertainty, and macroeconomic policy uncertainty.

In terms of firm-level uncertainty, this research constructs a variable to proxy potential demand-side uncertainty following Kumar and Zhang (2019) who provided a theoretical model for calculating unexpected demand shock using data of sales, inventory, output and firm characteristics. Kumar and Zhang (2019) demonstrate that in a stockout-avoidance model, within-firm deviation of inventory share from optimal inventory share reveals information about unanticipated demand shocks[2].

As shown in equation (5.4), I regress the ratio of a firm's sales to the value of total available output on a set of firm characteristics and region/industry/time fixed effects.

$$ln(\frac{Sales_{i,j,k,t}}{Inventory_{i,j,k,t-1} + Output_{i,j,k,t}}) = f(Z_{i,j,k,t}) + \theta_j + \theta_k + \theta_t + \theta_{i,j,k,t} \tag{5.4}$$

where the subscripts i, j, k, and t represent firm, 4-digit industry, city, and year, respectively. In equation (5.4), the sales ratio is defined as the ratio of end-of-year sales to the total amount of products available for sale in each period, which is the sum of output and beginning-of-year inventory. $Z_{i,t}$ denotes firm characteristics including firm size, age and ownership. θ_j, θ_k, θ_t are 4-digit industry fixed effects, city fixed effects, and year fixed effects. Given that the logarithm of sales ratio is no more than 0, equation (5.4) will be regressed industry by industry at the 2-digit level using the Tobit estimation and the estimated residual term $\hat{\theta}_{i,j,k,t}$ captures the potential demand-side shocks.

Existing literature about uncertainty (e.g., Bo, 2001; Caglayan et al., 2012) usu-

[2]See p306-p310 of Kumar and Zhang (2019) for the detailed theoretical derivation.

ally uses a moving standard deviation within a short-term period for variables of interest to proxy uncertainties. Following this method, a four-year moving standard deviation of the residual term $\hat{\theta}_{i,j,k,t}$ is calculated to proxy the firm-level uncertainty which captures some information from the demand side.

$$Industry\_Uncertainty_{ind,t} = \sigma_{ind,t}(\hat{\theta}_{i,j,k,t}) \tag{5.5}$$

In addition, this research also estimates the industry-level uncertainty at the 2-digit industry level as the standard deviation of firms' unexpected demand shock within the same 2-digit industry and time, by assuming that firms in the same industry face the same uncertainty at any given time, as shown in equation (5.5).

With regard to the macro-level economic policy uncertainty (EPU), the news-based China EPU index[3] measured using the method of Baker et al. (2016) is used. This China EPU index is estimated by constructing "a scaled frequency count of articles about policy-related economic uncertainty in the South China Morning Post (SCMP), Hong Kong's leading English-language newspaper" (Baker et al., 2013). It is a country-level uncertainty, capturing the overall uncertainties relating to economic policies.

It is expected that the coefficient of uncertainties is negative. Because of the characteristic of irreversibility or partial irreversibility, it is valuable to postpone investment when the future is uncertain (Dixit and Pindyck, 1994). Firms need to make investment timing decisions trading off the benefits of additional information gained from waiting against those gained by early commitment (Bernanke, 1983). Moreover, the real options theory suggests that by waiting for the uncertainty to be resolved before deciding to invest in the irreversible capital, managers can prevent potentially substantial losses by abandoning the irreversible investment if the outcome is unfavourable (Bulan, 2005). The coefficient of the interaction term is possibly positive if the empirical results support the hypothesis that highway proximity helps mitigate the negative impact of uncertainties on firms' investment.

[3] The EPU index is accessible from the website *www.policyuncertainty.com.*

Table 5.10: Summary statistics for uncertainty variables

	Observation	Mean	Min	Max	Std.Dev.
Firm-level uncertainty	1,158,087	0.111	1.37e-07	1.672	0.127
Industry-level uncertainty	1,232,336	0.333	0.0443	0.747	0.120
Economic policy uncertainty	1,334,772	85.57	55.69	129.2	22.09

Table 5.10 shows the summary statistics for the uncertainty variables.

5.5.3.3 Estimation result

Table 5.11 shows how highway proximity affects investment through the uncertainty channel. Columns (1), (3), and (5) present the results without an interaction term. The coefficients of firm-level uncertainty, industry-level uncertainty and economic policy uncertainty are all significantly negative, which is in line with the real option theory (Dixit and Pindyck, 1994). The coefficients of highway proximity in columns (1), (3), and (5) are significantly positive, showing a robust and causal effect of highway proximity on firms' investment.

Columns (2), (4), and (6) display the estimation of adding interaction terms. The coefficients of the interaction terms between uncertainty and highway proximity are consistently positive at the 1% confidence level, showing that better highway proximity will help firms mitigate the negative impact of uncertainties. Specifically, column (2) indicates that the average marginal effect of firm-level uncertainty on investment is -0.676. Column (4) shows that the average marginal effect of industry-level uncertainty on investment is -4.63. Column (6) shows that the average marginal effect of economic policy uncertainty on fixed investment is -0.195. The results are consistent with the hypothesis. As a result of improved highway networks, firms can better cope with uncertainties through flexible supply chains and better inventory management and reduce the costs associated with unanticipated demand shocks. In addition, the integration of markets engendered by large-scale highway construction may inspire manufacturing firms to expand in their markets. Thus when firms have the motivation to expand given a realized successful investment, the net present value under the option to expand would be larger compared with not expanding, therefore

Table 5.11: Uncertainty channel: interaction term

Dep. Var.: investment	(1)	(2)	(3)	(4)	(5)	(6)
Highway proximity	1.450***	0.888*	1.491***	-3.942***	1.509***	-4.035***
	(3.64)	(1.94)	(3.90)	(-4.21)	(3.95)	(-3.99)
Firm-level uncertainty	-1.199***	-3.276***				
	(-3.77)	(-3.40)				
Firm-level uncertainty*proximity		4.915**				
		(2.28)				
Industry-level uncertainty			-7.089***	-11.641***		
			(-8.79)	(-9.79)		
Industry-level uncertainty*proximity				13.238***		
				(5.40)		
Economic policy uncertainty (EPU)					-0.191***	-0.227***
					(-24.85)	(-21.55)
EPU*proximity						0.060***
						(5.23)
Observations	1,157,447	1,157,447	1,251,590	1,251,590	1,251,590	1,251,590
R-squared	0.069	0.069	0.069	0.066	0.070	0.066
Under identification test	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification test	589.280	309.369	240.792	132.379	644.368	357.335
Over identification test	0.180	0.324	0.936	0.995	0.208	0.475
Control variables	YES	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES

Note: instrument variables for columns (1), (3), (5) are least cost path (2004NEN plan) and straight-line instruments; instrument variables for columns (2), (4), (6) are least cost path (2004NEN), straight line instruments, channel variable interacted with Ming courier routes and channel variable interacted with least cost path (1992NTHS). The Kleibergen-Paap rk Wald F statistic values are well above the corresponding critical value to pass the weak-identification test. The overidentification test reports the Hansen J statistic p-value, which is well above the critical value for the overidentification test (0.05).

encouraging the incentive to invest. In addition, the government's announcements of national highway projects with clear goals provide some expectations of future highway networks and their associated benefits. Thus, highway construction could also mitigate firms' concerns about country-level economic policy uncertainty and encourage them to invest and expand.

5.6 Do Highways Improve Investment Quality?

This research has explored that better highway proximity can stimulate the quantity of fixed investment by reducing firms' financial constraints, releasing additional internal funds via inventory reduction, and mitigating the negative impact of uncertainties. This section further explores whether better highway proximity improves the quality of investment. Theoretically, if the investment goes to firms with initially higher marginal revenue products of capital (MRPK), the return on new investment would be larger (Bau and Matray, 2023), indicating a higher quality of investment.

To this end, examining whether the increased investment induced by better highway proximity goes to firms with higher MRPK can provide useful information. The firm-level MRPK is calculated following the methodology in Asker et al. (2014) and Wooldridge (2009). The full sample is then split into two categories based on the median value of MRPK. Table 5.12 shows the subgroup estimation result using firm-level investment as the dependent variable. Four instruments are used respectively: least-cost path IV constructed based on the 2004NEN plan (columns 1-2) and the 1992NTHS plan (columns 3-4), straight-line IV based on the 2004NEN plan (columns 5-6), and historical IV based on the Ming dynasty's courier routes (columns 7-8).

Overall, the coefficients of highway proximity are significantly positive no matter for low-MRPK firms or high-MRPK firms, except for columns 3-4[4]. This further confirms the crowding-in effect of highway infrastructure on the quantity of investment. In addition, the coefficients of highway proximity in high-MRPK firms are significantly higher than those in low-MRPK firms, suggesting that firms with higher marginal returns receive more investment. This evidence supports that better highway infrastructure not only stimulates the quantity of corporate investment but also improves the quality of investment by allocating more investment to firms with higher marginal returns of capital.

[4]The insignificant results in columns 3-4 are possibly explained by the poor performance in the LCP (1992NTHS) instrument, which is weakly identified.

Table 5.12: Firm investment heterogeneity by MRPK

Dep. Var.: investment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LCP (2004NEN)		LCP (1992NTHS)		Straight lines		Ming routes	
MRPK category	low	high	low	high	low	high	low	high
Highway proximity	0.878*	2.464***	3.018	17.679	1.265**	3.211***	1.849**	8.149***
	(1.77)	(3.36)	(1.56)	(1.22)	(2.25)	(3.78)	(2.34)	(4.57)
Observations	598,599	594,159	598,599	594,159	598,599	594,159	598,599	594,159
R-squared	0.078	0.055	0.066	-0.359	0.077	0.049	0.074	-0.028
Under identification test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification test	695.503	320.177	57.342	2.459	509.776	258.385	252.458	91.788
Coefficient difference	-1.586*		-14.66		-1.946*		-6.300***	
	(-1.790)		(-1.005)		(-1.911)		(-3.229)	
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Robust Z-statistics corrected for clustering at the firm level are reported in parenthesis. Significant coefficients are indicated by ***, **, *, for significance at the 1%, 5% and 10% levels, respectively. Control variables are the same as in the baseline estimation. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak-identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 16.38. Coefficient difference reports the significance of the difference in the coefficient of highway proximity between low-MRPK firms and high-MRPK firms with the following statistic (Almeida et al., 2021): $Z = \frac{\beta_{low} - \beta_{high}}{\sqrt{SE(\beta_{low})^2 + SE(\beta_{high})^2}}$.

5.7 Robustness Tests

5.7.1 Using different highway measures

To give robust evidence that firms tend to increase their fixed investment when they have better access to the highway, two additional highway access measures are used, namely, the logarithm of highway distance and the relative highway proximity (RHP). Table 5.13 shows the 2SLS regression result using four different instruments, least cost paths based on the 2004 NEN plan, least cost paths based on the 1992 NTHS plan, straight-line routes, and Ming courier routes, respectively.

Panel A shows the results of using the logarithm of highway distance as a highway

Table 5.13: Alternative highway measures

Dep. Var.: investment	(1) LCP_NEN	(2) LCP_NTHS	(3) Straight_line	(4) Ming_routes
Panel A: use ln(highway distance) as highway variable				
Ln (highway distance)	-0.259***	-0.334**	-0.307***	-0.498***
	(-3.39)	(-2.57)	(-4.06)	(-4.98)
Observations	1,251,590	1,251,590	1,251,590	1,251,590
R-squared	0.072	0.072	0.072	0.072
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	3.7e+04	1.1e+04	3.0e+04	2.1e+04
Panel B: use the relative highway proximity as highway variable				
RHP	4.772***	6.490**	5.743***	9.414***
	(3.39)	(2.57)	(4.06)	(4.97)
Observations	1,251,590	1,251,590	1,251,590	1,251,590
R-squared	0.072	0.072	0.072	0.071
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	1.5e+04	4460.539	1.4e+04	8775.172
Control variables	Yes	Yes	Yes	Yes
Company/Year/Industry/Province FE	Yes	Yes	Yes	Yes
Instruments				
Least cost path (2004NEN)	Yes			
Least cost path (1992NTHS)		Yes		
Straight line routes			Yes	
Ming courier routes				Yes

Note: The standard errors are clustered at the firm level. Significant coefficients are indicated by ***, **, *, for significance at the 1%, 5%, and 10% levels, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak-identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 16.38.

access variable. The smaller the log distance, the better the highway access. The coefficient of the log distance is significantly negative, no matter which method and instrument are used. Panel B uses relative highway proximity (RHP) as a highway variable. A higher RHP means better highway access. The results are also robust, indicating the crowding-in effect of highway improvement on private investment.

5.7.2 Industry-province clustered standard errors

In the previous estimation, the standard errors are clustered at the firm level, allowing a firm's observations to be correlated within the sample period. This section considers the possible situation that firms in the same region and the same industry may be affected by the same policies, thus they may be correlated. By assuming that firms are correlated within the same 2-digit industry and the same province but independent between different industries and provinces, Table 5.14 reports the estimation result using an industry-province cluster. The estimation result is quite robust with different highway measures and different instruments. The coefficient of interest is significant and is consistent with the expectation in columns (1), (3) and (4), showing that the improvement of highway accessibility is beneficial to corporate investment. The insignificant coefficient only happens when using the least-cost path constructed based on the 1992 NTHS plan. The weak identification test indicates that highway proximity is weakly instrumented using the least-cost path (1992NTHS) (panel A, column 2), which is not the best instrument possibly because of its lower density than the least-cost path constructed based on the 2004 NEN plan.

Table 5.14: Standard errors clustered at the industry-province level

Dep. Var.: investment	(1) LCP_NEN	(2) LCP_NTHS	(3) Straight_line	(4) Ming_routes
Panel A: highway proximity as highway variable				
Highway proximity	1.100**	4.574	1.577***	3.120***
	(2.25)	(1.30)	(2.82)	(3.31)
Observations	1,055,120	1,055,120	1,055,120	1,055,120
R-squared	0.070	0.043	0.068	0.058
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	301.251	6.113	256.983	70.895
Panel B: use ln(highway distance) as highway variable				
Ln (highway distance)	-0.204**	-0.267	-0.264***	-0.449***
	(-2.27)	(-1.55)	(-2.91)	(-3.57)
Observations	1,055,120	1,055,120	1,055,120	1,055,120
R-squared	0.072	0.072	0.072	0.072
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	2622.671	294.594	755.058	706.050
Panel C: use the relative highway proximity as highway variable				
RHP	3.775**	5.168	4.948***	8.538***
	(2.26)	(1.55)	(2.89)	(3.56)
Observations	1,055,120	1,055,120	1,055,120	1,055,120
R-squared	0.072	0.072	0.072	0.071
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	1371.134	168.295	572.170	429.115
Control variables	Yes	Yes	Yes	Yes
Company/Year/Industry/Province FE	Yes	Yes	Yes	Yes
Instruments				
Least cost path (2004NEN)	Yes			
Least cost path (1992NTHS)		Yes		
Straight line routes			Yes	
Ming courier routes				Yes

Note: Robust Z-statistics corrected for clustering at the industry-province level are reported in parenthesis. Significant coefficients are indicated by ***, **, *, for significance at the 1%, 5%, and 10% levels, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak-identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 16.38.

5.7.3 Different buffer (5km)

The time-varying instrument routes are originally calculated by interacting the 10 km buffer of actual highways with alternative instrumental routes. This section shows that the results are still robust by using different buffers (5km, for example) to compute time-varying IVs. Table 5.15 shows the robust results of using three different highway accessibility measures and different instruments constructed using a 5km buffer.

Table 5.15: IVs calculated by 5km buffer

Dep. Var.: investment	(1) LCP_NEN	(2) LCP_NTHS	(3) Straight_line	(4) Ming_routes
Panel A: highway proximity as highway variable				
Highway proximity	1.258***	1.625**	0.840***	2.111***
	(3.76)	(2.39)	(2.96)	(4.88)
Observations	1,251,590	1,251,590	1,251,590	1,251,590
R-squared	0.070	0.068	0.071	0.065
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	1437.513	367.792	1813.283	878.277
Panel B: use ln(highway distance) as highway variable				
Ln (highway distance)	-0.273***	-0.269**	-0.194***	-0.441***
	(-3.77)	(-2.41)	(-2.97)	(-4.95)
Observations	1,251,590	1,251,590	1,251,590	1,251,590
R-squared	0.072	0.072	0.072	0.072
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	4.4e+04	1.5e+04	5.0e+04	2.7e+04
Panel C: use the relative highway proximity as highway variable				
RHP	5.005***	5.037**	3.472***	8.099***
	(3.77)	(2.41)	(2.97)	(4.94)
Observations	1,251,590	1,251,590	1,251,590	1,251,590
R-squared	0.072	0.072	0.072	0.071
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	1.6e+04	6583.141	2.2e+04	1.2e+04
Control variables	Yes	Yes	Yes	Yes
Company/Year/Industry/Province FE	Yes	Yes	Yes	Yes
Instruments				
Least cost path (2004NEN)	Yes			
Least cost path (1992NTHS)		Yes		
Straight line routes			Yes	
Ming courier routes				Yes

Note: Robust Z-statistics corrected for clustering at the firm level are reported in parenthesis. Significant coefficients are indicated by ***, **, *, for significance at the 1%, 5%, and 10% levels, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak-identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 16.38.

5.7.4 Historical IVs

In terms of the historical instrument, one may argue that the historical instrument of the Ming dynasty is not perfect as the Ming's courier routes do not reach seven provinces (Jilin, Heilongjiang, Hainan, Qinghai, Inner Mongolia, Tibet, and Xinjiang). It might also be pointed out that Ming routes may not have a similar road density to the actual highways.

To ensure these issues would not change the consistency of the main results, Table 5.16 shows the IV estimation of using a combination of two time-changing instruments based on the Qing Dynasty's routes and Ming Dynasty's routes. With the full sample, Columns (1) and (2) use historical instruments calculated using a 10 km buffer and a 5 km buffer, respectively. No matter which measure of highway accessibility is used (panels A, B, C), the coefficients of interest are always significant and robust, confirming the crowding-in effect.

In columns (3) and (4), observations located in the seven provinces are excluded from the IV regression. No matter which buffer and which highway measure are used, the coefficients of interest are robust and in line with the hypothesis. The weak identification and under-identification tests are all passed in columns (1)-(4). Because the number of instruments (Ming courier routes and Qing courier routes) is larger than the number of endogenous variables (highway accessibility), the Hanson J statistic is used for the overidentification test of all instruments. The p-values are larger than the critical value (0.05) in all cases, indicating that the combination of the two historical instruments is both valid and exogenous.

5.7.5 Further control for the endogeneity issue of targeted cities

It is possible to argue that the least cost paths and straight lines cannot fully address the endogeneity issue as the targeted city points were endogenously chosen by government planners. To further control this issue, this research further excluded the observations located in the targeted cities of the NTHS plan. This method is rea-

Table 5.16: Additional IV result using both Ming and Qing historical instruments

Dep. Var.: investment	(1)	(2)	(3)	(4)
	Full sample		Drop 7 provinces	
	10km buffer	5km buffer	10km buffer	5km buffer
Panel A: highway proximity as highway variable				
Highway proximity	2.995***	2.104***	2.956***	2.090***
	(4.71)	(5.00)	(4.62)	(4.93)
Observations	1,251,590	1,251,590	1,214,801	1,214,801
R-squared	0.059	0.065	0.060	0.066
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	189.923	443.492	186.446	435.384
Overidentification test	0.129	0.947	0.124	0.972
Panel B: use ln(highway distance) as highway variable				
Ln (highway distance)	-0.497***	-0.431***	-0.492***	-0.425***
	(-4.97)	(-4.86)	(-4.89)	(-4.75)
Observations	1,251,590	1,251,590	1,214,801	1,214,801
R-squared	0.072	0.072	0.072	0.072
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	1.0e+04	1.4e+04	1.0e+04	1.3e+04
Overidentification test	0.143	0.115	0.143	0.092
Panel C: use the relative highway proximity as highway variable				
RHP	9.587***	8.183***	9.541***	8.130***
	(5.07)	(5.00)	(4.97)	(4.90)
Observations	1,251,590	1,251,590	1,214,801	1,214,801
R-squared	0.071	0.071	0.072	0.072
Under identification test	0.000	0.000	0.000	0.000
Weak identification test	4422.445	5797.780	4396.287	5769.642
Overidentification test	0.319	0.327	0.291	0.255
Control variables	Yes	Yes	Yes	Yes
Company/Year/Industry/Province FE	Yes	Yes	Yes	Yes
Instruments				
Ming courier routes	Yes	Yes	Yes	Yes
Qing courier routes	Yes	Yes	Yes	Yes

Note: Robust Z-statistics corrected for clustering at the firm level are reported in parenthesis. Significant coefficients are indicated by ***, **, *, for significance at the 1%, 5%, and 10% level, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The Kleibergen-Paap rk Wald F statistic values are well above the corresponding critical value to pass the weak-identification test. The overidentification test reports the Hansen J statistic p-value, which is well above the critical value for the overidentification test (0.05).

sonable as cities outlined in the NTHS plan are provincial capitals or big cities with more developed economies. Once observations in these targeted areas are dropped, the remaining firm observations have all access to highways by chance. It is worth mentioning that the principle is not on the basis of the targeted cities in the NEN

Table 5.17: Drop observations located in the targeted NTHS cities

Dep. Var.: investment	(1)	(2)	(3)	(4)	(5)	(6)
		10km buffer			5km buffer	
Panel A: highway proximity as highway variable						
Highway proximity	1.015*	2.490**	1.283**	0.904*	2.105**	0.294
	(1.71)	(2.39)	(2.34)	(1.73)	(2.54)	(0.63)
Observations	444,095	444,095	444,095	444,095	444,095	444,095
R-squared	0.073	0.069	0.073	0.073	0.070	0.074
Under identification test	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification test	609.138	159.672	615.799	710.964	220.779	757.743
Panel B: ln (highway distance) as highway variable						
Ln (highway distance)	-0.187*	-0.566**	-0.226**	-0.184*	-0.567**	-0.060
	(-1.71)	(-2.43)	(-2.35)	(-1.73)	(-2.57)	(-0.63)
Observations	444,095	444,095	444,095	444,095	444,095	444,095
R-squared	0.074	0.074	0.074	0.074	0.074	0.074
Under identification test	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification test	2.2e+04	3530.111	2.4e+04	2.7e+04	4787.937	2.7e+04
Panel C: relative highway proximity as highway variable						
RHP	3.610*	10.843**	4.275**	3.509*	10.579**	1.108
	(1.71)	(2.43)	(2.35)	(1.73)	(2.57)	(0.63)
Observations	444,095	444,095	444,095	444,095	444,095	444,095
R-squared	0.074	0.074	0.074	0.074	0.074	0.074
Under identification test	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification test	7556.397	1359.860	9437.309	8282.495	1689.154	1.1e+04
Control variables	YES	YES	YES	YES	YES	YES
Company/Year/Industry/Province FE	YES	YES	YES	YES	YES	YES
Instruments						
Least cost path (2004NEN)	YES			YES		
Least cost path (1992NTHS)		YES			YES	
Straight line routes			YES			YES

Note: Robust Z-statistics corrected for clustering at the firm level are reported in parenthesis. Significant coefficients are indicated by ***, **, *, for significance at the 1%, 5%, and 10% levels, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak-identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 16.38.

plan, as the 323 targeted cities include not only large cities but also medium cities, which share 90% of the urban population and 96% of trade sales. Moreover, more than 90% of manufacturing firms are located in the NEN-targeted cities, which might encourage the problem of selection bias if the majority of the observations are excluded.

Approximately 36% of firm observations are located beyond the targeted NTHS cities. Table 5.17 shows the IV regression result excluding observations located in the targeted NTHS cities. The estimation results are quite robust with different highway measures (panels A, B, C), different highway buffers (10km or 5km), and different instruments (least cost path or straight lines).

5.8 Conclusion

This research investigates the causal effect of highway accessibility on firms' investment decisions, using a geo-coded firm-level panel dataset for Chinese manufacturing firms in the period from 1998 to 2007. To address the endogeneity issue of highway construction, several time-varying instruments are used to shed light on causality, including the least cost paths and straight lines constructed based on the targeted city points outlined in the highway construction planning, and historical routes of the Ming and Qing dynasties. The FE-2SLS estimation results show that better access to highways increases firm investment, supporting the crowding-in effect of public transportation investment. I find that highway proximity promotes corporate investment through at least three mechanisms, that is, by reducing firms' financial constraints, releasing additional internal funds via inventory reduction, and mitigating the negative impact of uncertainties. In addition, further estimation result shows that better highway infrastructure increases both the quantity and quality of corporate investment by allocating more investment to firms with higher marginal returns.

There are some insights for policymakers. First, infrastructure investment is crucial for economic development. Investment in transportation infrastructure tends to stimulate private investment, which thus contributes to economic growth. Secondly, infrastructure development plays an essential role in reducing market segmentation and local protectionism, as the improved transportation network facilitates market competition and expansion, and better access to distant suppliers and external finance. This is in line with the recent government policy of building a unified domestic market in China. Thirdly, the results on the financial constraint channel indicate the need for further financial sector reform and more efficient resource reallocation towards the private sector. Despite their low profitability and poor financial health, SOEs are more likely to obtain loans from the formal banking system with low interest rates, whereas more efficient private companies face more stringent borrowing constraints. The development of better transport infrastructure such as highways provides private firms with better access to creditors, alleviates financial constraints and thus contributes to investment and growth.

5.9 Appendix: Real Capital Stock and Investment

As firms only report their nominal fixed assets at the original purchase price or net nominal value of fixed assets, it is necessary to eliminate systematic bias in estimating capital stock related to firms' age, by converting them into comparable real values across firms and across times (Brandt et al., 2012).

Following Brandt et al. (2012), the real capital stock is estimated based on the nominal fixed assets at the original purchase price. The procedure for estimating the real capital stock is as follows:

First, the following formula is used to estimate the initial nominal and real capital stock in the year of establishment.

$$NK_{it_0} = \frac{NK_{it_d}}{(1 + r_{ps})^{t_d - t_0}} \tag{5.6}$$

$$RK_{it_0} = \frac{NK_{it_0}}{P_{t_0}} \tag{5.7}$$

where NK_{it_0} and RK_{it_0} are the nominal and real capital stock of firm i in the year of establishment, t_0 is the establishment year of firm i, t_d is the year when enterprise i first appeared in the database, NK_{it_d} is the original value of the fixed asset when the company i appeared in the database in the first year. r_{ps} is the estimated average growth rate of the nominal capital assets between 1993 and 1998 in province p and two-digit industry s, by using the 1993 annual enterprise survey. P_{t_0} is the investment deflator index of t_0 period, constructed in Brandt and Rawski (2008).

Then, the real capital stock for each firm in year t is calculated by the following formula. Before t_d, the real fixed investment is calculated by multiplying the nominal capital stock of the previous year by the growth rate, divided by the Brandt-Rawski investment deflator. After t_d, the real fixed investment is equal to the change in the firm's nominal capital stock at original purchase prices, divided by the Brandt-

Rawski investment deflator. Depreciation is calculated by the perpetual inventory method, by assuming an average depreciation rate of 9%.

$$RK_{it} = \begin{cases} \dfrac{NK_{it-1} * r_{ps}}{P_t} + (1-\delta)RK_{it-1}, & t \leq t_d \\ \dfrac{NK_{it} - NK_{it-1}}{P_t} + (1-\delta)RK_{it-1}, & t \geq t_d \end{cases} \tag{5.8}$$

Firm-level fixed investment ratio is then calculated as the ratio of real fixed investment to real capital stock. The real value of the fixed investment in year t is equal to the difference between the real capital stock of end of year t and end of year $t-1$, adding the real value of deprecation (RD_{it}) in year t. The Brandt and Rawski investment deflator is used to deflate the nominal deprecation.

$$(\frac{I}{K})_{it} = \frac{RK_{it} - RK_{it-1} + RD_{it}}{RK_{it}} \tag{5.9}$$

Chapter 6

Highway Infrastructure and Capital Misallocation: Evidence from China

6.1 Introduction

Resource misallocation has been a central perspective in understanding cross-country differences in both productivity and income (Restuccia and Rogerson, 2013, 2017). Capital misallocation, in particular, is commonly regarded as the prevailing empirical phenomenon, especially in developing countries such as China (Wu, 2018) [1]. One large stream of literature has identified the specific sources of capital misallocation, such as financial and informational frictions (e.g., Gopinath et al., 2017; Midrigan and Xu, 2014; David et al., 2016), policy distortions (e.g., Lagos, 2006; Song et al., 2011; Wu, 2018), and adjustment costs (e.g., David and Venkateswaran, 2019). This research adds to this stream of literature by investigating highway infrastructure development as a specific source affecting capital misallocation.

China experienced rapid highway transportation development following the two major highway infrastructure projects by the Chinese government, that is, the National Trunk Highway System project in 1992 and the National Expressway Network project in 2004. Over the sample period, the length of highways expanded from 8,700 kilometres in 1998 to 53,900 kilometres in 2007 in China. A better highway transportation network increases the travel speed of road transportation, which is heavily relied upon by manufacturing firms[2]. This promotes market integration and is likely to facilitate resource allocation efficiency.

Existing literature concludes that highway infrastructure can promote productivity (e.g., Holl, 2012, 2016; Li and Arreola-Risa, 2017). Thus, even without changing capital stock, firm-level marginal return of capital (MRPK) will change accordingly because of the increase in productivity. However, the increase in firm-level productivity doesn't guarantee a reduction in MRPK dispersion[3]. Chapter 5 has provided

[1]For instance, Hsieh and Klenow (2009) document that reallocating capital among firms would account for the majority of gains in India and China. Brandt et al. (2013) argue that most of the within-province distortions in China's non-agricultural economy are the result of capital misallocation between the non-state and state sectors. Zhang et al. (2023) conclude that capital misallocation is much greater than labour misallocation among China's manufacturing firms.

[2]During 1998-2007, around 75% of freights are transported by road infrastructure.

[3]Both theoretically and empirically, dispersion in returns of capital is commonly used to measure capital misallocation in influential literature. For instance, marginal revenue product of capital

initial findings that better highway infrastructure increases both the quantity and quality of corporate investment by encouraging more investment to firms with higher marginal returns. However, whether, and how, better highway infrastructure promotes the allocative efficiency of capital needs a deeper understanding.

Intuitively, highway infrastructure may affect capital allocative efficiency through at least four channels. First, better highway proximity is likely to affect revenue-based productivity volatility, which captures uncertainties from both the supply and demand side. On the one hand, better highway infrastructure can alleviate supply-side uncertainty. By reducing the transit time and uncertainties associated with supply chains, a better highway infrastructure facilitates efficient and faster transportation of goods and services between regions and cities. With better connections upstream and downstream, better highway proximity also contributes to improved input and supply management efficiency. On the other hand, better highway infrastructure may affect demand-side uncertainty. Having improved highway connectivity can enable companies to reach a larger market. Better transportation networks mitigate uncertainties associated with inventory management and order fulfilment, reducing demand-side uncertainties. With more reliable transportation networks and improved market access, the improvement in highway accessibility may reduce productivity volatility by improving market access, improving supply chains, and providing a more stable business environment. Because of the presence of adjustment cost, dispersion in marginal revenue product of capital (MRPK) will occur naturally even in a frictionless market since an optimal capital stock determined in the previous period may no longer be optimal after a productivity shock occurs (Asker et al., 2014). If better highway infrastructure affects productivity volatility, it will then affect MRPK dispersion due to adjustment costs.

Secondly, highway infrastructure may affect markup dispersion, which is one of the sources of capital misallocation (David and Venkateswaran, 2019). The expansion in highways has two opposing effects on markup: (1) lower transportation costs would allow firms to have easier access to cheaper intermediate goods and reduce the cost of production, resulting in higher profit margins for firms and an increase in

(MRPK) is applied in Gopinath et al. (2017), Wu (2018) and Ek and Wu (2018); Dispersion in the average product of capital (APK), on the other hand, is applied in Midrigan and Xu (2014) and David and Venkateswaran (2019) to estimate capital misallocation.

markups, and (2) with better market integration and increased competition, firms may reduce markups to attract customers. If the impact of highway infrastructure on markups is heterogeneous among different firms, then it is likely to affect the overall dispersion of markups, and therefore, capital misallocation.

Thirdly, if highway infrastructure has a quantity effect on fixed investment by increasing the availability of external finance, then it is expected to have a quality effect on capital allocative efficiency. Highway networks play an important role in reshaping economic geography. This is primarily accomplished through intercity commuting and information transmission (Duan et al., 2020). Transport accessibility also helps to identify investment opportunities more efficiently and reduces the risks associated with multi-country investments, as it enhances the accessibility and quality of mediated information (Giroud, 2013; Bernstein et al., 2016; Duan et al., 2020). Therefore, improved highway networks may facilitate access to external financial sources with a wider geographic scope, reducing financial constraints. Constraint firms can therefore increase their investment. Since financial constraint is one of the important sources of capital misallocation in China (Ek and Wu, 2018), highway infrastructure may affect capital misallocation via financial constraint.

Fourthly, policy distortion may enter as a moderating effect. The government may provide favourable treatment to some firms with political connections through a variety of channels, such as low-interest loans, tax breaks, subsidies, and awards of government contracts (Restuccia and Rogerson, 2013). State-owned firms (Brandt et al., 2013; Song et al., 2011), for instance, may be less reactive to the improvement of highways because of their political connections with the government. Thus, industries dominant with private-owned capital may benefit more from the highway improvement, compared with industries with higher policy distortions.

To test whether and how the rapid development of highway infrastructure affects capital allocative efficiency, this research applies the firm-level data from the Annual Survey of Industrial Firms covering the period from 1998 to 2007, and the panel of geo-referenced highway maps over the sample period. MRPK is computed from Cobb-Douglas production functions by industry. Following the literature, the cross-sectional dispersion of MRPK calculated at the 4-dight industry-province level[4] is

[4]Since highway infrastructure is better developed in coastal provinces than that in inland re-

applied to capture the inefficiency of capital allocation. Highway proximity is calculated as the inverse of the unweighted average distance to the nearest highway among firms in the 4-digit industry-province level. As a result of the endogeneity of highway construction, three types of time-varying instruments are constructed based on the least-cost paths (based on the 2004 NEN highway project), historical routes (a combination of Ming Dynasty and Qing Dynasty courier routes), and straight lines (based on the 2004 NEN highway project), respectively.

It is found that better highway proximity promotes a better allocative efficiency of capital and reduces the dispersion of MRPK. Specifically, the estimation results indicate that a 0.1 unit increase in highway proximity over the sample period can lead to 0.03-0.04 unit decrease in MRPK dispersion. Moreover, there are at least four mechanisms through which highway infrastructure reduces MRPK dispersion: (1) productivity volatility. With decreased productivity volatility caused by better highway proximity, the new capital level in the next period is less likely to be largely different from the optimal level, therefore resulting in a smaller dispersion in the static measure of MRPK dispersion. (2) markup dispersion. Better highway proximity reduces markup dispersion by imposing heterogeneous effects on firm-level markups, i.e., firms with higher markup levels reduce more than those with lower markup levels. (3) financial constraints. Industries with higher financial constraints can benefit from better transportation networks and increase their capital allocative efficiency. (4) policy distortion enters as a moderating effect. Industries with lower policy interventions (i.e., with lower state-owned and foreign-owned capital shares or lower subsidy levels) tend to benefit more from highway development.

The contribution of this research is threefold. First, it contributes to the literature on highway infrastructure. Current literature about how highway infrastructure affects capital allocation efficiency is limited. For instance, Asturias et al. (2019) estimate how India's transportation infrastructure affects welfare via the mechanism of allocative efficiency. Kailthya and Kambhampati (2022) focus on how India's road transportation stimulates value-added productivity and provide findings relating to the effect of road infrastructure on the within-industry reallocation of resources

gions, MRPK dispersion within an industry-province-year group would better highlight the role of highway infrastructure. In addition, due to industry protectionism within the province, it is assumed that there are fewer industry interactions.

across firms (Olley and Pakes (1996) covariance). Liu et al. (2021) investigate the impact of highway networks on allocative efficiency across both firms and counties in China from 1998 to 2007 through two channels, i.e., firm-level factor (capital and labour) distortions and markups. However, none of them provides a detailed discussion of how transportation infrastructure affects capital misallocation or capital allocative efficiency. This research thus fills this gap by investigating whether and how China's highway infrastructure development affects the dispersion in MRPK.

Second, this research builds on the literature on capital misallocation but deviates from it. For instance, because of the presence of capital adjustment cost, Asker et al. (2014) highlight the importance of productivity volatility in explaining the dispersion of static measures of MRPK dispersion. My research borrows this idea but focuses on how highway infrastructure influences productivity volatility and builds on the findings of David and Venkateswaran (2019) regarding the sources of capital misallocation, including markup dispersion. In summary, this research borrows from the literature on the sources of capital misallocation and contributes to the understanding of highway proximity as a potential source affecting capital misallocation.

Thirdly, this research identifies the causal relationship between highway proximity and MRPK dispersion with detailed highway routes and instrumental routes. Rather than applying provincial road stock as the proxy of transportation development (e.g., in Li and Li, 2013; Lin et al., 2019b), this measure of highway proximity is constructed based on firm-level highway access, which better highlights the heterogeneity of highway proximity at the industry-province level. To address the endogeneity of highway construction, three types of time-varying instruments are constructed based on the least-cost paths, historical routes, and straight lines, respectively. Compared to Liu et al. (2021) which just applies the least-cost paths based on the 1992 NTHS highway project, my construction of instruments is more comprehensive. This construction of least-cost paths and straight lines is on the basis of 2004's NEN project which covers the routes of the NTHS project and extends the construction plan of the highway network. Therefore, this construction of instrumental routes provides a similar density as the actual highways.

The remainder of this chapter is structured as follows. Section 2 presents a literature review on resource misallocation and capital misallocation. Section 3 illustrates the model specification, key variable definition, and estimation method. Section 4 reports stylized facts, summary statistics and empirical results of baseline models. Section 5 explores the underlying mechanisms through which highway proximity affects capital misallocation. Section 6 provides extensive robustness checks, and section 7 concludes the chapter.

6.2 Literature Review

6.2.1 Resource misallocation

6.2.1.1 Definition and measurement of resource misallocation

A large body of literature has examined the causes of low total factor productivity (TFP) in poor countries and the differences in TFP across countries (e.g., Lagos, 2006; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). A common explanation is the slow adoption of frontier technology as well as inefficient use of technology in low-income countries (Restuccia and Rogerson, 2013, 2017), and misallocation has emerged as a complementary explanation that low-income countries allocate resources inefficiently.

Theoretically, efficient allocation maximizes final output (net of fixed costs). It consists of two components: the first component identifies which establishments will operate ('selection effect') and the second component determines how labour and capital will be allocated across those establishments ('(mis)allocation effect') (Restuccia and Rogerson, 2017). By allocating inputs in order to maximize output, all producers will have the same marginal products of labour and capital with positive inputs. However, if either of the decisions in the two components is distorted, the economy will have lower output, resulting in a lower aggregate TFP due to constant aggregate factor inputs (Restuccia and Rogerson, 2013).

The misallocation channel

Narrowly speaking, the nature of resource misallocation captures the situation that the given amount of labour and capital is misallocated across individual producers. In the absence of distortions, this allocation of resources depends mainly on productivity, since more resources will be allocated to establishments with higher physical productivity (TFPQ) so that their higher output results in lower prices and the same revenue productivity (TFPR) as smaller establishments (Hsieh and Klenow, 2009). Many distortions, such as policy distortions (e.g., Lagos, 2006; Song et al., 2011; Brandt et al., 2013) and market imperfection (e.g., Gopinath et al., 2017; Midrigan and Xu, 2014; David et al., 2016) can potentially prevent resources from being allocated to more productive producers thus resulting in resource misallocation. For instance, subsidies to low-productivity establishments, or taxes on high-productivity establishments, will result in a higher share of resources being allocated to low-productivity establishments (Restuccia and Rogerson, 2008).

The theoretical model without reflecting selection effects, developed by Hsieh and Klenow (2009), indicates that the allocation of resources across firms is influenced not only by firm productivity but also by output and input distortions. According to this model, the degree to which resource allocation is dictated by distortions rather than by firm productivity will result in a variation in the marginal revenue products of inputs across firms and the adverse effects of distortions on aggregate productivity can be captured in the variance of revenue productivity. TFPR dispersion in this case is used in Hsieh and Klenow (2009) to proxy firm-level distortions given that revenue productivity should be the same across firms if without distortions. In Asker et al. (2014) and Ding et al. (2016a), it can also be seen that the large and persistent dispersion of productivity across firms to some extent indicates market distortions that impede optimal resource allocation.

Because the efficient allocation of inputs equals marginal products across all active producers, it provides the opportunity to identify the extent of misallocation by examining dispersion in marginal products (Restuccia and Rogerson, 2017). Gong and Hu (2016) extend Hsieh and Klenow (2009)'s study by relaxing the assumption of constant returns to scale for differentiated products. They suggest that when the condition of constant return to scale fails, gauging frictions in resource allocation through variation in revenue productivity will overestimate resource misallocation in China. In their view, marginal revenue products of labour and capital can better measure distortions since 'MRPL and MRPK should be equal across firms within an industry without distortions regardless of the returns to scale'.

From an alternative perspective, Bartelsman et al. (2013) claim that the within-industry size-productivity covariance is a reliable measure for assessing the impact of misallocation both theoretically and empirically. This motivation comes from (1) the positive correlation between distributions of productivity and size in firm-level data evidence and size distribution theories (e.g., Melitz, 2003) and (2) the authors' cross-country evidence on the substantial variation in the strength of the productivity-size relationship across countries, industries, and over time. The researchers, therefore, propose the misallocation hypothesis that the observed size-productivity covariance may be induced by policy distortions and can contribute to the observed differences in aggregate performance. A theoretical model is provided with heterogeneous firms facing adjustment frictions and distortions. In addition, they allow for policy distortions affecting resource allocation among existing firms as well as in the selection of firms. The hypothesis is then estimated based on a number of moments generated from a manufacturing firm-level database for seven European countries and the United States. They measure the within-industry covariance between size and productivity using the Olley and Pakes (1996) decomposition method and conclude that size-productivity covariance caused by policy distortions accounts for noticeable differences in aggregate performance.

The selection channel

From a conceptual perspective, the selection issue that determines which establishments will operate is a special case of misallocation, since the non-operation of an establishment equals zero inputs (Restuccia and Rogerson, 2013). In related work, Lagos (2006) constructs an aggregation model of TFP showing how individual production decisions affect the aggregate relation between outputs, inputs, and TFP and how labour-market policies influence TFP through the mechanism of selection effects. Specifically, individual production decisions (e.g., deciding which production units remain operational during idiosyncratic shocks) shape both the level and the aggregate relation between outputs, inputs, and TFP, and those production decisions are affected by labour-market policies.

Some dynamic industry models incorporate the selection mechanism by relating firms' productivity levels to their survival and performance, for instance, in Melitz (2003) which analyzes the intra-industry effects of international trade, and in Foster et al. (2008) which investigate the determinants of market selection and productivity growth in industries. Reallocation of market shares to more efficient producers, either by shifting market shares among incumbents or by entry and exit, is one of the main mechanisms of aggregate productivity movements in those theories. In addition, the selection effect is one of the major mechanisms through which trade openness enhances resource allocation. For instance, both Melitz (2003) and Ding et al. (2016a) agree that exposure to trade will encourage more productive firms to enter the export market while forcing the least productive firms to exit the market. This will result in a smaller productivity dispersion and an increase in aggregate productivity through selection and market share reallocation mechanisms.

Nevertheless, some literature argues that it is empirically challenging to observe potential producers who do not operate, thus limiting the availability to measure selection effects without additional structure (Restuccia and Rogerson, 2017). For instance, when estimating resource misallocations in China and India versus the United States, Hsieh and Klenow (2009) only study establishments with positive production without reflecting any selection effects in terms of entry and exit.

6.2.1.2 Literature identifying the overall extent of misallocation

One stream of literature attempts to identify the overall extent of resource misallocation and aggregate productivity loss as a consequence of misallocation without specifying the specific underlying causes of misallocation (e.g., Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Zhang et al., 2023). The common feature of their theoretical framework is the inclusion of generic distortions such as distortions in capital input prices and labour prices, or both, and then formulating aggregate productivity based on the misallocation of capital and labour.

General evidence

A neoclassical growth model with heterogeneous establishments is proposed and calibrated to US data by Restuccia and Rogerson (2008). Their model considered the possibility of diminishing returns to scale in the production function and relaxed the assumptions of constant return to scale. The calibrated version of the model focuses on generic policy distortions that lead to heterogeneous prices among individual producers when leaving aggregate relative prices or aggregate factor accumulation unchanged. It is documented that this will result in a reallocation of resources among establishments. For instance, subsidies to low-productivity establishments or taxes on high-productivity establishments will result in a higher share of resources being allocated to low-productivity establishments. The reallocation of resources resulting from such idiosyncratic policy distortions can lead to significant decreases in output and productivity in the range of 30% to 50%, even if the underlying technology range across establishments is the same across all policy configurations. Their findings also show that large TFP losses could be generated only by taxes that were negatively related to establishment-level productivity, i.e., higher taxes on productive establishments.

Busso et al. (2013) explore the degree of resource misallocation within Latin American countries and its overall effect on the heterogeneity of firm productivity based on manufacturing firm-level data from ten Latin American countries. They find that resource misallocation and productivity heterogeneity are much larger in Latin American countries than in the United States. Depending on the countries and years examined, an efficient allocation of resources could increase manufacturing TFP by 45% to 127%.

Dias et al. (2016) examine the evolution of resource misallocation between 1996 and 2011 in the Portuguese economy using firm-level data from all sectors including agriculture, manufacturing and services. Based on the three-factor production framework of labour, capital and intermediate inputs, it is found that within-industry misallocations have almost doubled over the sample period. Deterioration in allocation efficiency is particularly pronounced in the service sector, with five industries contributing 72% of the overall variation. If TFPR had been equal across firms within an industry, value-added would have been boosted by 48% and 79% above actual levels in 1996 and 2011, respectively, over the sample period. They also find that capital distortions contribute more to potential value-added efficiency gains, particularly in the service sector. Overall, deteriorating allocation efficiency may have reduced annual growth by approximately 1.3 percentage points from 1996 to 2011.

China-related evidence

Hsieh and Klenow (2009) utilize a standard monopolistic competition model with heterogeneous firms to demonstrate how distortions in labour prices and capital prices that drive wedges between the marginal products of labour and capital will depress aggregate productivity. Based on their theoretical framework, they examine the overall extent of misallocation and its contribution to aggregate manufacturing productivity in India and China versus the United States using microdata on manufacturing establishments. It is found that there are substantial gaps in the marginal products of inputs across plants within industries in China and India compared with the United States. A hypothetical reallocation of capital and labour that equalizes marginal products to the extent observed in the United States would yield manufacturing TFP gains of 30%–50% in China and 40%–60% in India. Moreover, capital accumulation in response to aggregate TFP gains would boost output by roughly twice as much. According to their estimation, deteriorating allocative efficiency may have cut 2% off India's manufacturing TFP growth from 1987 to 1994, while winnowing its distortions may have increased China's TFP by 2% between 1998 and 2005.

Gong and Hu (2016) extends the study of Hsieh and Klenow (2009) by relaxing the assumption that returns to scale are constant for differentiated products. As a result of the efficient reallocation of both capital and labour in 1998, 2005, and 2007, aggregate TFP in China would have increased by 60%, 45%, and 41% respectively. The magnitudes are much smaller than the findings of Hsieh and Klenow (2009) that capital and labour reallocation could boost aggregate TFP by 115% in 1998 and 87% in 2005. Gong and Hu (2016) attribute this difference to the constant return to scale assumption.

Compared with Hsieh and Klenow (2009), Brandt et al. (2013) investigate factor misallocation at a more aggregate level in China's non-agricultural economy and analyse its impact on aggregate productivity. In particular, they focus on the misallocation between provinces and between the non-state and state sectors due to large geographical and ownership barriers in China. Rather than studying cross-sectional dispersion as in Hsieh and Klenow (2009), they explore the evolution of factor misallocation over time for the long period from 1985 to 2007 and decompose the overall TFP loss into those caused by between-province factor market distortions and within-province inter-sectoral factor market distortions. They find that within-province distortions dropped sharply between 1985 and 1997, contributing to 0.52% of non-agricultural TFP growth per year, but the distortions have increased significantly in the last ten years, resulting in a 0.5% reduction in non-agricultural TFP growth. Specifically, most of the within-province distortions appear to be the result of capital misallocation between the non-state and state sectors. In their estimation, they found that factor misallocation across provinces and sectors resulted in at least 20% reductions in non-agricultural TFP, with distortions within provinces accounting for more than half the entire TFP loss.

More recently, Zhang et al. (2023) applied a heterogeneous firm model with the constant return to scale assumption to investigate market distortion and factor misallocation among China's manufacturing firms over the period from 1998 to 2007. A substantial amount of capital and labour misallocation occurs in Chinese manufacturing enterprises, and capital misallocation is much greater than labour misallocation. This implies a large potential to increase aggregate productivity in China's manufacturing industry should resource is efficiently reallocated. It is estimated that by eliminating the misallocation between capital and labour, China's manufacturing TFP could grow by 149% in 2007.

6.2.2 Capital misallocation

6.2.2.1 Definition and measurement of capital misallocation

As highlighted earlier, resource misallocation refers to the allocative inefficiency of inputs including labour and capital. Capital misallocation, in particular, speaks to the allocative inefficiency of capital. There has been extensive evidence of capital misallocation, both in developing countries and in particular in China (Wu, 2018).

For instance, Hsieh and Klenow (2009) document that reallocating capital among firms would account for the majority of gains in India and China. Dias et al. (2016) find that capital distortions contribute more to potential value-added efficiency gains in the Portuguese economy, particularly in the service sector. Brandt et al. (2013) argue that most of the within-province distortions in China's non-agricultural economy are the result of capital misallocation between the non-state and state sectors. Zhang et al. (2023) document that capital misallocation is much greater than labour misallocation among China's manufacturing firms.

Banerjee and Moll (2010) shed light on why capital misallocation persists over time by distinguishing between capital misallocation on the intensive and the extensive margins. On the intensive margin, capital misallocation refers to the situation in which marginal products of capital are not equalized among all agents who utilize capital at positive rates. Misallocation on the intensive margin is misallocation in the traditional sense and is the main concern of empirical evidence. On the extensive margin, there is capital misallocation if the sum of individual outputs were to increase by redistributing capital from one individual to another with equal or zero marginal product. Extensive margins exist only when production is nonconvex, or when some individuals have zero capital. Since it is difficult to observe potential producers who do not operate, it is likely to have higher levels of misallocation than the data on marginal product would suggest. In their theoretical discussion, Banerjee and Moll (2010) conclude that the intensive margin of misallocation should gradually disappear under general conditions, while the extensive margin misallocation may persist.

Capital misallocation is on the intensive margin in most literature. Both theoretically and empirically, dispersion in returns of capital is commonly used to measure capital misallocation in influential literature. For instance, marginal revenue product of capital (MRPK) is applied in Gopinath et al. (2017), Wu (2018) and Ek and Wu (2018) which investigate the role of financial frictions as the potential source of capital misallocation; dispersion in the average product of capital (APK), on the other hand, is applied in Midrigan and Xu (2014) and David and Venkateswaran (2019) to estimate capital misallocation.

There is an increase in literature considering the adjustment cost of capital at the individual producer level (e.g., Cooper and Haltiwanger, 2006; Asker et al., 2014; David and Venkateswaran, 2019). Asker et al. (2014) consider a standard dynamic investment model in which firms can acquire all inputs in a frictionless spot market but face capital adjustment cost and firm-specific productivity shock. Across nine data sets spanning 40 countries, they find that capital adjustment costs coupled with productivity shocks drive the dispersion in MRPK among producers. Further estimation suggests that a large proportion of both the level and variation of MRPK dispersion across industries within countries and across countries can be explained by the time-series variation in TFPR across industries and countries. It can be shown that an optimal capital stock determined in the previous period may no longer be optimal after a productivity shock occurs. Therefore, dispersion in MRPK will occur. In this extreme case, resource allocation may well be efficient in a dynamic sense while being inefficient in a static setting. According to the idea, some 'base level' misallocation is attributable not only to price and policy distortions but also to adjustment costs or other misspecifications. This also highlights the importance of using panel data rather than cross-sectional data when examining the extent of misallocation if part of the misallocation is caused by adjustment costs and its induced time-series variations in TFPR (Restuccia and Rogerson, 2017). One reasonable way would be to recognise the effect of adjustment costs and productivity shocks when examining the sources of misallocation using panel data. For instance, David and Venkateswaran (2019) acknowledges adjustment costs and productivity shocks as part of sources of capital misallocation (defined as the dispersion in value-added/capital).

6.2.2.2 Literature identifying specific causes of capital misallocation

One large stream of literature seeks to identify the specific sources of capital misallocation, such as financial and informational frictions (e.g., Gopinath et al., 2017; Midrigan and Xu, 2014; David et al., 2016), policy distortions (e.g., Lagos, 2006; Song et al., 2011; Wu, 2018), and adjustment costs (e.g., David and Venkateswaran, 2019). The following literature review summarizes this stream of literature with a focus on capital misallocation.

The sources of capital misallocation have gained increasing attention in recent years.

Before going to the majority of literature that focuses on particular sources while abstracting from others, it would be more informative to go first to relevant literature that explores the sources of capital misallocation with a robust decomposition within a unified framework. One typical example is David and Venkateswaran (2019) which presents a model of investment with multiple factors interfering with the equalization of static capital products. Using this model, they decompose the role of capital adjustment costs, informational frictions (in the form of imperfect information about firm-level fundamentals, such as demand or productivity), as well as a number of firm-specific factors (i.e., heterogeneity in production technologies and markup, size-dependent policies and financial constraints) into explanations of capital misallocation captured by value-added/capital (ARPK) dispersion using firm-level production data from Chinese manufacturing firms and U.S. Compustat.

Using data on China's manufacturing firms from 1998 to 2009, they discover the economic significance of adjustment costs and informational frictions in influencing investment dynamics. These factors, however, account for only a small fraction of ARPK dispersion among Chinese firms, about 1% and 10%, respectively, resulting in losses of 1% and 8% in aggregate total factor productivity (in comparison with the undistorted first-best). This indicates that a significant proportion of ARPK dispersion in China is explained by firm-specific factors. Specifically, factors correlated with productivity and ones that are essentially permanent account for about 47% and 44% of overall ARPK dispersion, respectively, leading to 38% and 36% losses in TFP. Among the firm-specific factors, they identify that unobserved variation in markups and production technologies in China can only account for 4% and 23%, respectively, of ARPK dispersion.

Their methodology has also been applied to publicly traded firms in the United States to serve as a benchmark in comparison with the magnitudes in the case of China. It is not surprising that the overall dispersion of ARPK in US firms is much smaller. Comparatively, a larger share of the observed dispersion (about 11%) is due to adjustment costs, which reduce aggregate TFP by about 2%. Uncertainty (informational frictions) and other correlated factors (e.g., markup) play a smaller role in US firms than in Chinese firms. These factors explain about 7% and 14% of overall ARPK dispersion, respectively, cutting aggregate TFP by 1% and 3%. Even in the United States, factors other than informational and technological frictions play an important role in capital allocations, explaining about 65% of ARPK dispersion, with associated TFP losses of 13%.

Overall, it can be demonstrated that much of the ARPK dispersion is not the result of informational frictions or adjustment costs, but rather of other firm-specific factors that are systematically correlated with productivity/size or factors that are uncorrelated with productivity but are almost permanent. Unobserved heterogeneities in demand and production technologies contribute more to the observed ARPK dispersion in the U.S. than that in China where size-dependent policies and/or financial imperfections may have a greater impact.

Another work (Alam, 2020) discovers the sources and factors that lead to capital misallocation as well as its cyclical nature using European firm-level data from 2005 to 2014. To assess the sources of capital misallocation, Alam (2020) applies the multilevel model to decompose the variance in MRPK into three components, namely, misallocations caused by variations among firms within industries, variations between industries, and variations within firms over time. Estimated evidence suggests that more than 50% of capital misallocations can be attributed to variations between firms within the same industry. For this reason, the researcher has attempted to find factors that are associated with capital misallocation at the firm level including firm age, labour size, leverage ratio, net worth, and TFP shocks. As capital adjustment costs and credit constraints may cause inaction or lags in capital adjustments, it is specifically argued that both net worth (capturing financial frictions) and TFPR shocks (capturing capital adjustment costs) should cause the dispersion in MRPK. Among all firm-level factors examined, net worth, measured as total assets minus liabilities divided by sales, is the most important contributor to capital misallocation, which explains roughly 10% of capital misallocation within industries. Moreover, firms' net worth accounts for approximately 30% of the cyclicality of capital misallocation.

Financial frictions

A growing body of literature contends that financial friction is one of the unignorable contributors to capital misallocation. Using producer-level data from Korean manufacturing between 1991-1999, Midrigan and Xu (2014) evaluate the role played by financial frictions in reducing aggregate productivity. Based on a model of establishment dynamics, financial frictions can distort aggregate productivity in two ways. It is demonstrated that, on the one hand, finance friction distorts decisions regarding entry and technology adoption, which in turn reduces the productivity of individual producers. On the other hand, financial frictions produce misallocation among existing producers by causing an inefficient distribution of marginal products of capital among them. According to their model parameterizations consistent with the data, they predict relatively modest losses as a result of capital misallocation but potentially significant losses due to inefficiency in entry and technology adoption. Entry and technology adoption decisions require large long-term investments that pay off gradually over time, making them difficult to finance internally. By contrast, capital misallocation caused by financial friction cannot generate large productivity losses as more productive producers build up internal funds over time and aren't constrained by their borrowing capacity. In addition, in a heterogeneous agent model with financial constraints and forward-looking savings behaviour, Moll (2014) finds that self-financing mitigates capital misallocation from financial constraints in the long run under persistent idiosyncratic productivity shocks.

Buera et al. (2011) agree that frictions in the financial system distort capital allocation across heterogeneous production units as well as entry/exit decisions, affecting both the aggregated and sectoral TFP. It can be argued that despite self-financing having the potential to alleviate the resulting misallocation, doing so is more difficult in sectors with larger scales and higher financing needs. In their model, industries with larger scales, such as the manufacturing industry, have more financial needs and are therefore more vulnerable to financial frictions. Their quantitative analysis suggests that a substantial part of cross-country differences in output per worker, aggregate and sectoral TFP and the capital-to-output ratio can be explained by financial frictions.

Gopinath et al. (2017) propose a model with size-dependent financial frictions. Their theoretical framework implies that MRPK dispersion across firms is explained by binding borrowing constraints, costs of capital adjustment, and capital accumulation risk. Using data from Spanish manufacturing firms, they find that the decline in real interest rates results in significant declines in sectoral productivity since capital is misallocated to firms that have higher net worth but are probably less productive.

Ai et al. (2020) construct a general equilibrium model linking intermediation activities in the financial sector to capital reallocation processes in non-financial firms. They show that agency frictions in the financial sector affect capital reallocation efficiency across firms and cause aggregate economic fluctuations. In this model, shocks to financial frictions lead to a deterioration of capital misallocation and manifest themselves as a variation in aggregate TFP.

Karabarbounis and Macnamara (2021)'s analysis of capital misallocation is based on a model in which firms operate under different kinds of financial constraints, that is, private firms borrow with collateral constraints, while public firms issue long-term bonds with default risks. In the model, productive private firms cannot quickly reach their optimal capital level when they face collateral constraints. In contrast, due to low borrowing costs on the debt market, productive public firms are able to overcome financial constraints. It is found that the effect of financial frictions on capital misallocation is larger among private firms compared to public firms using data from the United States.

For China-specific research, it has been shown in Ek and Wu (2018) that financing constraint does have a significant effect on capital misallocation. In their theoretical framework, the notion of investment to cash flow sensitivity, which is a common measure of financing constraint, is linked to the dispersion of the marginal revenue product of capital, a direct measure of inefficiency in allocative allocation. It can be argued that since the existence of both constrained and unconstrained firms displays significant and insignificant investment to cash flow sensitivities, MRPKs must vary across firms, resulting in capital misallocation. Applying an error-correction investment model to U.S. Compustat data and Chinese manufacturing firms and in several sub-samples of Chinese firms, their estimates of investment-cash flow sensitivities indicate a loss in total factor productivity of 5% and 15% for the balanced and unbalanced panels of Chinese firms, respectively.

In addition, Xiao et al. (2022) extend the HK model (Hsieh and Klenow, 2009) by considering both credit constraints and heterogeneous financing costs in relation to capital misallocation and TFP. Their model predicts that financial frictions could exacerbate capital misallocation and TFP losses. Their empirical evidence indicates that on average around 120.7% of annual manufacturing TFP losses are caused by credit constraints in Chinese industrial firms over the periods 2004-2007 and 2011-2013.

Informational friction

David et al. (2016) propose a theoretical model linking imperfect information to resource misallocation, aggregate productivity and output. In the model, firms make input decisions based on a variety of noisy sources of information. As a result of this information friction, factors are misallocated between firms, reducing aggregate productivity and output. Estimations relying on data from the United States, China, and India show substantial losses in productivity by 7-10% in China and India caused by informational friction. It is also revealed that firms rely largely on private information within the firm whereas learning from financial markets plays a relatively minor role even in the United States.

In related work, David and Venkateswaran (2019)'s theoretical and empirical evidence suggests that informational friction can account for 10% of the overall ARPK dispersion in China and 7% of the ARPK dispersion among US firms.

Adjustment cost and productivity shocks

Asker et al. (2014) consider a standard dynamic investment model in which firms can acquire all inputs in a frictionless spot market but face capital adjustment cost and firm-specific productivity shock. Across nine data sets spanning forty countries, they find that capital adjustment costs coupled with productivity shocks drive the dispersion in MRPK among producers. Their estimation suggests that a large proportion of both the level and variation of MRPK dispersion across industries within countries and across countries can be explained by the time-series variation in TFPR across industries and countries. The implication is that dispersion in MRPK will occur naturally as an optimal capital stock determined in the previous period may no longer be optimal after a productivity shock occurs. As documented, the estimated productivity variation consists of a simplified form that reflects a variety of time-varying shocks on production, such as demand shocks, infrastructure shocks, variations in markups due to changes in demand or market structure, and changes in informational barriers.

However, the effects of adjustment cost and productivity shocks have been found to have a modest role in explaining capital misallocation. In related work, David and Venkateswaran (2019)'s theoretical and empirical estimation decomposes the comprehensive set of causes of capital misallocation. It is found that adjustment cost plays a modest role that only explains around 1% of the overall capital misallocation in China and 11% of the capital misallocation among US firms.

Another work from Alam (2020) finds that more than 50% of capital misallocations can be attributed to variations between firms within the same industry, using European firm-level data from 2005 to 2014. For this reason, the author attempts to find factors that are associated with capital misallocation at the firm level including firm age, labour size, leverage ratio, net worth, and TFP shocks. As capital adjustment costs and credit constraints may cause inaction or lags in capital adjustments, it is specifically argued that both net worth (capturing financial frictions) and TFPR shocks (capturing capital adjustment costs) should cause the dispersion in MRPK. Among all firm-level factors examined, net worth is the most important contributor to capital misallocation, which explains roughly 10% of capital misallocations within industries. Whereas TFPR shocks can only explain around 0.93% of the capital misallocation.

Policy distortion

Policy distortions are non-market factors that are generated by rules, regulations, and institutions and lead to dispersion in MRPK (Wu, 2018). Some countries provide favourable treatment to companies with political connections through a variety of channels, such as low-interest loans, tax breaks, subsidies, and awards of government contracts (Restuccia and Rogerson, 2013). This is especially the case in China. For instance, state-owned firms may benefit from lower interest rates on loans from government-owned banks, as well as easier access to the highly regulated stock market when compared with other ownership types; Companies that bring in foreign direct investment may benefit from special investment tax breaks and subsidies (Wu, 2018). Ownership, therefore, is usually regarded as a proxy for policy distortions in China.

According to Song et al. (2011), resource misallocation between private and state-owned enterprises in China's manufacturing sector is a major cause of productivity loss. Similar findings are presented by Brandt et al. (2013). They investigate factor misallocation in China's non-agricultural economy and decompose the overall productivity loss into within-province distortions (between state and non-state sectors) and between-province distortions (within sectors). Over the entire period from 1985 to 2007, misallocation depressed aggregate non-agricultural TFP by an average of 20%. They also found that over half of productivity loss can be attributed to increasing capital misallocation between state and non-state sectors within provinces. It can be argued that government policies that promote investments in the state sector over investments in the more productive non-state sector are responsible for the increased capital misallocation between 1998 and 2007.

More recently, Wu (2018) focuses on both policy distortions and financial frictions as the sources of capital misallocation in China. Wu (2018) first proposes an investment model with a very general specification for financial constraints (either cost-constrained or quantity-constrained). Firm-specific factors operating through financial frictions and policy distortions in determining cost constraints and quantity constraints are discussed based on the theoretical framework. An identification strategy is then applied to separate the policy-distortion effect and the financial friction effect on the dispersion of MRPK (capital misallocation) across firm ownership. In particular, Wu (2018) uses ownership to proxy a bundle of policy distortions and assumes an investment-promoting programme that offers favourable treatment to some firms with a specific ownership type (e.g., SOEs). Treatment is to lower the generalized user cost of capital and may be provided in several ways, such as tax credits or a low-interest bank loan. In addition to their treatment status, firms also differ in a set of characteristics proxying financial frictions that affect MRPK. The average treatment effect of the program on capital misallocation can then be decomposed into the 'average treatment effect on the treated' (ATT) and the 'selection bias' (SB). The ATT effect indicates how much the MRPK of those firms receiving policy treatment has been reduced compared to what their MRPK would have been without the treatment. The SB effect in the design, on the other hand, captures the effect of financial frictions based on the assumption that the average MRPK of those treated and untreated could have been different even without policy intervention as a result of financial frictions.

Applying firm-level panel data from China's Annual Industrial Survey to this identification approach, it is estimated that aggregate TFP losses caused by financial frictions range from 7.3% to 9.4% over the period from 2000 to 2007 in a hypothetical economy without policy distortions. However, the actual economy experiences an average aggregate TFP loss of 27.5% each year, implying that around 70% of productivity loss is because of policy distortions. Moreover, it is identified that MRPK in China has been reduced by 15.5% as a result of policy distortions, which can serve as one possible explanation for China's unusually high investment rate.

Based on firm-level survey data from 2002 to 2004, Dollar and Wei (2007) investigate systematic distortions in capital allocation that result in the dispersion in MRPK across firm ownership, regions, and sectors. They find that state-owned firms continue to experience significantly lower average returns on capital than other types of firms even after a quarter-century of reforms. Similarly, certain regions and sectors consistently have lower returns to capital than others. If China succeeds in allocating its capital more effectively, it could reduce its investment intensity by 5% of GDP without sacrificing economic growth.

Other sources

David et al. (2022) discover a link between capital misallocation and macroeconomic risk. In their model, the optimal condition for investment indicates that the marginal product of capital (MPK) and its dispersion are both determined by heterogeneities in firm-level risk exposure and the magnitude of risk premiums. Firms with greater exposure to aggregate shocks have a higher capital cost and therefore, ceteris paribus, invest less and have a higher marginal return. MPK dispersion thus may reflect not only true misallocation but also 'risk-adjusted capital allocation' in the case of firms that are differentially exposed to macroeconomic risks. According to their estimates, risk considerations (i.e., dispersion in firm-level risk premia and aggregate risk exposure) are responsible for around 25% of MPK dispersion among

US firms and explain a considerable persistent component of MPK at the firm level. Their framework also reveals a novel relationship between risk considerations and aggregate TFP via the effects on capital allocation. That is, the effects of exogenous shocks on TFP are amplified by risk-based MPK dispersion, which generates negative skewness in TFP and reduces long-run levels of TFP by about 5%.

6.2.3 Transportation and allocative efficiency

Asturias et al. (2019) estimate the welfare gains from India's Golden Quadrilateral (GQ) large-scale transportation project. They developed a model of internal trade with variable markup that includes mechanisms via which transportation infrastructure impacts welfare. Misallocation in their case arises because of dispersion in markups across producers. Allocative efficiency, in particular, is a channel that quantifies the welfare gains from infrastructure improvements. It has been shown that reducing transportation costs in India might generate benefits through the allocative efficiency mechanism if high transportation costs result in low levels of allocative efficiency. A 2.7% increase in real income is empirically found after calibrating the model to the Indian manufacturing sector, and 7.4% of this increase can be attributed to allocative efficiency. Different states place different emphases on allocative efficiency, which in some states can contribute up to 18% of the gains overall. Changes in labour income, productivity effectiveness, and typical markups that impact states' terms of trade account for the remaining welfare gains.

Using panel data on Indian industrial firms from 1998 to 2012, Kailthya and Kambhampati (2022) discover that a 1% increase in road density stimulates value-added productivity by 0.25%. In addition, they provide findings relating to the effect of road infrastructure on the within-industry reallocation of resources across firms, since inefficient resource allocation among enterprises impacts overall productivity. Using the Olley and Pakes (1996) covariance term for each state-industry pair by year as the measure of allocative efficiency, it is evidenced that industries with higher road density saw a favourable reallocation of resources from low-productivity plants to high-productivity plants.

Liu et al. (2021) investigate the impact of highway networks on allocative efficiency across both firms and counties in China between 1998 and 2007. It has been argued that better highway networks are likely to affect firm-level distortions through two channels, i.e., firm-level factor (capital and labour) distortions and markups. First, the development of a better highway network decreases transportation costs, which helps to reduce firms' capital and labour wedges, thus improving aggregate allocative efficiency. Secondly, the improved highway network has two competing effects on markups. On the one hand, as a better highway network facilitates market integration, the demand of each firm increases thus driving up markups. On the other hand, new markets can increase supply, resulting in lower markups due to greater competition. Hence, a more integrated market can therefore affect markups at the firm level, thereby affecting distortions at the firm level.

With the assumption of constant return to scale production function, Liu et al. (2021) decompose TFPR into markup, and capital and labour wedges (or equivalently, the marginal product of capital and the marginal product of labour). They first estimate the effect of county-level market integration (proxied by the distance to the nearest highway of the county), which is instrumented using Faber (2014)'s least cost path spanning tree networks, on the overall distortions at the firm level (measured as the logarithm of firm-level TFPR). They find a positive coefficient of log distance to log TFPR and conclude that as the counties' distance to highways decreases, the overall firm-level distortions decline. They further estimate the impacts of market integration on markup, capital wedges and labour wedges, and find positive and significant coefficients when the dependent variable is capital wedges or labour wedges but an insignificant coefficient in terms of markup. Their empirical estimation concludes that highway network expansion improves allocative efficiency, mainly by facilitating more efficient factor allocations across firms. However, the market integration effect and the competition effect on firm-level markups are either equivalent or too small to cause a significant shift in markups.

6.3 Specification

6.3.1 Motivation and definition of capital misallocation

The motivation and definition of capital misallocation follows Hsieh and Klenow (2009) and Asker et al. (2014). Following Asker et al. (2014), the following Cobb-Douglas production function begins the process:

$$Y_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M} \tag{6.1}$$

where $Y_{it}, A_{it}, K_{it}, L_{it}$, and M_{it} denote output quantity, technology, capital, labour, and intermediate inputs, respectively, for firm i at time t. Firms face constant output elasticities with respect to capital, labour and intermediate inputs: $\alpha_K > 0, \alpha_L > 0, \alpha_M > 0$.

The firm operates in a monopolistic market with an isoelastic downward-sloping demand curve [5]:

$$Y_{it} = D_{it} P_{it}^{-\frac{1}{\eta}} \tag{6.2}$$

where D_{it} and P_{it} denote stochastic demand shifter and price of good i at time t, respectively. $\eta \in (0, 1)$ is the inverse of demand elasticity [6].

Thus the firm's revenue R_{it} has the following relation:

$$R_{it} = Z_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} M_{it}^{\beta_M} \tag{6.3}$$

[5] Both demand function and production function are industry specific.

[6] For the ease of measurement, η is assumed as constant and industry-specific.

where $Z_{it} = D_{it}^{\eta} A_{it}^{1-\eta}$ and $\beta_X = \alpha_X(1-\eta)$ for $X \in \{K, L, M\}$. Because of the unavailability of price and quantity information, productivity is measured based on the above revenue-based production function, where we define $z_{it} = ln(Z_{it})$ as revenue-based productivity, or TFPR as introduced by Foster et al. (2008).

Marginal revenue product of capital is measured as follows:

$$\frac{\partial R_{it}}{\partial K_{it}} = \beta_K \frac{Z_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} M_{it}^{\beta_M}}{K_{it}} \tag{6.4}$$

$$MRPK_{it} = ln(\beta_K) + ln(R_{it}) - ln(K_{it}) \tag{6.5}$$

where $MRPK_{it}$ denotes the marginal revenue product of capital (in natural logarithm).

Following Hsieh and Klenow (2009) by introducing firm-level distortions, wedges of capital, labour and intermediate inputs are denoted by τ_{Kit}, τ_{Lit}, τ_{Mit}, respectively. Thus, it is possible to denote $(1+\tau_{Kit})P^K$, $(1+\tau_{Lit})P^L$, $(1+\tau_{Mit})P^M$ as the unit cost of using capital, labour and intermediate inputs, respectively. Without distortions, i.e., when $\tau_{Xit} = 0$ for $X \in \{K, L, M\}$, firms will have the same unit cost of inputs: P^K, P^L, and P^M.

Firm i chooses $\{K_{it}, L_{it}, M_{it}\}$ to maximise its gross profit, represented by π_{it}:

$$\pi_{it} = \max_{K_{it}, L_{it}, M_{it}} R_{it} - (1+\tau_{Kit})P^K K_{it} - (1+\tau_{Lit})P^L L_{it} - (1+\tau_{Mit})P^M M_{it} \tag{6.6}$$

Under the first-order conditions:

$$\frac{\partial R_{it}}{\partial K_{it}} = (1 + \tau_{Kit})P^K \tag{6.7}$$

$$\frac{\partial R_{it}}{\partial L_{it}} = (1 + \tau_{Lit})P^L \tag{6.8}$$

$$\frac{\partial R_{it}}{\partial M_{it}} = (1 + \tau_{Mit})P^M \tag{6.9}$$

Profit maximization implies that marginal revenue product should equal unit cost (proportional to input distortions). The specific focus here is the distortions of capital. If capital is perfectly allocated without any distortions, firms will end up with the same unit cost of capital and there will be no dispersion in MRPK. Due to reasons such as policy distortions and financial constraints, however, firms face heterogeneous input prices and distortions. Thus, in this theoretical framework, the dispersion of marginal revenue product of capital can proxy the overall misallocation of capital.

The overall misallocation of capital is a combined outcome of several sources affecting MRPK dispersion. One large stream of literature seeks to identify the specific sources of capital misallocation, such as financial and informational frictions (e.g., Gopinath et al., 2017; Midrigan and Xu, 2014; David et al., 2016), policy distortions (e.g., Lagos, 2006; Song et al., 2011; Wu, 2018), and adjustment costs (e.g., David and Venkateswaran, 2019).

It can be seen that the dispersion of MRPK is a cross-sectional dispersion or static measure of dispersion, which is commonly applied in the existing literature. Since capital faces high adjustment costs, Asker et al. (2014) highlight the importance of capital adjustment cost and productivity volatility in explaining cross-sectional MRPK dispersion. Even if firms acquire all inputs in a frictionless market, dispersion in MRPK will occur naturally since an optimal capital stock determined in the previous period may no longer be optimal after a productivity shock occurs. Thus it is important to consider adjustment costs and productivity volatility when investigating MRPK dispersion.

Specifically, this research attempts to investigate how highway infrastructure improvement affects the overall distortion of capital allocation. Intuitively, better highway infrastructure is likely to promote capital allocative efficiency through several dimensions, e.g., by reducing markup dispersion and productivity shocks and affecting MRPK dispersion through the channel of financial constraints and policy frictions. It is therefore assumed that highway proximity will affect the overall dispersion of MRPK or the heterogeneity of the wedge of capital.

To this end, it is assumed that the MRPK dispersion is a function of highway proximity (H) and a set of factors (Θ) affecting the heterogeneity of the unit cost of using capital. This is defined as follows:

$$Dispersion(MRPK_{it}) = f(\Theta) + \gamma H_{jpt} \tag{6.10}$$

where j and p denote industry and province respectively. MRPK dispersion is assumed to be affected by highway proximity and a set of factors denoting sources such as policy distortion, adjustment cost, and financial frictions.

6.3.2 Empirical specification

To investigate the overall effect of highway infrastructure on capital misallocation, the baseline estimation is specified as follows:

$$Dispersion_{jpt} = \alpha_0 + \alpha_1 Highway_{jpt} + \phi X_{jpt} + \phi Z_{pt} + \gamma_{j^*} + \delta_p + \delta_t + \mu_{jpt} \tag{6.11}$$

where the dependent variable, $Dispersion_{jpt}$, is MRPK dispersion within 4-digit industry j and province p at year t [7], which is defined by the standard deviation

[7] Here I don't use MRPK dispersion within 4-digit industry j at year t because of the marked regional differences in highway accessibility. Since highway infrastructure is better developed in coastal provinces than in inland regions, MRPK dispersion within an industry-province-year group would better highlight the role of highway infrastructure. In addition, due to industry protectionism within the province, it is assumed that there are fewer industry interactions across the provinces. In the robustness test, 4-digit industry-level MRPK dispersion is applied to show the robustness effect.

of MRPK. In the robustness test, the interquartile range (IQR) of MRPK (i.e., the difference between the 75th and 25th percentiles) is used as an alternative measure of MRPK dispersion.

The main independent variable, highway proximity, is calculated as the inverse of the unweighted average distance to the nearest highway among firms in the 4-digit industry j and province p at year t:

$$Highway_{jpt} = \frac{1}{\sum_{i=1}^{n} distance_{i \in j,p,t}/n} \tag{6.12}$$

where $distance_{i \in j,p,t}$ is firm i's distance to the nearest highway at year t. n is the number of firms within the 4-digit industry j and province p at year t. A larger value of $Highway_{jpt}$ indicates better average highway accessibility. A negative sign of α_1 is expected if better highway proximity helps reduce MRPK dispersion.

X_{jpt} includes a set of control variables at the industry-province-year level covering variables of policy distortions, competition and trade openness. Following Ding et al. (2016a), two ownership variables are included, SOE_{jpt} and FOE_{jpt}, which are defined as the share of state-owned capital and foreign capital in total capital within the same 4-digit industry j and province p in year t, respectively. Ownership is usually regarded as a proxy for policy distortions in China (Wu, 2018). State-owned firms may benefit from lower interest rates on loans from government-owned banks, as well as easier access to the highly regulated stock market when compared with other ownership types; Companies that bring in foreign direct investment may benefit from special investment tax breaks and subsidies. It is therefore expected that SOE_{jpt} and FOE_{jpt} are positively associated with MRPK dispersion.

Following Ding et al. (2019), government subsidy is another proxy of policy distortion. $Subsidy_{jpt}$ is calculated as the ratio of total subsidy to the output of firms in the industry j and province p at year t. Subsidies, as a type of policy invention, may generate distortions in capital prices and negatively affect capital allocation.

Following Alam (2020) and Doerr et al. (2022), the Herfindhl-Hirschman Index (HHI) is used to control within-industry competition status or market concentration. The HHI index is calculated by squaring the market share of each competing firm in the 4-digit industry j and province p at year t.

$$HHI_{jpt} = \sum_{i=1}^{n} s^2_{i \in jpt} \tag{6.13}$$

where $s^2_{i \in jpt}$ is the square of firm i's sales share within the 4-digit industry j and province p at year t. A higher value of HHI is interpreted as a lower degree of competition in the industry. Tougher competition is expected to reduce MRPK dispersion since inefficient firms find it difficult to survive in a competitive market (Syverson, 2011).

The variable $export_{jpt}$ denoting trade exposure is controlled as well. It is measured as the sum of export value in the industry j and province p at year t divided by the sum of output in the same industry-province-year group. Both Melitz (2003) and Ding et al. (2016a) agree that exposure to trade will encourage more productive firms to enter the export market while forcing the least productive firms to exit the market. Thus, more exposure to international trade may promote better capital allocation efficiency.

Z_{pt} includes three provincial-level variables including other roads' density, waterway density and rail density. Other transportation options may correlate with highway infrastructure and may affect MRPK dispersion. As this research only considers highway infrastructure rather than all road infrastructure, other roads' density is controlled, which is calculated by the ratio of the total length of other roads at the provincial level to the provincial area. Similarly, waterway density is defined as the total length of waterways to the provincial area, and rail density is defined as the total length of railways to the provincial area.

Equation (6.11) also includes 2-digit industry-specific effect, γ_{j^*}, province-specific fixed effect, δ_p, time-specific fixed effect, δ_t, and idiosyncratic error term, μ_{jpt}. Those terms capture unspecified industry-specific, province-specific, time-specific and other factors affecting MRPK dispersion.

6.3.3 Estimation method

Because of the endogeneity of highway construction, three types of time-varying instrumental routes are constructed including least-cost paths (based on the 2004 NEN highway project), historical routes (a combination of Ming dynasty and Qing dynasty courier routes), and straight lines (based on the 2004 NEN highway project). The industry-province-year level instruments are constructed as follows:

$$IV_{jpt} = \frac{1}{\sum_{i=1}^{n} instrumental\_distance_{i \in j,p,t}/n} \tag{6.14}$$

where $IV \in \{LCP, Historical, Strightline\}$ denotes three instruments constructed based on the three instrumental routes mentioned above, $instrumental\_distance_{i \in j,p,t}$ is firm i's distance to the nearest instrumental routes at year t, n is the number of firms within the 4-digit industry j and province p at year t. Those instruments are used in the 2SLS estimation.

6.4 Stylized Facts and Baseline Result

6.4.1 MRPK and MRPK dispersion

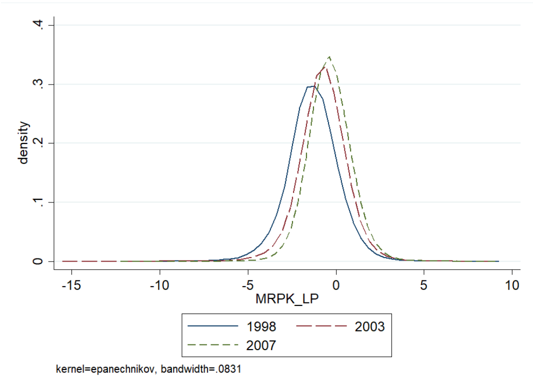
The measure of MRPK is on the basics of equation (6.5): To compute β_K, the revenue-based production function is estimated by industry using a variety of estimation approaches including Olley and Pakes (1996); Levinsohn and Petrin (2003); Wooldridge (2009); Ackerberg et al. (2015); Capital (in natural logarithm) $ln(K_{it})$ is calculated by the perpetual inventory method following Brandt et al. (2012); $ln(R_{it})$ is measured as the natural logarithm of revenue, which is deflated by output price deflators. The main dataset to compute $mrpk$ is the Annual Survey of Industrial Firms (ASIF) database over the period of 1998-2007.

The distributions of MRPK (in logarithm) in Chinese manufacturing industries are plotted in figure 6.1, where MRPK is estimated based on the LP method, LP method with ACF correction, OP method, OP method with ACF correction, and Wooldridge method, respectively. Each subfigure shows the MRPK dispersion in the years 1998, 2003 and 2007. Over time, MRPK distribution not only displays an increasing central tendency but also demonstrates a lower degree of dispersion. That is, both the medium value of MRPK and the peak density near the medium MRPK increase over time, and the MRPK dispersion in 1998 has a thicker left tail than in 2003 and 2007. This indicates a dynamic restructuring process of capital during the period of 1998-2007 in the Chinese manufacturing sector.

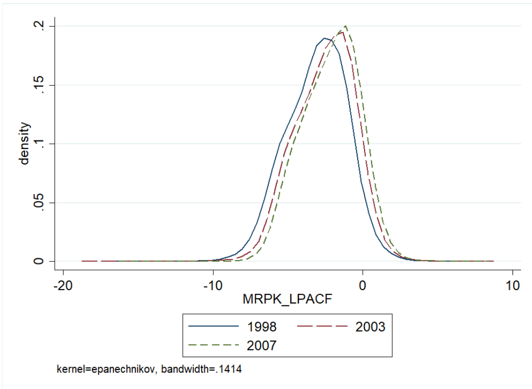
Table 6.1 shows the summary statistics of MRPK distribution to support the above dynamic patterns in figure 6.1. There is an increasing tendency for both mean and median values of MRPK, no matter which method is applied to estimate MRPK. This indicates that the marginal return of capital in manufacturing firms can increase over time on average. The last three columns report the standard deviation, 75-25 percentile difference and 90-10 percentile difference among all sample firms each year, which are used to denote the dispersion/distribution of MRPK in each year. There is a robust declining trend for all three dispersion measures, implying an overall increased efficiency in allocating capital over time.

Table 6.1: Summary statistics of MRPK distribution

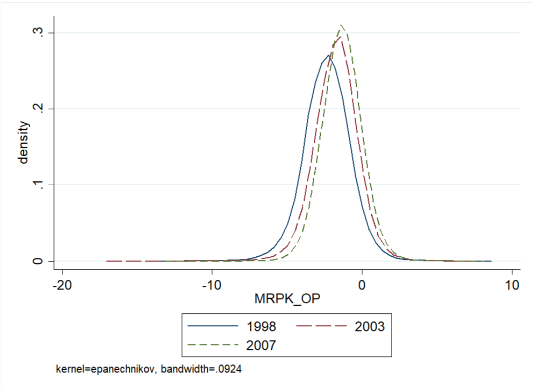
Variable	Year	Mean	Median	Standard deviation	p75-p25	p90-p10
MRPK_LP	1998	-1.31	-1.32	1.47	1.78	3.51
	2003	-0.74	-0.73	1.37	1.63	3.22
	2007	-0.37	-0.39	1.24	1.56	3.02
MRPK_LPACF	1998	-3.07	-2.93	2.07	2.90	5.28
	2003	-2.52	-2.36	2.02	2.88	5.18
	2007	-2.15	-2.01	1.95	2.81	5.07
MRPK_OP	1998	-2.35	-2.33	1.57	1.98	3.78
	2003	-1.75	-1.71	1.48	1.83	3.55
	2007	-1.35	-1.36	1.35	1.74	3.34
MRPK_OPACF	1998	-2.09	-2.03	1.60	1.99	3.86
	2003	-1.50	-1.43	1.51	1.85	3.64
	2007	-1.10	-1.08	1.38	1.76	3.42
MRPK_WRDG	1998	-1.77	-1.77	1.47	1.77	3.49
	2003	-1.20	-1.19	1.37	1.63	3.21
	2007	-0.83	-0.85	1.24	1.56	3.02



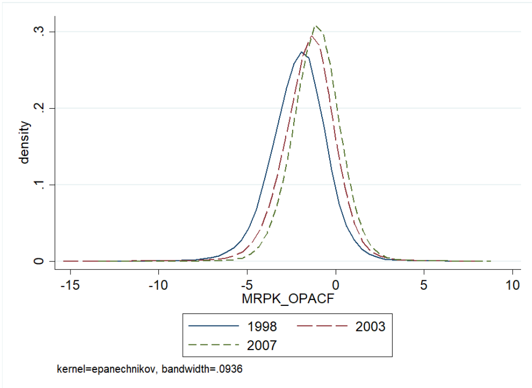
(a) LP method



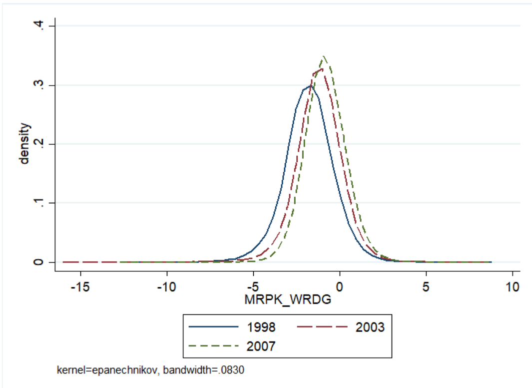
(b) LP method with ACF correction



(c) OP method



(d) OP method with ACF correction



(e) Wooldridge (WRDG) method

Figure 6.1: MRPK distribution in Chinese manufacturing industries

6.4.2 Data and Summary statistics

Table 6.2: Summary statistics

variable	mean	p75	p50	p25	Sd.	N
SD_MRPK_OP	1.154	1.306	1.134	0.981	0.266	35074
SD_MRPK_LP	1.150	1.301	1.133	0.980	0.261	35074
SD_MRPK_OPACF	1.154	1.306	1.134	0.980	0.268	34406
SD_MRPK_LPACF	1.168	1.322	1.138	0.980	0.286	32514
SD_MRPK_WRDG	1.150	1.300	1.133	0.981	0.260	35074
IQR_MRPK_OP	1.475	1.724	1.423	1.156	0.483	35074
IQR_MRPK_LP	1.475	1.725	1.425	1.156	0.482	35074
IQR_MRPK_OPACF	1.473	1.721	1.420	1.154	0.482	34406
IQR_MRPK_LPACF	1.480	1.730	1.424	1.157	0.490	32514
IQR_MRPK_WRDG	1.475	1.724	1.424	1.156	0.481	35074
Proximity	0.118	0.149	0.085	0.046	0.116	35074
SOE	0.183	0.274	0.076	0.007	0.237	35074
FOE	0.252	0.427	0.158	0.019	0.263	35074
HHI	0.125	0.160	0.102	0.054	0.106	35074
export	0.161	0.235	0.067	0.006	0.211	31252
subsidy	0.003	0.003	0.001	0	0.011	31252
rail density	0.020	0.024	0.014	0.012	0.016	35074
river density	0.070	0.076	0.029	0.006	0.097	35074
rroad density	0.568	0.749	0.458	0.340	0.330	35074

Note: MRPK is constructed based on the OP approach, OPACF approach, LP approach, LPACF approach and Wooldridge approach, respectively. MRPK dispersion is measured by either the standard deviation of MRPK or the interquartile range (IQR) of MRPK (i.e., the difference between the 75th and 25th percentiles). I exclude observations if the industry-province-year group has fewer than 10 firms.

A number of datasets are used in this research, including firm-level production data, geo-referenced highway routes, a series of geographic information data for the construction of instruments and a set of province-level data for control variables, which are the same as in previous chapters. Specifically, firm-level data is from the Annual Survey of Industrial Firms (ASIF) database over the period from 1998 to 2007, which is collected by the National Bureau of Statistics of China. This survey provides detailed information on each firm's basic identifying information such as industry and location, financial information such as debt and asset, and production information such as input and output. The information in this dataset is commonly used in the literature (e.g., Hsieh and Klenow, 2009; Song and Wu, 2015; Wu, 2018) to quantify resource misallocation, capital misallocation, and aggregate productivity loss in China.

Table 6.2 reports the summary statistics of the main variables, including the mean value, 75th quantile, 50th quantile, 25th quantile, standard deviation and observation of each variable. The number of observations ranges from 31252-35074. Most of the variables are calculated at the industry-province-year level, except the three transportation density variables which are at the province-year level. Since this research focuses on the dispersion of MRPK, I exclude observations if the industry-province-year group has fewer than 10 firms.

The first five variables are the standard deviation of MRPK measured based on the OP approach, OPACF approach, LP approach, LPACF approach and Wooldridge approach, respectively. The statistics of each sd dispersion variable are quite similar, with a mean value of 1.15-1.16, and a standard deviation of 0.26-0.28. The second five variables are the interquartile range (IQR) of MRPK (i.e., the difference between the 75th and 25th percentiles) constructed with different approaches. Similarly, the mean value of each IQR dispersion is approximately 1.47-1.48, with a standard deviation of 0.48-0.49. Highway proximity is measured as the inverse of the unweighted average distance to the nearest highway among firms within the same industry and province. The mean value and medium value are 0.118 and 0.085 respectively. The time trend of average highway proximity in Figure 6.2 shows the rapid increase of average highway proximity in China, changing from 0.063 in the year 1998 to 0.17 in the year 2007. SOE and FOE are the share of state-owned capital and foreign capital in total capital within the same 4-digit industry and province each year, respectively. The mean foreign capital share (0.252) is higher than the average state-owned capital share (0.183). The data also shows the heterogeneities in SOE and FOE with a standard deviation of 0.237 and 0.263, respectively. Herfindhl-Hirschman Index (HHI) is used to proxy within-industry-province competition status, and a higher value of HHI means a lower degree of competition. The HHI value at the 75th quantile and 25th quantile is 0.16 and 0.054, respectively, indicating an overall high competition level. The mean export-to-output ratio is 0.161, with a standard deviation of 0.211. The mean and medium values of the subsidy-to-output ratio are 0.3% and 0.1% respectively. At least 25% industry-province observations do not receive subsidies from the government. Railway density and river density are much lower than the density of other roads (excluding highways).

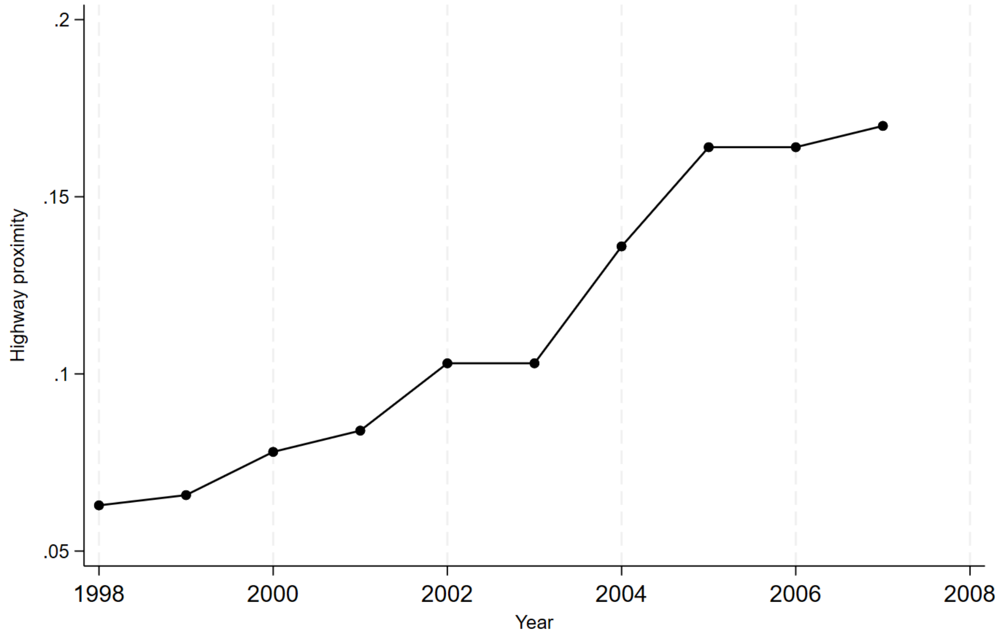


Figure 6.2: Average highway proximity during 1998-2007

6.4.3 Baseline estimation result

Baseline estimation results are reported in Table 6.3, which uses the standard deviation of MRPK as the dependent variable. The dependent variable in columns (1)-(5) is constructed based on the OP approach, OPACF approach, LP approach, LPACF approach and Wooldridge approach, respectively. Each estimation applies three instrumental variables including the least cost path instrument (LCP IV), Historical instrument (Historical IV) and Straight-line instrument (Straight-line IV). The first-stage estimation result shows that both LCP IV and Historical IV have a positive and significant correlation with highway proximity, whereas the effect of Straight-line IV is less significant. Anyhow, the Straight-line IV is regarded as less efficient as it is constructed with straight lines based on the highway routes documented in the official NEN project. Comparatively, the LCP IV is the most efficient one since the routes are constructed fully based on land cover and geographic information rather than regional economic development information. All of the first-stage estimation results passed the three identification tests, suggesting the IVs are not weakly identified, under-identified or over-identified.

The second-stage estimation results suggest that the effect of highway proximity is significantly negative and robust regardless of the construction method of MRPK.

This shows that better highway proximity indeed promotes a better allocative efficiency of capital and reduces the dispersion of MRPK. Specifically, the estimation results indicate that a 0.1 unit increase in highway proximity over the sample period can lead to a 0.03-0.04 unit decrease in MRPK dispersion.

As proxies for policy distortion in China, both state-owned capital shares (SOE) and foreign capital shares (FOE) have significantly positive effects on MRPK dispersion, which is in line with the discussion in Ding et al. (2016a) and Wu (2018). Government subsidy, another proxy of policy distortion or government intervention (Ding et al., 2019), has positive effects on MRPK dispersion as well, although the coefficient is not always significant. Overall, larger policy distortion, in general, may generate distortions in capital prices and negatively affect capital allocation. The insignificant sign of the HHI index shows that tougher competition does not have significant effects on MRPK dispersion. A larger export-to-output ratio is associated with lower MRPK dispersion. Since exposure to trade will encourage more productive firms to enter the export market while forcing the least efficient firms to exit the market (Melitz, 2003), more exposure to international trade is likely to promote better capital allocation efficiency. Better railway density and the density of other types of roads (excluding highways) both have positive effects on capital allocation efficiency. While larger river density is positively associated with MRPK dispersion. Since the waterway is less important in manufacturing firms' transportation (accounting for less than 10% of freight volume) and is only available in some regions, it is therefore likely to have opposite effects on capital allocation efficiency.

Table 6.3: Baseline estimation result: standard deviation of MRPK

VARIABLES	(1) OP	(2) OPACF	(3) LP	(4) LPACF	(5) WRDG
Second-stage result: standard deviation of MRPK (SD_MRPK) as dependent variable					
Proximity	-0.306***	-0.351***	-0.321***	-0.409***	-0.321***
	(0.090)	(0.089)	(0.086)	(0.106)	(0.086)
SOE	0.089***	0.097***	0.088***	0.107***	0.087***
	(0.015)	(0.016)	(0.015)	(0.019)	(0.017)
FOE	0.035**	0.043***	0.044***	0.051***	0.045***
	(0.015)	(0.015)	(0.015)	(0.018)	(0.015)
HHI	-0.014	-0.005	-0.004	-0.028	-0.002
	(0.030)	(0.029)	(0.030)	(0.034)	(0.031)
export	-0.073***	-0.062**	-0.075***	-0.068***	-0.075***
	(0.025)	(0.025)	(0.025)	(0.026)	(0.024)
subsidy	0.379***	0.304**	0.129	0.361**	0.097
	(0.141)	(0.147)	(0.204)	(0.166)	(0.193)
rail_density	-1.195*	-0.920	-1.158*	-0.678	-1.227*
	(0.622)	(0.628)	(0.611)	(0.693)	(0.626)
river_density	0.723**	0.734**	0.867***	0.856**	0.829**
	(0.355)	(0.347)	(0.335)	(0.387)	(0.338)
rroad_density	-0.027**	-0.021	-0.025*	-0.011	-0.022*
	(0.013)	(0.013)	(0.013)	(0.015)	(0.013)
First-stage result: highway proximity as dependent variable					
LCP IV	0.644***	0.659***	0.644***	0.640***	0.644***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Historical IV	0.352***	0.355***	0.352***	0.367***	0.352***
	(0.038)	(.039)	(0.038)	(0.038)	(0.038)
Straight-line IV	0.006	0.007	0.006	0.008*	0.006
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	234.396	237.579	234.396	260.146	234.396
Overidentification test	0.585	0.126	0.176	0.317	0.157
Observations	30,412	29,869	30,412	28,214	30,412
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES

Note: Robust standard errors corrected for 4-digit industry-level clustering are reported in parenthesis. Significant coefficients are indicated by ***, **, * for significance at the 1%, 5% and 10% level, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 22.30. The dependent variable of SD_MRPK in columns (1)-(5) is constructed based on the OP approach, OPACF approach, LP approach, LPACF approach and Wooldridge approach, respectively. I exclude observations if the industry-province-year group has fewer than 10 firms.

6.5 Possible Mechanisms

The baseline estimation shows that improved highway proximity helps to reduce MRPK dispersion. This section further investigates the potential mechanisms through which highway proximity improves the allocative efficiency of capital. Existing literature identifies specific sources of capital misallocation, such as productivity shock and adjustment cost (e.g., Asker et al., 2014), markup dispersion (e.g., David and Venkateswaran, 2019), financial frictions (e.g., Gopinath et al., 2017; Midrigan and Xu, 2014), and policy distortions (e.g., Song et al., 2011; Wu, 2018). Following this stream of literature, this research tests how highway proximity affects MRPK dispersion by examining how it affects the sources of capital misallocation. To be specific, it tests (1) whether highway proximity affects productivity volatility; (2) how highway proximity influences markup dispersion; (3) whether highway infrastructure reduces MRPK dispersion via the channel of financial constraints; and (4) the heterogeneous effects of highway proximity on capital misallocation conditioning on government intervention.

6.5.1 Volatility of TFPR

Profit maximization implies that the marginal revenue product of capital should equal the unit cost of capital. If capital can be adjusted smoothly and without friction, firms will end up with the same unit cost of capital and there will be no static dispersion in MRPK. However, firms face adjustment costs[8]. Asker et al. (2014) highlight the importance of capital adjustment cost associated with the dy-

[8]On the one hand, fixed investment is at least partially irreversible due to reasons such as a shortage of secondary market for fixed capital (Speight and Thompson, 2006), especially for industry-specific or highly specialized capital goods (Ding et al., 2013), or a lemon's problem occurred in reselling capital because of the asymmetric information of quality (Akerlof, 1970). On the other hand, firms face non-competitive capital markets with financial frictions and informational frictions.

namic production inputs in explaining the dispersion of static measures of capital misallocation. Even if firms acquire all inputs in a frictionless market, dispersion in MRPK will occur naturally since an optimal capital stock determined in the previous period may no longer be optimal after a productivity shock occurs. Across nine datasets spanning forty countries, they find that industries exhibiting larger time-series productivity volatility have larger cross-sectional MRPK dispersion. Similar findings are found in Alam (2020) that both net worth (capturing financial frictions) and TFPR shocks (capturing capital adjustment costs) can cause the dispersion in MRPK, using European firm-level data.

Motivated by the existing literature, it is worth investigating whether highway proximity affects MRPK dispersion through the channel of productivity shocks and adjustment costs. Intuitively, better highway proximity is likely to affect revenue-based productivity volatility, which captures uncertainties from both the supply side and demand side. On the one hand, better highway infrastructure can alleviate supply-side uncertainty. Better highway infrastructure facilitates more efficient and quicker transportation of goods and services between regions and cities, which reduces transit time and uncertainties associated with supply chains. Better highway proximity also helps improve the management efficiency of inputs and supply with better upstream and downstream connections. On the other hand, better highway infrastructure may affect demand-side uncertainty. Improved highway connectivity can enhance market access allowing firms a wider customer base. In addition, a better transportation network mitigates uncertainties related to logistics, inventory management, and order fulfilment, further reducing demand-side uncertainty. Thus, the improvement in highway accessibility may affect productivity volatility by facilitating market access, providing better supply chains and a more stable business environment with a more reliable transportation network.

If better highway proximity indeed helps reduce productivity volatility, it will then reduce the static measure of MRPK dispersion, following the theoretical and empirical evidence of Asker et al. (2014) that larger productivity shock variance is associated with larger cross-sectional MRPK dispersion. To empirically test this hypothesis, Table 6.4 reports the estimation result regarding the causal effect of highway proximity on productivity volatility. The volatility of TFPR is measured as the year-

Table 6.4: Channel estimation: TFPR volatility

VARIABLES	(1) sd(Δop)	(2) sd($\Delta opacf$)	(3) sd(Δlp)	(4) sd($\Delta lpacf$)	(5) sd($\Delta wrdg$)
Proximity	-0.205*	-0.243**	-0.221*	-0.229*	-0.239**
	(0.121)	(0.121)	(0.124)	(0.118)	(0.096)
Observations	24,612	24,612	24,612	24,612	31,150
Control variables	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Instruments					
LCP IV	YES	YES	YES	YES	YES
Historical IV	YES	YES	YES	YES	YES
Straight-line IV	YES	YES	YES	YES	YES
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	158.317	158.317	158.317	158.317	236.146
Overidentification test	0.3054	0.1272	0.3931	0.2583	0.0004

Note: The dependent variable in each column is the standard derivation of productivity shock. Productivity is calculated using different methods, including the OP method, LP method, ACF method and WRDG method. Robust standard errors corrected for 4-digit industry-level clustering are reported in parenthesis. Significant coefficients are indicated by ***, **, * for significance at the 1%, 5% and 10% level, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 22.30.

industry-province standard deviation of the TFPR firm shock, i.e., $SD_{jpt}(z_{it} - z_{it-1})$, where TFPR ($z_{it}$) is measured by various approaches including the OP approach, OPACF approach, LP approach, LPACF approach and Wooldridge approach. For instance, $sd(\Delta op)$ in column (1) means the dependent variable is the standard deviation of TFPR shock, where the TFPR is measured based on the OP approach. The estimation result in column (1) shows that a 0.1 unit increase in highway proximity will lead to a 0.02 unit decrease in TFPR volatility. This causal effect is robust when using different measures of TFPR, as shown in columns (2)-(5). It is in line with the hypothesis that highway infrastructure development can affect MRPK dispersion via the mechanism of productivity shocks. With decreased productivity volatility caused by better highway proximity, the new capital level in the next period is less likely to be largely different from the optimal level, therefore resulting in a smaller dispersion in the static measure of MRPK dispersion.

6.5.2 Markup

6.5.2.1 Motivation and assumption

The role of markup dispersion as a source of misallocation has recently been discovered in the literature (e.g., Edmond et al., 2015; Lu and Yu, 2015; Asturias et al., 2019; David and Venkateswaran, 2019). With markup dispersion, firms with lower markups produce more than optimal, while those with higher markups use input resources less than optimal, leading to inefficiencies (Lu and Yu, 2015). Asturias et al. (2019) estimate the welfare gains from India's Golden Quadrilateral (GQ) large-scale transportation project. They developed a model of internal trade with variable markup that includes mechanisms via which transportation infrastructure impacts welfare. Misallocation in their case arises because of dispersion in markups across producers. Although not the most important source of capital misallocation, David and Venkateswaran (2019) conclude that unobserved variation in markups in China accounts for 4% of capital misallocation.

There are two opposing effects of highway expansion on markup and this may therefore affect the heterogeneity of markup within an industry (markup dispersion): (1) Lower transportation costs would allow firms to have easier access to cheaper intermediate goods and reduce the cost of production, resulting in higher profit margins for firms and an increase in markups. (2) With better market integration and increased competition, firms may reduce markups to attract customers. Since better highway infrastructure decreases the costs and transit time of transporting goods and services between regions, it encourages market expansion and induces increased competition. Firms may lower their markups to remain competitive in a highly competitive market. In contrast, fewer competitive markets allow firms to charge higher markups without losing customers.

Existing evidence shows different conclusions about how highway infrastructure affects firm-level markups. For instance, the second channel is supported by Liu et al. (2019a) which investigates how highway infrastructure expansions in China affect firm productivity and productivity gaps between private and state firms. They find that lower transportation costs lead to higher productivity and better firm selection by inducing fiercer competition (lower markups). The findings in Liu et al. (2019a) show that better highway infrastructure in China reduces firm-level markups, suggesting a higher competition level faced by manufacturing firms, while Liu et al. (2021) concludes an overall insignificant effect of highway network expansion on firm-level markup, suggesting the two opposing effects are either equivalent or too small to have an overall significant effect.

Rather than just focusing on firm-level markups, it is important to consider if and how highway infrastructure affects markup dispersion, which is one of the unignorable sources of capital misallocation and resource misallocation. If the impact of highway infrastructure on markups is heterogeneous among different firms, then it is likely to affect the overall dispersion of markups. It is hypothesised that better highway proximity may reduce markup dispersion, with the expectation that the negative effect of firm-level highway proximity on markup should be larger for firms with higher markups. For those firms with already low markup levels, it is less likely for them to largely reduce their markup even with high competition levels, whereas firms with higher markup levels tend to have a higher potential to significantly reduce their markups to attract more customers. Thus, the heterogeneous effects of highway proximity at the firm level can be used to explain how highway infrastructure affects markup dispersion at the industry-province level. To test this potential mechanism, this research first examines the overall effect of highway proximity on markup dispersion and then looks at the firm-level heterogeneous effects.

6.5.2.2 Markup estimation

Markup is commonly defined as the ratio of price to marginal cost (Lu and Yu, 2015; David and Venkateswaran, 2019). However, product prices and marginal costs are rarely included in firm-level data. Addressing this problem, De Loecker and Warzynski (2012) develop a method to estimate markups without specifying how firms compete on the market using the estimation of a production function. This method has been followed and extended in recent research such as Lu and Yu (2015); David and Venkateswaran (2019); Liu et al. (2019b, 2022).

Markup variation is measured by the following two methods:

(1) First method

In David and Venkateswaran (2019), it follows the methodology of De Loecker and Warzynski (2012) and assumes a common materials elasticity across firms within an industry. The optimal condition of cost minimization implies equation (6.15):

$$\frac{P_{it}^{M}M_{it}}{P_{it}Y_{it}} = (1-\hat{\zeta})\frac{MC_{it}}{P_{it}} \tag{6.15}$$

where $\frac{P_{it}^{M}M_{it}}{P_{it}Y_{it}}$ is the materials' share of revenue, $1-\hat{\zeta}$ is the elasticity of the materials, $\frac{MC_{it}}{P_{it}}$ is the inverse of markup in which MC_{it} and P_{it} denote the marginal cost of the firm and the price of output, respectively.

Since the focus in David and Venkateswaran (2019) is markup dispersion, assuming common materials elasticity across firms within an industry, the within-industry dispersion in the materials' share of revenue maps one-for-one into (log) markup dispersion. I follow this method to proxy markup dispersion at the industry-province-year level.

(2) Second method

The basic theoretical framework in section 6.3 assumes a specific type of demand function with constant demand elasticity. In this subsection, the assumption is relaxed, defining $P_{it} = P(Y_{it})$.

Profit maximization implies $MC_{it} = MR_{it}$:

$$MC_{it} = \frac{\partial P_{it}Y_{it}}{\partial Y_{it}} = (\frac{\partial P_{it}}{\partial Y_{it}}\frac{Y_{it}}{P_{it}} + 1)P_{it} \tag{6.16}$$

Following De Loecker and Warzynski (2012), define markup $\mu_{it} = \frac{P_{it}}{MC_{it}}$. Thus the inverse of markup equals demand elasticity plus 1.

$$u_{it}^{-1} = \frac{\partial P_{it}}{\partial Y_{it}}\frac{Y_{it}}{P_{it}} + 1 \tag{6.17}$$

The first-order condition of profit maximization implies:

$$\frac{\partial R_{it}}{\partial K_{it}} = \alpha_K u_{it}^{-1} \frac{P_{it} Y_{it}}{K_{it}} = (1 + \tau_{Kit}) P^K \quad (6.18)$$

$$\frac{\partial R_{it}}{\partial L_{it}} = \alpha_L u_{it}^{-1} \frac{P_{it} Y_{it}}{L_{it}} = (1 + \tau_{Lit}) P^L \quad (6.19)$$

$$\frac{\partial R_{it}}{\partial M_{it}} = \alpha_M u_{it}^{-1} \frac{P_{it} Y_{it}}{M_{it}} = (1 + \tau_{Mit}) P^M \quad (6.20)$$

$$\pi_{it} = P_{it} Y_{it} - (1 + \tau_{Kit}) P^K K_{it} - (1 + \tau_{Lit}) P^L L_{it} - (1 + \tau_{Mit}) P^M M_{it} \quad (6.21)$$

$$= (1 - \frac{\alpha_K + \alpha_L + \alpha_M}{\mu_{it}}) P_{it} Y_{it} \quad (6.22)$$

Assume the constant return to scale, i.e., $\alpha_K + \alpha_L + \alpha_M = 1$.

Rearranging the above equation will derive the equation that identifies firm-level markups, the same as the method in Liu et al. (2021):

$$\mu_{it}^{-1} = 1 - \frac{\pi_{it}}{P_{it} Y_{it}} \quad (6.23)$$

In the empirical estimation, firm-level markup and within-industry-province variation of markup are measured following equation 6.23.

6.5.2.3 Estimation result

Table 6.5 reports the estimation results at the industry-province level. The dependent variable in column (1) is the standard deviation of markup measured based on method 1; in column (2) is the standard deviation of markup measured applying method 2. The estimation result shows that highway proximity has a significantly negative effect on markup dispersion, suggesting the mechanism that highway proximity can reduce capital misallocation through the channel of markup variation.

For a further investigation of how highway proximity affects markup dispersion, figure 6.3 reports the quantile coefficients at the firm level by using the estimation

Table 6.5: Channel estimation: Markup dispersion

	(1)	(2)
VARIABLES	sd_markup_m1	sd_markup_m2
proximity	-0.036**	-0.367***
	(0.017)	(0.110)
Observations	30,412	30,412
Control variables	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
Province FE	YES	YES
Instruments		
LCP IV	YES	YES
Under identification test	0.000	0.000
Weak identification test	620.216	620.216
Overidentification test	0.000	0.000

Note: The dependent variable in column (1) is the standard deviation (sd) of markup measured based on method 1; in column (2) is the sd of markup measured applying method 2. Control variables include SOE, POE, HHI, export, subsidy, railway density, river density and other road density. The instrument is the least cost path instrument.

method of quantile IV regression. The independent variable, firm-level highway proximity, is calculated as the inverse of the firm's distance to the nearest highway, which is instrumented with three instruments, namely, the LCP instrument, the historical instrument, and the straight-line instrument, calculated using the same method as firm-level highway proximity. The dependent variable, firm-level markup, is measured by method 2. Overall, the firm-level estimation result suggests that the negative effect of highway proximity is dominant over the positive effect. The coefficient of highway proximity on markup is significantly negative from the P20 quantile to the P80 quantile, while the magnitude of the absolute value is larger and larger from P20-P80. This indicates that firms with higher markups reduce more than those with lower markups when facing better highway proximity. It supports the result in Table 6.5, i.e., better highway proximity reduces markup dispersion by imposing heterogeneous effects on different firms.

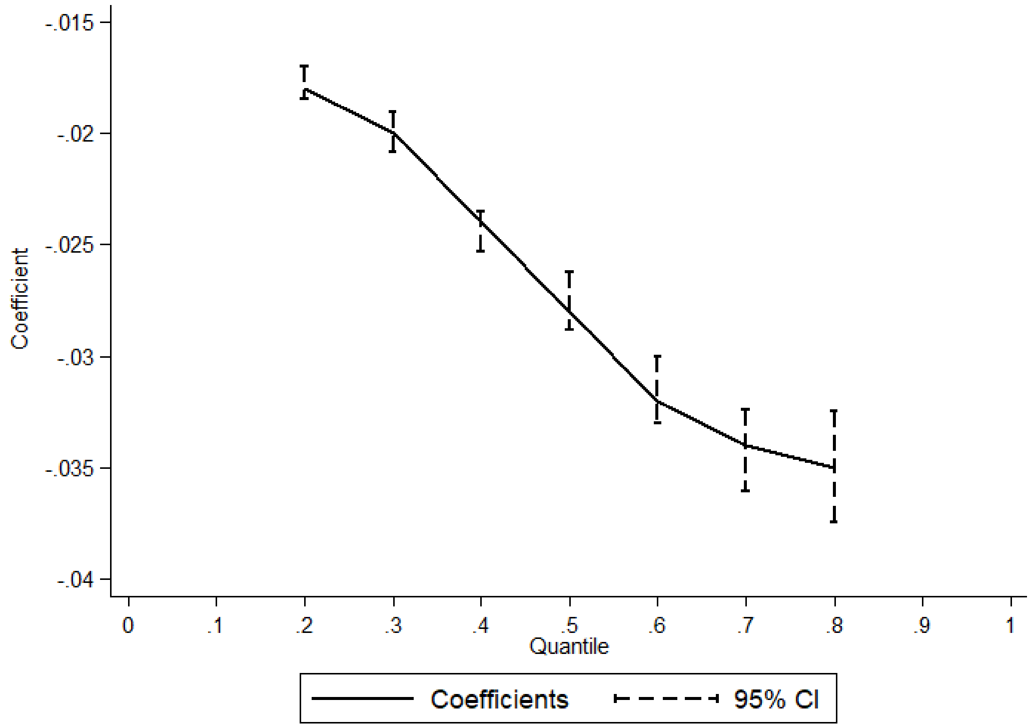


Figure 6.3: Quantile coefficient plot for firm-level markup

6.5.3 Financial constraint

There is a growing body of literature arguing that financial friction contributes to capital misallocation (e.g., Midrigan and Xu, 2014; Moll, 2014; Gopinath et al., 2017; Ek and Wu, 2018; Karabarbounis and Macnamara, 2021). Midrigan and Xu (2014) argue that financial frictions can distort aggregate productivity in two ways. On the one hand, financial friction distorts decisions regarding entry and technology adoption, which in turn reduces the productivity of individual producers. On the other hand, financial frictions produce misallocation among existing producers by causing an inefficient distribution of marginal products of capital. They find modest losses because of capital misallocation but potentially significant losses following from inefficiency in entry and technology adoption. This is supported by Moll (2014) who finds that self-financing mitigates capital misallocation from financial constraints in the long run under persistent idiosyncratic productivity shocks. Buera et al. (2011) argued that despite self-financing having the potential to alleviate the resulting misallocation, doing so is more difficult in sectors with larger scales and higher financing needs, such as the manufacturing industry. Their quantitative analysis suggests that a substantial part of cross-country differences in output per worker, aggregate and sectoral TFP and the capital-to-output ratio can be explained by financial frictions. Gopinath et al. (2017) propose a model with size-dependent financial frictions. Their theoretical framework implies that MRPK dispersion across firms is explained by binding borrowing constraints, costs of capital adjustment, and capital accumulation risk. Ai et al. (2020) show that agency frictions in the financial sector affect capital reallocation efficiency across firms and cause aggregate economic fluctuations. Karabarbounis and Macnamara (2021) find that the effect of financial frictions on capital misallocation is larger among private firms compared to public firms using data from the United States.

For China-specific research, it has been shown in Ek and Wu (2018) that financing constraint does have a significant effect on capital misallocation. In their theoretical framework, the notion of investment to cash flow sensitivity, which is a common measure of financing constraint, is linked to the dispersion of the marginal revenue product of capital, a direct measure of inefficiency in allocative allocation. It is argued that since the existence of both constrained and unconstrained firms displays significant and insignificant investment-cash flow sensitivities, MRPKs must vary across firms, resulting in capital misallocation. Applying an error-correction investment model to U.S. Compustat data and Chinese manufacturing firms and in several sub-samples of Chinese firms, their estimates of investment-cash flow sensitivities indicate a loss in total factor productivity of 5% and 15% for the balanced and unbalanced panels of Chinese firms, respectively. David and Venkateswaran (2019) show that inefficient factors such as size-dependent policies or financial imperfections explain capital misallocation more than unobserved heterogeneity in production technologies among China's manufacturing firms.

Since financial friction is one of the contributors to capital misallocation that cannot be ignored, this subsection tests whether highway transportation may affect capital misallocation via financial friction. A significant role played by the expansion of highway networks is in reshaping the spatial distribution of economic geography and fostering the development of economic activities. This is primarily accomplished through intercity commuting and information transmission (Duan et al., 2020). Further, accessibility to transportation reduces the risk of long-distance investment deals, as it improves mediated information accessibility and quality, reducing information asymmetries and helping to identify investment opportunities more efficiently (Giroud, 2013; Bernstein et al., 2016; Duan et al., 2020). As a result, an improved highway network may facilitate the availability of external financial sources with a larger geographic scope, thereby reducing financial constraints. Constraint firms can, therefore, increase their investment.

Table 6.6: Subgroup regression based on firm size

VARIABLES	(1) op	(2) opacf	(3) lp	(4) lpacf	(5) wrdg
	Panel A: industries dominated by small-sized firms				
Proximity	-0.421***	-0.485***	-0.421***	-0.595***	-0.410***
	(0.147)	(0.158)	(0.146)	(0.186)	(0.150)
Observations	14,501	14,263	14,501	13,340	14,501
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	63.602	61.212	63.602	114.051	63.602
Overidentification test	0.6094	0.2166	0.2144	0.0797	0.2161
	Panel B: industries less dominated by small-sized firms				
Proximity	-0.128	-0.180	-0.154	-0.214	-0.163
	(0.128)	(0.127)	(0.120)	(0.140)	(0.119)
Observations	14,837	14,566	14,837	13,887	14,837
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	153.485	170.000	153.485	145.930	153.485
Overidentification test	0.5106	0.1848	0.4352	0.8752	0.4702
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Instruments					
LCP IV	YES	YES	YES	YES	YES
Historical IV	YES	YES	YES	YES	YES
Straight-line IV	YES	YES	YES	YES	YES

Note: subgroup regression based on the medium value of small firms share at the 4-digit industry-province level. The dependent variable in each column is the standard deviation of MRPK. Control variables include SOE, POE, HHI, export, subsidy, railway density, river density, and other road density.

To test this possible mechanism, two types of subgroup regression based on firm size and capital intensity are conducted. First, according to the official standards for the classification of firm size, a firm is defined as a small-sized firm if it has less than 300 employees. For each industry-province pair, I first calculate the share of small-sized firms, and then subgroup the sample into industries dominated by small-sized firms and industries less dominated by small-sized firms, based on the medium

Table 6.7: Subgroup regression based on capital intensity

VARIABLES	(1) op	(2) opacf	(3) lp	(4) lpacf	(5) wrdg
	Panel A: high capital intensity				
Proximity	-0.298**	-0.410***	-0.401***	-0.446***	-0.366***
	(0.131)	(0.129)	(0.131)	(0.155)	(0.125)
Observations	14,350	14,091	14,350	13,228	14,350
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	152.815	162.503	152.815	141.011	152.815
Overidentification test	0.2316	0.1740	0.1357	0.0410	0.1367
	Panel B: low capital intensity				
Proximity	-0.130	-0.162	-0.155	-0.212	-0.169
	(0.129)	(0.125)	(0.124)	(0.130)	(0.123)
Observations	14,925	14,668	14,925	13,986	14,925
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	155.165	147.515	155.165	179.555	155.165
Overidentification test	0.4777	0.3759	0.6510	0.2301	0.5330
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Instruments					
LCP IV	YES	YES	YES	YES	YES
Historical IV	YES	YES	YES	YES	YES
Straight-line IV	YES	YES	YES	YES	YES

Note: subgroup regression based on the medium value of capital intensity at the 4-digit industry level. The dependent variable in each column is the standard deviation of MRPK. Control variables include SOE, POE, HHI, export, subsidy, railway density, river density, and other road density.

value of small firm share. Hadlock and Pierce (2010) find that firm size is one of the most useful predictors of financial constraint levels. Smaller firms may have more difficult access to external funds because of the adverse selection problems, whereas larger firms are more diversified and find it easier to raise external capital (Ding et al., 2012; Hovakimian, 2011). Thus, industries dominated by small-sized firms are more likely to suffer more financial constraints, whereas those with a low proportion of small-sized firms are less likely to have financial constraints. Table 6.6 shows the estimation result. In panel A, the coefficient of highway proximity on MRPK dispersion is significantly negative, showing that better highway proximity improves the allocative efficiency of capital for industries with higher financial constraints. However, the coefficient of interest in panel B is insignificant in all cases, indicating that industries with lower financial constraints are not affected as much compared with more constraint firms. This provides evidence that highway proximity can affect capital dispersion via the mechanism of financial constraints. Industries with higher financial constraints can benefit from better transportation networks and increase their capital investment.

In addition to the subgroup estimation based on firm size, Table 6.7 further reports the subgroup estimation result according to the medium value of 4-digit industry capital intensity. Capital intensity is calculated as the ratio of total capital expenditure to total labour force in each 4-digit industry. Industries with high capital intensity have high capital requirements and tend to face financial constraints (Cowan and Raddatz, 2013). On the one hand, a high level of operating leverage is characteristic of capital-intensive industries, which have a high ratio of fixed costs to variable costs. Those industries need a high volume of revenue to create positive returns on investment. On the other hand, capital-intensive industries tend to rely more on external finance because of the large volume of capital expenditure and are more likely to be affected by imperfect financial markets. In addition, the payback period for fixed assets is typically long, which means it takes time to recoup the initial investment and begin generating profits. Financial risk and uncertainty related to this extended timeline make it challenging for firms to attract external financing. The estimation result in Table 6.7 provides the robustness result regarding the potential financial constraint channel, i.e., the negative effect of highway proximity on MRPK dispersion is significant and larger in industries with high capital intensity than those with low capital intensity.

6.5.4 Policy distortion

In addition to financial frictions, policy distortion is another source affecting capital misallocation (e.g., Dollar and Wei, 2007; Wu, 2018). The government may provide favourable treatment to some companies with political connections through a variety of channels, such as low-interest loans, tax breaks, subsidies, and awards of government contracts (Restuccia and Rogerson, 2013). Although it is unlikely that highway networks may affect policy distortions, policy distortion may enter as

Table 6.8: Estimation result on policy distortion

VARIABLES	(1) op	(2) opacf	(3) lp	(4) lpacf	(5) wrdg
	Panel A: high private capital share				
Proximity	-0.489***	-0.610***	-0.567***	-0.638***	-0.554***
	(0.123)	(0.126)	(0.124)	(0.143)	(0.124)
Observations	13,463	13,246	13,463	12,610	13,463
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	111.058	132.440	111.058	105.982	111.058
Overidentification test	0.5969	0.4838	0.4630	0.2789	0.4844
	Panel B: low private capital share				
Proximity	-0.095	-0.123	-0.124	-0.128	-0.128
	(0.126)	(0.130)	(0.124)	(0.147)	(0.124)
Observations	16,208	15,904	16,208	14,942	16,208
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	102.972	98.183	102.972	126.027	102.972
Overidentification test	0.6418	0.6888	0.4574	0.3063	0.4055
	Panel C: high state-owned capital share				
Proximity	-0.006	-0.080	-0.078	-0.044	-0.101
	(0.239)	(0.239)	(0.239)	(0.261)	(0.235)
Observations	3,493	3,480	3,493	3,291	3,493
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	59.200	59.127	59.200	59.192	59.200
Overidentification test	0.1841	0.1540	0.1679	0.1859	0.1476
	Panel D: low state-owned capital share				
Proximity	-0.338***	-0.390***	-0.363***	-0.441***	-0.361***
	(0.099)	(0.101)	(0.093)	(0.124)	(0.093)
Observations	26,253	25,730	26,253	24,295	26,253
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	276.957	286.436	276.957	258.002	276.957
Overidentification test	0.4229	0.1640	0.2119	0.1151	0.2113
Control variables	YES	YES	YES	YES	YES
Year/Industry/Province FE	YES	YES	YES	YES	YES
Instruments					
LCP IV	YES	YES	YES	YES	YES
Historical IV	YES	YES	YES	YES	YES
Straight-line IV	YES	YES	YES	YES	YES

Note: subgroup regressions based on the industry-province-year level private capital share and state-owned capital share, respectively. The full sample is subgrouped into Panel A and Panel B based on the medium value of the private capital share. Observations are further subgrouped to Panel C if the stated-owned capital share is no less than 50% and to Panel D otherwise. The dependent variable in each column is the standard deviation of MRPK. The control variables include export, HHI, subsidy, railway density, river density and density of other roads excluding highways.

Table 6.9: Subgroup regression based on subsidy to output share

VARIABLES	(1) op	(2) opacf	(3) lp	(4) lpacf	(5) wrdg
		Panel A: high subsidy share			
Proximity	-0.071	-0.199	-0.143	-0.297**	-0.124
	(0.146)	(0.145)	(0.147)	(0.150)	(0.146)
Observations	14,354	14,062	14,354	13,448	14,354
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	136.491	133.571	136.491	125.670	136.491
Overidentification test	0.5790	0.4395	0.4391	0.4732	0.4052
		Panel B: low subsidy share			
Proximity	-0.427***	-0.425***	-0.411***	-0.500***	-0.423***
	(0.129)	(0.126)	(0.126)	(0.138)	(0.125)
Observations	14,417	14,210	14,417	13,271	14,417
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	69.022	72.566	69.022	95.834	69.022
Overidentification test	0.6627	0.5566	0.7134	0.4370	0.5467
Observed difference	-0.355**	-0.226	-0.269*	-0.204	-0.299**
Empirical p-value	0.040	0.100	0.085	0.190	0.045
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Instruments					
LCP IV	YES	YES	YES	YES	YES
Historical IV	YES	YES	YES	YES	YES
Straight-line IV	YES	YES	YES	YES	YES

Note: subgroup regression based on the medium value of the subsidy to output share. The dependent variable in each column is the standard deviation of MRPK. Control variables include SOE, POE, HHI, export, railway density, river density, and other road density.

a moderating effect. It is more likely to observe heterogeneous effects of highway proximity on capital misallocation conditioning on government interventions.

Ownership is usually regarded as a proxy for policy distortions in China (Brandt et al., 2013; Song et al., 2011). For instance, state-owned firms may benefit from lower interest rates on loans from government-owned banks, as well as easier access to the highly regulated stock market when compared with other ownership types. Companies that bring in foreign direct investment may benefit from special investment tax breaks and subsidies (Wu, 2018). Private firms, on the other hand, are regarded as facing lower policy distortions and are more reactive to highway improvement. To this end, this research calculates the state-owned capital share and private capital share at the 4-digit industry-province level for each year. Table 6.8 reports the estimation result. First, the full sample is subgrouped into panel A and panel B based on the medium value of private capital share[9]. This shows that the negative effect of highway proximity on MRPK dispersion is mainly driven by industries dominated by private-owned capital. Industries dominated by state-owned capital and foreign-owned capital are less affected by better highway infrastructures. Secondly, since state-owned capital (or SOE firms) is the most commonly used proxy of policy distortions in the relevant literature, the full sample is further subgrouped into group panel C with high state-owned capital shares if the share is no less than 50%, and group panel D with shares lower than 50%. Similarly, the negative effect of highway proximity is only significant for observations with lower policy distortions (panel D). Firms with higher policy interventions find it easy to receive external or internal financial sources and thus are unresponsive to the benefits of highway infrastructure. In contrast, industries with higher private capital shares are more reactive to better proximity, for instance, by increasing their investment due to lower uncertainties and internal and external financial constraints caused by better highway infrastructure.

In addition to ownership, government subsidy is another proxy of policy distortion (Ding et al., 2019). Industries with a higher subsidy share receive more government intervention. Subsidies targeted at particular industries or sectors can divert resources from more productive uses, therefore resulting in an inefficient allocation of resources. Table 6.9 shows the subgroup estimation based on the medium value of the subsidy to output share. The estimation result in panel B shows a significant negative effect of highway proximity on MRPK dispersion among observations with lower government intervention. However, better highway proximity generally has an insignificant impact on industries with high subsidy shares. Columns 1-3 and column 5 indicate that the effect of highway proximity on MRPK dispersion is larger in observations with lower subsidy share (government intervention), suggesting the heterogeneous effects.

[9]The medium value of the private capital share is 56.2%

6.6 Robustness Rsults

6.6.1 Using IQR dispersion of MRPK

Since the IQR dispersion of MRPK is less sensitive to the outliers compared with the standard deviation of MRPK. To address the concern of outliers, Table 6.10 reports the estimation result by using IQR dispersion of MRPK at the industry-province-year level as the dependent variable. This shows that the negative effect of highway proximity on MRPK dispersion is robust to alternative dispersion measures, which are not driven by outliers.

6.6.2 Using weighted average highway proximity

In the baseline estimation, highway proximity is calculated as unweighted regardless of the size of each firm. In this section, highway proximity is calculated as the inverse of the weighted average distance to the nearest highway among firms within the 4-digit industry j and province p at year t:

$$Highway_{jpt} = \frac{1}{\sum_{i=1}^{n} distance_{it\in j,p} * s_{it\in j,p}} \tag{6.24}$$

where $distance_{it\in j,p}$ is firm i's distance to the nearest highway at year t. $s_{it\in j,p}$ is firm i's employment share within the 4-digit industry j and province p at year t. A larger value of $Highway_{jpt}$ indicates better highway accessibility. With the concern that the size of firms may matter in measuring industry-level highway proximity, i.e., more output within the industry j and province p is produced with higher or lower highway accessibility.

Table 6.11 shows the estimation result by using weighted highway proximity. The dependent variable in panel A is the standard deviation of MRPK and in panel B is the IQR dispersion of MRPK. The estimation results indicate that the effect of highway proximity on MRPK dispersion is robust to alternative measures of highway

Table 6.10: Robustness estimation result: IQR dispersion of MRPK

VARIABLES	(1) OP	(2) OPACF	(3) LP	(4) LPACF	(5) WRDG
Second-stage result: IQR dispersion of MRPK (IQR_MRPK) as dependent variable					
Proximity	-0.681***	-0.692***	-0.644***	-0.709***	-0.645***
	(0.167)	(0.163)	(0.169)	(0.171)	(0.169)
SOE	0.154***	0.163***	0.159***	0.170***	0.159***
	(0.031)	(0.031)	(0.031)	(0.035)	(0.031)
FOE	0.076***	0.091***	0.081***	0.111***	0.084***
	(0.028)	(0.027)	(0.028)	(0.030)	(0.028)
HHI	0.083	0.105*	0.076	0.096	0.072
	(0.058)	(0.059)	(0.058)	(0.062)	(0.059)
export	-0.112**	-0.112**	-0.123***	-0.129***	-0.120***
	(0.045)	(0.046)	(0.044)	(0.045)	(0.044)
subsidy	0.786***	0.651**	0.328	0.786***	0.338
	(0.279)	(0.328)	(0.481)	(0.279)	(0.483)
rail_density	0.927	0.871	0.498	0.650	0.529
	(1.216)	(1.186)	(1.206)	(1.234)	(1.212)
river_density	1.713**	1.663**	1.925***	1.572**	1.904***
	(0.671)	(0.659)	(0.672)	(0.682)	(0.672)
rroad_density	-0.019	-0.017	-0.018	-0.007	-0.020
	(0.024)	(0.024)	(0.023)	(0.025)	(0.023)
First-stage result: highway proximity as dependent variable					
LCP IV	0.644***	0.659***	0.644***	0.640***	0.644***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Historical IV	0.352***	0.355***	0.352***	0.367***	0.352***
	(0.037)	(0.039)	(0.037)	(0.038)	(0.037)
Straight-line IV	0.007	0.006	0.007	0.007	0.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	234.581	237.788	234.581	260.445	234.581
Overidentification test	0.1360	0.1310	0.1175	0.1746	0.1074
Observations	30,412	29,869	30,412	28,214	30,412
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES

Note: Robust standard errors corrected for 4-digit industry-level clustering are reported in parenthesis. Significant coefficients are indicated by ***, **, * for significance at the 1%, 5% and 10% level, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 22.30. The dependent variable of IQR_MRPK in columns (1)-(5) is constructed based on the OP approach, OPACF approach, LP approach, LPACF approach and Wooldridge approach, respectively. I exclude observations if the industry-province-year group has fewer than 10 firms.

Table 6.11: Robustness estimation result: weighted average highway proximity

VARIABLES	(1) OP	(2) OPACF	(3) LP	(4) LPACF	(5) WRDG
	Panel A: standard deviation of MRPK as dependent variable				
Proximity	-0.311***	-0.357***	-0.326***	-0.416***	-0.326***
	(0.092)	(0.090)	(0.088)	(0.107)	(0.088)
Observations	30,412	29,869	30,412	28,214	30,412
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	137.208	143.792	137.208	157.124	137.208
Overidentification test	0.6513	0.1644	0.1905	0.4190	0.1716
	Panel B: IQR dispersion of MRPK as dependent variable				
Proximity	-0.700***	-0.709***	-0.663***	-0.726***	-0.665***
	(0.170)	(0.164)	(0.172)	(0.173)	(0.171)
Observations	30,412	29,869	30,412	28,214	30,412
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	137.208	143.792	137.208	157.124	137.208
Overidentification test	0.1387	0.1471	0.1201	0.1784	0.1113
Control variables	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Instruments					
LCP IV	YES	YES	YES	YES	YES
Historical IV	YES	YES	YES	YES	YES
Straight-line IV	YES	YES	YES	YES	YES

Note: Robust standard errors corrected for 4-digit industry-level clustering are reported in parenthesis. Significant coefficients are indicated by ***, **, * for significance at the 1%, 5% and 10% level, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 22.30. The dependent variable in panel A is the standard deviation of MRPK, where MRPK is constructed using various production estimation approaches. The dependent variable in panel B is the IQR dispersion of MRPK. I exclude observations if the industry-province-year group has fewer than 10 firms.

proximity. Better highway proximity overall promotes better allocative efficiency of capital.

Table 6.12: Robustness estimation result: 4-digit industry-level estimation

VARIABLES	(1) OP	(2) OPACF	(3) LP	(4) LPACF	(5) WRDG
	Panel A: unweighted highway proximity				
Proximity	-0.604**	-0.604**	-0.604**	-0.604**	-0.604**
	(-2.47)	(-2.47)	(-2.47)	(-2.47)	(-2.47)
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	408.930	408.930	408.930	408.930	408.930
Overidentification test	0.199	0.199	0.199	0.199	0.199
	Panel B: weighted highway proximity				
Proximity	-0.583**	-0.583**	-0.583**	-0.583**	-0.583**
	(-2.34)	(-2.34)	(-2.34)	(-2.34)	(-2.34)
Under identification test	0.000	0.000	0.000	0.000	0.000
Weak identification test	140.925	140.925	140.925	140.925	140.925
Overidentification test	0.167	0.167	0.167	0.167	0.167
Observations	3,332	3,332	3,332	3,332	3,332
Instruments	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES

Note: Robust standard errors corrected for 4-digit industry-level clustering are reported in parenthesis. Significant coefficients are indicated by ***, **, * for significance at the 1%, 5% and 10% level, respectively. The under-identification test shows the p-value of Kleibergen-Paap rk LM statistic. The weak identification test reports the correspondingly robust Kleibergen-Paap rk Wald F statistic when clustered standard error is applied. The critical value to pass the weak identification test is 22.30. The dependent variable is the standard deviation of MRPK at each 4-digit industry-year level, which is constructed based on the OP approach, OPACF approach, LP approach, LPACF approach and Wooldridge approach, respectively, in columns (1)-(5). I exclude observations if the industry-year group has fewer than 10 firms. Control variables include SOE, POE, HHI, export, and subsidy.

6.6.3 4-digit industry-level estimation

The baseline estimation applies a 4-digit industry-province level estimation to highlight the importance of regional highway infrastructure development. In this section, variables are all constructed at the 4-digit industry level, and the estimation result is reported in table 6.12. The estimation result is in line with the baseline estimation, showing that better industry-level highway proximity reduces the dispersion of MRPK.

6.7 Conclusion

This research is designed to contribute to the literature by examining the causal effect of highway proximity on MRPK dispersion, using a geo-coded firm-level panel dataset for Chinese manufacturing firms and the geo-referenced highway routes over the period of 1998-2007. In order for this chapter to address the endogeneity concern of non-random highway distribution, three types of time-varying instruments are constructed based on the least-cost paths (based on the 2004 NEN highway project), historical routes (a combination of Ming Dynasty and Qing Dynasty courier routes), and straight lines (based on the 2004 NEN highway project), respectively. The estimation result shows that better highway proximity reduces the dispersion of MRPK. Specifically, the baseline estimation results indicate that a 0.1 unit increase in highway proximity over the sample period can lead to a 0.03-0.04 unit decrease in MRPK dispersion. The causal effect of highway proximity on MRPK dispersion is robust, by using either the standard deviation of MRPK or the interquartile range (IQR) of MRPK; either unweighted or weighted average highway proximity; either 4-digit industry-province level estimation or 4-digit industry level estimation; and by applying alternative measures to estimate MRPK.

Specifically, there are four channels through which highway infrastructure influences MRPK dispersion, that is, by reducing both productivity volatility and markup dispersion, and by inducing heterogeneous effects on MRPK dispersion through financial constraints and policy distortion. First, better highway proximity can affect revenue-based productivity volatility, which captures uncertainties from both the supply side and the demand side. By reducing productivity volatility, highway infrastructure will result in lower dispersion in the static measure of MRPK dispersion, as the new capital level in the next period is less likely to be dramatically different than the optimal level. Secondly, better highway access reduces markup dispersion by imposing heterogeneous effects on firm-level markups, i.e., those with higher markup levels reduce more than those with lower markup levels. Thirdly, industries with higher financial constraints can benefit from better transportation networks and increase their capital allocative efficiency, since better highway proximity helps constrained firms increase the availability of external and internal finance (evidence supported in part of Chapter 5). Fourthly, industries with lower policy interventions (i.e., with lower state-owned and foreign-owned capital shares or lower subsidy levels) tend to largely reduce the dispersion of MRPK, implying a better allocative efficiency of capital, whereas insignificant effects are found on industries with high policy interventions.

The policy implication of this research is to emphasise the benefits of large-scale highway construction from the perspective of capital misallocation. Resource misallocation, including capital misallocation, is one important reason for cross-country differences in both productivity and income (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2013, 2017). According to the estimation results, improving transportation infrastructure in developing countries will be a good policy tool for the government to improve the resource allocative efficiency and therefore facilitate the aggregate productivity and income.

Chapter 7

Conclusion

China experienced rapid highway expansion following the two major highway infrastructure projects by the Chinese Government, that is, the National Trunk Highway System project in 1992 and the National Expressway Network project in 2004. This thesis explores how firms' investments are affected by the rapid expansion of China's highway network, using a geo-coded firm-level panel dataset for Chinese manufacturing firms and geo-referenced highway networks in the period between 1998 and 2007. To identify the causal relationship, two possible endogenous issues are addressed, namely, the endogenous construction of highways and the endogenous location of firms.

The first research indicates a robust causal effect of highway proximity on the reduction in firm-level total inventories and input inventories. After controlling the demand proxy such as sales or sales surprise, the estimation result shows that better access to highways could encourage firms to lower their input inventories and total inventories. Specifically, highway investment in China contributed to the decline in firm-level inventories between 1998 and 2007, that is, an additional dollar of highway spending in China reduced, on average, the input inventory stock by about 3.910-10.010 cents and the total inventory stock by around 6.730-25.523 cents. Moreover, the estimation indicates that highways can affect firms' total inventories, input inventories, and finished goods indirectly through the channel of demand proxies (sales and sales surprise). The positive effects of sales on firms' total/input/output inventories are larger for firms with improved highway proximity. The total effect of sales surprise on total inventories and input inventories would be larger if the firm had better access to the highway infrastructure. However, the indirect channel effect is limited as highway proximity would not influence firms' inventory level through the channel of sales growth or excess sales growth.

The second research concludes that better access to highways increases firm investment, supporting the crowding-in effect of public transportation investment. The estimation results are robust when using alternative time-varying instruments and addressing the concern of endogenous firm locations. In addition, the mechanism analysis shows that highway proximity promotes corporate investment through at least three mechanisms, that is, by reducing firms' financial constraints, releasing additional internal funds via inventory reduction, and mitigating the negative impact of uncertainties. It is also found that the highway effect on fixed investment is larger for firms with higher marginal capital returns.

The third research contributes to the literature by examining the causal effect of highway proximity on capital misallocation as proxied by MRPK dispersion. The estimation result shows that better highway proximity reduces the dispersion of MRPK. Specifically, the estimation results indicate that a 0.1 unit increase in highway proximity over the sample period can lead to a 0.03-0.04 unit decrease in MRPK dispersion. Moreover, there are four channels through which highway infrastructure influences MRPK dispersion, that is, by reducing both productivity volatility and markup dispersion and by inducing heterogeneous effects on MRPK dispersion through financial constraints and policy distortion.

Overall, this thesis contributes to the literature on transportation infrastructure from the perspectives of inventory and fixed investments and capital allocative efficiency. Highway infrastructure development in China benefits manufacturing firms by improving the management efficiency of inventory, encouraging the quantity of fixed investment and facilitating the allocative efficiency of capital among firms.

There are some policy implications. Firstly, infrastructure development is crucial for economic development. Improvement in transportation infrastructure tends to stimulate private investment, which is a key determinant of economic growth. This provides implications for infrastructure development for other developing countries such as Sub-Sahara Africa. Secondly, infrastructure development plays an essential role in reducing market segmentation, as the improved transportation network facilitates market competition and expansion, and better access to distant suppliers and external finance, thus facilitating the flow of inputs and products. This is in line with the recent government policy of building a unified domestic market in China, that is, establishing a unified market access system and developing a unified domestic market for productivity factors and resources. Thirdly, this thesis emphasises the benefits of large-scale highway construction from the perspective of capital misallocation. Resource misallocation, including capital misallocation, is one important reason for cross-country differences in both productivity and income (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2013, 2017). According to the estimation results, improving transportation infrastructure in developing countries will be a good policy tool for the government to improve the resource allocative efficiency and therefore facilitate the aggregate productivity and income. Fourthly, SOEs are less efficient compared with private firms, which thus suggests the importance of further market reform and source reallocation to the private sector, in order to benefit more from the construction of highway infrastructure.

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