Essays on Infrastructure and Economic Growth

Guohao Yang

TESI DOCTORAL UPF / Year 2019

THESIS SUPERVISOR
Jaume Ventura and Dávid Krisztián Nagy
Department d'Economia i Empresa

Universitat Pompeu Fabra Barcelona

To my parents, Wowen Yang and Shaoai Hu

Acknowledgements

I am deeply indebted to my advisers, Jaume and David. If it were not for their continuous support and encouragement, it would have been impossible to complete this thesis. I owe special thanks to Manuel Garcia-Santana, Andrea Linarello and Giacomo Ponzetto for their comments and helpful suggestions, as well as other professors and participants in International Lunch Seminars for their comments. I also want to thank Marta and Laura for their excellent work, which has always meant a great deal to UPF students.

I would like to express my gratitude to my friends for making my life as a PhD student in Barcelona so memorable. I owe my thanks to my friends, Guillem, Fernando, Jenny, Marta, My Lan. I am also thankful to my Chinese friends: Donghai, Erqi, Haozhou, Jianxing, Jingjing, Lang, Renbin, Rui, Shangyu, Shengliang, Tongbin, Xinghua and Yucheng. I am profoundly grateful to my wife for sharing all the moments, good or bad, in my life.

My thanks also go to my parents for their endless support, understanding and love.

Abstract

This thesis aims to better understand China's structural change and productivity growth in recent decades. In the first chapter, I study the impact of infrastructure, i.e., highway construction, on China's participation in Global Value Chains(GVCs). To guide my empirical exercise, I incorporate within-country geography into a quantitative trade model featuring sequential production. The model shows that a city's proximity to domestic markets increases its participation in GVCs, while a city's proximity to foreign markets may reduce its participation in GVCs. This paper empirically evaluates how China's ambitious highway construction during the period between 2000 and 2006 determined its own participation in GVCs. In the second chapter, I study the impact of knowledge import on the productivity growth of Chinese manufacturing firms. Consistent with the prediction of the model, knowledge import in skill-intensive industry has a stronger impact on manufacturing firms' productivity growth.

Resum

La tesis se propone conocer mejor el cambio estructural de China y el crecimiento de su productividad en las últimas décadas. En el primer capítulo, se estudia el impacto de la infraestructura (por ejemplo la construcción de carreteras) en la participación de China en las Cadenas Globales de Valor (CGV). Para ello se propone un ejercicio empírico que incorpora las diferencias geográficas del país, en un modelo cuantitativo de comercio, caracterizado por su producción secuencial. Los resultados indican que la proximidad que tenga una ciudad con los mercados internos, aumentará su participación en las CGV, mientras que la cercanía con mercados los internacionales la reduciría. Este capítulo evalúa empíricamente cómo la ambiciosa construcción de carreteras en China durante el período comprendido entre 2000 y 2006, determinó su propia participación en las CGV. En el segundo capítulo, se estudia el impacto de la importación de conocimiento sobre el crecimiento de la productividad de las empresas manufactureras chinas. En consonancia con las predicciones del modelo, se constata que la importación de conocimiento exhibido por la industria basada en el conocimiento, tiene un mayor impacto en el crecimiento de la productividad de las empresas manufactureras.

Preface

The goal of this thesis is to help us better understand the recent growth experience in China. The thesis is composed of two chapters, which look at two important issues, infrastructure and knowledge import, and how these affect China's growth. Analysing Chinaâs growth experience helps us to better understand two important issues in the literature. Firstly, the literature in international trade provides a number of theoretical models and empirical exercises in understanding the impact of cross-country trade cost reduction on global trade patterns. However, less is known about how within-country trade cost reduction affects a country's trade pattern. Secondly, the literature provides credible identification on how technology or knowledge diffusion via Foreign Direct Investment (FDI) internationally. But less is known about how international trade diffuses knowledge and there is little credible identification on this effect. The second chapter credibly identifies how advanced knowledge embodied in goods may transfer knowledge from developed countries to a developing country, i.e., China.

The first chapter studies the impact of trade cost reduction on a country's participation in Global Value Chains (GVCs), measured by the gap between its import and export upstreamness. In this paper, export and import upstreamness are defined as the share of exporting and importing upstream goods. To explain China's stronger participation in GVCs, I incorporate within-country geography into a trade model $\grave{a}\ la$ Antràs and de Gortari (2017), which examines the decision-making process through which a firm decides where to source its intermediate goods and where to sell its final products. The model shows that a city's proximity to domestic markets increases its participation in GVCs, while a city's proximity to foreign markets may reduce its participation in GVCs. This paper empirically evaluates how China's ambitious highway construction during the period 2000 to 2006 determined its own participation in GVCs. This is done by extending Faber (2014)'s algorithm, which calculates the least cost-trunk path, to include the time variation in the highway's construction. The results show that a one standard deviation (std) increase in a city's proximity to large domestic markets leads to a strong 1.2 std increase in GVC participation, while a one std increase in a city's proximity to foreign markets leads to a weak 0.5 std decrease in GVC participation. Results from structural estimation show that solely replacing the highway in 2000 with the one in 2006 increased aggregate welfare by 11%, spatial inequality by 13% and participation in the domestic value chain to serve the foreign market by 1.9%. These results highlight the strong impact of China's highway construction on its GVC participation, and social welfare between 2000 and 2006.

The second chapter studies the impact of knowledge import from the US, Ger-

many and Japan on the productivity growth of Chinese manufacturing firms. To conceptually approach the impact of knowledge import on productivity growth, I extended the stylized model from Buera and Oberfield (2016) into a multi-industry version, which examines how manufacturing firms learn from the knowledge embodied in import products. The model shows that productivity growth is faster in comparatively dis-advantaged industries under a system of trade openness than under autarky. To test this prediction, I construct a measure of knowledge import and compare the productivity growth of firms in city-industry pairs that receive a large amount of knowledge import with those of city-industry pairs that receive little knowledge import. The result shows that a one standard deviation increase in knowledge import leads to a 0.24% increase in manufacturing productivity growth, and an additional 0.25% in productivity growth in skill-intensive industry.

Contents

List of Figures

List of Tables

Chapter 1

INFRASTRUCTURE AND GLOBAL VALUE CHAIN POSITION: EVIDENCE FROM CHINA

1.1 Introduction

Recent decades have been seen the emergence of global value chains (GVCs), in which production stages for individual goods are broken apart and fragmented across countries (Antras et al., 2012; Baldwin, 2006; Johnson and Noguera, 2012; Fally, 2012; Johnson and Noguera, 2017; Antràs and de Gortari, 2017; Brandt et al., 2013). At the same time, researchers have begun to pay considerable attention to the possible drivers of the segmentation of production into individual countries: differences in technology (Grossman and Rossi-Hansberg, 2012; Costinot et al., 2013), information and communication technology (Baldwin and Venables, 2013) and firm organization (Antràs and Chor, 2013; Alfaro et al., 2015). Within this research, Antràs and de Gortari (2017) proposed an elegant, yet untested theory to argue that trade costs play a central role in shaping the geography of GVCs and the landscape of global production. Unfortunately, the long period of the slow reduction in trade costs across the globe[1] made it difficult to credibly identifying the actual effect of trade costs on GVCs.

To overcome this difficulty and deepen our understanding of the forces driving the geography of GVCs, I study the effect of the fast-growing highway network in

[1] Antràs and de Gortari (2017) documented the gradual decrease in iceberg trade cost with the World Input-Output Table from 1995 - 2011 using methods proposed by Head and Ries (2001).

China from 2000 to 2006 on China's specialization in GVCs, via Chinese cities' participation in GVCs. China's ambitious highway investment program in recent decades has provided a good empirical setting for the investigation of the effect of trade costs on GVCs. Compared to the highway construction programs in other developed countries[2], the speed of highway development in China is astonishing, and the total length of highway in use within the nation's borders grew from 375 km in 1984 to 130,000 km in 2016. The road quality of, and congestion, and driving speed on the newly built highway are in sharp contrast to pre-existing national and local roads, thereby dramatically reducing trade costs by reducing bilateral travelling time.[3] In general, the average bilateral car travelling hours across all the city-pairs in China by car decreased from around 40 hours in 2000 to less than 24 hours in 2006. The average number of Chinese cities reached from each Chinese city within six hours' driving rose from 2.6 in 2000 to 4.7 in 2006.[4]

To empirically measure Chinese cities' participation in GVCs , I propose a measure of a city's export and import upstreamness in line with Chor et al. (2016).[5] Intuitively, a city's export upstreamness can be thought of as the share of relatively upstream intermediate products in the city's exports, while import upstreamness is defined analogously as a city's imports. If the trade cost is proportional to the gross value of the products being transported, that trade cost accumulates along the product chain, and hence a larger share of value added is wasted for transporting less upstream product (Antràs and de Gortari, 2017). As a result, a city's specialization in producing and exporting upstream product is less sensitive to its trade cost with international markets. For example, Guangzhou, the capital city of Canton Province in South China, has five international ports, and specializes in exporting 'Manufacturing Goods in Leather, Fur, Feather (30)' and 'Manufacturing Goods in Clothing, Shoes Caps (31)'[6]. In 2000, its export share in these two

[2] Garcia-Milà and Montalvo (2011) looked at changes in highways in Spain during 1984-2000, a period with large infrastructure investment. While in 1984 Spain had 2,286km of highways and dual carriageways, in 2000 that number had increased to 10,443 km, the bulk of the change being an upgrade of national roads to high capacity roads.

[3] Hummels (2013) showed that the travelling hour is essential in affecting transportation trade cost.

[4] I calculate all these numbers using both the highway and the 1999 local road network. In doing this, I assume that bilateral traveling hours between any two cities are only affected by these two road networks.

[5] An industry j's upstreamness is a weighted average of the number of stages from final demand at which j enters as an input in production processes (Fally, 2012; Antras et al., 2012). Therefore, the larger industry j's upstreamness is, the farther away it is from consumers for this industry j. With this measure, I combine a city's international export and import value across different industries to develop its export and import upstreamness, respectively.

[6] These two categories of industries come directly from the industry classification of China's Input-Output Table

industries, which were downstream according to my measures and mainly used to serve consumer demand[7], consisted of more than 20% of its aggregate exports.[8]

To guide my empirical analysis and formalize the above intuition, I construct an extended version of the trade model in Antràs and de Gortari (2017) that also incorporates within-country geography. My framework considers the problem of how a firm in a city chooses the location from which it sources its intermediate goods and the location where it will sell its final products. With the sequential nature of production, the local firm takes into account the fact that the impact of transportation costs becomes more pronounced as it moves towards less upstream production. In line with my former intuition, if a city in China has low trade cost with international markets due to highways, it should specialize in producing and exporting less upstream products. Moreover, the model generates the following three testable novel implications: Firstly, if a region in China has low trade cost for large domestic markets, its import upstreamness is higher while export upstreamness is lower. This prediction also stems from the fact that more upstream production is less sensitive to trade costs. Specifically, an increase in import upstreamness in view of a reduction in trade costs with domestic markets generates a stronger demand for exporting less upstream products to other large nearby cities. In the same context, reduction in export upstreamness is due to a drop in the cost of sourcing upstream goods from these cities, which reduces the marginal cost in producing less upstream products. Secondly, I show that the difference between import and export upstreamness of a city serves as a good proxy for its domestic value-added share in gross exports. A wider gap between a city's import and export upstreamness is associated with a higher share of domestic value-added in its gross export (Koopman et al., 2014; Kee and Tang, 2016). This is because a city's proximity to domestic markets increases its relative importance in sourcing from other large nearby cities, and hence raises its domestic value-added share in exports, while proximity to foreign markets does the opposite. Finally, I also show that a reduction in a city's trade cost with the domestic market may increase the share of ordinary exports, while a reduction in a city's trade cost with foreign markets brings down the share of ordinary exports.[9] I classify GVCs that are involved

[7]From the calculation with China's Input-Output Table in 2007, the upstreamness for these two industries, 'Manufacturing Goods in Leather, Fur, Feather (30)' and 'Manufacturing Goods in Clothing, Shoes, Cap (31)' are 2.17 and 2.71, respectively. Regarding upstreamness measures, these two industries are rather downstream compared to the average upstreamness of around 3.5 across all industries in China.

[8]This number is from the author's calculation with international trade data from the customs office.

[9]There are two major export structures, consisting of more than 90% of aggregate exports in China: ordinary exports and processing exports.

in a region's second stage exporting as either ordinary exports or processing exports, depending on where they source their upstream intermediate-goods.

To test the main predictions from my framework, I need to address the challenge that the highway placement is not random. I do so by applying an instrumental variable (IV) $\grave{a}\ la$ Faber (2014)'s 'Euclidean straight line spanning tree network'. Faber (2014)'s idea is to compare the economic outcomes of peripheral counties on the highway that was built to link large metropolitan centres with the peripheral counties off the highway. On top of Faber (2014), I also use the timing of the highway's construction to develop an IV of each year t, connecting only the targeted cities that were reached by the actual highway network in that year. Another issue is that travelling hours via highways are poor proxies of bilateral traveling hours between cities, especially in the early years when few highways were available. To resolve the issue, I calculate travelling hours using both highways and the 1990 local road network. To address the concern that the placement of local roads is not random, I instrument them with the 1962 road network as in Baum-Snow (2007) and Baum-Snow et al. (2017). The basic logic behind this method is that the historical road network provides a cost-effective way to build the 1990 local road network solely by upgrading the historical road in 1962, and the placement of the historical road is less likely to be affected by unobserved factors from today. I follow Baum-Snow et al. (2017) transforming measures of the travelling hours into a measure of proximity to nearby large domestic markets, as well as a measure of proximity to the nearest ports that provide a connection to the foreign market.

I find the following reduced-form evidence consistent with the three theoretical predictions of the model. In line with the first prediction, I find that a one standard deviation increase in proximity to foreign markets leads to a significant nearly one standard deviation decrease in a city's export upstreamness and significant decrease of a 1.26 standard deviation in import upstreamness. Then, a one standard deviation increase in proximity to large domestic markets results in a significant 4.7 standard deviations increase in a city's import upstreamness. In line with the second prediction, I find that a one standard deviation increase in proximity to foreign markets leads to a significant 0.5 standard deviations decrease in a city's domestic value-added ratio in its aggregate export, while a one standard deviation increase in proximity to large domestic markets causes a 0.5 standard deviation increase in this value-added share. These three results reconfirm the fact that sourcing upstream intermediate goods becomes more important as bilateral trade costs decrease. In line with the third prediction, I find that a one standard deviation increase in access to large domestic markets leads to a 2.1 standard deviation increase in ratio between ordinary and processing exports, while a one standard deviation increase in access to foreign markets leads to a 1.3 standard deviation decrease in this ratio. All these findings confirm the belief that the decline in bilateral trade costs across Chinese cities has played a critical role in China's stronger GVC participation.

I conduct robustness checks for my baseline results. One concern is that trade cost measures based on the highway network may not affect different production stages differently within GVCs as suggested by my model. To address this concern, I provide suggestive evidence by estimating the elasticity of a city's final consumption and intermediate goods with respect to the city's travelling hours to its nearest international port solely via the highway network, respectively. One other concern is that the way I measure a city's proximity to large local markets only captures its proximity to nearby final demands, which may not capture the effect of proximity to nearby intermediate-goods markets addressed in my model. To resolve this issue, I construct a new measure of a city's access to nearby intermediate-goods markets using manufacturing TFP from nearby markets. Another concern in my empirical study is the validity of my highway network, which may fail to capture the effects specified in Faber (2014); Baum-Snow et al. (2017). To address this concern, I do similar empirical exercises as in Faber (2014) and provide extra evidence for how local manufacturing firms react to the expansion of the highway system.

I quantify the model to 233 prefecture-level cities in China by estimating the key parameters using General Methods of Moments (GMM). The parameters governing the a city's productivity is identified by GDP share; the parameters related to intermediate-goods share in final-goods, a city's foreign trade cost not related with highway network are jointly identified by a city's ratio between international intermediate-goods trade and its gdp and a city's ratio between international final-goods trade and its gdp. In addition, my estimation also successfully captures the un-targeted features in the data such as the international trade distribution across cities.

My finding is that reducing inter-city trade cost have a strong impact on a city's welfare and this may also increase a city reliance on nearby city's intermediate-goods to serve the international markets. This result is based on the comparative statics between two equilibrium in 2000 and 2006. My benchmark estimation is based on international trade across Chinese cities in 2000 and the bilateral trade cost implied by highway between 2000 and 2006. To counterfactually simulate the equilibrium in 2006, I reduce the bilateral trade frictions to recover Chinese city's international trade flows in year 2006. Over the six years, highway construction in China leads to increase in aggregate welfare with around 10%, while spatial inequality around 11%. Cities within China increase 1.9% of their participation in Domestic Value Chains (DVCs), which means that they use intermediate-goods from other Chinese cities or provide more intermediate-goods to other Chinese cities, to serve the international markets.

This paper connects two fields of active research: global value chain production and transportation infrastructure. Recent developments in the literature of transportation infrastructure has found a significant impact of transportation infrastructure on local economic outcomes (Redding and Turner, 2015), while the latest literature in global value chains links the quantitative trade model with dynamic programming, which generates a prediction regarding a region's specialization in GVCs (Fally, 2012; Antras et al., 2012). To the best of my knowledge, I provide the first causal estimates on how transportation infrastructure improvement affects a country's participation in GVCs (Yi, 2003; Antràs and de Gortari, 2017).

Redding and Turner (2015) provided a conceptual framework to explain how transportation infrastructure construction affects the geography of the economic activity. Their model incorporates labor mobility into a Krugman style trade model while neglecting intermediate input sourcing for local firms. This paper underlines how trade cost reduction due to highway construction affects not only the consumer's access to final products but also the firm's access to intermediate inputs.

The spatial distribution of global production networks has been an active area in international trade. The literature on GVCs, including Yi (2003, 2010); Antràs and de Gortari (2017), estimates that the implied iceberg trade cost from bilateral trade flows suggested by Head and Ries (2001) quantifies the effect of trade cost reduction on the geography of GVCs and welfare. However, this does not guarantee that trade cost reduction will be exogenous, which makes it difficult to claim a causal relationship between trade cost and a region's specialization in GVCs. To fill this gap, I use highway construction in China between 2000 - 2006 as a large-scale, natural experiment to identify the impact of trade cost reduction on a country's specialization in GVCs. In particular, I develop instrumental variables for the highway network, combining the approaches of Faber (2014) and Baum-Snow et al. (2017).

The structure of the paper is as follows. Section 2 introduces methodologies to measure a city's participation in GVCs. Section 3 provides motivating facts on the geography of international trade in China, the dynamic of China's GVCs participation and the geography of GVCs. Section 4 outlines the conceptual model, then Section 5 describes the regression specification to verify the model prediction.

Section 6 presents the reduced form evidence, then Section 7 provides robustness check to the regression results.

1.2 Methodology: Measure of a City's Participation in GVCs

This section presents the methodology for measuring an industry's upstreamness and a city's participation in GVCs. Fally (2012) and Antras et al. (2012) construct a measure of the relative production line position of different industries. With this industry's upstreamness measure, I construct a city's import and export upstreamness to capture its participation in GVCs.

I use two datasets to construct these measures. First, I use China's Input-Output Table in 2002 to construct its industry's upstreamness. China's Input-Output Table reports the value of an industry's exports, final consumption, and intermediate goods used by other industries. Then, I use the universe of China's International Trade data at the transactions level between 2000 and 2006 to construct a city's participation in GVCs. Coded using an 8-digit classification based on Harmonized System (HS), this data reports a firm's free-on-board value, price, amount, and unit of export and import across countries. Furthermore, it provides geographical information about each firm, such as its address and corresponding custom office where the individual transaction was processed. [10]

An Industry Upstreamness

An Industry Upstreamness captures its relative production line position in an economy Alfaro et al. (2015). In other words, if the output of an industry primarily serves as intermediate goods, then the upstreamness of this industry is high. The upstreamness of industry i, U_i, is the average number of steps a product takes as intermediate goods before reaching final consumption. Following Chor et al. (2016), U_i is conceptualized as a weighted average of the number of stages from final demand at which i enters as an input in the economy's production processes.

$$U_i = \frac{F_i}{Y_i} + 2\frac{\sum_{j=1}^{N} \hat{d}_{ij} F_j}{Y_i} + 3\frac{\sum_{j=1}^{N}\sum_{k=1}^{N} \hat{d}_{ik}\hat{d}_{kj} F_j}{Y_i} + ...$$

[10]The original customs data is in HS8-year level. I aggregated the data to the HS6-year level so that it can be compatible with information found in the city year-book, Input-Output Table 2007, and the 4-digit Chinese Industrial Classification (CIC).

Where Y_i is the gross output of industry i, F_i is the final use of the production in industry i, and $\hat{d}_{ij}$ is the cost of using input from industry i to produce one dollar's worth of output for industry j. To account for the impact of international trade on domestic factor share, $\hat{d}_{ij}$ is scaled by a factor of $\frac{Y_i}{Y_i - X_i + M_i}$, which gives:

$$\hat{d}_{ij} = d_{ij} \frac{Y_i}{Y_i - X_i + M_i}$$

where X_i is the total export of industry i and M_i is the total import of industry i.

As stated in Antras et al. (2012), a higher value of U_i indicates greater upstreamness of an industry and on average more steps taken before the final demand. Table (1.1) and Table (1.2) present the upstreamness of the five top and bottom industries. We can see that they have similar characteristics to the ten most and least upstreamness industries in the US IO 2002 data (Antras et al., 2012; Antràs and Chor, 2013). Table (1.1) lists the five least upstream industries in the economy, all in the service sectors, the outputs of which serve mainly the final demand in the economy. The five most upstream industries in Table (1.2) include 'Waste Processing' 'Coal Mining', 'Basic Chemical Products', 'Oil and Gas Exploration' and 'Non-ferrous Metal Mining'. The outputs in all these industries cannot be consumed directly, but rather serve as important intermediate products for other industries that are much closer to final consumption.

Table 1.1: The Five Industries with the Lowest Upstreamness

Social Welfare	1
Public Management	1.02555
Construction	1.05749
Sports	1.05989
Public Facility Management	1.07386

A City's Participation in GVCs

With this industry upstreamness, I determine a city's GVCs participation by calculating the import and export upstreamness of a city. With the export and import value at the city level, city c's export(U_{ct}^X) and import(U_{ct}^M) can be expressed as follows:

$$U_{ct}^X = \sum_{j=1}^{N} \frac{X_{cjt}}{\sum_j^N X_{cjt}} U_j, U_{ct}^M = \sum_{j=1}^{N} \frac{M_{cjt}}{\sum_{j=1}^N M_{cjt}} U_j$$

Table 1.2: The Five Industries with the Highest Upstreamness

Waste Processing	5.17387
Coal Mining	5.26147
Basic Chemical/Materials	5.26915
Oil and Gas Exploration	5.43773
Non-ferrous Metal Mining	5.73685

where X_{cjt} and M_{cjt} are export and import value for product i of city c at year t, respectively. Following Chor et al. (2016), I construct the aggregate measure of export and import upstreamness for China, denoted by a capital C:

$$U_{Ct}^{X} = \sum_{j=1}^{N} \frac{X_{Cjt}}{\sum_{j}^{N} X_{Cjt}} U_j = \sum_{c} \frac{X_{ct} U_{ct}^{X}}{\sum_{c} X_{ct}}$$

$$U_{Ct}^{M} = \sum_{j=1}^{N} \frac{M_{Cjt}}{\sum_{j=1}^{N} M_{Cjt}} U_i = \sum_{c} \frac{M_{ct} U_{ct}^{M}}{\sum_{c} M_{ct}}$$

where X_{Cjt} and M_{Cjt} are export and import value for product i in China at year t, respectively. These expressions show us that the contribution of a city c's export upstreamness to the aggregate export upstreamness, depends on this city's export share in the whole economy. Constructing a city's import upstreamness is analogous.

Given a city's import (U_{ct}^{x}) and export upstreamness (U_{ct}^{x}), I take their difference to capture a city's participation in GVCs:

$$\Delta_{c,t} = U_{ct}^{m} - U_{ct}^{x} = (\sum_{i=1}^{N} \frac{M_{cit}}{\sum_{i}^{N} M_{cit}} - \sum_{i=1}^{N} \frac{X_{cit}}{\sum_{i=1}^{N} X_{cit}}) U_i$$

This measure captures city i's participation in GVCs in year t. The motivations for using this measure to capture a city's participation in GVC is two-fold: first, I will show in my model that the gap between import and export upstreamness is associated with a city's value-added in export. In addition, Table (1.3) shows that a city's gap between import and export upstreamness correlates positively with its welfare[11].

[11]The literature suggests that under globalization, a country's value-added in export should decrease rather than increase(Johnson and Noguera, 2012), which implies that a country's welfare should correlate negatively with the the domestic value-added of its exports.

Table 1.3: Correlation between a city's fundamental and Gap between Import and Export Upstreamness

	(1)	(2)	(3)	(4)	(5)	(6)
	$ln(gdp_{i,t})$	$ln(gdp^{ind}_{i,t})$	$ln(wage_{i,t})$	$ln(gdp^{per}_{i,t})$	$ln(GOV^{exp}_{i,t})$	$ln(GOV^{rev}_{i,t})$
$\Delta_{i,t}$	0.134***	0.156***	0.111***	0.129***	0.0279***	0.0152*
	(0.0236)	(0.0281)	(0.0222)	(0.0225)	(0.00958)	(0.00896)
Cons.	8.380***	11.89***	2.894***	1.337***	-1.813***	-2.001***
	(0.0208)	(0.0248)	(0.0196)	(0.0198)	(0.00843)	(0.00788)
R^2	0.904	0.897	0.466	0.859	0.891	0.823
City-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1845	1845	1784	1845	2067	2067

Robust Standard errors in parentheses. I also cluster standard errors at city level
$ln(gdp_{i,t})$ refers to a city's gdp, $ln(gdp_{i,t})$ refers to a city's gdp, $ln(wage_{i,t})$ refers to a city's manufacturing wages, $ln(gdp^{per}_{i,t})$ refers to a city's manufacturing wages, gdp per capita, $ln(GOV^{exp}_{i,t})$ refers to a city's government spending, $ln(GOV^{rev}_{i,t})$ refers to a city's government revenue.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.3 Motivating Facts: International Trade in China between 2000 and 2006

This section presents key patterns of international trade for Chinese cities between 2000 and 2006. In this period, a city's location was more important than an industry's characteristics in explaining the extent to which an industry engaged in international trade (Fact 1). The city's geographic location played a crucial role in shaping a city's export and import upstreamness (Fact 2). During this time, big cities' exportupstreamness decreased $--$ indicating that large cities became more specialized in exporting downstream products $--$ while import upstreamness increased for both large and small cities (Fact 3). All these observations infer that a city's geographic position is important in explaining its participation in GVCs.

Fact 1: Cities' Participation in International Trade

A city's location is important in explaining the extent to which its industries engaged in international trade during the period from 2000 to 2006. Table 1.4 shows the R-squared and adjusted R-squared of regressing a city's trade value (sum of each industry's imports and exports) of all the city's industries and industry fixed effects for each year, respectively. Column 3 and 7 in this table show that, controlling a city's location explains more than 13% of the variation in its international trade over the years, which is significantly larger than the R-squared solely controlling the industry fixed effect, which explains around 2%.

For more downstream industries in international trade, a city's location explains a larger share of international trade variation than for upstream industries. Columns 1, 2, 5 and 6 in Table 1.4 show that a city's location explains around 17% of the variation in trade value across all industries for downstream industries ($U_j < 3.2$), while it explains slightly smaller share of variation (around 10%) in trade value for upstream industries ($U_j > 3.2$). This result suggests that a city's international trade in more downstream industries is more sensitive to its geographic location.

Fact 2: Geography of GVCs

While a city's location is important in explaining its international trade value for less upstream industries, the level of import and export upstreamness differs across locations. Figure 1.1 plots the geography of export upstreamness and Figure 1.2 plots the import upstreamness in 2006 at the city level. [12] Figure 1.1 shows that cities near international port (black triangle) in the eastern coast area have lower

[12]Threshold of each group is automatically set by ArcGis.

Table 1.4: A City's International Trade Across Industries: Variation Explained

	R^2				Adj. R^2			
	city	city	city	industry	city	city	city	industry
year	U_i¿3.2	U_i¡3.2	full	full	U_i¿3.2	U_i¡3.2	full	full
2000	0.147	0.202	0.162	0.025	0.128	0.180	0.151	0.021
2001	0.177	0.190	0.180	0.023	0.159	0.169	0.170	0.020
2002	0.138	0.175	0.150	0.022	0.119	0.154	0.139	0.019
2003	0.117	0.178	0.136	0.021	0.099	0.157	0.126	0.018
2004	0.099	0.166	0.117	0.019	0.081	0.145	0.107	0.016
2005	0.086	0.151	0.103	0.019	0.068	0.130	0.093	0.016
2006	0.080	0.143	0.095	0.019	0.061	0.122	0.086	0.016

This table explains the international trade variation at the city-industry level. For the trade value at the city-industry level, I regress trade value on each dummy, and take both R^2 and adj.-R^2
'city' refers to city fixed effect. 'industry' refers to industry fixed effect. 'U_i' refers to industry upstreamness.

level of export upstreamness (in lighter colour) than the ones far away from the eastern coast. In Figure 1.2, cities close to the eastern coast have lower import upstreamness (in slightly lighter colour), than the cities in the far west. Moreover, Figure 1.2 shows that cities close to the provincial capitals (black cross) have higher import upstreamness (in slightly darker colour) than the ones far away from the provincial capitals. These two figures suggest that a city's proximity either to large domestic markets or foreign markets plays a vital role in determining its participation in GVCs.[13] (black cross), have higher import upstreamness (in slightly darker colour) than the ones far away from the provincial capitals. These figures suggest that a city's proximity either to domestic large markets or foreign markets plays a vital role in determining its participation in GVCs.

Fact 3: The dynamics of GVCs participation

Following the national trend, Figure 1.3 shows that the average upstreamness gap of Chinese cities also widened during the period 2000 and 2006. I show this by running the following regression specification, which coincides with the aggregated trend that the gap between import and export upstreamness was enlarging in China from 2000 to 2006, as illustrated in Figure 1.3 (Chor et al., 2016), the

[13]The provincial capital is the political centre of a province in China, usually with a much higher population

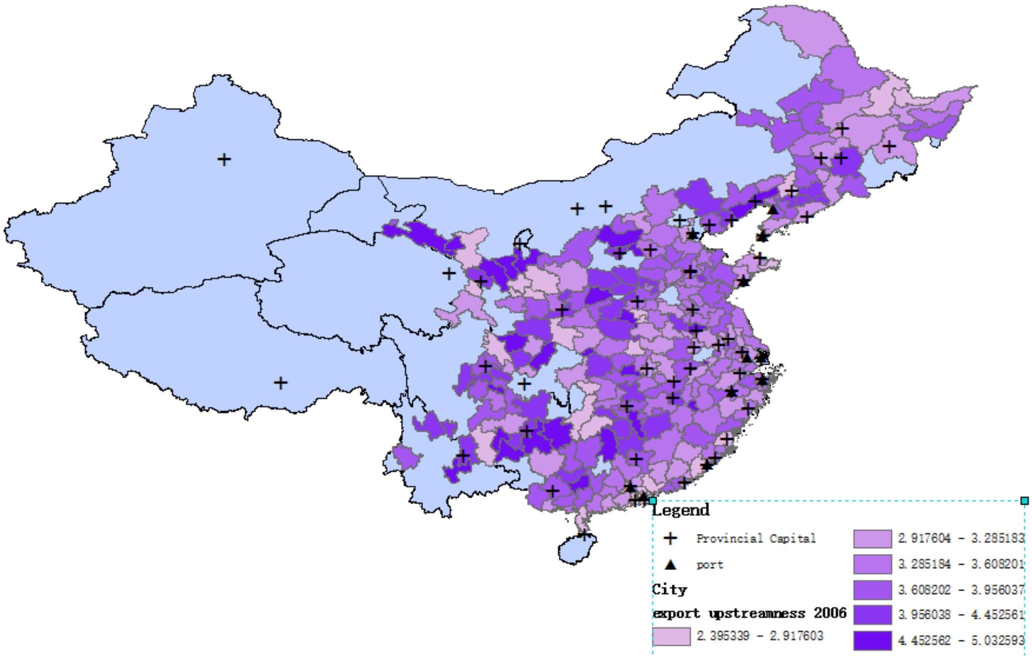

Figure 1.1: Geography of Export Upstreamness in 2006

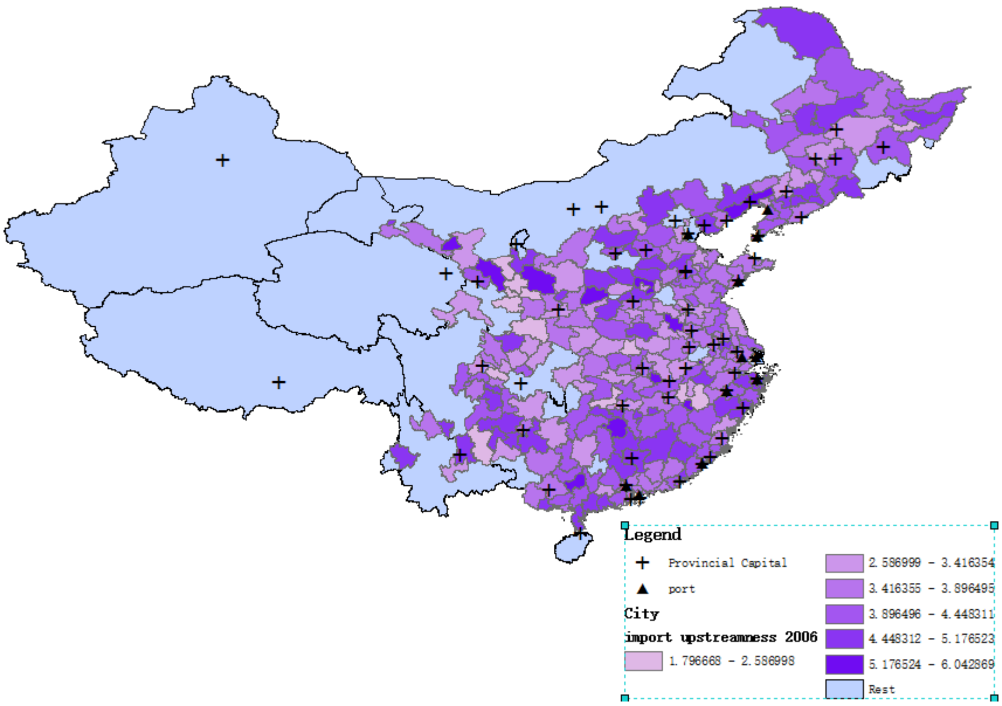

Figure 1.2: Geography of Import Upstreamness in 2006

average upstreamness gap of the Chinese cities was also widening in the same period. I show this by running the following regression specification:

$$\{U^x_{i,t}, U^m_{i,t}, U^m_{i,t} - U^x_{i,t}\} = \beta + \alpha_i + \delta_t Year_t + \epsilon_{i,t}$$

where α_i captures the city-level fixed effect, δ_t captures the time fixed effect. $U^x_{i,t}$ and $U^m_{i,t}$ are export and import upstreamness for region i at year t, respectively. $U^m_{i,t} - U^x_{i,t}$ is the gap between these two upstreamness measures. For all the regression results in Table 1.5, I control the city-level fixed effect, which accounts for different institutions, labour costs, language, culture, and I cluster the standard errors at the city level, so that the estimated effect δ_t only indicates the time variation for all three regressions.

The first three columns in Table 1.5 show that from 2004 to 2006, a city's import upstreamness experienced on average a 20% significant increase, while the export upstreamness did not show significant change for the same period. As a result, the gap between import and export upstreamness widened, driven by an increase in $U^m_{i,t}$.

Moreover, we can observe that the gap between import and export upstreamness varied between small and large cities during the period between 2004 and 2006. To empirically verify this observation, I define a dummy variable to indicate the population size of a city: 1 if a city had more than a population of 0.2 million in 1990[14] and 0 otherwise. Then, I introduce an interaction term of this population-size dummy variable and a set of dummy variables for each year into the model. The results in column 4 to 6 of Table 1.5 show that cities with a large population size experienced a gradual drop in export upstreamness, which implies that large cities became more specialized in exporting downstream products. It also shows that all cities experienced a gradual increase of around 20% in import upstreamness, although this trend was weaker for small cities than large cities.

1.4 Conceptual Framework

In this section, I rationalize the empirical patterns in the previous section by presenting a multi-regional trade model *à la* Antràs and de Gortari (2017) to study the forces driving a region's specialization in GVCs. This model considers the problems of how a firm in a region sequentially determines the location from which to source intermediate goods and the location where it sells the final products. The

[14]The metropolitan centres of this size in 1990 were targeted cities that the highway had to pass by.

Table 1.5: The Dynamics of a City's Import and Export Upstreamness

	(1)	(2)	(3)	(4)	(5)	(6)
	$U^x_{i,t}$	$U^m_{i,t}$	$\Delta_{i,t}$	$U^x_{i,t}$	$U^m_{i,t}$	$\Delta_{i,t}$
$(Year = 2001)$	-0.0209	-0.0186	0.00424	-0.0190	-0.0207	0.00370
	(0.0354)	(0.0522)	(0.0581)	(0.0339)	(0.0551)	(0.0582)
$(Year = 2002)$	0.0333	0.0496	0.0123	0.0397	0.0543	0.0123
	(0.0334)	(0.0466)	(0.0532)	(0.0313)	(0.0482)	(0.0535)
$(Year = 2003)$	0.0291	0.0919*	0.0549	0.0288	0.0904*	0.0537
	(0.0314)	(0.0477)	(0.0537)	(0.0296)	(0.0501)	(0.0539)
$(Year = 2004)$	0.0589*	0.160***	0.122**	0.0486	0.152***	0.119**
	(0.0309)	(0.0465)	(0.0517)	(0.0295)	(0.0487)	(0.0523)
$(Year = 2005)$	0.0250	0.224***	0.212***	-0.00704	0.207***	0.218***
	(0.0334)	(0.0506)	(0.0561)	(0.0310)	(0.0532)	(0.0565)
$(Year = 2006)$	0.0413	0.288***	0.274***	0.0265	0.284***	0.271***
	(0.0346)	(0.0489)	(0.0552)	(0.0332)	(0.0509)	(0.0554)
$(Big = 1) \times (Year = 2001)$				0.0625*	0.0555	0.00644
				(0.0332)	(0.0509)	(0.0554)
$(Big = 1) \times (Year = 2002)$				0.0488	0.0247	-0.0161
				(0.0319)	(0.0462)	(0.0513)
$(Big = 1) \times (Year = 2003)$				-0.0567**	0.209***	0.282***
				(0.0288)	(0.0384)	(0.0462)
$(Big = 1) \times (Year = 2004)$				-0.0607**	0.165***	0.247***
				(0.0271)	(0.0408)	(0.0476)
$(Big = 1) \times (Year = 2005)$				-0.0887***	0.139***	0.225***
				(0.0267)	(0.0389)	(0.0448)
$(Big = 1) \times (Year = 2006)$				-0.0504*	0.0740*	0.134***
				(0.0281)	(0.0445)	(0.0494)
Cons.	3.773***	4.250***	0.469***	3.780***	4.254***	0.469***
	(0.0464)	(0.141)	(0.143)	(0.0487)	(0.143)	(0.143)
R^2	0.784	0.708	0.691	0.805	0.705	0.700

Robust standard errors in parentheses. City fixed effects are included.
$(Big = 1)$ is a dummy variable for prefectures with more than 0.5 million register population in 1990.
In year t, $U^x_{i,t}$ indicates city i's export upstreamness, $U^m_{i,t}$ indicates city i's import upstreamnes and $\Delta^m_{i,t}$ indicates difference between city i's import and export upstreamness.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

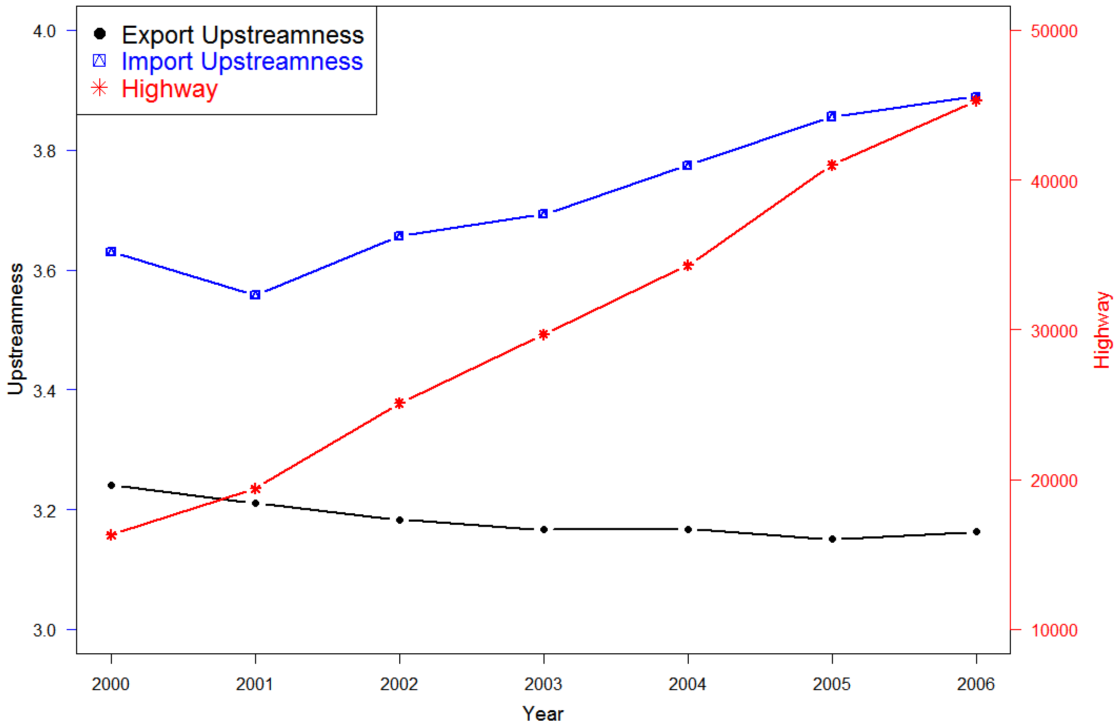

Figure 1.3: Aggregate Dynamics for the Highway and Export & Import Upstreamness

sequential nature in production suggests that the impact of trade friction becomes more pronounced as it moves towards less upstream production stages. As a result, a region's different production stages may respond differently to the trade cost reduction with both domestic and foreign markets. This ultimately affects its GVCs participation. In this section, I first outline the basic setup. Then, I characterize the equilibrium distribution of GVCs, and derive the implications of the model that can be used to guide empirical exercises.

1.4.1 Setup

The whole economy is composed of N + 1 regions. These N + 1 regions include N regions (or cities) inside China, indexed by i and n and the rest of the world, indexed by r. Each region i is exogenously endowed with a mass of consumers L_i and characterized by its trade friction to other regions. Each consumer owns one unit of labour which they supply inelastically.[15]

Production of a final good is associated with two subsequent production stages. The outputs of the first production stage serve exclusively as the intermediate goods for the second production stage and the outputs in the second stage are only used as final consumption.

Preferences Consumers in region n derive their utility from consuming a continuum of final-good varieties (index by ω). Each final consumption good ω belongs to a continuum of final goods over a set Ω. Preferences are CES and given by:

$$U(\{y_i^F(\omega)\}_{\omega\in\Omega_n}) = (\int_{\omega\in\Omega}(y_i^F(\omega))^{(\sigma-1)/\sigma}d\omega)^{(\sigma/\sigma-1)}, \sigma > 1$$

Where σ is the elasticity of substitution

Technology Each final good ω is produced by a firm by organizing a specific value chain $l(\omega)$ under perfect competition. Once operated, this firm needs to look for a location to source their upstream intermediate inputs, a location to produce its final product and a destination to sell it. The production of each final good indexed by ω corresponds to one value chain $l(\omega)$. This value chain $l(\omega)(= \{l_1(\omega), l_2(\omega), l_3(\omega)\})$ indicates the location for input sourcing of stage 1 production $l_1(\omega)$, the location of stage 2 production $l_2(\omega)$ and the location $l_3(\omega)$ where this product will be sold.

Each stage is subject to different production functions. The production of the second stage in region i is Cobb-Douglas, which combines both labour from region i and the intermediate input produced in region $l_1(\omega)$:

$$f_i^{(2)}(L_i^{(2)}(\omega)) = (L_i^{(2)}(\omega)/a_i^{(2)})^{\alpha_2}(m_{l_1(\omega)i})^{1-\alpha_2}$$

Where $L_i^{(2)}$ is the labour used in producing goods ω in stage 2 for region i, $a_i^{(2)}$ is the unit labour requirement of stage 2 in region i and $m_{l_1(\omega)i}$ is the intermediate input from region $l_1(\omega)$

If this upstream intermediate input is produced in region i, the production can be written:

$$f_i^{(1)}(L_i^{(1)}(\omega)) = L_i^{(1)}(\omega)/a_i^{(1)}$$

[15]The assumption for two sequential production stages in my model is just for simplicity and the basic logic goes through in a model with more than two sequential production stages.

Where $L_i^{(1)}(\omega)$ represents the labour used to produce good ω's stage 1 product in region i and $a_i^{(1)}$ is the unit labour requirement in region i for stage 1.

Cost Minimization In my setting, each firm has full information of each region's productivity in each production stage, wage and bilateral trade cost as in Antràs and de Gortari (2017). Under this condition, each firm maximizes its profit by minimizing the overall cost when producing final good ω via $l(\omega)$. In particular, if the final goods are to serve consumers in region $l_3(\omega)$ (= n), this cost minimization problem for the final good price ($p^F_{l(\omega)}$) becomes:

$$argmin_l p^F_{l(\omega)} = argmin_l (a^{(1)}_{l^1} w_{l^1})^{\alpha_1\beta_1} (a^{(2)}_{l^2} w_{l^2})^{\alpha_2\beta_2} (\tau_{l^1 l^2})^{\beta_1} (\tau_{l^2 n})$$

where $\beta_1 = 1 - \alpha_2$, $\alpha_1 = 1$, $\beta_2 = 1$ and $\sum_{n=1}^{2} \alpha_n \beta_n = 1$

The cost minimization problem considers the real geography of the economy so that when organizing its production chain, a firm should not only take into account the unit production cost of a location i ($a_i^{(k)} w_i, k \in \{1, 2\}$) but also its trade cost ($\tau_{ij}, j \neq i$) to the rest of the economy. Intuitively, if a region i has low unit production cost in the first stage $a_i^{(1)} w_i, k \in \{1, 2\}$ but is located far away from the other regions, a firm is less likely to source their upstream product from region i.

This cost minimization problem also suggests that the impact of trade cost on transporting final goods ($\tau_{l^2 n}$) is stronger than that of transporting intermediate good products ($\tau_{l^1 l^2}$) within the same production chain. If one assumes that transporting trade costs are proportional to the gross value of a product, the iceberg trade cost would accumulate along the production chain and transportation cost erode more value when transporting goods in the more downstream stages (Antràs and de Gortari, 2017). For example, within the same production chain $l(\omega)$, if the iceberg trade costs for both upstream intermediate goods ($\tau_{l^1 l^2}$) and final goods ($\tau_{l^2 n}$) decreases by 10%, consequentially, the effect of the former on the final good price $p^F_{l(\omega)}$ would be only $10\% \times \beta_1$, while the effect from the latter is $10\% > 10\% \times \beta_1$, with $0 < \beta_1 < 1$.

Share of GVCs To tractably solve the cost minimization problem, it is necessary to introduce randomness to the overall cost of production (Antràs and de Gortari, 2017) rather than to the productivity at each stage as in Moxnes and Johnson (2016) and Eaton and Kortum (2002).[16] To address this issue, I adopt the 'Lead-

[16]The product of variables following Fréchet distribution does not necessarily follow Fréchet distribution.

Firm Approach' in Antràs and de Gortari (2017)[17] by assuming that the overall 'productivity' of a value chain is based on Fréchet distribution. Intuitively, any production chain $l(\omega)$ will be associated with an average cost that is a function of trade cost, primary factor costs and the stage-specific technology of the regions involved in the production chain. To be more precise, the overall 'productivity' of a given chain l is given by:

$$Pr(\prod_{j=1}^{2} a_{l^j(\omega)}^{(j)}(\omega)^{\alpha_j \beta_j} \geq a) = exp\{-a^{\theta} \prod_{j=1}^{2} (T_{l^j(\omega)})^{\alpha_j \beta_j}\}$$

which is equivalent to assume that $\prod_{j=1}^{2} a_{l^j(\omega)}^{(j)}(\omega)^{\alpha_j \beta_j}$ is distributed Frechet with a shape parameter θ, and a location parameter that is a function of the technology in all the locations in the chains, measured by $(T_{l^j(\omega)})^{\alpha_j \beta_j}$. With the adopted 'Lead-Firm' approach, I can characterize the share of a good following production path l_n over all the possible production paths that serve region n as:

$$\pi_{l_n} = \frac{(T_{l^1} w_{l^1}^{-\theta})^{\alpha_1 \beta_1} (T_{l^2} w_{l^2}^{-\theta})^{\alpha_2 \beta_2} (\tau_{l^2 l^1})^{-\beta_1 \theta} \tau_{nl^2}^{-\theta}}{\Theta_n}$$

where $\Theta_n = \sum_j \sum_k (T_k w_k^{-\theta})^{\alpha_1 \beta_1} (T_j w_j^{-\theta})^{\alpha_2 \beta_2} (\tau_{jk})^{-\beta_1 \theta} \tau_{nj}^{-\theta}$

Implication for a region's participation in GVCs This subsection derives a city's import and export upstreamness implied by the model. Antràs and de Gortari (2017) argued that it is possible to derive a tractable GVC following a probabilistic approach as discussed above. Unfortunately, this GVC share is not directly observed in the Chinese international trade dataset, which requires the development of a region's model-implied import and export upstreamness, which is comparable with the data. To do so, I first derive explicitly a region's import and export value with this tractable GVC share. Next, I compute a region's import and export upstreamness with the import and export values implied by the model.

First, consider the implications of my model for region i's stage 1 export. Notice that for stage 1's output to flow from region i to the foreign region r, it must be the case that region i is in position 1 in a chain serving any region $k \in \{1, 2, ..., N+1\}$ via the foreign region r in position 2. Define the set of GVCs flowing through region i at position 1 and through foreign region r at position 2: $\Lambda_{i \to r}^{1} = \{l = \{i, r, k\} | k \in \{1, 2, ..., N+1\}\}$. With this notation, region

[17] Antràs and de Gortari (2017) proposed two alternative approaches: the 'Lead-Firm Approach' and the 'Decentralized Approach', both of which deliver the same equilibrium results.

i's export flow in stage 1 becomes:

$$
\begin{aligned}
ex_i^{(1)} &= \sum_{k=1}^{N+1} \pi_{l\{i,r,k\}} w_k L_k \\
&= \sum_{k=1}^{N+1} (T_k w_k^{-\theta})^{\alpha_1\beta_1} (T_i w_i^{-\theta})^{\alpha_2\beta_2} (\tau_{ik})^{-\beta_1\theta} (\tau_{ri})^{-\theta} \frac{w_r L_r}{\Theta_r}
\end{aligned}
$$

The total trade flow of stage 2's output from region i in China to the foreign region r can be derived from summing up all the value chains $l = \{k, i, r\}$ ($k \in \{1, 2, .., N+1, r\}$) that finally serve the foreign region, but with a different source of locations (k) in stage 1. Analogously, region i's export flow in the first stage and its import flow in all stages can be computed (in the appendix).

When computing the export and import value for each region, I impose the assumption that the foreign region does not import the upstream product from China to produce final goods to serve any region in China. I do so by ruling out production paths by which a region in China exports its upstream intermediate goods and reimports the final products produced from the intermediate good. This is consistent with the findings in Koopman et al. (2014) that the Chinese value-added in its imports is negligible, implying that an ignorance of this production path would not severely bias our results.

To use this model implied export and import value to compute a region's participation in GVCs, I first express a region's import and export upstreamness as follows:

$$
U_i^x = 2\frac{ex_i^1}{ex_1^1 + ex_1^2} + \frac{ex_i^2}{ex_1^1 + ex_1^2} = 1 + \frac{1}{1 + ex_1^2/ex_1^1} \sim ex_1^1/ex_1^2 \tag{1.1}
$$

$$
U_i^m = 2\frac{im_i^1}{im_i^1 + im_i^2} + \frac{im_i^2}{im_i^1 + im_i^2} = 1 + \frac{1}{1 + im_i^2/im_i^1} \sim im_i^1/im_i^2 \tag{1.2}
$$

where U_i^x and U_i^m represent region i's export and import upstreamness, respectively; ex_i^1 and ex_i^2 represent region i's export value in production stage 1 and 2; im_i^1 and im_i^2 represent region i's import value in production stage 1 and 2.

This simple two-stage setting allows me to restructure a region's export and import upstreamness as a function of export ratio between the first and second stage, as shown in equation (1.1) and (1.2), respectively. Intuitively, a region's export or import upstreamness is its export or import share of upstream products, respectively. With the model-implied export and import flows, region i's export and import upstreamness can be explicitly written as:

$$U_i^x \sim \frac{ex_i^{(1)}}{ex_i^{(2)}} = \frac{\beta_1 (T_i w_i^{-\theta})^{\alpha_1\beta_1} (T_r w_r^{-\theta})^{\alpha_2\beta_2} (\tau_{ri})^{-\beta_1\theta}}{(T_r w_r^{-\theta})^{\alpha_1\beta_1} [(T_i w_i^{-\theta})^{\alpha_2\beta_2} (\tau_{ir})^{-(\beta_1+1)\theta}] + \sum_{j\neq r} (T_j w_j^{-\theta})^{\alpha_1\beta_1} (T_i w_i^{-\theta})^{\alpha_2\beta_2} (\tau_{ij})^{-\beta_1\theta} \tau_{ri}^{-\theta}} \tag{1.3}$$

$$U_i^m \sim \frac{im_i^{(1)}}{im_i^{(2)}} = \frac{\beta_1 (T_i w_i^{-\theta})^{\alpha_2\beta_2} (\tau_{ir})^{-(1+\beta_1)\theta} \frac{w_r L_r}{\Theta_r} + \beta_1 \sum_{j\neq r} (T_i w_i^{-\theta})^{\alpha_2\beta_2} (\tau_{ir})^{-\beta_1\theta} \tau_{ji}^{-\theta} \frac{w_j L_j}{\Theta_j}}{(T_r w_r^{-\theta})^{\alpha_2\beta_2} (\tau_{ir})^{-\theta} \frac{w_i L_i}{\Theta_i}} \tag{1.4}$$

These expressions correspond to my third motivating fact that a city's imports and exports vary across locations. This model provides explicit formulas for a region's import or export upstreamness as a function of a region's trade cost (τ_{ij}, τ_{ir}), productivity($T_i^{(k)}, k \in \{1, 2\}$), endogeneous local wage (w_i) and price index (Θ_i). Given region i's wage (w_i) and price index (Θ_i), trade cost reduction on export and import upstreamness varies by production stage and market type, i.e., domestic or foreign, with which trade costs have reduced. To be more precise, I list the following proposition explaining how a reduction in trade costs affects a city's participation in GVCs.

Proposition 1 *Given a region's wage and its price index:*

(1) A reduction in region i's trade cost with domestic ($\tau_{ik}, k \neq r$) or foreign markets (τ_{ir}) brings down its export upstreamness.

(2) A reduction in region i's trade costs with domestic markets ($\tau_{ik}, k \neq r$) increases its import upstreamness, while the effect of a reduction in trade costs with foreign markets on import upstreamness is ambiguous.

Equation (1.4) shows that a reduction in region i's trade costs with domestic (τ_{ij}) markets increases its import upstreamness, while equation (1.3) shows that a reduction in its trade costs to foreign markets (τ_{ir}), reduce its export upstreamness. A common channel exists through which these two predictions come. Under the assumption that a product's trade costs are proportional to its gross value, trade costs would accumulate along the production chain and erodes greater value for more downstream products (Antràs and de Gortari, 2017). If region i's trade costs with foreign markets reduce, it would be more specialized in producing and exporting downstream products to foreign markets, because downstream products are more sensitive to trade cost reduction (Antràs and de Gortari, 2017). Similarly, region i's reduction in trade costs with nearby domestic markets makes it ideal for exporting downstream products to these markets, thus indirectly raising the demand for importing upstream products in domestic markets.

Equation (1.3) shows that a reduction in region i's trade costs with domestic (τ_{ij}) markets reduces its export upstreamness, while equation (1.4) shows that the effect of a reduction in trade cost with foreign markets (τ_{ir}) on import upstreamness is unclear. The intuition of the impact of trade cost reduction with domestic markets on export upstreamness is straightforward, since it indirectly reduces marginal costs for downstream production by lowering the cost of sourcing from domestic markets. While the intuition of the impact of trade cost reduction with foreign markets on import upstreamness is less direct, it requires an investigation of the location of the preceding stage of region i's upstream import within the GVCs. If region i's upstream imports are mainly to produce downstream products which serve the foreign markets ($\beta_1(T_i w_i^{-\theta})^{\alpha_2\beta_2}(\tau_{ir})^{-(1+\beta_1)\theta}\frac{w_r L_r}{\Theta_r}$), the declined trade costs with foreign markets may affect both its upstream imports and downstream exports. Given a higher foreign trade cost elasticity $(1+\beta_1) > 1$ in this set of GVCs, a reduction in trade cost with foreign markets generates a stronger response for upstream imports than downstream imports, resulting in increased import upstreamness. If, on the other hand, region i's upstream imports are basically used to produce downstream outputs for domestic markets ($\beta_1 \sum_{j\neq r}(T_i w_i^{-\theta})^{\alpha_2\beta_2}(\tau_{ir})^{-\beta_1\theta}\tau_{ji}^{-\theta}\frac{w_j L_j}{\Theta_j}$), its import upstreamness would decrease rather than increase due to lower foreign trade cost elasticity ($\beta_1 < 1$) in this set of GVCs if trade costs with foreign markets decrease.

Implication for a country's participation in GVCs Given the definition of region i's import and export upstreamness in equation (1.1), (1.2), (1.3) and (1.4), it is necessary to see how the local reduction in trade costs affects a country's participation in GVCs. The impact of a region's trade cost reduction with domestic and foreign markets may have an impact on a country's aggregate imports (U_A^m) and export upstreamness (U_A^x) is as follows:

$$U_A^x = \sum_{i\neq r} \frac{ex_i^{(1)} + ex_i^{(2)}}{\sum_{j\neq r}(ex_j^{(1)} + ex_j^{(2)})} U_i^x \sim \sum_{i\neq r} \frac{ex_i^{(1)}}{\sum_{j\neq r}(ex_j^{(1)} + ex_j^{(2)})},$$

$$U_A^m = \sum_{i\neq r} \frac{im_i^{(1)} + im_i^{(2)}}{\sum_{j\neq r}(im_j^{(1)} + im_j^{(2)})} U_i^m \sim \sum_{i\neq r} \frac{im_i^{(1)}}{\sum_{j\neq r}(im_j^{(1)} + im_j^{(2)})}.$$

Proposition 2 *Given wage (w_i) and price index (Θ_i), a minor reduction in domestic region i's trade costs with domestic region k from ($\tau_{ki} \rightarrow \tau'_{ki}$) such that both changes in aggregate export ($\frac{\Delta(\sum_{j\neq r}(ex_j^{(1)}+ex_j^{(2)}))}{\sum_{j\neq r}(ex_j^{(1)}+ex_j^{(2)})} \rightarrow 0$) and import ($\frac{\Delta(\sum_{j\neq r}(im_j^{(1)}+im_j^{(2)}))}{\sum_{j\neq r}(im_j^{(1)}+im_j^{(2)})} \rightarrow 0$) are negligible, the impact of this bilateral trade cost reduction ($\tau_{ki} \downarrow$) on aggregate export upstreamness (U_A^x) and import upstreamness (U_A^m) as follows:*

$$\frac{\partial U_A^x / \partial \tau_{ki}^{-\beta_1 \theta}}{U_A^x} \rightarrow 0, \tag{1.5}$$

$$\frac{\partial U_A^m / \partial \tau_{ki}^{-\beta_1 \theta}}{U_A^m} \sim \underbrace{(T_i w_i^{-\theta})^{\alpha_2 \beta_2}}_{\text{unit cost of production}} \cdot \overbrace{\left(\frac{w_k L_k}{\Theta_k} + \frac{w_i L_i}{\Theta_i}\right)}^{\text{Connection with the local markets}} \cdot \tau_{ir}^{-\beta_1 \theta} \cdot \tau_{ki}^{-(1-\beta_1)\theta}, \tag{1.6}$$

and a minor reduction in domestic region i's trade costs with foreign region r from ($\tau_{ri} \rightarrow \tau'_{ri}$), results in a change in aggregate upstreamness as follows:

$$\frac{\partial U_A^x / \partial \tau_{ki}^{-\beta_1 \theta}}{U_A^x} \sim (T_i w_i^{-\theta})^{\alpha_1 \beta_1}, \tag{1.7}$$

$$\frac{\partial U_A^m / \partial \tau_{ri}^{-\beta_1 \theta}}{U_A^m} \sim \underbrace{(T_i w_i^{-\theta})^{\alpha_2 \beta_2}}_{\text{unit cost of production}} \cdot \left(\frac{w_r L_r}{\Theta_r} \tau_{ri}^{-\frac{\theta}{\beta_1}} + \overbrace{\sum_{j \neq r} \tau_{ji}^{-\theta} \frac{w_j L_j}{\Theta_j}\right)}^{\text{Connection with the local markets}}, \tag{1.8}$$

Proposition 2 shows us the aggregate impact of region i's trade cost reduction with domestic or foreign markets. Equation (1.5) shows that the region i's trade cost reduction with another domestic region k (τ_{ik}) might have a negligible impact on China's aggregate export upstreamness, since the effect of τ_{ik}'s reduction on $ex_i^{(1)}$ is negligible. Equation (1.7) shows that the impact of region i's trade costs with foreign market r on aggregate export upstreamness is proportional to region i's unit cost of production ($T_i w_i^{-\theta}$). Equation (1.6) suggests that the impact of region i trade cost reduction with another domestic region k is proportional to region i's unit cost of production and its connection with the local markets, while the impact of a reduction in region i's trade costs with foreign markets is determined by these two forces as in equation (1.8).

Implication for a City's Domestic Content in Export China's recent increase in domestic content in value-added is receiving increasing attention (Koopman et al., 2014; Kee and Tang, 2016). However, this paper is among the first attempts to relate geography with a region's domestic value-added in export. By definition, a region's domestic content in its export is one minus its share of foreign value-added in its gross exports[18]:

$$\begin{aligned} D_i^{ex} &= 1 - \beta_1 \pi_{l(r,i,r)} w_r L_r \\ &= 1 - \frac{(1-\alpha_2\beta_2)(T_r w_r^{-\theta})^{\alpha_1\beta_1}[(T_i w_i^{-\theta})^{\alpha_2\beta_2}(\tau_{ir})^{-(\beta_1+1)\theta}]}{ex_i^{(1)} + ex_i^{(2)}} \end{aligned}$$

The model delivers the following proposition that links a city's domestic value-added in export with its specialization in GVCs:

Corollary 1 *Given wage (w_i) and the price index (Θ_i), its domestic content (D_i^{ex}) in exports is negatively associated with the export upstreamness (U_i^x) and positively associated with the gap between imports (U_i^m) and exports upstreamness (U_i^x):*

$$D_i^{ex} = 1 - \alpha_1 \tau_{ir}^{-\theta}(U_i^x - 1)\left(\frac{T_r w_r^{-\theta}}{T_i w_i^{-\theta}}\right)^{\alpha_1\beta_1 - \alpha_2\beta_2} \tag{1.9}$$

In a special case with $\alpha_1\beta_1 = \alpha_2\beta_2$, region i's domestic content in export can be expressed as:

$$D_i^{ex} = 1 - \alpha_1 \tau_{ir}^{-\theta}(U_i^x - 1)$$

(Proof in the appendix)

This expression explicitly shows how a city's domestic value-added in exports is affected by the trade costs with domestic and foreign markets, respectively. To be specific, a fall in region i's trade costs with foreign markets brings down the domestic value-added ratio because sourcing upstream products from foreign markets becomes much cheaper. Additionally, this is accompanied by a reduction in this region's export upstreamness from proposition 1, suggesting that the share of GVCs associated with importing and re-exporting to the foreign markets ($l(r,i,r)$) in downstream exports has increased. However, a reduction in region i's trade costs with domestic markets may increase domestic value-added ratio by

[18]For simplicity, the domestic content in export is defined in a more indirect way. One can always back out the direct expression for this ratio as $D_i^{ex} = \frac{ex_i^{(1)} + ex_i^{(2)} - (1-\alpha_2\beta_2)(T_r w_r^{-\theta})^{\alpha_1\beta_1}[(T_i w_i^{-\theta})^{\alpha_2\beta_2}(\tau_{ir})^{-(\beta_1+1)\theta}]}{ex_i^{(1)} + ex_i^{(2)}}$

reducing export upstreamness.

This expression also shows that the upstreamness gap between imports and exports is a good indicator for domestic value-added in its exports. First, a reduction in a region's trade costs with the foreign markets brings down domestic value-added, import upstreamness and export upstreamness, if this reduction in foreign trade costs is large enough to create a large increase in final domestic demand $(w_i L_i, i \neq r)$. This implies that a reduction in a region's domestic content in export is accompanied by narrowing gap between import and export upstreamness, which weakens this region's participation in GVCs. Then, a reduction in a region's trade costs with the domestic markets brings down export upstreamness, while raising its domestic value-added and import upstreamness. This implies that an increase in a region's domestic content in its exports is associated with its widening gap between import and export upstreamness, which strengthens this region's participation in GVCs.

Implication for Trade Organization This subsection shows how to use my model analyze two of the most important export regimes in China: ordinary exports and processing exports. Ordinary exports in China is the common export activity that firms engaged in ordinary export need to design, manufacture and market their products. As a result, firms involved in ordinary exports have relatively high domestic value-added in their exported products. While firms involved in processing exports only receive designs, products moulds or semi-finished goods from foreign multinational firms and provide contract manufacturing services accordingly. Firms, engaged in processing exports, receive tax exemption from importing intermediate goods, while the products from using these intermediate goods can only serve foreign markets exclusively. As a result, the domestic value-added in exports is comparably lower than for ordinary exports.

With different level of reliance on importing intermediate products in ordinary and processing exports, I can characterize the GVCs with exporting flows in the second stage from any region i in China to the rest of the world as either ordinary or processing exports.[19] For example, I label the production path $l = \{r, i, r\}$ as region i's processing exports, because this production path involves producing downstream products to serve foreign region r with imported intermediate goods. With this labeling methodology, the ratio between ordinary and processing exports of a region can be given as follows:

[19] I abstract from other differences between these two types of trade in this exercise, because my model may not capture each aspect of their differences.

Corollary 2 *Given wage (w_i) and price index (Θ_i), the export ratio (R_i^x) between sourcing domestically and abroad in downstream production is negatively associated with export upstreamness:*

$$R_i^x = \frac{2 - U_i^x}{U_i^x - 1}\beta_1\left(\frac{T_i w_i^{-\theta}}{T_r w_r^{-\theta}}\right)^{\alpha_1\beta_1 - \alpha_2\beta_2}\tau_{ir}^{\theta} - 1 \qquad (1.10)$$

In a special case with $\alpha_1\beta_1 = \alpha_2\beta_2$, region i's export ratio (R_i^x) can be simplified as:

$$R_i^x = \frac{2 - U_i^x}{U_i^x - 1}\beta_1\tau_{ir}^{\theta} - 1$$

(Proof in the appendix)

This expression shows region i's ratio between ordinary and processing exports as a function of export upstreamness and trade costs with foreign markets. Processing exports ares very sensitive to trade costs with foreign markets, since a reduction in region i's trade costs to foreign markets increases the share of processing exports in this region. The main intuition is that region i's trade costs with foreign markets affect both its import of intermediate goods and export of final production, both of which are crucial for processing exports, thus rendering processing exports responsive to trade cost reduction with foreign markets.

1.4.2 Numerical Exercise

To complement the analysis in the previous section, I visualize the response of a region's export and import upstreamness due to trade cost reduction with either domestic or foreign markets in general equilibrium, respectively. Consider an economy with 3 + 1 regions, 3 inside China and 1 the rest of the world. To isolate the effect of trade cost reduction on GVCs, some symmetric assumptions are necessary: (1) The regions inside China are homogeneous in productivity at all stages ($T_i^{(1)} = T_n^{(1)}$, $T_i^{(2)} = T_n^{(2)}$, $T_i^{(1)} \neq T_i^{(2)}$), market size and trade cost ($\tau_{ij} = \tau_{ik}; j,k \neq i; i,j,k \neq r$ and $\tau_{ir} = \tau_{nr}, i \neq n$) with all the markets; (2) The production function for final product is Cobb-Douglas, with $\alpha_1\beta_1 = \alpha_2\beta_2$.

Figure 1.4 shows the simulated dynamics of region 1's export and import upstreamness assuming the iceberg trade costs between region 1 and region 2 (τ_{12}) reduce from 1.4, i.e., the average trade cost between Chinese cities in 2000, to 1.1, i.e., the average trade cost between cities in 2006, all other trade costs being constant. In line with proposition 1, as region 1's trade costs with region 2 declines, its import upstreamness increases while its export upstreamness decreases. This result suggests that, incorporating the general equilibrium effect will not overturn the effect of trade cost reduction with domestic markets on upstreamness as stated in proposition 1.

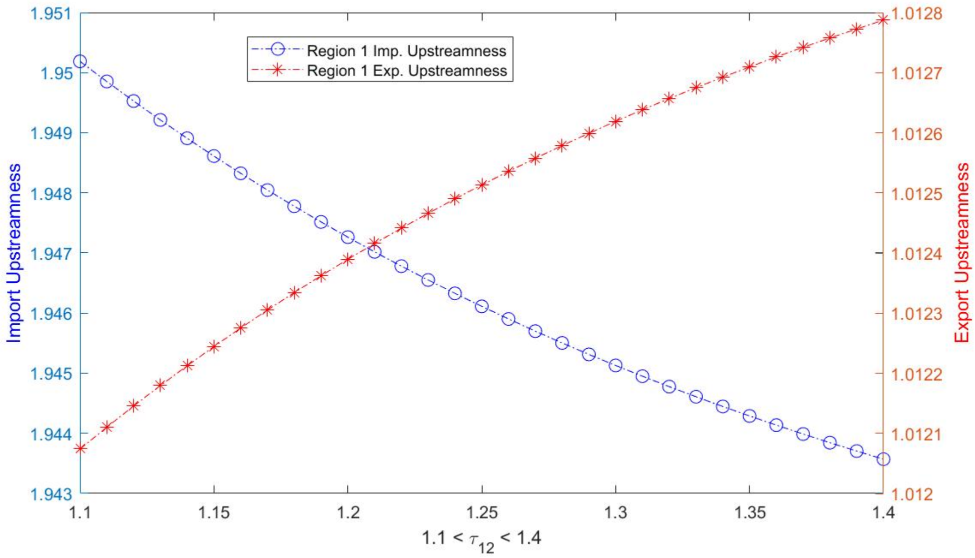

Figure 1.4: Reduction of Trade Costs between Region 1 and 2

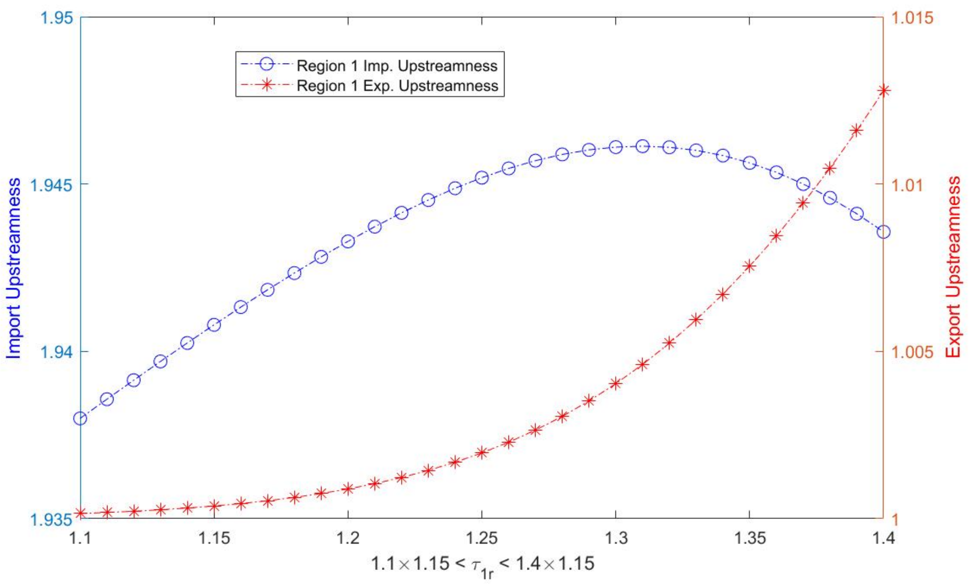

Figure 1.5: Reduction of Trade Costs between Region 1 and Foreign Region r

Similarly, Figure (1.5) shows the dynamic of region 1's export and import upstreamness given the trade cost reduction with the rest of the world from 1.4 to 1.1, while keeping other trade costs constant. In line with proposition 1, as region 1's trade costs with foreign region r decline, its export upstreamness decreases and its import upstreamness reacts non-monotonically; first it increases then it decreases. This is because the associated rise in final domestic demand dampens the response of upstream imports to the trade cost reduction with foreign region r for higher trade costs. In particular, the rise in final demands from domestic regions increases the share of GVCs ($l(r,1,k), k \in \{1,2,3\}$) that import upstream products to serve domestic markets in upstream imports, while decreasing the share of GVCs ($l(r,1,r)$) that import upstream products to serve domestic markets in upstream imports. However, the foreign trade cost elasticity of the former sets of GVCs ($l(r,1,k), k \in \{1,2,3\}$) in upstream imports is less than the latter sets ($l(r,1,r)$), which implies that the foreign trade elasticity of upstream imports from region 1 reduces as in equation (1.4). This effect shifts region 1's import upstreamness downwards as its trade costs with foreign markets further decreases.

1.5 Empirical Assessment

In this section, I employ fast-growing highway construction in China as a large-scale natural experiment to test the main predictions of my model. The following subsections are organized as follows: firstly, I provide the background information of highway building in China during 2000-2006; I then introduce the basic setup for my reduced form exercise to test my model under the context of highway construction; and finally I address the problem of non-randomness in highway placement by developing a novel approach to constructing dynamic instrumental highways.

Five datasets are employed for this empirical exercise. First, I use Geo-referenced administrative boundary data for the year 2005 from the ACASIAN Data Center. This dataset provides a city-level geographic information system (GIS) dividing the surface of China into 33 provinces and 349 cities. Following Baum-Snow et al. (2017); Baum-Snow (2007), I only include the 'Han' District 19 with 284 cities.[20] Second, I use city-level socioeconomic records from Provincial Statistical Yearbooks for the years 1990 and 1997 and from 2000 to 2006. The Provincial Statistical Yearbook series reports city level GDP, education level of the population and population size. Third, geo-referenced highway networks were obtained

[20]The 'Han' districts which consist of more than 90% of China's aggregate production and the incorporation of non-'Han' may be subject to over-sampling of poor prefectures Baum-Snow et al. (2017)

from the ACASIAN Data Center. Highway routes were digitized on the basis of a collection of high-resolution road atlas sources published between 1998 and 2010.[21] These dense atlas sources made it possible to classify local road segments into different types of routes: city routes, provincial highway routes, rural routes. Finally, the other two datasets are China's 2002 Input-Output Table and China's international trade data, which were introduced in the previous section.

1.5.1 Highway Network: Background

Since the 1990s, China had initiated its '7 - 5' highway construction project, which means that the main highway network consists of seven horizontal and five vertical routes. The main object of this project is to connect all the provincial capitals and cities with registered population at least half million, targeted regional centres as well as the national borders. The construction of this program had been divided into two different phases: the 'kick-off' phase(1992 - 1997), and 'rapid development' phase(1998 - 2007). This highway network was initially planned to be completed by 2020 but was completed way ahead of schedule at the end of 2007. This was largely due to the 'Fiscal Stimulus Program' after the 1997 Asian financial crisis. Specifically, before 1990 the total length of highway in use in China was less than 0.3 km, however, during the 'rapid development' phase, the total traffic mileage of the highway increased from less than 1.6 km to more than 53,000 km. Figures (1.6) - (1.8) visualize the evolution of the highway network in 1998, 2003 and 2007, respectively.

1.5.2 Empirical Strategies

In this section, I introduce the baseline specification of my reduced form exercise. As illustrated in my model, trade costs with domestic and foreign markets play different roles in shaping a city's GVC participation. However, it is difficult to distinguish a city's trade costs with the domestic and foreign market using a dummy variable in the highway network (Faber, 2014). I propose a regression specification, which differentiates the impact from domestic and foreign markets via the highway network:

$$Y_{i,t} = \beta_0 + \beta_1 ln(LMA_{i,t}) + \beta_2 ln(FMA_{i,t}) + \beta_3 X_{i,t} + \delta_i + \alpha_t + \epsilon_{i,t} \quad (1.11)$$

where $Y_{i,t}$ indicates the variables of my interest: city i's import ($U^m_{i,t}$) or exports ($U^x_{i,t}$) upstreamness, domestic content in its exports ($D^x_{i,t}$), ratio between ordinary

[21] For detailed information, you can check Faber (2014) or see my appendix. Geo-referenced highway routes were obtained from the ACASIAN Data Center. Geo-referenced local road routes were obtained from the National Geo-center of China (NGCC).

and processing export ($R^x_{i,t}$) in year t; $LMA_{i,t}$ is city i's local market access and $FMA_{i,t}$ is city i's foreign market access; $X_{i,t}$ are control variables including city i's manufacturing productivity, average education level, total population size, population density and share of manufacturing production in year t; δ_i indicates city level fixed effect and α_t indicates year fixed effect.

Key Variables and Controls

The key variables are local market access and foreign market access, which capture the impact of city i's trade costs with domestic and foreign markets. $LMA_{i,t}$ is constructed as the sum of the surrounding markets' (accessible within six hours) final demands divided by respective iceberg trade costs:

$$LMA_{i,t} = \sum_j \frac{Y_{j,1990}}{\tau_{ij}^{\theta}} \tag{1.12}$$

Where $Y_{j,1990}$ is the GDP of city j in 1990 within six hours driving from city i by road network, $\tau_{ij,t}$ is the iceberg trade cost between city i and j of year t.

In line with my model, the proximity to nearby large domestic markets captures the average size of local markets city i has access to. Intuitively, the higher the GDP of nearby city j in 1990 or the lower its corresponding trade costs with city i $\tau_{ij,t}$ in year t, the larger the local market access for city i is. In addition, proposition 1 suggests that a city's proximity to domestic large markets is only affected by trade costs, but not the change in final demand of the markets.[22] City j's final demand in $LMA_{i,t}$ is proxy by city j's GDP in 1990 and the variation of $LMA_{i,t}$ across time is determined by trade cost reduction via highway construction. Moreover, I pick $\theta = 4$ as in (Antràs and de Gortari, 2017).

To capture the impact of city i's trade costs with foreign markets on its import and export upstreamness, I construct the $FMA_{i,t}$ as the following:

$$FMA_{i,t} = \tau_{ip,t}^{-\theta} \tag{1.13}$$

Where $\tau_{ip,t}$ represents the iceberg trade costs with the nearest international ports. There are nine international ports located in the following eastern coastal cities in China: Tianjin, Yantai, Shanghai, Shenzhen, Ningbo, Guangzhou, Qingdao, Xiamen, Dalian, where more than 80% of international trade in China takes place.

[22]To evaluate the effects of trade cost reduction incorporating the general equilibrium effect, I structurally estimate the whole model in a later section.

I control for a set of time-varying variables and city-fixed effect, which may otherwise contaminate the estimation of a city's proximity to both domestic and foreign markets. The city-fixed effects stands for some time-invariant unobservables that might bias the estimates if they are not included, e.g., a city's distance to the sea, to the nearest targeted metropolitan centres and some regional policies that were constant over the time under study. In addition, I include some observed time-varying variables that may affect a city's participation in GVCs, which includes a city's year-specific manufacturing TFP, constructed by the average productivity of manufacturing firms' in this city.[23] This is because my model suggests that a city with higher productivity has lower marginal production costs. This enhances its participation in GVCs.

I also control for the average education level of a city, indexed by the share of students at each educational level. This is because Lee and Yi (2018) suggested that the demand for highly skilled workers in downstream production is much stronger. A city with a larger supply of educated workers may specialize in producing less upstream products, which is not covered by my model. In addition, China had unilaterally reduced its import tariff in the period studied, which may have had a large impact on industry's productivity, output and specialization (Baum-Snow et al., 2017; Brandt and Morrow, 2017; Brandt et al., 2013).

To isolate the effect of import tariffs on a city's GVC participation, I control for a city-level import tariff by aggregating the import tariff of all the industries in the city. I then weighed the city-import tariff against the value of import through ordinary trade. Lastly[24], Duranton et al. (2014) suggests that an industry's output with a high 'weight-to-value' ratio is more likely to be affected by highway construction. To ensure that my estimate is not driven by this mechanism, I control for a city's 'weight-to-value' level in exports by aggregating the 'weight-to-value' of all the industries in a city weighted by this city's export. Summary statistics for the key variables can be found in Table (1.13) and (1.14).

Iceberg Trade Cost

Equation (1.12) and (1.13) show that the measures of LMA and FMA depends largely on how we measure the bilateral iceberg trade costs. To connect iceberg

[23]To obtain the manufacturing TFP at the city-level, I first estimate the manufacturing TFP of each firm with Levinsohn-Petrin then aggregate the firm-level manufacturing TFP into the city-level weighted by each firm's value-added.

[24]Only imports through ordinary trade are subject to imports tariff, while imports through processing trade are tariff exempt.

trade cost with the highway network, I follow the theory of Limao and Venables (2001); Hummels (2013); Baum-Snow et al. (2017) that bilateral iceberg trade costs can be approximated by bilateral traveling time:

$$\tau_{ij,t} = 1 + 0.004T_{ij,t}^{0.8} \tag{1.14}$$

Where $T_{ij,t}$ measures the traveling hours between city i and j in year t

To calculate bilateral trade costs from this formula, I compute each city-pair's bilateral travelling time in year t by calculating the least travelling hours between each city-pair with the help of the tool box 'ERSI'[25] in ArcGis, which provides the highway network at year t and local road network in year 1999. The average travelling speed on the 1999 local road network is 30 km/h, while that of the highway is 90 km/h, three times as much as the former, implying that highway connection can be expected to significantly reduce the bilateral traveling hours.[26]

Exogenous Variation

To identify the impact of trade costs in the model, one needs to bear in mind that the highway placement is not random. The highway is more likely to pass by cities that are economically prosperous or politically important. I address this problem by applying an instrumental highway used in $\grave{a}\ la$ Faber (2014)'s 'Euclidean Straight Line Spanning Tree Network'. Faber (2014)'s idea is to compare the economic outcomes of peripheral counties on the highway that was built to link large metropolitan centres with the peripheral counties off the highway. As a result, the sole object of Faber (2014)'s algorithm in building this instrumental highway is to connect all the large metropolitan centres with the shortest distance trunk path. Extending Faber (2014)'s algorithm, I also use the timing of the highway construction to develop an IV for each year t, connecting only the targeted cities that were reached by the actual highway network in that year. The evolution of the instrumental highway networks are shown in Figures (1.9), (1.10) and (1.11).[27]

A related issue is that the 1999 local road network used to calculate travelling

[25]With the help of 'ERSI' in ArcGIS, I can derive the origin-destination matrix(OD matrix) between any two cities, which delivers the city-pair's bilateral traveling time. This OD matrix offers us the hours it takes to travel from one place to another, through the least cost path of our combined roadmap.

[26]The reason for including the 1999 local road network is that the highway network is very sparse in its early construction period, which makes it difficult to calculate the traveling hours of each city-pair.

[27]Importantly, I drop all the targeted cities in my final regression.

hours, is not random, either. To address this concern, I introduce a second instrument, the 1962 road network as in Baum-Snow et al. (2017). As argued in Baum-Snow et al. (2017), the more recent transportation infrastructure and the road network in 1962 served different purposes, the 1962 road network was built to move agricultural goods to local markets, while the modern one was mainly to ship products between large cities and to the provincial capitals. The basic logic behind the application of this instrumental local road network is that the historical road network provides a cost-effective way to build the 1990 local road network. This historical road network in 1962 is less likely to be affected by unobserved factors of today.

Instrumented Variables

To identify the effect of trade cost reduction solely through the highway network, it is necessary to construct instrumental variables for both 'Local Market Access' (LMA) and 'Foreign Market Access' (FMA) with my time-varying instrumental highway and 1962 local road networks. In particular, I use equation (1.14) to compute the inverse of a city's implied trade cost to the nearest ports from instrumental road networks:

$$FMA_{i,t}^{iv} = (\tau_{ir,t}^{iv})^{-\theta}$$

where $\tau_{ir,t}^{iv}$ measures city i's iceberg trade costs to the nearest international ports through the instrumental network in year t.

To construct corresponding instrumental variables for LMA, I also use equation (1.14) to sum up the inverse trade costs with the cities within six hours' drive on the instrumental road networks. Particularly, the average driving speed on the instrumental highway is 90 km/h, and 30 km/h that on the 1962 local road network.:

$$LMA_{i,t}^{iv} = \sum_j \frac{1}{(\tau_{ij,t}^{iv})^{\theta}}$$

where $\tau_{ij,t}^{iv}$ measures iceberg trade costs between city i and j through the instrumental network in year t. I compute both $\tau_{ij,t}^{iv}$ and $\tau_{ir,t}^{iv}$ with equation (1.14) using both the instrumental highway and 1962 local road network

This instrument emphasizes the average number of reachable markets, discounted by geographical proximity. A higher instrumental value indicates two possibilities: that city i can reach more markets and that it takes fewer driving hours from city i to these markets. Without being contaminated by the final demand of nearby markets or the endogenous placement of the highway, this measure could identify the impact of trade costs on a city's GVC participation. Summary statistics for the instrumental variables can be found in Tables (1.13) and (1.14).

1.6 Main Results

This section reports the empirical results of the impact of trade cost reduction through the highway network on a city's GVC participation. First, I show that my instrumental variables effectively predicted a city's proximity to domestic and foreign markets. Using these reliable instrumental variables, I empirically show that the impact of a city's trade cost reduction on its GVC participation, its domestic value-added ratio in exports, and its export organization are all in line with the predictions of my model.

1.6.1 Results from first stage regression

Columns 1 and 2 in Table (2.5) present the results of the first stage regression and the instrumental variables strongly correlate with a city's proximity to local and foreign markets. To be specific, a 1% increase in the average number of reachable markets is associated with a 1.3% increase in the proximity to local markets, implying that the number of reachable markets is an important factor in shaping a city's accessibility to local markets. The effect estimated in this empirical exercise is close to that of the least cost path IV on proximity in Faber (2014) , which stands at around 0.3%. Regarding foreign markets, the results show that a 1% increase in instrumental inverse trade costs to foreign markets is associated with a 0.3% increase in actual inverse trade costs to foreign markets, which is the same scale estimated by Faber (2014). All these results are robust if applying weights by population size shown in Columns (3) and (4). Given these results, the estimated value of a city's population's, education level is reasonable. In terms of the control variable, the results show that populous cities are more likely to increase their access to local markets through the highway.

1.6.2 Evidence for trade costs on a city's GVC participation

Table (1.16) reports the second stage estimation results on a city's participation in GVCs. Columns (6) and (7) show that a one standard deviation increase in proximity to local markets that are within six hours drive leads to a 4.6 standard deviation increase in a city's import upstreamness, but has no significant effect on a city's export upstreamness. A one standard deviation increase in the inverse iceberg trade costs to the nearest international ports, leads to almost a significant one standard deviation decrease in a city's export upstreamness and a 1.26 standard deviation decrease in import upstreamness. Column (8) in Table (1.16) shows that given a city's export upstreamness, a one standard deviation increase in its proximity to large domestic markets leads to a 1.16 increase in the gap between import and export upstreamness, while a one standard deviation increase in its proximity to foreign markets leads to a 0.48 standard deviation decrease in this upstreamness gap. These results show that only proximity to local markets enlarges the gap between import and export upstreamness and strengthens a city's participation in GVCs, however, it does not hold for a city's the proximity to foreign markets.

Regarding control variables, a city with a higher 'weight-to-value' ratio in exports has a higher average export and import upstreamness. A city's import tariff is negatively associated with its import upstreamness, which suggests that a city's trade cost reduction with foreign markets has a similar impact to a city's import tariff reduction on import upstreamness.[28] The population of a city is negatively associated with its export upstreamness as shown in all the Columns in Table (1.16), which implies that a city with a large population size specializes in producing downstream goods.

In addition, columns (1) - (4) in Table (1.16) present results estimated with OLS, according to which the effect of proximity to domestic and foreign markets on upstreamness is quantitatively smaller than that estimated using IV. One possible explanation for this is that the highway is planned to connect economically prosperous places, but also places specialize in producing upstream products.

Table (1.18) shows that a city with high export or import upstreamness is more likely to get connected. This implies that if cities getting connected by highway are those with strong comparative advantages in producing upstream products, these cities may respond weakly to trade cost reduction implied by the highway. Columns (5) and (6) show that the effect of LMA changes with and without FMA, respectively. Because I use a city's inverse driving hours to the nearest international ports to measure the effect of access to foreign markets, which may also capture the effect of a city's access to the nearest port cities. Figure (1.12) and (1.13) show that the LMA is positively correlated with FMA, which may explain the effect of city i's LMA on its export upstreamness ($U^x_{i,t}$) in Column (6) is insignificantly positive, while this effect is negative after taking away this city's FMA.

[28]The import tariff is determined by the central government, not the individual city. As a result, reducing a city's import tariff means that the industries in China that have large import tariffs in China have a significantly large share of this city's imports.

These three results are in line with proposition 1 in my model. The effect of a city's proximity to large domestic markets on its import upstreamness is quantitatively large. This confirms the proposition that a reduction in a region's trade costs with domestic markets increases its import upstreamness. Meanwhile, the negative effect of a city's proximity to foreign markets on its export upstreamness confirms the proposition 1. This indicates that a fall in a city's trade costs with foreign markets reduces its export upstreamness. Both phenomena coincided with the national trend in decreasing export upstreamness and increasing import upstreamness.

1.6.3 Evidence for trade costs on a city's domestic content in export

The model also generates predictions of the impact of trade cost reduction through the highway network on a city's domestic content share in its exports. The results of the empirical exercise are presented in Table 1.17. In practice, I construct a city's domestic value-added in exports by aggregating firms' domestic value-added ratio following Kee and Tang (2016); Brandt and Morrow (2017). Column (3) in Table 1.17 shows that a one standard deviation increase in proximity to local markets leads to a 1.77 standard deviation increase in a city's domestic value in its exports, while a one standard deviation increase in inverse iceberg trade costs with foreign markets leads to a 1.35 standard deviation decrease in a city's domestic value in this city's exports. This result is in line with the second prediction of my model that a reduction in trade costs with domestic markets shifts the sourcing of upstream intermediate goods from foreign to domestic markets, while reduction in trade costs with foreign markets does the opposite.

1.6.4 Evidence for trade costs on a city's export organization

Now I provide evidence on how trade cost affects a city's choice of export organization, an important factor for a country's value-added in exports (Baum-Snow et al., 2017), by regressing the ratio between ordinary and processing exports on local and foreign market access. Columns (4) and (6) in Table (1.19) show that a one standard deviation increase in the access to foreign markets leads to a 1.35 standard deviation decrease in the ratio between ordinary and processing exports, while a one standard deviation increase in LMA leads to a 2.1 standard deviation increase in this ratio. This result is in line with proposition 3 in my model that a reduction of a city's trade costs with domestic markets drives up the share of ordinary exports while declined trade costs with foreign markets brings down this share. All these results support the argument that a reduction in a city's trade costs with large domestic markets strengthens its participation in GVCs, while a reduction in a city's trade costs with foreign markets does the opposite.

1.7 Robust Check

While my baseline results confirm the main predictions of my model, two concerns still need to be addressed: (i) the key assumption in my model, i.e., the production sequentiality, might not be supported by the data; (ii) the baseline reduced form results due to trade cost reduction with domestic markets might be sensitive to how I index a city's proximity to local markets. In the following subsection, I address the first concern regarding production sequentiality by estimating the foreign trade cost elasticity of intermediate and final consumption products. As regards the second concern, I propose a novel measure of a city's local market access that captures its access to local intermediate goods markets.

1.7.1 Trade Cost Elasticity

One reasonable concern is that if the assumption of production sequentiality holds in the Chinese context, China's trade data should reveal this feature. Sequential production means that the elasticity of trade costs with foreign markets is always smaller for more upstream products, if trade costs of transporting goods is proportional to its gross value (Antràs and de Gortari, 2017). If this assumption holds, I should observe in the data that the foreign trade cost elasticity of intermediate products is lower than that of final consumption products. To test this assumption formally, I propose the following specification:

$$ln(Trade_{j_i,t}) = \alpha + \beta \times ln(Hour_{ip_i,t}) + \gamma \times Intermediate_{j_i} \times ln(Hour_{ip_i,t}) + X_{i,t} + \epsilon_{i,t}$$

where $Trade_{j_ip_i,t}$ is the import or export value for product j (HS4 classification) in city i of year t, $Hour_{ip_i,t}$ is the least traveling hours from city i to its nearest international port in year t, $X_{i,t}$ includes a set of time-varying variables of city i in year t, i.e., education level, manufacturing productivity, population and wage. $Intermediate_{j_i}$ is a dummy variable that is equal to 1 if product j in city i is intermediate goods according to the BEC classification.

This specification enables me to directly compare the foreign trade cost elasticity of intermediate goods with that of final goods. The estimated value for $\hat{\beta}$, i.e., the elasticity of trade costs with foreign markets for final products, should be negative, while the estimated value for $\hat{\gamma}$, i.e., the elasticity of trade costs with foreign markets for intermediate products, should be positive according to my model (Antràs and de Gortari, 2017). In principle, I should observe in the results that

$|\hat{\beta}| > \hat{\gamma} > 0$.

Table (1.20) reports the estimated foreign trade cost elasticity of both intermediate and final goods, which validates the 'sequential production' assumption. Columns (6) and (8) presents the results in the full regression specification including IV and OLS, respectively. In particular, Column (6) shows that a 1% increase in driving hours between city i and its nearest port reduces trade in final products 0.7%, while a 1% increase in driving hours between city i and its nearest port only reduces trade in intermediate products by 0.42%. The estimated trade cost elasticity for both intermediate and final products in column (8) with 'OLS' is smaller, compared to the corresponding estimates in column (6), respectively. Controlling for the time-varying variables dramatically reduced the estimate of trade cost elasticity. In particular, a 1% increase in a city's travelling hours to the nearest port leads to a 1.2% decrease in trade value from column (1) without controls, while a 1% increase in a city's travelling hours to the nearest port leads to a 0.4% decrease in trade value from column (2) with controls. My result is also comparable to that of Antràs and de Gortari (2017), i.e., that a 1% increase in distance between two regions is associated with 1% decrease in trade using the World-Input-Output-Database.

1.7.2 Sensitivity Check

While proximity to local markets in my model highlights both the importance of access to final goods markets and intermediate goods markets, the variable 'Local Market Access' constructed in equation (1.12) only captures a city's access to the final markets rather than the nearby intermediate markets. I address this problem by proposing a 'Local Intermediate Market Access' (LIMA), which measures the average productivity of nearby markets. In particular, this LIMA is constructed as the sum of the manufacturing TFP discounted by the respective iceberg trade costs of the surrounding markets':

$$LIMA_{i,t} = \sum_j \frac{TFP_{j,1998}}{\tau_{ij,t}^{\theta}}$$

where $TFP_{j,1998}$ measures manufacturing TFP in year 1998 of city j, which is within six hours drive of city i.

In line with my model, city i's proximity to nearby domestic intermediate goods markets captures city i's average productivity for upstream intermediate goods in nearby markets. Intuitively, the higher the manufacturing TFP of nearby city j in 1998 or the lower its corresponding trade costs with city $\tau_{ij,t}$ in year t, the stronger the local intermediate market access for city i.

I replace the Local Market Access in equation (1.11) with this newly constructed Local Intermediate Market Access and rerun the reduced form regression. Table (1.21) reports these results which confirm the main predictions of my model. A one standard deviation increase in a city's nearby intermediate goods producers' productivity leads to a 1.3 standard deviation increase in a city's import upstreamness, 2.5 standard deviation increase in a city's domestic value-added in export and 1.58 standard deviation increase in a city's ratio between ordinary exports and processing exports. In addition, the positive impact of a city's access to intermediate goods producers' productivity on both a city's domestic value-added in its export and ratio between ordinary and processing exports is stronger than that of a city's access to final domestic demand. This further confirms the idea that proximity to nearby large markets increases a city's domestic value-added in exports, mainly through increasing the sourcing of intermediate goods from these markets.

1.7.3 Validity of the Instrumental Highway Network

The concern regarding IV validity is that if my dynamic instrumental highway network can capture the effects of the highway network on a city's specialization in GVCs, this novel instrumental highway can also help identify the effects in Faber (2014). To do that, I apply my instrumental highway to test the impact of the highway network on local production as in Faber (2014), and Faber (2014) shows that the peripheral counties on the highway networks experienced lower industry production growth than the peripheral counties away from the highway networks. The channel behind this result is that a reduction in trade costs between a large and a small region facilitates more capital (Redding and Turner, 2015) to relocate from the small to the large region. To formalize this exercise, I return to the baseline regression specification in equation (1.11), because this regression specification enable us to estimate the impact of the highway network on a city's GVCs.

The main idea of this test is that, if my empirical exercise can capture the main effects as in Faber (2014), the estimated result of 'Local Market Access' (LMA) on industry production should be negative ($\beta_1 < 0$), because a city's improved access to nearby metropolitan centres may bring down its own industry production through strong import competition from this metropolitan centre.

Table (1.22) presents the results of the replication exercise. Columns (1) to (4) in Table 1.22 present the main results for the impact of a city's access to local markets on local industry production. Specifically, a one standard error increase in a city's access to nearby final markets leads to a 1.42 standard deviation decrease in its industry production share in GDP and a 0.7 standard deviation decrease in its industry production level. These results show that a peripheral city's access to nearby markets through the highway network reduces both the importance of industry production and the value of industry production itself. The OLS estimation shown in column (1) failed to capture or in column (4) underestimated the impact of LMA on industry production share in a city's GDP compared with IV estimation.

To provide more evidence on the effects of the highway network on a local economy, I extend the validity test to explore how a city's government spending is affected by better access to nearby local markets. Column (8) in Table (1.22) shows that a one standard deviation increase in a city's access to the nearest international ports results in a 1.40 standard deviation decrease in government spending, while access to the nearest local market has no significant effect on government spending. It is possible that the proximity to international ports may not necessarily capture the effect from the foreign markets but rather the effect from the metropolitan centre where the international port is located. To validate this hypothesis, I show in column (7) the regression excluding a city's access to the nearest international port, which shows that a one standard error increase in a city's access to local markets leads to a 1.38 standard deviation decrease in government spending.

Table (1.23) provides more detailed evidences for the impact of the highway network on a city's production factors, i.e., labour and capital, which is directly related to the key channel in Faber (2014). This key channel is that once trade costs between a large and a small region decreases, more 'foot loose' capital, which facilitates industry production, will flow from the small to the large region. Columns (4), (6) and (7) show that a one standard deviation increase in a city's access to nearby local markets leads to a 1.3 standard deviation decrease in the average wage of workers in industry sectors (Baum-Snow et al., 2017), a 0.4 standard deviation decrease in a city's total employment in industry sectors and a 1.05 standard deviation decrease in physical capital. The highway network has a larger impact on physical capital than both employment and wage in industry sectors, which is consistent with the main channel proposed by Faber (2014). In addition, columns (9) and (10) show that the highway network has no significant impact on a city's population, which is consistent with Faber (2014). This implies that the placement of the highway network had no significant impact on inter city migration in the priod 2000 - 2007.

1.8 Structural Estimation

In this section, I first extend the simple version of my model in section 4 into one with N($\geq$ 4) and 1, the rest of the world, which can be subjected to real data. In theory, the only difference between the full-fledged model in this section and the one in section 4 is that I introduce roundabout production networks here to better fit the model.[29] Then, I quantify this model into (N =) 233 Chinese cities plus 1 region representing the rest of the world (ROW). All 234 locations can trade with each other. Both internal (between cities) and international (the city and the rest of the world) migration are not allowed. In the rest of this section, I put the geographic structure, population data and income data together to calibrate and estimate the parameters of the model.

1.8.1 The Full Fledge Model

The model in this section extends the simple version of the model in section 4 by including the roundabout production network to better fit the data. This means that the local production of each stage uses a composite factor, comprising of both labour and an aggregator of final-good varieties that corresponds to the CES aggregato. In other words, part of the final-good production is not absorbed by consumers, but rather local producers use them as intermediate goods. Specifically, for the cost of this composite factor to be c_i for region or city i I need a Cobb-Douglas aggregator:

$$c_i = w_i^{\gamma_{k(i)}} P_i^{1-\gamma_{k(i)}}$$

where $k(i) \in \{C, r\}$ and I allow $\gamma_{k(i)}$ to represent locations within or outside China. $k(i) = C$ if locations are cities inside China. I will use this composite cost of unit production to replace the unit cost of wage as in the previous model.

According to the share of GVCs in section 4.1, the final-goods share of location i can be given:

$$\pi_{ij}^F = \frac{\sum_n (T_n c_n^{-\theta})^{\alpha_1 \beta_1} (T_j c_j^{-\theta})^{\alpha_2 \beta_2} \kappa_{nj}^{-\beta_1 \theta} \kappa_{ij}^{-\theta}}{\Theta_i} w_i L_i$$

With the share of GVCs in section 4.1 and the expenditure share of final-goods, the intermediate-goods share of location i can be expressed as follows:

$$\pi_{ji}^X = \frac{\pi_{ji}^F \frac{1-\gamma_{k(i)}}{\gamma_{k(i)}} w_i L_i + \beta_1 \sum_n w_n L_n Pr(\Delta_{j \to i,n}) / \gamma_{k(n)}}{\sum_j \pi_{ji}^F \frac{1-\gamma_{k(i)}}{\gamma_{k(i)}} w_i L_i + \beta_1 \sum_j \sum_n w_n L_n Pr(\Delta_{j \to i,n}) / \gamma_{k(n)}}$$

[29]It is always possible to have a roundabout production networks in the simple model in this section, which will not overturn my basic results.

where $Pr(\Delta_{j\to i,n})$ refers to the share of trade flows from location j to i, which is used to produce final outputs to serve location n.

1.8.2 Quantifying the Structural Parameters

My parameter space contains the following structural parameters:

$$\{\alpha_2, \gamma_C, \gamma_r, \theta\}$$

And one location-stage-specific vectors $\{T_i\}, i \in \{1, 2.., 233, r\}$ and one origin-destination-specific matrix $\{\kappa_{ij}\}$. I calibrate some of the parameters based on the approaches in the literature, and estimate the rest with my structural model.

1.8.3 Calibration

θ is the critical parameter that affects $\kappa_{ij}^{-\theta}$, while the moments I use for our structural estimation in the following do not identify θ. I set θ to be equal to 5 as in the literature according to Antràs and de Gortari (2017); Eaton and Kortum (2002).

The bilateral trade costs of location i within China and any location j is defined as:

$$\kappa_{ij} = \tau_{ij} d_{ij}.$$

where τ_{ij} is the transportation costs are derive from the highway network, and d_{ij} captures the trade friction that is not affected by the highway network. Specifically, I parameterise this trade friction as follows:

$$d_{ij} = \begin{cases} 1, j \neq r \\ d_{ir}, j = r \end{cases}$$

where $d_{ir}(= d_{ri})$ captures the trade friction away from highway network between location i and the rest of the world. This trade cost between a Chinese city and the rest of the world captures the effects from location-specific import and export tariff, subsidies from local governments and location specific international trade policies etc.

The motivation to decompose international trade friction is two-folds: first, the highway network only partially captures the international trade costs between a city in China with the rest of the world. If I only use the driving hours between location i and the rest of the world to measure the full international trade cost, this may lead me to underestimating the actual trade friction between this location and the rest of the world. Then, some cities inside China may receive subsidies from the local government to increase international trade value as a means to promote local economy growth. Whether or not a city receives subsidies from local or central government and the size of these subsidies may not depend on the driving hours from this city to the nearest international port. Table (1.6) shows us the ratio between a city's import value and its gdp and the ratio between a city's export value and its gdp. This table shows that the ratio between import or export values and local gdp is at least twice larger for targeted cities than non-targeted cities.

Table 1.6: The ratio between International trade and local GDP

Variable	Obs	Mean	Std	Min	Max	target	Year
$\frac{ex_i^X+ex_i^F}{gdp_i}$	53	0.0173	0.0166	0.0011	0.0812	Yes	2000
$\frac{ex_i^X+ex_i^F}{gdp_i}$	180	0.0078	0.0223	0.0000	0.2428	No	2000
$\frac{im_i^X+im_i^F}{gdp_i}$	53	0.0127	0.0180	0.0005	0.1052	Yes	2000
$\frac{im_i^X+im_i^F}{gdp_i}$	180	0.0055	0.0199	0.0000	0.2106	No	2000
$\frac{ex_i^X+ex_i^F}{gdp_i}$	53	0.0235	0.0237	0.0021	0.1218	Yes	2006
$\frac{ex_i^X+ex_i^F}{gdp_i}$	180	0.0116	0.0237	0.0000	0.1620	No	2006
$\frac{im_i^X+im_i^F}{gdp_i}$	53	0.0159	0.0208	0.0005	0.1022	Yes	2006
$\frac{im_i^X+im_i^F}{gdp_i}$	180	0.0076	0.0194	0.0000	0.1658	No	2006

The bilateral trade costs of location i and location j (τ_{ij}) is identified from the highway and local road network in 2000 as in my reduced form estimation and the iceberg trade cost between city i and city j. I also calibrate the size of each city inside China to its actual population in 2000.

1.8.4 Estimation

Having pinned down the matrix of trade cost $\tau_{ij}^{-\theta}$, market size L_i, I jointly estimate the remaining parameters, $\{\alpha_2, d_{ir}, \gamma_C, \gamma_r, T_i\}$ by targeting specific moments derived from the Chinese Trade dataset via the generalized method of moments (GMM) with Particle Swarm Optimization Algorithm, which helps me to find the global optimal. The parameters to be estimated by GMM is summarized as:

$$\Theta = \{d_{ir}, T_1, ..., T_{N+1}, \alpha_2\}$$

where τ_{cw} is China's international trade cost, $T_j^{(i)}$ is the productivity of region j of stage i, α_2 measures the importance of stage 1 production, and N + 1 represents N cities and one rest of the world.

My estimation strategy is to find the vector $\hat{\Theta}$ such that

$$\hat{\Theta} = argmin_{\Theta}[S - S(\hat{\Theta})]\hat{W}[S - S(\hat{\Theta})]'$$

In benchmark case, I assume the weighting matrix equals identity matrix

$$W = I$$

S is a vector of data moments that we explain in detail later in this section, $S(\theta)$ is the counter-part moments generated by the model, which depends on the input parameter θ, and Wc is the weighting matrix. The model is computationally heavy to evaluate, because I have 2 production stages and 234 locations, which means that I need to evaluate $12812904 (= 234^3)$ possible production chains. Therefore, I use an iterative particle swarm optimization (PSO) algorithm to take advantage of large scale parallel computing power in solving this minimization problem. I provide the details of our algorithm in the appendix.

These moments include: (i) the ratio between the sum of the imports and exports of intermediate-goods and local gdp ($\frac{im_i^X + ex_i^X}{w_i L_i}$); (ii) the ratio between the sum of the imports and exports of final-goods and local gdp ($\frac{im_i^F + ex_i^F}{w_i L_i}$); (iii) any city i's income share of all the cities in the sample ($\frac{w_i L_i}{\sum_j w_j L_j}$).

The motivation for targeting these sets of moments are the following. First, the income share across different cities is to capture the productivity across different cities (T_i). Then, I allow the value-added share of production for cities in China (γ_C) and the rest of the world (γ_r) to be different, which can be identified by the ratio between intermediate-goods trade and local gdp and the ratio between final-goods trade and local gdp. Due to China's processing trade policy, the processing exporter in China may rely heavily on imported intermediate goods to produce their products, which may result in relatively low value-added in China's products. Third, the ratio between international trade values and GDP, either for intermediate goods or final goods, across different cities, helps identify the part of a city's foreign trade costs not driven by the highway network.

1.8.5 Estimation Results

Now I turn to discussing the estimation results of the overall model. The differences between intermediate-goods trade and final goods trade regarding gdp result in an estimate of α_2 much smaller than one. In my estimation with only the international trade data, I obtain $\alpha_2 = 0.34$. The estimated variables for the share of composite factors used γ_C, γ_R, the productivity vector of a city's border costs with the rest of the world are shown in Tables (1.26) and (1.27).

Table 1.7: Estimated Parameters

Variable	α_2	γ_C	γ_R	$\frac{\sum_{i \neq r} T_i}{N}$	T_r	$\frac{\sum_{i \neq r} d_{ir}}{N}$
	0.34	0.31	0.61	78.9	100.63	1.29

Table (1.24) compares the data and the targeted moments in each quantile. The value for the ratio between intermediate-goods trade and gdp ($\frac{ex_i^X + im_i^X}{gdp_i}$) and the ratio between final-goods trade and gdp ($\frac{ex_i^F + im_i^F}{gdp_i}$) are estimated with a relatively high accuracy, with correlation equal to 95% and 90% with their empirical counter-parts, respectively. The way gdp share fits ($\frac{gdp_i}{\sum_{i \neq r gdp_i}}$) is also satisfactory (the correlation with empirical counterpart is 0.8), but with some discrepancies with the empirical counterpart.

Table (1.25) compares the results of the model with the data on moment conditions that are not directly targeted. The first two rows present the comparison of a city's trade share across all the cities. Those values are also matched relatively accurately in this case, with an 0.80 correlation. The third to tenth row report the comparison of export share in intermediate-goods, total export share, import share in intermediate-goods and total import share. All of these groups attain a good comparison with their empirical counterparts, with correlations of 0.80, 0.75, 0.81 and 0.80, respectively.

As I have mentioned in section 8.3, the bilateral trade costs arising from the highway network may not fully capture the actual trade cost between a city and foreign markets. Table (1.8) presents the results of regressing this extra trade cost for the city on some city variables. To run this regression, I have chosen variables such as whether a city is a targeted city, its distance to the nearest port, its distance to the nearest targeted cities, city-level productivity and education level. Columns (1) - (6) in this table indicate that only the dummy for targeted cities and the distance to the nearest targeted cities significantly correlate with this trade cost, which indicates that this estimated trade cost may capture special treatments such as beneficial policies, trade subsidies etc, granted by the government to promote international trade.

Table 1.8: The Trade Cost d_{ir} between a City and the Foreign Market

	(1)	(2)	(3)	(4)	(5)	(6)
	$border_{ir}$	$border_{ir}$	$border_{ir}$	$border_{ir}$	$border_{ir}$	$border_{ir}$
Targeted	-0.145***					-0.165***
	(0.0339)					(0.0491)
$ln(FMA_{i,2000})$		0.327				0.618
		(0.366)				(0.406)
$ln(dist_{i-targeted})$			0.0143**			-0.000457
			(0.00708)			(0.0104)
$ln(TFP_{i,2000})$				-0.0161		0.00875
				(0.0236)		(0.0232)
$ln(edu_{i,2000})$					-0.00246	0.0266
					(0.0574)	(0.0628)
R^2	0.0670	0.00354	0.0184	0.00251	0.00000804	0.0955

Robust standard errors in parentheses and number of observation 233
'Targeted' is a dummy for targeted cities, '$ln(dist_{i-targeted})$' measures the distance to the nearest targeted cities, '$ln(TFP_{i,2000})$' measures city i's manufacturing TFP in year 2000
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.8.6 Counterfactual: 2006 Highways

After estimating the key parameters of my full-fledge model, I next explore how counterfactual reduction in trade costs by replacing the highway network in 2000 with the highway network in 2006, holding other parameters constant, alter a city's demand for intermediate goods and final goods, thereby affecting the real income and positioning of countries in GVCs.

The aggregate and distributional effect on real income of highway construction

The real income for location i is defined as:

$$w_i^{real} = \frac{w_i}{P_i} = (\frac{c_i^\theta}{\Theta_i})^{\frac{1}{\gamma_{k(i)}\theta}}$$

In measuring the real-wage gain from trade liberalization, I take the difference of real wages between two periods and divide this difference by the adjusted real wage implied by the highway network in 2006:

$$\frac{\hat{w}_i^{real} - w_i^{real}}{\hat{w}_i^{real}}$$

where $\hat{w}_i^{real}$ is the real wage if I replace the highway network in 2000 with the one in 2006 while keeping other parameters constant.

For the sample of cities in my estimation, the gains from the highway network in 2006 range from a value of 4.2% percent for the ShiYan city in Hubei Province to 26.7% percent for MaoMing in Guangdong province. By calculating the real-wage growth average weighted by city' population, the aggregate real-wage growth is around 10.6%.

How important is sequential production in affecting the gain from real wages and the distribution of real-wage growth under trade cost reduction? One important factor is the share of intermediate-goods in final consumption, which is measured by α_2. The lowerα_2 suggests a greater importance of upstream intermediate goods in producing final goods and a trade cost elasticity of intermediate goods.

Table (1.9) shows us the welfare gain and its distribution across different cities after the highway's construction with different α_2. If α_2 is lower, the aggregate growth of welfare is much higher with highway construction. This is because local firms react more strongly in sourcing upstream intermediate goods to highway construction. On the other hand, lower α_2 may also result in higher dispersion in welfare, which implies that inequality across cities is much greater. This is because allowing firms to better adjust their intermediate goods used in final-good production amplifies the effect of trade cost on welfare. Cities receiving larger reductions in trade costs with domestic or foreign markets, may benefit more from highway construction. Another issue worthy of our attention is that migration is not allowed due to the *hukou* policy friction, which means that people can not migrate from one city to another to arbitrage away real wage difference. This also contributes to greater inequality across cities with lower α_2.

China's integration with the rest of the world

A city's import and export upstreamness To resonate my reduced-form results on a city's value-added share in its exports, I revisit the impact of the highway network on a city's participation in GVCs. I do so by replicating my reduced-form exercise using a city's export and import upstreamness derived by the model to

Table 1.9: The real wage gain and dispersion with different

α_2	0.7	0.5	0.34	0.3	0.2	0.1
$\frac{\hat{w}_A^{real} - w_A^{real}}{\hat{w}_A^{real}}$	0.09	0.10	0.11	0.13	0.14	0.16
$\frac{\sigma_{\hat{w}_A^{real}} - \sigma_{w_A^{real}}}{\sigma_{\hat{w}_A^{real}}}$	0.10	0.10	0.13	0.15	0.17	0.18

$\sigma_{w_A^{real}}$ represents the dispersion of real wage across different cities.

measure its participation in GVCs. In particular, I use diff-in-diff to replicate the reduced form exercises

Table (1.10) shows us that a one standard deviation increase in the change of local market access is associated with a 0.6 standard deviation increase in the change in import upstreamness, while a one standard deviation increase in the change of foreign market access is associated with a 0.7% standard deviation decrease in the change of export upstreamness and a 0.44% standard deviation decrease in the change of import upstreamness. These results are consistent with the results in my reduced form results.

Table 1.10: The impact of trade cost reduction on a city's participation in DVCs and GVCs

	(1)	(2)	(3)	(4)	(5)
	ΔU_i^x	ΔU_i^m	$\Delta DVCs_i$	$\Delta GVCs_i$	$\Delta(DVCs_i + GVCs_i)$
$ln(\Delta LMA_i)$	0.0038	0.0234***	0.0030**	0.0013	0.0032**
	(0.0026)	(0.0053)	(0.0001)	(0.00003)	(0.0001)
$ln(\Delta FMA_i)$	-0.774***	-0.223**	0.0213	0.0081**	0.0294
	(0.0544)	(0.0716)	(0.0015)	(0.00025)	(0.00167)
Cons.	-0.0221	-0.150***	-0.0021**	-0.0001	-0.0022**
	(0.0181)	(0.0362)	(0.0007)	(0.0002)	(0.0008)
R^2	0.895	0.330	0.207	0.0478	0.202

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

So what is the effect of highway construction on China's aggregate export and import upstreamness? The results show that after replacing the highway network in 2000 with the one in 2006, China's import upstreamness increased by around

1%, which explains around 20% of the aggregate trend in real data. In addition, the model shows that before and after highway construction, the decreases in aggregate export upstreamness is 0.4%.

A city's prevalence in Domestic Value Chains and Global Value Chains

The estimated model allows me to calculate a city's participation in domestic value chains (DVCs) and global value chains (GVCs) in serving the foreign markets, which are not directly observed in the data. City i's participation in DVCs simply explains, in combining with value-added from other cities, how much city i's value-added contributes to final demand in foreign markets. I capture this effect using the following expression:

$$DVCs_i = \sum_j (\alpha_1 \beta_1 \pi_{l(i,j,r)} + \alpha_2 \beta_2 \pi_{l(j,i,r)})$$

where $l(j, i, r)$ captures the production process of sourcing upstream products from location j, producing final products in location i and consuming these final products in the rest of the world.

City i's participation in GVCs simply explains, in combining with value-added from foreign markets, how much city i's value-added contributes to final demand in foreign markets. I capture this effect using the following expression:

$$GVCs_i = \alpha_1 \beta_1 \pi_{l(i,r,r)} + \alpha_2 \beta_2 \pi_{l(r,i,r)}$$

An important caveat is that, due to the use of a bundle of materials at each stage, what a location contributes to final demand for the rest of the world embody value-added in other locations.

Table (1.10) shows that a one standard deviation increase in change in local market access is associated with a 4% increase in participation in DVCs, while a one standard deviation increase in the change in foreign market access is associated with a 2% increase in participation in GVCs.

So, what is the impact of highway construction on the aggregate participation in either DVCs or GVCs in serving foreign markets? The results show that, after replacing the highway network in 2000 with the one in 2006, while keeping other parameters unchanged, the participation in DVCs increases by around 1.9%, and the effect on participation in GVCs is -1.3%. These results are consistent with the fact that highway construction tends to raise the value-added in China's gross exports.

1.9 Conclusion

This paper incorporates within-country geography into a trade model pioneered by Antràs and de Gortari (2017). The tractability of the GVC distribution in this paper's theoretical model allows the following predictions: a region's proximity to domestic markets enhances its participation in GVCs, while its proximity to foreign markets may weaken its participation. In addition to the trade model, this paper also uses a novel time-varying instrumental highway network to reveal the impact of the dramatic expansion of China's highway system during the period from 2000 to 2006 on its participation in GVCs.

To the best of my knowledge, this paper is the first to emphasize the importance of transportation infrastructure for the source location of firms' intermediategoods. This key piece of the puzzle cannot be overlooked if one wants to explain a country's participation in GVCs. Incorporating the process through which a firm sources its intermediate goods enables a better understanding of the role of intranational trade integration on a country's international trade integration. It also contributes to the recent debate on why China's domestic value-added in exports has increased under rising globalization (Brandt and Morrow, 2017; Koopman et al., 2014).

The application of this paper's frameworks can go beyond the effect of the recent expansion of China's highway network on its GVC participation. Future research can extend the current model to incorporate labour migration and agglomerationâthis was not a focus of the paper since tight migration restrictions during the studied period limited the role of the highway network regarding labour mobility. China has gradually relaxed its restrictions on migration and experienced massive intra-national migration, from the rural west to the east coast, in recent periods. How has the relaxation of migration friction in recent decades contributed to the rising importance of domestic value-added in exports? How would a city's position in GVCs be affected due to the expansion of the highway network? How did highway network or other transportation infrastructure contribute to local welfare, if it is much easier for people in China to move from one place to another?

1.10 Appendix

1.10.1 A region's Import and Export Value

Import and Export Value of different stages By listing all the possible value chain in table 3, the import value of products from stage 1 or 2 is by summing up all the possible values:

$$im_1^{(1)} = \beta_1 \sum_{k=1}^{N+1} Pr(\Lambda^1_{r\to 1}, k)(w_k L_k) = \beta_1 (\sum_{i=1}^{N+1} \frac{w_i L_i}{\Theta_i} \tau_{i1}^{-\theta})(T_1 w_1^{-\theta})^{\alpha_2\beta_2}(T_r w_r^{-\theta})^{\alpha_1\beta_1}\tau_{1r}^{-\beta_1\theta}$$

$$im_1^{(2)} = \beta_2 Pr(\Lambda^2_{r\to 1}, 1)(w_1 L_1) = \beta_2 \frac{w_1 L_1 \tau_{1r}^{-\theta}}{\Theta_1}(\sum_{i=1}^{N+1}(T_i w_i^{-\theta})^{\alpha_1\beta_1}(T_r w_r^{-\theta})^{\alpha_2\beta_2}\tau_{ir}^{-\beta_1\theta})$$

where $im_1^{(1)}$ and $im_1^{(2)}$ represent the import value of region 1 for stage 1 and 2, respectively; I use N + 1 and r to index the rest of the world interchangeably

where $Pr(\Lambda^2_{r\to 1}, 1)$ is the probability of importing of region 1 from the rest of the world for the second stage or final consumption and $Pr(\Lambda^2_{r\to 1}, 1)$ is the probability of importing of region 1 from region 4 for the first stage, serving region k.

Given that the assumption that 're-import' from the rest of the world to regions in China is not allowed, the total export value of stage 1 and 2 for region 1 are given by:

$$ex_1^{(1)} = \beta_1 Pr(\Lambda^1_{1\to r}, r)(w_r L_r) = \beta_1 \frac{w_r L_r}{\Theta_r}(T_r c_r^{-\theta})^{\alpha_2\beta_2}(T_1 c_1^{-\theta})^{\alpha_1\beta_1}\tau_{1r}^{-\beta_1\theta}$$

$$ex_1^{(2)} = \beta_2 Pr(\Lambda^2_{1\to r}, 1)(w_r L_r) = \beta_2 \frac{w_r L_r \tau_{1r}^{-\theta}}{\Theta_4}(\sum_{i=1}^{N}(T_1 c_1^{-\theta})^{\alpha_2\beta_2}(T_i c_i^{-\theta})^{\alpha_1\beta_1}\tau_{1i}^{-\beta_1\theta})$$

where $ex_1^{(1)}$ and $ex_1^{(2)}$ represent the export value of region 1 for stage 1 and 2, respectively.

1.10.2 Proof of Corollary

Proof of Corollary 1 Given a region's domestic value-added content in its export:

$$\begin{aligned}
D_i^{ex} &= 1 - \frac{(1-\alpha_2\beta_2)(T_r w_r^{-\theta})^{\alpha_1\beta_1}[(T_i w_i^{-\theta})^{\alpha_2\beta_2}(\tau_{ir})^{-(\beta_1+1)\theta}]}{ex_i^{(1)} + ex_i^{(2)}} \\
&= 1 - (U_i^x - 1)\frac{(1-\alpha_2\beta_2)(T_r w_r^{-\theta})^{\alpha_1\beta_1}[(T_i w_i^{-\theta})^{\alpha_2\beta_2}(\tau_{ir})^{-(\beta_1+1)\theta}]}{ex_i^{(1)}} \\
&= 1 - \alpha_1 \tau_{ir}^{-\theta}(U_i^x - 1)(\frac{T_r w_r^{-\theta}}{T_i w_i^{-\theta}})^{\alpha_1\beta_1 - \alpha_2\beta_2}
\end{aligned}$$

Proof of Corollary 2 From the third implication of my simple model, I define the ratio between ordinary and processing export in my model as the ratio of export value in second stage between using intermediate-goods from domestic markets and from foreign markets.

With this definition and equation (1.3), the ratio between ordinary and processing export in my model becomes:

$$
\begin{aligned}
R_i^x &= \frac{(T_r w_r^{-\theta})^{\alpha_1\beta_1}[(T_i w_i^{-\theta})^{\alpha_2\beta_2}(\tau_{ir})^{-(\beta_1+1)\theta}]}{\sum_{j\neq r}(T_j w_j^{-\theta})^{\alpha_1\beta_1}(T_i w_i^{-\theta})^{\alpha_2\beta_2}(\tau_{ij})^{-\beta_1\theta}\tau_{ri}^{-\theta}} \\
&= \frac{2-U_i^x}{U_i^x-1}\beta_1\left(\frac{T_i w_i^{-\theta}}{T_r w_r^{-\theta}}\right)^{\alpha_1\beta_1-\alpha_2\beta_2}\tau_{ir}^{\theta}-1
\end{aligned}
$$

1.10.3 Summery Statistics, Main Results and Road Atlas

Table 1.11: Summary Statistic for Export Share

Year	min	p25	mean	p50	max	sd	N
2000	0.0000	0.0000	0.0064	0.0003	0.9884	0.0260	14354
2001	0.0000	0.0000	0.0064	0.0003	0.9710	0.0257	14468
2002	0.0000	0.0000	0.0063	0.0003	0.9693	0.0256	14800
2003	0.0000	0.0000	0.0058	0.0002	0.9724	0.0237	15651
2004	0.0000	0.0000	0.0057	0.0002	0.9812	0.0244	16279
2005	0.0000	0.0000	0.0056	0.0002	0.9355	0.0238	16699
2006	0.0000	0.0000	0.0053	0.0002	0.8352	0.0222	17295
Total	0.0000	0.0000	0.0059	0.0002	0.9884	0.0244	109546

Table 1.12: Summary Statistic for Import Share

Year	min	p25	mean	p50	max	sd	N
2000	0.0000	0.0000	0.0071	0.0002	0.7561	0.0314	13074
2001	0.0000	0.0000	0.0071	0.0002	0.7226	0.0311	13124
2002	0.0000	0.0000	0.0070	0.0002	0.8865	0.0316	13259
2003	0.0000	0.0000	0.0068	0.0002	0.7538	0.0309	13757
2004	0.0000	0.0000	0.0067	0.0002	0.9514	0.0309	13927
2005	0.0000	0.0000	0.0066	0.0002	0.8927	0.0300	14086
2006	0.0000	0.0000	0.0065	0.0001	0.8031	0.0301	14229
Total	0.0000	0.0000	0.0068	0.0002	0.9514	0.0309	95456

Table 1.13: Summary Statistics of the Main Variables in the Data for year 2000 and 2006

	Year: t = 2000				Year: t = 2006			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
$ln(LMA_{i,t})$	5.30	1.61	0.10	9.37	5.76	1.73	0.20	9.54
$ln(FMA_{i,t})$	0.49	0.08	0.29	0.63	0.52	0.06	0.34	0.63
$ln(LMA^{iv}_{i,t})$	-3.55	0.84	-6.38	-0.71	-3.52	0.85	-6.28	-0.26
$ln(FMA^{iv}_{i,t})$	0.47	0.10	0.22	0.63	0.51	0.06	0.34	0.63
$ln(TFP_{i,t})$	0.83	0.69	-3.02	2.84	0.96	0.53	-0.98	2.38
$ln(population^{den}_{i,t})$	5.46	1.21	0.55	7.80	5.46	1.23	0.58	7.78
$U^{x}_{i,2000}$	3.58	0.69	1.47	5.51	3.61	0.60	2.25	5.51
$U^{m}_{i,2000}$	3.70	0.83	0.90	6.09	3.98	0.75	2.04	6.04
$ln(Tariff^{im}_{i,2000})$	2.35	0.11	1.77	2.89	1.76	0.09	1.14	2.14
$V^{x}_{i,t}$	1.41	2.06	0.02	17.88	1.31	1.85	0.08	21.32
$ln(edu_{i,t})$	1.56	0.24	1.01	2.31	1.72	0.25	1.04	2.41
$ln(Labor_{i,t})$	5.81	0.71	2.77	8.04	5.83	0.70	2.87	8.07
$ln(wage_{i,t})$	2.02	0.36	1.28	3.42	2.65	0.24	2.05	3.38
$gdp^{first}_{i,t}$	22.26	11.80	0.38	61.24	16.97	10.30	0.12	61.94
$gdp^{third}_{i,t}$	35.48	7.53	8.55	71.67	36.40	8.50	9.87	70.91
N	280				280			

Table 1.14: Summary Statistics of the Main Variables in the Data from year 2000 to 2006

	Year: $2000 \leq t \leq 2006$			
	Mean	S.D.	Min	Max
$ln(LMA_{i,t})$	5.52	1.70	0.10	9.54
$ln(FMA_{i,t})$	0.51	0.07	0.29	0.63
$ln(LMA^{iv}_{i,t})$	-3.54	0.84	-6.38	-0.26
$ln(FMA^{iv}_{i,t})$	0.49	0.09	0.22	0.63
$ln(TFP_{i,t})$	0.88	0.60	-3.02	2.88
$ln(population^{den}_{i,t})$	5.46	1.23	0.50	11.85
$U^{x}_{i,t}$	3.61	0.65	1.47	5.51
$U^{m}_{i,t}$	3.80	0.78	0.90	6.09
$ln(Tariff^{im}_{i,t})$	1.96	0.25	0.86	2.90
$ln(V^{x}_{i,t})$	1.43	2.25	0.02	27.67
$ln(edu_{i,t})$	1.65	0.26	0.44	3.49
$ln(Labor_{i,t})$	5.81	0.70	2.77	8.07
$ln(wage_{i,t})$	2.29	0.37	1.27	5.22
$gdp^{first}_{i,t}$	19.58	11.02	0.12	61.94
$gdp^{third}_{i,t}$	36.20	7.83	3.59	71.67
N	1960			

Table 1.15: First Stage Regression Results of 2SLS

	(1) $ln(LMA_{i,t})$	(2) $ln(FMA_{i,t})$	(3) $ln(LMA_{i,t})$	(4) $ln(FMA_{i,t})$	(5) $ln(LMA^{tfp}_{i,t})$	(6) $ln(LMA^{tfp}_{i,t})$
$ln(LMA^{iv}_{i,t})$	0.258***	0.004*	0.259***	0.004**	0.447***	0.448***
	(0.083)	(0.002)	(0.083)	(0.002)	(0.122)	(0.122)
$ln(FMA^{iv}_{i,t})$	1.157	0.192***	0.981	0.186***	-1.378	-1.473
	(1.071)	(0.027)	(1.068)	(0.028)	(1.070)	(1.090)
$TFP_{i,t}$	0.022	-0.001	0.019	-0.001	0.006	0.004
	(0.040)	(0.001)	(0.040)	(0.001)	(0.037)	(0.037)
$ln(population^{den}_{i,t})$	0.093	-0.004*	0.095	-0.004*	0.087	0.087
	(0.113)	(0.003)	(0.115)	(0.003)	(0.108)	(0.109)
$ln(Tariff^{im}_{i,t})$	0.320	0.003	0.332*	0.003	0.423*	0.430*
	(0.196)	(0.004)	(0.200)	(0.004)	(0.249)	(0.251)
$V^x_{i,t}$	-0.013	-0.001	-0.008	-0.000	-0.016	-0.013
	(0.013)	(0.000)	(0.013)	(0.000)	(0.014)	(0.014)
$ln(edu_{i,t})$	-0.018	-0.004***	-0.020	-0.004***	-0.032	-0.033
	(0.051)	(0.001)	(0.051)	(0.001)	(0.048)	(0.048)
$ln(Labor_{i,t})$	-0.133	-0.004*	-0.141	-0.004*	-0.121	-0.125
	(0.100)	(0.002)	(0.104)	(0.002)	(0.116)	(0.118)
$Gdps_{i,t}$	0.001	0.000*	0.001	0.000*	0.002	0.002
	(0.003)	(0.000)	(0.003)	(0.000)	(0.002)	(0.002)
$U^x_{i,t}$			-0.063*	-0.002**		-0.035
			(0.033)	(0.001)		(0.033)
Cons.	4.091***	0.512***	4.420***	0.525***	2.001*	2.180*
	(1.125)	(0.026)	(1.167)	(0.028)	(1.138)	(1.186)
F	18.026	28.352	17.502	28.232	12.987	12.410
R^2	0.981	0.962	0.981	0.963	0.962	0.962

Robust standard errors in parentheses and the number of observation is 1300.

City-fixed effects and year-fixed effects are controlled. Targeted cities are removed from each of the regression.

In year t, $TFP_{i,t}$ represents city i's manufacturing productivity.$ln(population^{den}_{i,t})$ represents city i's population density, $ln(Tariff^{im}_{i,t})$ represents the import tariff of ordinary importers of city i

$V^x_{i,t}$ represents city i's export 'weight-to-value' ratio. $ln(edu_{i,t})$ represents city i's education level and $Gdps_{i,t}$ is city i's industrial production share

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.16: The impact of highway network on a city's GVCs participation

	(1) $U^x_{i,t}$	(2) $U^x_{i,t}$	(3) $U^m_{i,t}$	(4) $\Delta_{i,t}$	(5) $U^x_{i,t}$	(6) $U^x_{i,t}$	(7) $U^m_{i,t}$	(8) $\Delta_{i,t}$
$ln(LMA_{i,t})$	-0.057	-0.011	0.157**	0.159**	-0.300	0.421	1.055*	0.986*
	(0.040)	(0.044)	(0.077)	(0.078)	(0.234)	(0.376)	(0.597)	(0.592)
$ln(FMA_{i,t})$		-4.665***	-6.749*	-5.983*		-17.303**	-23.967*	-21.126*
		(1.744)	(3.545)	(3.524)		(8.450)	(12.287)	(12.206)
$TFP_{i,t}$	0.008	-0.009	-0.047	-0.045	-0.022	-0.071*	-0.086	-0.075
	(0.036)	(0.036)	(0.058)	(0.058)	(0.034)	(0.041)	(0.066)	(0.065)
$ln(population^{den}_{i,t})$	0.029	0.004	0.186	0.185	0.038	-0.084	0.002	0.016
	(0.110)	(0.107)	(0.232)	(0.232)	(0.111)	(0.119)	(0.273)	(0.268)
$ln(Tariff^{im}_{i,t})$	0.134	0.138	-1.874***	-1.897***	0.259	0.133	-1.829***	-1.851***
	(0.177)	(0.182)	(0.454)	(0.458)	(0.211)	(0.214)	(0.519)	(0.520)
$V^x_{i,t}$	0.077***	0.074***	0.019	0.007	0.071***	0.077***	0.028	0.016
	(0.016)	(0.016)	(0.019)	(0.020)	(0.015)	(0.016)	(0.022)	(0.022)
$ln(edu_{i,t})$	0.050	0.021	0.037	0.033	-0.019	-0.087	-0.060	-0.045
	(0.061)	(0.063)	(0.120)	(0.120)	(0.056)	(0.068)	(0.138)	(0.135)
$ln(Labor_{i,t})$	-0.178*	-0.197*	-0.260*	-0.228*	-0.185*	-0.139*	-0.194	-0.171
	(0.107)	(0.110)	(0.145)	(0.132)	(0.110)	(0.080)	(0.118)	(0.113)
$ln(wage_{i,t})$	-0.044	-0.051	-0.067	-0.058	-0.041	-0.101*	-0.147*	-0.131
	(0.039)	(0.038)	(0.075)	(0.075)	(0.038)	(0.056)	(0.084)	(0.083)
$Gdps_{i,t}$	0.000	0.001	0.002	0.002	0.003	0.007*	0.007	0.006
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.004)	(0.006)	(0.005)
$U^x_{i,t}$				-0.836***				-0.836***
				(0.075)				(0.078)
Cons.	4.953***	7.731***	10.998***	9.729***	6.550***	12.293***	15.425***	13.406**
	(1.143)	(1.503)	(3.056)	(2.995)	(2.154)	(3.789)	(5.596)	(5.601)
R^2	0.870	0.870	0.750	0.772	0.859	0.845	0.703	0.738
Estimation	OLS	OLS	OLS	OLS	IV	IV	IV	IV

Robust Standard errors in parentheses and number of observation is 1300.City-fixed effects and year-fixed effects are controlled. Targeted cities are removed from each of the regression.
In year t, $TFP_{i,t}$ represents city i's manufacturing productivity, $ln(population^{den}_{i,t})$ represents city i's population density, $ln(Tariff^{im}_{i,t})$ represents the import tariff of ordinary importers of city i
$V^x_{i,t}$ represents city i's export 'weight-to-value' ratio, $ln(edu_{i,t})$ represents city i's education level and $Gdps_{i,t}$ is city i's industrial production share.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.17: The impact of highway network on a city's domestic content in export

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$D^{ori}_{i,t}$	$D^{val}_{i,t}$	$D^{ori}_{i,t}$	$D^{val}_{i,t}$	$D^{ori}_{i,t}$	$D^{val}_{i,t}$	$D^{ori}_{i,t}$	$D^{val}_{i,t}$
$ln(LMA_{i,t})$	-0.009	0.002	-0.009	0.003	0.234**	0.273**	0.230**	0.268**
	(0.013)	(0.014)	(0.013)	(0.014)	(0.109)	(0.116)	(0.108)	(0.115)
$ln(FMA_{i,t})$	-0.998*	-1.329**	-0.919*	-1.227**	-5.454*	-6.338**	-5.220*	-6.068**
	(0.522)	(0.581)	(0.522)	(0.574)	(2.891)	(3.050)	(2.874)	(3.026)
$TFP_{i,t}$	0.011	0.011	0.011	0.011	0.005	0.005	0.007	0.007
	(0.013)	(0.013)	(0.013)	(0.013)	(0.011)	(0.012)	(0.011)	(0.012)
$ln(population^{den}_{i,t})$	-0.080	-0.103	-0.080	-0.104	-0.112	-0.144	-0.113	-0.145
	(0.115)	(0.115)	(0.113)	(0.113)	(0.116)	(0.118)	(0.114)	(0.115)
$ln(Tariff^{im}_{i,t})$	0.117	0.136	0.118	0.137*	-0.007	-0.010	-0.007	-0.010
	(0.079)	(0.083)	(0.079)	(0.083)	(0.087)	(0.095)	(0.087)	(0.095)
$V^x_{i,t}$	0.016**	0.019**	0.014	0.017*	0.011**	0.012**	0.007	0.008
	(0.008)	(0.009)	(0.009)	(0.009)	(0.005)	(0.006)	(0.005)	(0.006)
$ln(edu_{i,t})$	-0.049**	-0.033	-0.050**	-0.034	-0.055*	-0.058*	-0.052*	-0.056*
	(0.025)	(0.029)	(0.025)	(0.029)	(0.030)	(0.032)	(0.030)	(0.032)
$ln(Labor_{i,t})$	0.119	0.107	0.123	0.113	0.126	0.109	0.132*	0.116
	(0.073)	(0.069)	(0.075)	(0.071)	(0.077)	(0.073)	(0.079)	(0.076)
$ln(wage_{i,t})$	0.040***	0.037***	0.040***	0.038***	0.011	0.005	0.012	0.006
	(0.015)	(0.014)	(0.015)	(0.014)	(0.015)	(0.016)	(0.015)	(0.016)
$Gdps_{i,t}$	-0.001	-0.000	-0.001	-0.000	0.000	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$U^x_{i,t}$			0.023	0.030*			0.044**	0.050***
			(0.017)	(0.018)			(0.017)	(0.019)
Cons.	1.185	1.441	1.028	1.237	2.433	2.974*	2.127	2.621
	(1.008)	(1.013)	(1.020)	(1.020)	(1.640)	(1.707)	(1.641)	(1.704)
R^2	0.711	0.704	0.712	0.705	0.628	0.612	0.635	0.620
Estimation	OLS	OLS	OLS	OLS	IV	IV	IV	IV

Robust standard errors in parentheses and number of observation is 1300.City- and year-fixed effects are controlled, while targeted cities are removed in the regression.
In year y, $TFP_{i,t}$ represents city i's manufacturing productivity, $ln(population^{den}_{i,t})$ represents city i's population density, $ln(Tariff^{im}_{i,t})$ represents the import tariff of ordinary importers of city i.
$V^x_{i,t}$ represents city i's export 'weight-to-value' ratio, $ln(edu_{i,t})$ represents city i's education level and $Gdps_{i,t}$ is city i's industrial production share.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.18: The correlation between a City's Participation in GVCs and Highway Connection

	(1)	(2)	(3)	(4)
	$U^x_{i,t}$	$U^m_{i,t}$	$V^x_{i,t}$	$V^m_{i,t}$
$Connect_{i,t}$	0.146***	0.082**	0.202**	0.380**
	(0.031)	(0.038)	(0.099)	(0.164)
Cons.	3.523***	3.680***	1.442***	1.732***
	(0.046)	(0.057)	(0.129)	(0.202)
R^2	0.013	0.018	0.003	0.013

Standard errors in parentheses and there are 1300 observations.
Targeted cities are removed from the regression.
$Connect_{i,t}$ is a dummy variable, which is equal to 1 if
city i is reached by highway in year t.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.19: The impact of highway network on a city's export organization

	(1)	(2)	(3)	(4)	(5)	(6)
	$R^x_{i,t}$	$R^x_{i,t}$	$R^x_{i,t}$	$R^x_{i,t}$	$R^x_{i,t}$	$R^x_{i,t}$
$ln(LMA_{i,t})$	-0.001	0.0162	1.988*	1.917*	2.432*	2.364*
	(0.151)	(0.151)	(1.134)	(1.099)	(1.278)	(1.227)
$ln(FMA_{i,t})$	-2.680	-2.704	-20.960**	-20.350**	-25.030***	-24.700***
	(2.414)	(2.423)	(8.393)	(8.538)	(9.118)	(9.157)
$ln(TFP_{i,t})$	0.067	0.066	-0.054	-0.032	-0.008	-0.001
	(0.123)	(0.122)	(0.144)	(0.137)	(0.137)	(0.133)
$ln(population^{den}_{i,t})$	-1.790***	-1.867***			-2.365***	-2.379***
	(0.673)	(0.662)			(0.810)	(0.808)
$U^x_{i,t}$	-0.009	-0.054			0.053	-0.001
	(0.184)	(0.181)			(0.218)	(0.210)
$ln(Tariff^{im}_{i,t})$	0.712	0.789	-0.467	-0.561	-0.628	-0.602
	(0.820)	(0.836)	(0.841)	(0.819)	(0.923)	(0.911)
$V^x_{i,t}$	0.151***	0.148***			0.169***	0.165***
	(0.046)	(0.045)			(0.056)	(0.054)
$ln(edu_{i,t})$	0.209	0.205			0.225	0.221
	(0.205)	(0.184)			(0.240)	(0.214)
$ln(Labor_{i,t})$	0.167	0.155	0.479	0.460	0.288	0.263
	(0.239)	(0.227)	(0.450)	(0.430)	(0.394)	(0.370)
$ln(wage_{i,t})$	-0.013	-0.026			-0.194	-0.187
	(0.132)	(0.135)			(0.165)	(0.162)
$Gdps_{i,t}$	-0.001	-0.005			-0.013	-0.019
	(0.013)	(0.014)			(0.016)	(0.015)
Cons.	13.290**	13.790***	-3.145	-2.637	14.960*	15.630*
	(5.338)	(5.173)	(6.196)	(5.849)	(8.346)	(8.059)
R^2	0.714	0.712	0.609	0.615	0.595	0.601
Estimated	OLS	OLS	IV	IV	IV	IV
Weight	$ln(Labor_{i,t})$	No	$ln(Labor_{i,t})$	No	$ln(Labor_{i,t})$	No
Obs.	1380	1380	1300	1300	1300	1300

Robust standard errors in parentheses. In total, there are 1300 observations.City- and year-fixed effects are controlled, while targeted cities are removed in the regression.
In year y, $TFP_{i,t}$ represents city i's manufacturing productivity, $ln(population^{den}_{i,t})$ represents city i's population density.
$ln(Tariff^{im}_{i,t})$ represents the import tariff of ordinary importers of city i, $V^x_{i,t}$ is city i's export 'weight-to-value' ratio,$ln(edu_{i,t})$ represents city i's education level and $Gdps_{i,t}$ is city i's industrial production share
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.20: The Elasticity of International Trade with Traveling Hours to the Nearest Ports

$ln(Trade_{i,t})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ln(Hour_{ip,t})$	-1.294***	-0.477	-0.731***	-0.268**	-1.526***	-0.789**	-0.944***	-0.526***
	(0.212)	(0.343)	(0.085)	(0.105)	(0.213)	(0.338)	(0.089)	(0.111)
$ln(Hour_{ip,t}) \times Inter.$					0.291***	0.363***	0.314***	0.388***
					(0.041)	(0.048)	(0.037)	(0.044)
$ln(TFP_{i,t})$		0.132*		0.154**		0.130*		0.157**
		(0.079)		(0.075)		(0.078)		(0.073)
$ln(edu_{i,t})$		0.271		0.284		0.277		0.295
		(0.232)		(0.226)		(0.231)		(0.228)
$ln(population_{i,t}^{den})$		-0.229		-0.162		-0.168		-0.096
		(0.540)		(0.578)		(0.544)		(0.589)
$ln(wage_{i,t})$		0.694***		0.768***		0.684***		0.776***
		(0.190)		(0.156)		(0.185)		(0.156)
$ln(Labor_{i,t})$		0.275*		0.345**		0.259*		0.340*
		(0.147)		(0.172)		(0.149)		(0.174)
Cons.	16.088***	11.816***	14.854***	10.232**	16.207***	11.737***	14.900***	9.842**
	(0.464)	(3.770)	(0.185)	(4.023)	(0.460)	(3.761)	(0.187)	(4.081)
$Obs.$	25324	20680	28987	23823	25324	20680	28987	23823
adj. R^2	0.121	0.123	0.125	0.126	0.129	0.135	0.134	0.139
City-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Targeted Cities	No	No	No	No	No	No	No	No
Estimated	IV	IV	OLS	OLS	IV	IV	OLS	OLS

Robust Standard errors in parentheses. City-fixed effects and year-fixed effects are controlled. Targeted cities are removed from the regression.

In year y, $TFP_{i,t}$ represents city i's manufacturing productivity, $ln(population_{i,t}^{den})$ represents city i's population density. $ln(Tariff_{i,t}^{im})$ represents the import tariff of ordinary importers of city i, $V_{i,t}^{x}$ represents city i's export 'weight-to-value' ratio, $ln(edu_{i,t})$ represents city i's education level and $Gdps_{i,t}$ is city i's industrial production share.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.21: Sensitivity Test Using a different measure of 'Local Market Access'

	(1)	(2)	(3)	(4)	(5)	(6)
	$U^x_{i,t}$	$U^m_{i,t}$	$\Delta^x_{i,t}$	$D^x_{i,t}$	$D^{ori,x}_{i,t}$	$R^x_{i,t}$
$ln(LIMA_{i,t})$	0.236	0.646**	0.610*	0.222***	0.191**	1.473*
	(0.196)	(0.310)	(0.315)	(0.078)	(0.075)	(0.783)
$ln(FMA_{i,t})$	-4.587**	-4.933*	-4.223	-1.982***	-1.649**	-17.330***
	(1.790)	(2.682)	(2.714)	(0.685)	(0.681)	(6.200)
$ln(TFP_{i,t})$	-0.043	-0.031	-0.024	0.010	0.010	0.065
	(0.031)	(0.055)	(0.055)	(0.011)	(0.010)	(0.129)
$ln(population^{den}_{i,t})$	-0.108	0.211	0.228	-0.129	-0.102	-2.407***
	(0.113)	(0.237)	(0.237)	(0.110)	(0.110)	(0.702)
$ln(Tariff^{im}_{i,t})$	0.139	-1.761***	-1.783***	0.010	0.005	0.096
	(0.202)	(0.524)	(0.526)	(0.081)	(0.075)	(0.714)
$V^x_{i,t}$	0.076***	0.008	-0.003	0.010*	0.009*	0.150***
	(0.015)	(0.018)	(0.020)	(0.006)	(0.005)	(0.050)
$ln(edu_{i,t})$	-0.056	0.024	0.032	-0.046*	-0.043*	0.227
	(0.058)	(0.122)	(0.121)	(0.027)	(0.025)	(0.215)
$ln(Labor_{i,t})$	-0.174**	-0.249**	-0.222**	0.0856	0.102	0.300
	(0.078)	(0.120)	(0.113)	(0.065)	(0.068)	(0.376)
$ln(wage_{i,t})$	-0.073	-0.090	-0.079	0.017	0.025*	-0.029
	(0.044)	(0.081)	(0.082)	(0.013)	(0.013)	(0.150)
$gdp^{first}_{i,t}$	-0.008*	0.012*	0.014*	0.002	0.002	-0.012
	(0.004)	(0.007)	(0.007)	(0.002)	(0.002)	(0.014)
$gdp^{third}_{i,t}$	-0.001	-0.013**	-0.012**	-0.001	-0.001	-0.003
	(0.003)	(0.006)	(0.006)	(0.001)	(0.001)	(0.012)
$U^x_{i,t}$			-0.845***			
			(0.0801)			
Cons.	7.450***	9.859***	8.705***	1.631*	1.235	20.340***
	(1.482)	(2.680)	(2.711)	(0.971)	(0.980)	(6.566)
R^2	0.860	0.738	0.765	0.673	0.682	0.669
Estimated	IV	IV	IV	IV	IV	IV
Weighted	No	No	No	No	No	No
Obs.	1300	1300	1300	1300	1300	1300

Robust Standard errors in parentheses. City-fixed effects and year-fixed effects are controlled. Targeted cities are removed from each of the regression.
In year y, $TFP_{i,t}$ represents city i's manufacturing productivity, $ln(population^{den}_{i,t})$ represents city i's population density, $ln(Tariff^{im}_{i,t})$ represents the import tariff of ordinary importers of city i, $V^x_{i,t}$ represents city i's export 'weight-to-value' ratio, $ln(edu_{i,t})$ represents city i's education level and $Gdps_{i,t}$ is city i's industrial production share.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.22: The impact of highway network on industry production

	(1) $Indu_{i,t}^{share}$	(2) $ln(Indu_{i,t})$	(3) $Indu_{i,t}^{share}$	(4) $ln(Indu_{i,t})$	(5) $ln(GOV_{i,t})$	(6) $ln(GOV_{i,t})$	(7) $ln(GOV_{i,t})$	(8) $ln(GOV_{i,t})$
$ln(LMA_{i,t})$	-0.864	-0.061**	-10.100***	-0.460***	-0.036	-0.005	-0.280***	0.149
	(0.616)	(0.028)	(3.213)	(0.175)	(0.022)	(0.027)	(0.090)	(0.157)
$ln(FMA_{i,t})$	24.590**	1.256***	134.500***	4.988***		-0.905**		-7.521***
	(10.700)	(0.458)	(45.810)	(1.922)		(0.447)		(1.997)
$ln(TFP_{i,t})$	0.023	-0.053**	-0.386	-0.062**	-0.025	-0.022	-0.031	-0.009
	(0.602)	(0.024)	(0.604)	(0.024)	(0.032)	(0.032)	(0.029)	(0.030)
$ln(Labor_{i,t})$	2.703	0.664***	1.653	0.610***	-0.283***	-0.285***	-0.348***	-0.349***
	(1.861)	(0.160)	(1.387)	(0.113)	(0.076)	(0.074)	(0.084)	(0.070)
$ln(population_{i,t}^{den})$	4.546**	0.300***	6.907**	0.368***	0.082	0.064	0.069	-0.105
	(2.060)	(0.088)	(2.997)	(0.126)	(0.105)	(0.102)	(0.114)	(0.112)
$U_{i,t}^{x}$	-0.024	-0.024	0.262	-0.013	-0.063**	-0.065**	-0.071**	-0.080**
	(0.505)	(0.024)	(0.667)	(0.030)	(0.028)	(0.029)	(0.030)	(0.034)
$U_{i,t}^{m}$	0.046	0.002	0.232	0.008	0.008	0.008	0.003	-0.007
	(0.280)	(0.014)	(0.363)	(0.017)	(0.018)	(0.019)	(0.018)	(0.021)
$ln(Tariff_{i,t}^{im})$	-3.482*	-0.132	-0.459	0.048	0.127	0.113	0.161*	0.008
	(1.847)	(0.091)	(2.669)	(0.124)	(0.094)	(0.095)	(0.096)	(0.120)
$V_{i,t}^{x}$	0.131	0.006	-0.052	-0.002	0.004	0.003	-0.003	0.001
	(0.155)	(0.007)	(0.188)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)
$V_{i,t}^{m}$	-0.002	-0.001	0.008	-0.003	-0.005	-0.004	-0.004	-0.001
	(0.070)	(0.003)	(0.09)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
$ln(edu_{i,t})$	0.411	-0.002	1.681*	0.056	-0.058	-0.068	-0.051	-0.087
	(1.002)	(0.049)	(0.963)	(0.050)	(0.052)	(0.052)	(0.050)	(0.055)
R^2	0.941	0.980	0.198	0.832	0.822	0.824	0.159	0.0275
Obs.	1300	1300	1300	1300	1300	1300	1300	1300
City-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Targeted Cities	No	No	No	No	No	No	No	No
Estimated	OLS	IV	OLS	IV	OLS	OLS	OLS	OLS

Robust standard errors are in parentheses. City-fixed effects and year-fixed effects are controlled. Targeted cities are removed from the regressions.
In year y, $TFP_{i,t}$ represents city i's manufacturing productivity, $ln(population_{i,t}^{den})$ represents city i's population density, $ln(Tariff_{i,t}^{im})$ represents the import tariff of ordinary importers of city i, $V_{i,t}^{x}$ represents city i's export 'weight-to-value' ratio, $ln(edu_{i,t})$ represents city i's education level and $Gdps_{i,t}$ is city i's industrial production share.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.23: The impact of highway network on production factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$ln(wage_{i,t})$	$ln(employ_{i,t})$	$ln(cap_{i,t})$	lwagem	$ln(employ_{i,t})$	$ln(employ_{i,t})$	$ln(cap_{i,t})$	$ln(pop_{i,t})$	$ln(pop_{i,t})$
$ln(LMA_{i,t})$	0.064	0.088*	0.053	-0.397**	-0.149	-0.320**	-0.846***	0.022	0.049
	(0.052)	(0.049)	(0.052)	(0.189)	(0.180)	(0.127)	(0.299)	(0.039)	(0.038)
$ln(FMA_{i,t})$	-0.855	-2.534***	-1.525**	2.719	-2.651		1.408	0.540	
	(0.812)	(0.573)	(0.640)	(1.969)	(1.819)		(2.599)	(0.455)	
$ln(TFP_{i,t})$	-0.025	-0.083	-0.065	-0.035	-0.061	-0.057	-0.035	-0.007	-0.009**
	(0.036)	(0.097)	(0.106)	(0.039)	(0.102)	(0.098)	(0.117)	(0.004)	(0.004)
$ln(pop_{i,t}^{den})$	-0.364***	0.541***	0.058	-0.252*	0.710***	0.746***	0.291*	-0.059	-0.0634
	(0.106)	(0.171)	(0.156)	(0.145)	(0.123)	(0.126)	(0.172)	(0.108)	(0.109)
$U_{i,t}^{x}$	-0.0360	-0.080**	-0.014	-0.051	-0.021	-0.016	0.0511	-0.001	-0.005
	(0.037)	(0.034)	(0.037)	(0.040)	(0.026)	(0.027)	(0.045)	(0.005)	(0.004)
$U_{i,t}^{m}$	-0.021	-0.023	-0.054**	-0.001	0.005	0.008	-0.001	-0.004	-0.004
	(0.020)	(0.022)	(0.021)	(0.027)	(0.017)	(0.016)	(0.031)	(0.003)	(0.003)
$ln(Tariff_{i,t}^{im})$	0.489***	-0.192	0.0351	0.630***	-0.285*	-0.221	0.132	-0.005	-0.008
	(0.169)	(0.124)	(0.140)	(0.209)	(0.148)	(0.139)	(0.212)	(0.016)	(0.014)
$V_{i,t}^{x}$	0.001	-0.011	-0.019	-0.014	-0.013	-0.012	-0.035*	-0.001	-0.001
	(0.014)	(0.009)	(0.016)	(0.014)	(0.012)	(0.012)	(0.021)	(0.002)	(0.002)
$V_{i,t}^{m}$	0.0045	0.004	0.011**	0.006	-0.002	-0.003	0.004	0.001	0.000831
	(0.005)	(0.004)	(0.005)	(0.006)	(0.004)	(0.004)	(0.007)	(0.001)	(0.001)
$ln(edu_{i,t})$	-0.055	-0.200	-0.109	-0.045	-0.166	-0.157	-0.065	0.002	-0.005
	(0.080)	(0.127)	(0.126)	(0.083)	(0.109)	(0.115)	(0.119)	(0.008)	(0.008)
	(0.895)	(1.259)	(1.204)						
R^2	0.800	0.920	0.923	0.503	0.103	0.085	0.131	0.052	0.059
Obs.	1300	1300	1300	1300	1300	1300	1300	1300	1300
City-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Targeted Cities	No	No	No	No	No	No	No	No	No
Estimated	OLS	OLS	OLS	IV	IV	IV	IV	IV	IV

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.24: Model Fit of the Targeted Moments

Percen.	$\frac{\hat{ex}_i^X+\hat{im}_i^X}{\hat{gdp}_i}$	$\frac{ex_i^X+im_i^X}{gdp_i}$	$\frac{\hat{ex}_i^F+\hat{im}_i^F}{\hat{gdp}_i}$	$\frac{ex_i^F+im_i^F}{gdp_i}$	$\frac{\hat{gdp}_i}{\sum_{i\neq r}\hat{gdp}_i}$	$\frac{gdp_i}{\sum_{i\neq r}gdp_i}$
25%	0.0006	0.0010	4.56E-06	2.20E-05	5.65E-06	0.001664
50%	0.0030	0.0033	0.0004	0.0002	0.0015	0.0026
75%	0.0089	0.0086	0.0022	0.0008	0.0055	0.0047
80%	0.0107	0.0108	0.0030	0.0013	0.0078	0.0057
90%	0.0188	0.0188	0.0089	0.0046	0.0126	0.0099
95%	0.0393	0.0383	0.0209	0.0206	0.0157	0.0133
99%	0.1094	0.1105	0.0789	0.1479	0.0366	0.0273
$corr(y_i, \hat{y}_i)$	95%		90%		80%	

$corr(y_i, \hat{y}_i)$ measures the correlation between simulated data and real data

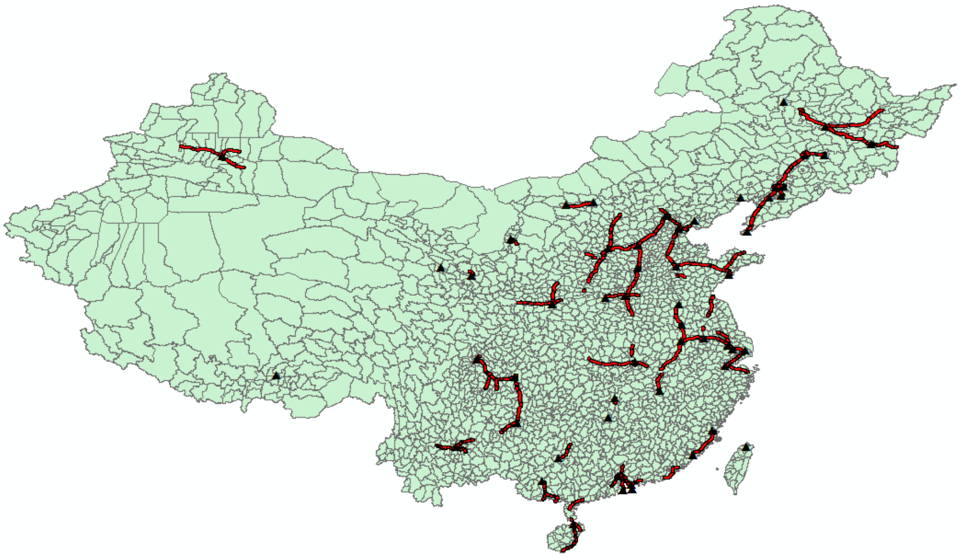

Figure 1.6: Highway Network in 1998

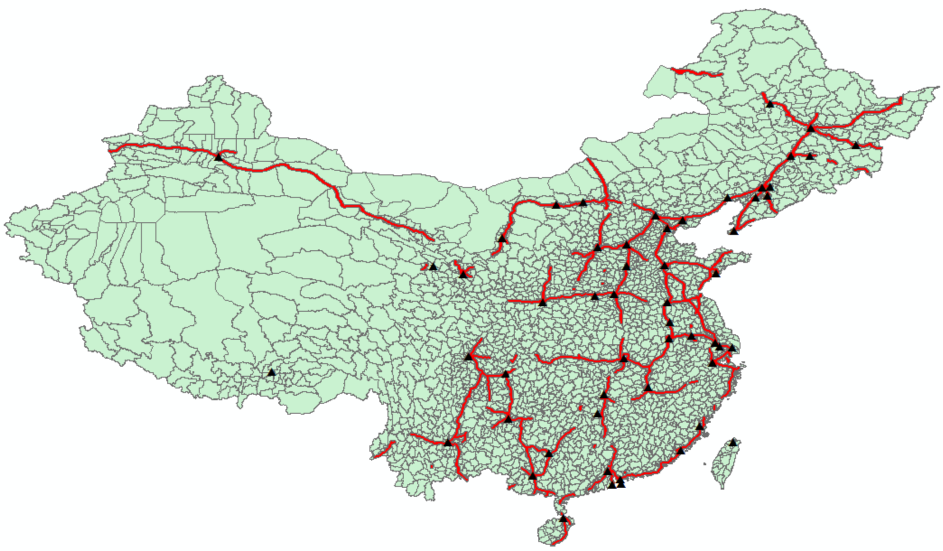

Figure 1.7: Highway Network in 2003

Table 1.25: Model Fit of Untargeted Moment

Percentile	25%	50%	75%	80%	90%	95%	99%	$corr(y_i, \hat{y}_i)$
$\frac{\hat{trade_i}}{\sum_{i \neq r} \hat{trade_i}}$	5.34E-07	0.0003	0.0021	0.0030	0.0086	0.0245	0.0722	80%
$\frac{trade_i}{\sum_{i \neq r} trade_i}$	8.96E-05	0.0003	0.0016	0.0024	0.0061	0.0205	0.1130	
$\frac{\hat{ex}_i^X}{\sum_{i \neq r} \hat{ex}_i^X}$	2.06E-07	0.0003	0.0022	0.0031	0.0085	0.0255	0.0735	80%
$\frac{ex_i}{\sum_{i \neq r} ex_i}$	0.0002	0.0005	0.0029	0.0035	0.0079	0.0224	0.0732	
$\frac{\hat{ex}_i}{\sum_{i \neq r} \hat{ex}_i}$	4.07E-07	0.0003	0.0022	0.0032	0.0084	0.0255	0.0733	75%
$\frac{ex_i}{\sum_{i \neq r} ex_i}$	0.0001	0.0004	0.0022	0.0028	0.0072	0.0230	0.0796	
$\frac{\hat{im}_i^X}{\sum_{i \neq r} \hat{im}_i^X}$	8.85E-07	0.0003	0.0020	0.0028	0.0089	0.0219	0.0814	81%
$\frac{im_i^X}{\sum_{i \neq r} im_i^X}$	3.41E-05	0.0002	0.0010	0.0017	0.0044	0.0174	0.1375	
$\frac{\hat{im}_i}{\sum_{i \neq r} \hat{im}_i}$	4.65E-07	0.0003	0.0020	0.0028	0.0088	0.0220	0.0817	80%
$\frac{im_i}{\sum_{i \neq r} im_i}$	3.57E-05	0.0003	0.0012	0.0017	0.0045	0.0169	0.1276	

For simplicity, $trade_i = ex_i^X + ex_i^F + im_i^X + im_i^F$, $ex_i = ex_i^X + ex_i^F$, $im_i = im_i^X + im_i^F$
$corr(y_i, \hat{y}_i)$ measures the correlation between simulated data and real data

Table 1.26: A city's productivity and border cost with the rest of the world (I)

city code	T_i	d_{ir}	city code	T_i	d_{ir}	city code	T_i	d_{ir}
1101	149.94	1.00	2203	52.74	1.42	3311	146.28	1.13
1201	67.14	1.14	2204	29.31	1.13	3401	8.16	1.05
1301	104.89	1.35	2205	47.66	1.33	3402	2.41	1.01
1302	134.01	1.44	2206	149.31	1.50	3403	149.65	1.50
1303	150.00	1.07	2207	119.47	1.49	3404	126.73	1.44
1304	94.80	1.46	2208	149.99	1.32	3405	0.22	1.38
1305	141.14	1.32	2301	145.15	1.31	3408	74.80	1.02
1306	7.57	1.32	2302	111.82	1.33	3410	149.54	1.00
1307	5.05	1.30	2303	144.65	1.44	3411	10.86	1.45
1308	146.72	1.45	2304	7.89	1.12	3412	93.84	1.00
1309	3.10	1.50	2307	71.83	1.05	3413	33.06	1.05
1310	16.04	1.50	2308	71.98	1.46	3415	121.77	1.50
1311	147.00	1.06	2309	0.01	1.00	3416	2.98	1.27
1401	22.19	1.02	2310	0.75	1.41	3418	110.97	1.14
1402	147.18	1.44	2311	1.41	1.43	3501	129.37	1.33
1403	113.80	1.50	2312	136.89	1.01	3502	140.55	1.11
1404	27.16	1.50	3101	93.55	1.08	3503	66.56	1.49
1405	147.60	1.48	3201	149.89	1.00	3504	60.61	1.16
1406	142.37	1.11	3202	14.54	1.40	3505	86.13	1.48
1407	141.21	1.49	3203	120.05	1.00	3506	149.98	1.50
1408	1.77	1.35	3204	149.50	1.23	3507	20.90	1.50
1409	40.99	1.50	3205	17.62	1.12	3508	39.11	1.03
1410	133.38	1.50	3206	10.83	1.23	3509	3.76	1.46
2101	133.71	1.44	3207	21.26	1.11	3601	146.94	1.02
2102	127.45	1.22	3208	25.73	1.30	3602	149.90	1.42
2103	49.50	1.50	3209	149.26	1.45	3603	1.99	1.22
2104	70.69	1.49	3210	147.80	1.45	3604	12.74	1.10
2105	149.71	1.45	3211	101.77	1.10	3605	75.99	1.28
2106	21.72	1.04	3212	6.01	1.50	3606	149.51	1.50
2107	112.01	1.37	3213	25.45	1.01	3607	6.08	1.48
2108	5.54	1.50	3301	28.40	1.15	3608	0.23	1.48
2109	99.53	1.05	3302	44.95	1.29	3609	93.64	1.02
2110	61.00	1.37	3303	142.24	1.00	3610	148.81	1.49
2111	145.68	1.49	3304	65.95	1.18	3611	13.09	1.48
2112	6.70	1.50	3305	47.53	1.33	3701	17.89	1.45
2113	64.93	1.18	3306	30.90	1.48	3703	12.37	1.50
2114	4.40	1.21	3307	22.14	1.49	3704	122.84	1.49
2201	148.93	1.49	3308	62.80	1.50	3706	148.27	1.49
2202	129.44	1.48	3310	146.12	1.01	3707	11.21	1.01

Table 1.27: A city's productivity and border cost with the rest of the world (II)

city code	T_i	d_{ir}	city code	T_i	d_{ir}	city code	T_i	d_{ir}
3708	149.04	1.45	4304	140.85	1.13	5103	55.60	1.48
3709	94.12	1.50	4305	0.04	1.09	5104	55.19	1.11
3710	19.14	1.50	4306	32.71	1.00	5105	149.92	1.48
3711	83.40	1.26	4307	4.90	1.37	5106	67.43	1.46
3712	84.99	1.50	4308	142.77	1.17	5107	140.03	1.50
3713	87.48	1.49	4309	2.54	1.26	5108	97.27	1.43
3714	21.61	1.45	4310	0.77	1.47	5109	2.81	1.49
3715	149.78	1.12	4312	86.36	1.47	5110	109.04	1.21
3716	149.98	1.22	4313	26.86	1.48	5111	85.19	1.01
4101	34.44	1.01	4401	0.68	1.40	5113	10.09	1.50
4102	149.51	1.50	4402	133.50	1.46	5114	149.98	1.16
4103	88.36	1.39	4403	142.73	1.02	5115	1.40	1.13
4104	0.03	1.21	4404	0.01	1.00	5116	127.39	1.44
4105	143.70	1.42	4405	0.09	1.49	5117	143.78	1.47
4107	26.74	1.09	4406	0.09	1.44	5120	0.37	1.43
4109	85.06	1.50	4408	10.22	1.22	5201	119.34	1.12
4110	149.98	1.49	4409	127.30	1.35	5202	49.09	1.18
4111	61.30	1.49	4412	111.69	1.13	5203	91.75	1.36
4112	144.01	1.04	4413	148.65	1.05	5204	126.61	1.50
4113	75.98	1.49	4414	150.00	1.48	5301	2.64	1.02
4114	120.34	1.05	4415	93.48	1.45	5303	65.40	1.15
4115	144.85	1.23	4416	149.34	1.40	5304	106.81	1.08
4116	149.47	1.02	4417	131.76	1.02	5305	20.63	1.19
4117	2.91	1.31	4418	46.78	1.43	6101	0.61	1.35
4201	135.90	1.00	4419	0.01	1.00	6102	0.14	1.41
4202	145.73	1.50	4420	13.46	1.10	6103	149.24	1.37
4203	147.70	1.10	4451	150.00	1.40	6104	142.65	1.43
4205	135.61	1.24	4452	146.19	1.29	6105	148.14	1.50
4206	44.49	1.44	4501	111.33	1.00	6106	0.23	1.46
4207	7.37	1.48	4502	148.58	1.01	6107	95.18	1.43
4208	11.54	1.50	4503	149.48	1.48	6108	149.78	1.03
4209	137.14	1.40	4504	19.06	1.36	6109	0.03	1.48
4210	136.98	1.34	4505	148.25	1.22	6201	110.01	1.07
4211	146.84	1.16	4506	3.02	1.05	6202	71.15	1.00
4212	82.14	1.50	4507	66.89	1.50	6203	11.10	1.43
4213	0.15	1.31	4508	12.22	1.45	6204	142.10	1.50
4301	8.17	1.44	4509	127.74	1.17	6205	0.32	1.05
4302	138.31	1.00	5001	147.86	1.02	6403	0.26	1.32
4303	34.78	1.50	5101	7.19	1.03			

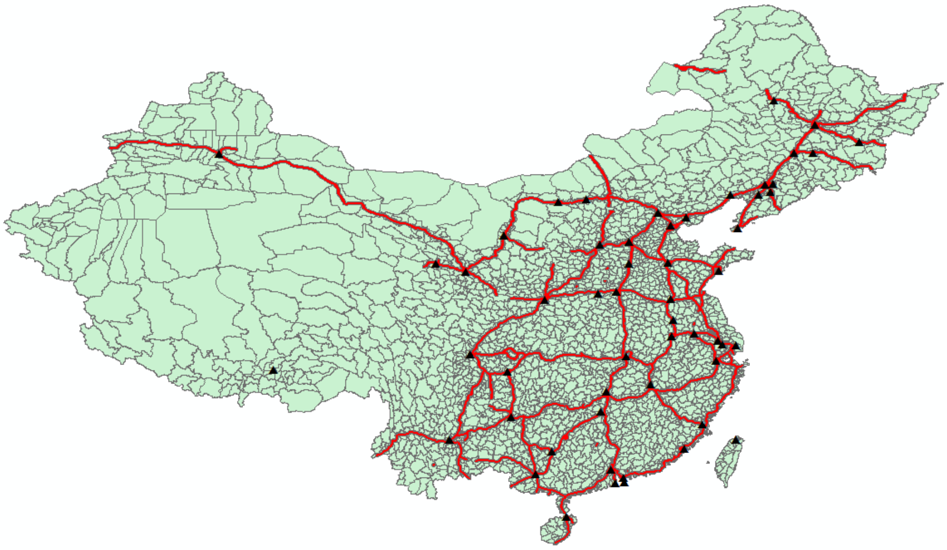

Figure 1.8: Highway Network in 2007

Figure 1.9: Instrumented Highway Network in 2000

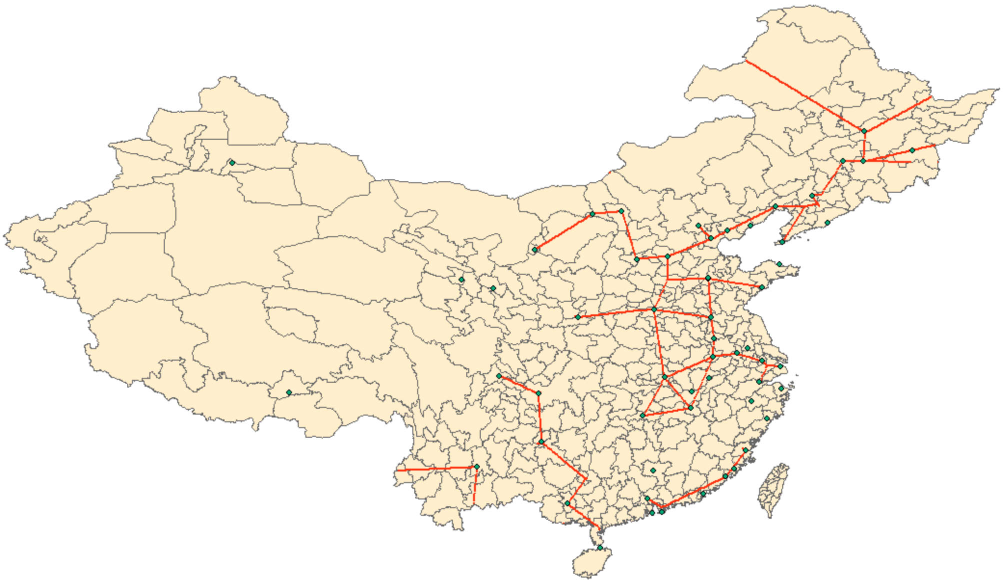

Figure 1.10: Instrumented Highway Network in 2003

Figure 1.11: Instrumented Highway Network in 2005

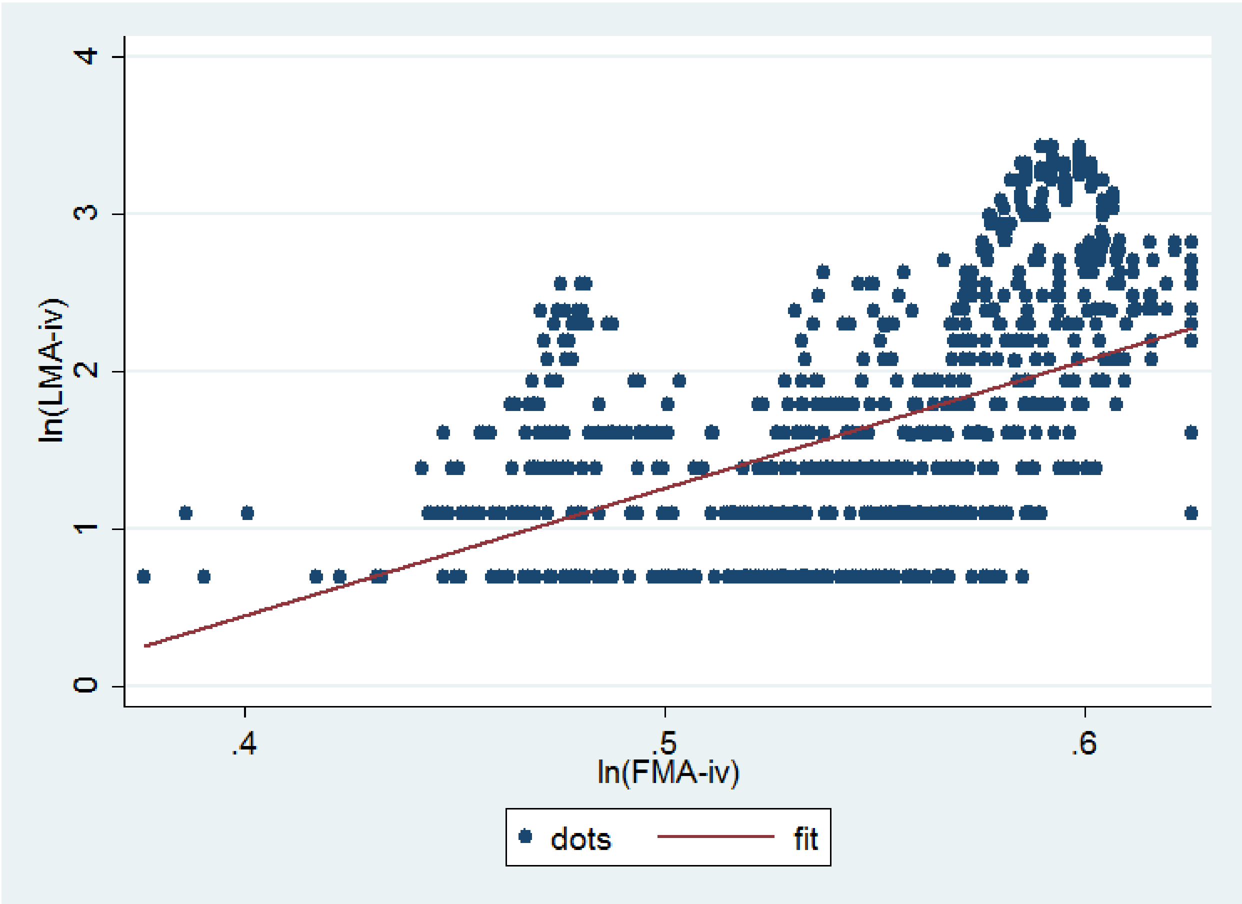

Figure 1.12: Correlation between $ln(FMA_{i,t}^{iv})$ and $ln(LMA_{i,t}^{iv})$

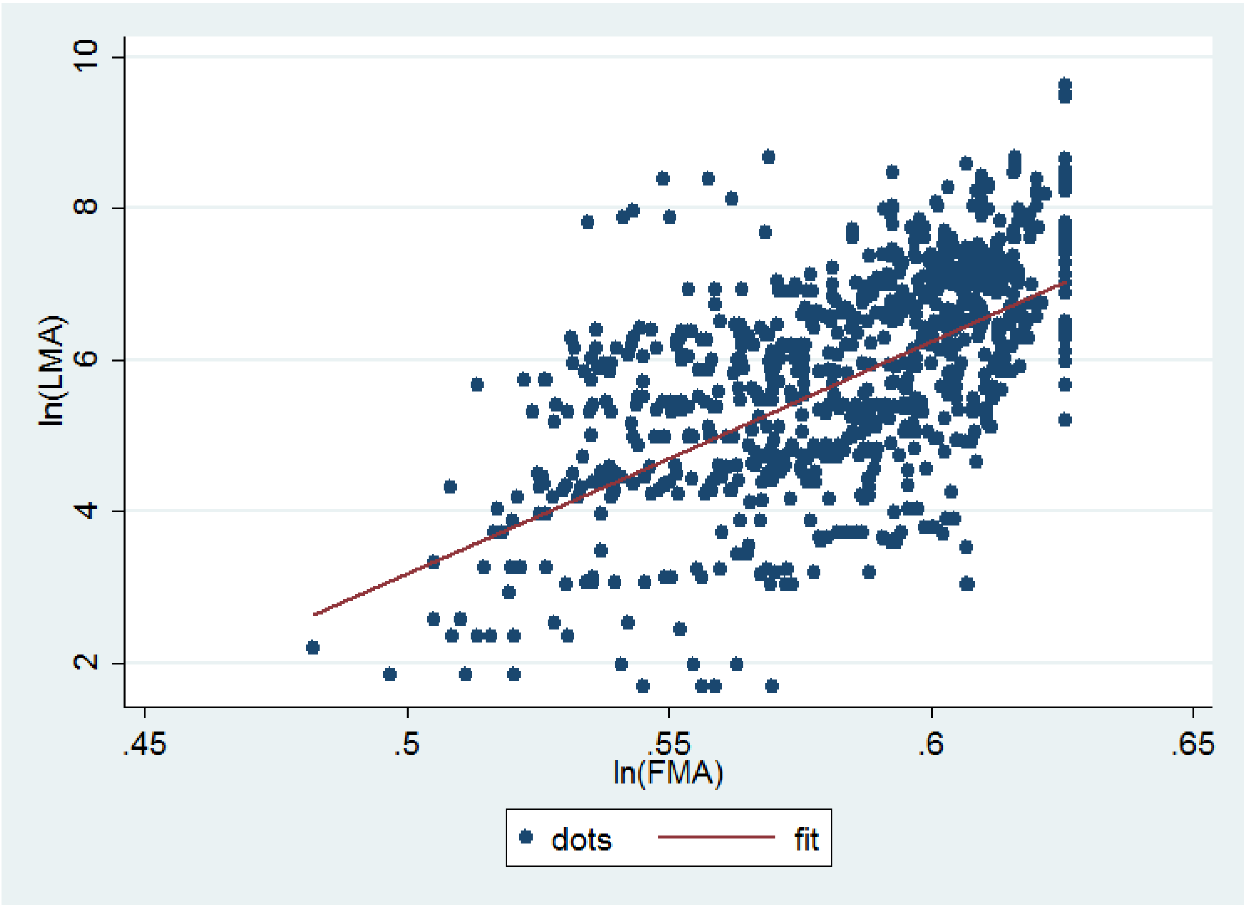

Figure 1.13: Correlation between $ln(FMA_{i,t})$ and $ln(LMA_{i,t})$

1.10.4 Algorithm of Structural Estimation

The parameters to be estimated by GMM is summarized as:

$$\Theta = \{d_{ir}, T_1, ..., T_{N+1}, \alpha_2\}$$

where τ_{cw} is China's international trade cost, $T_j^{(i)}$ is the productivity of region j of stage i, α_2 measures the importance of stage 1 production, and N + 1 represents N cities and one rest of the world.

Our estimation strategy is to find the vector $\hat{\Theta}$ such that

$$\hat{\Theta} = argmin_{\Theta}[S - S(\hat{\Theta})]\hat{W}[S - S(\hat{\Theta})]'$$

In benchmark case, we assume the weighting matrix equals identity matrix

$$W = I$$

My estimation process consisted of two layers.

Inner layer: the inner layer solves the model conditional on all inputs, including the parameter of interest Θ. The equilibrium conditions of the model are a large system of non-linear equations. I solve the system with a standard nested-loops algorithm:

Step 1: Start with an initial guess of the equilibrium wage and aggregate price distribution. Conditional on the guess, solve for bilateral iceberg trade cost, each possible GVC.

Step 2: Conditional on the equilibrium results solved in the previous step, compute the implied equilibrium wage and aggregate price distribution. Step 3: Compare the initial guess with the implied wage and aggregate price distribution. If the differences are below a certain threshold, exit the algorithm; otherwise, update the initial guess with the implied distribution and iterate back to step 1.

The outer layer of the algorithm solves the minimization problem conditional on the solutions provided in the inner layer. Conditional on an input vector Θ, the inner layer finds the distance between the model and the data moments; the outer layer will try to find the input vector Θ that minimizes the distance. I implement an iterative particle swarm optimization algorithm (PSO) to solve the minimization problem. At iteration t, the algorithm can be described as follows:

Step 1: Start with an initial input of the iteration, Θ_t.

Step 2: Define a subspace around Θ_t , and randomly draw n initial positions of Θ (particles) within the subspace. Denote the position of particle i as p(i)

Step 3: For each particle i, define a random neighborhood particle set and denote the neighborhood set of particle i as b(i).

Step 4: Evaluate the model at each of the n particles. Denote the global best solution as g^*, and the best solution within the neighborhood of particle i as $b^*(i)$.

Step 5: Update the position of each particle i as

$$p'(i) = W_1 \times p(i) + u(1) \times W_2 \times g^* + u(2) \times W_3 \times b^*(i)$$

where $p'(i)$ is the new position, p(i) is the old position, $u(.)$ are uniformly distributed random numbers, and $W(.)$ are weights.

Step 6: Iterate between steps 3 and 5 until all of the particles converge to the same position, or we can no longer improve g under certain stall limits.

Step 7: Check if the best solution from the previous step is an improvement over the initial guess, Θ_t: If it is an improvement, reset the stall counter to 0 and update the initial guess with the current best solution, then iterate starting from step 1 again. If it is not an improvement, add 1 to the stall counter, and restart from step 1 with the same initial guess, but different subspace and/or random seed.

Step 8 Exit if Θ_t cannot no longer be improved (stall counter exceeds stall limit).

Bibliography

Acharya, R. C. and Keller, W. (2007). Technology transfer through imports. Working Paper 13086, National Bureau of Economic Research.

Alfaro, L., Antrás, P., Chor, D., and Conconi, P. (2015). Internalizing global value chains: A firm-level analysis. Working Paper 21582, National Bureau of Economic Research.

Alvarez, F. E., Buera, F. J., and Lucas, Robert E, J. (2013). Idea flows, economic growth, and trade. Working Paper 19667, National Bureau of Economic Research.

Amiti, M. and Konings, J. (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *American Economic Review*, 97(5):1611–1638.

Antràs, P. and Chor, D. (2013). Organizing the global value chain. *Econometrica*, 81(6):2127–2204. From March 2013.

Antras, P., Chor, D., Fally, T., and Hillberry, R. (2012). Measuring the Upstreamness of Production and Trade Flows. *American Economic Review*, 102(3):412–416.

Antràs, P. and de Gortari, A. (2017). On the geography of global value chains. Number 23456 in Working Paper Series.

Baldwin, R. and Venables, A. J. (2013). Spiders and snakes: Offshoring and agglomeration in the global economy. *Journal of International Economics*, 90(2):245 – 254.

Baldwin, R. E. (2006). Multilateralising Regionalism: Spaghetti Bowls as Building Blocs on the Path to Global Free Trade. *The World Economy*, 29(11):1451–1518.

Baum-Snow, N. (2007). Did highways cause suburbanization? *The Quarterly Journal of Economics*, 122(2):775–805.

Baum-Snow, N., Brandt, L., Henderson, J. V., Turner, M. A., and Zhang, Q. (2017). Roads, Railroads, and Decentralization of Chinese Cities. *The Review of Economics and Statistics*, 99(3):435–448.

Bloom, N., Schankerman, M., and Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4):1347–1393.

Brandt, L. and Morrow, P. M. (2017). Tariffs and the organization of trade in china. *Journal of International Economics*, 104:85 – 103.

Brandt, L., Tombe, T., and Zhu, X. (2013). Factor Market Distortions Across Time, Space, and Sectors in China. *Review of Economic Dynamics*, 16(1):39–58.

Buera, F. J. and Oberfield, E. (2016). The Global Diffusion of Ideas. NBER Working Papers 21844, National Bureau of Economic Research, Inc.

Bustos, P. (2011). Trade liberalization, exports, and technology upgrading: Evidence on the impact of mercosur on argentinian firms. *The American Economic Review*, 101(1):304–340.

Che, Y. and Zhang, L. (2018). Human capital, technology adoption and firm performance: Impacts of china's higher education expansion in the late 1990s. *The Economic Journal*, 128(614):2282–2320.

Chor, D., Manova, K., and Yu, Z. (2016). The global production line position of chinese firms. In *Industrial Upgrading and Urbanization Conference, Stockholm*, volume 28, page 29.

Coe, D. T. and Helpman, E. (1995). International rd spillovers. *European Economic Review*, 39(5):859 – 887.

Costinot, A., Vogel, J., and Wang, S. (2013). An elementary theory of global supply chains. *Review of Economic Studies*, 80(1):109–144.

Duranton, G., Morrow, P. M., and Turner, M. A. (2014). Roads and trade: Evidence from the us. *The Review of Economic Studies*, 81(2):681–724.

Eaton, J. and Kortum, S. (1999). International technology diffusion: Theory and measurement. *International Economic Review*, 40(3):537–570.

Eaton, J. and Kortum, S. (2001). Trade in capital goods. *European Economic Review*, 45(7):1195 – 1235. International Seminar On Macroeconomics.

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5):1741–1779.

Faber, B. (2014). Trade integration, market size, and industrialization: Evidence from china's national trunk highway system. *The Review of Economic Studies*, 81(3):1046–1070.

Fally, T. (2012). Production Staging: Measurement and Factss.

Fons-Rosen, C., Kalemli-Ozcan, S., Sorensen, B. E., Villegas-Sanchez, C., and Volosovych, V. (2017). Foreign investment and domestic productivity: Identifying knowledge spillovers and competition effects. Working Paper 23643, National Bureau of Economic Research.

Garcia-Milà, T. and Montalvo, J. G. (2011). The impact of new highways on business location: new evidence from spain.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., and Topalova, P. (2010). Imported Intermediate Inputs and Domestic Product Growth: Evidence from India*. *The Quarterly Journal of Economics*, 125(4):1727–1767.

Grossman, Gene M.and Helpman, E. (1991). Quality ladders in the theory of growth. *The Review of Economic Studies*, 58(1):43–61.

Grossman, G. M. and Rossi-Hansberg, E. (2012). Task trade between similar countries. *Econometrica*, 80(2):593–629.

Head, K. and Ries, J. (2001). Increasing returns versus national product differentiation as an explanation for the pattern of u.s.-canada trade. *The American Economic Review*, 91(4):858–876.

Hummels, David L.and Schaur, G. (2013). Time as a trade barrier. *American Economic Review*, 103(7):2935–59.

Hyytinen, A. and Toivanen, O. (2011). Income inequality and technology diffusion: Evidence from developing countries*. *The Scandinavian Journal of Economics*, 113(2):364–387.

Johnson, R. C. and Noguera, G. (2012). Fragmentation and Trade in Value Added over Four Decades. (18186).

Johnson, R. C. and Noguera, G. (2017). A portrait of trade in value-added over four decades. *The Review of Economics and Statistics*, 99(5):896–911.

Kee, H. L. and Tang, H. (2016). Domestic value added in exports: Theory and firm evidence from china. *American Economic Review*, 106(6):1402–36.

Keller, W. (1997). Trade and transmission of technology. Working Paper 6113, National Bureau of Economic Research.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, 42(3):752–782.

Keller, W. (2009). International trade, foreign direct investment, and technology spillovers. Working Paper 15442, National Bureau of Economic Research.

Keller, W. and Yeaple, S. R. (2009). Multinational enterprises, international trade, and productivity growth: Firm-level evidence from the united states. *The Review of Economics and Statistics*, 91(4):821–831.

Koopman, R., Wang, Z., and Wei, S.-J. (2014). Tracing value-added and double counting in gross exports. *American Economic Review*, 104(2):459–94.

Krugman, P. R. (1987). Is free trade passe? *Journal of Economic Perspectives*, 1(2):131–144.

Lee, E. and Yi, K.-M. (2018). Global value chains and inequality with endogenous labor supply. Working Paper 24884, National Bureau of Economic Research.

Limao, N. and Venables, A. J. (2001). Infrastructure, geographical disadvantage, transport costs, and trade (english). *The World Bank economic review*, 15(3):451–479.

Lucas, Robert E, J. and Moll, B. (2011). Knowledge growth and the allocation of time. Working Paper 17495, National Bureau of Economic Research.

Manova, K. (2008). Credit constraints, heterogeneous firms, and international trade. Working Paper 14531, National Bureau of Economic Research.

Manova, K., Wei, S.-J., and Zhang, Z. (2015). Firm exports and multinational activity under credit constraints. *The Review of Economics and Statistics*, 97(3):574–588.

Matsuyama, K. (2000). A ricardian model with a continuum of goods under nonhomothetic preferences: Demand complementarities, income distribution, and north-south trade. *Journal of Political Economy*, 108(6):1093–1120.

Moxnes, A. and Johnson, R. C. (2016). Technology, trade costs, and the pattern of trade with multistage production.

Redding, S. J. and Turner, M. A. (2015). *Transportation Costs and the Spatial Organization of Economic Activity*, volume 5 of *Handbook of Regional and Urban Economics*, chapter 0, pages 1339–1398. Elsevier.

Thoenig, M. and Verdier, T. (2003). A theory of defensive skill-biased innovation and globalization. *American Economic Review*, 93(3):709–728.

Topalova, P. and Khandelwal, A. (2011). Trade liberalization and firm productivity: The case of india. *The Review of Economics and Statistics*, 93(3):995–1009.

Verhoogen, E. (2008). Trade, quality upgrading, and wage inequality in the mexican manufacturing sector. *The Quarterly Journal of Economics*, 123(2):489–530.

Yeaple, S. (2005). A simple model of firm heterogeneity, international trade, and wages. *Journal of International Economics*, 65(1):1–20.

Yi, K.-M. (2003). Can vertical specialization explain the growth of world trade? *Journal of Political Economy*, 111(1):52–102.

Yi, K.-M. (2010). Can multistage production explain the home bias in trade? *American Economic Review*, 100(1):364–93.

Yu, M. (2014). Processing trade, tariff reductions and firm productivity: Evidence from chinese firms. *The Economic Journal*, 125(585):943–988.

Chapter 2

KNOWLEDGE IMPORT AND PRODUCTIVITY GROWTH: EVIDENCE FROM CHINA

2.1 Introduction

In the postwar period, trade openness was crucial in affecting a country's economic development and its specialization. A series of papers (Matsuyama, 2000; Krugman, 1987) address the importance of export in affecting productivity growth across industries, and predict that trade openness will strengthen rather than weaken a country's comparative advantage. Yet, Che and Zhang (2018) documented the fact that the productivity growth of the Chinese manufacturing firms increased much faster in skilled-intensive industries than in unskilled-intensive industries.[1] This growth pattern in China seems to defy the predictions of the theory.

To resolve this puzzle, this paper addresses the importance of learning from import, i.e., import technology diffusion.[2] In recent decades, imports have become important in affecting developing countries' economic development and their specialization(Amiti and Konings, 2007; Goldberg et al., 2010; Topalova and Khandelwal, 2011; Yu, 2014). The import of knowledge-intensive and new products from technologically-advanced countries may trigger domestic technological learning within firms, which generates technology diffusion(Keller, 2009; Keller and Yeaple, 2009; Hyytinen and Toivanen, 2011; Buera and Oberfield, 2016)[3].

[1]Chinese firms are believed to have comparative advantages in skilled-intensive industries.

[2]The literature addresses the importance of knowledge diffusion through goods imports (Grossman, 1991; Eaton and Kortum, 2001; Coe and Helpman, 1995; Acharya and Keller, 2007)

[3]There are a couple of papers discussing channels for transmitting knowledge (Lucas and Moll, 2011; Alvarez et al., 2013)

The next question is to consider the importance, for example, of imports for Huawei's productivity growth and innovation activity from Qualcomm company.

To better understand how import may alter productivity growth across industries, this paper studies the impact of technology improvements in China's import products from the US, Germany and Japan on Chinese firms' productivity. Firstly, I develop a measure of knowledge imports that is based on the import value in the R&D intensive industry from three developed countries (Keller, 2004): the United States, Japan, and Germany.[4] If a city-industry pair in China receives high value in knowledge import, local firms in this city-industry pair are supposed to receive strong technology diffusion from the foreign country. The effect of knowledge import becomes more pronounced in industries with a comparative disadvantage in China because the import share is comparatively higher. Second, knowledge import in China is important in the sense that the import value from these three countries accounts for around 40% of China's total import in this period. Furthermore, the variation of knowledge import across city-industry pairs is large, and this makes China a perfect case to study our problem.

My empirical analysis is guided by a multi-industry dynamic model of knowledge diffusion featuring heterogeneous firms. The setup builds on Buera and Oberfield (2016). There are two countries (China and the foreign country) and two industries, an industry that uses only skilled labour (H), and an industry that only uses unskilled labour (L). Within each industry, there are two types of firms: importers and non-importers. Both types of firms interact with the sellers, including importers, non-importers, and foreign firms within the same industry. Interaction among firms can diffuse knowledge, which generates productivity growth. Under international trade openness, only the importers have the technology to interact with the foreign producers, which leads to a productivity growth difference between importers and non-importers. The tractability of my model allows me to generate the following predictions. First, the relative productivity growth between importers and non-importers within the same industry is higher in H-industry than L-industry under a liberalized international trade system. This is because the foreign sellers are comparatively more productive in H-industry than in L-industry, which generates relatively stronger technology diffusion for importers in H-industry than in L-industry. Second, the relative productivity growth rate between H- and L-industry is higher under a liberalized trade system than under autarky. This is because foreign sellers have comparative advantages in H-industry, and hence the aggregate technology diffusion is much stronger in H-

[4]The United States, Japan and Germany are technology leaders in the world, while other countries are technology followers as in Eaton and Kortum (1999)

than in L-industry. Third, the non-importers in H-industry and the foreign sellers in the L-industry retreat from the Chinese markets in the long run. This is because the importers and foreign sellers in H-industry outgrow the non-importers, while the importers and non-importers in L-industry outgrow foreign sellers.

To test the key predictions from my framework, I need to address the challenge that the knowledge import at the city-industry pair level is not random. I do so by applying 'Bartik's' idea in constructing an exogenous knowledge import. 'Bartik's' idea is to replace the actual import flow of China from one country with the total export value of this country to countries other than China while keeping the import share of this country within the industry at its initial level. In this case, the 'Bartik's' approach fully exploits the variation of bilateral trade flows of other country pairs at the intensive margin, which is exogenous to China's economic development. On top of 'Bartik,' I replace R&D expenditure in the US, Japan and Germany with R&D expenditure a decade ago when constructing my instrument, so that the R&D expenditure in the instrument is not affected by the import demand from China.

I find the following reduced-form evidence consistent with the three theoretical predictions of the model. In line with the first and second prediction, I find that a one standard deviation increase in knowledge import leads to a significant nearly 0.24% general increase in firm TFP. After controlling for the interaction between industry skill intensity and knowledge import, the impact of knowledge import itself becomes insignificant for the unskilled intensive industry, and a one standard deviation increase in knowledge import leads to a significant nearly 0.25% increase in firm TFP in skilled-intensive industry. Also in line with the first and second prediction, I find that a one standard deviation increase in knowledge import leads to a significant nearly 0.33% increase in firm's patent filing and 0.14% increase in a firm's patent quality. In line with the third prediction of the model, I find that a one standard deviation increase in knowledge import leads to a significant nearly 1% increase in a firm's total sales.

I conduct robustness checks for my baseline results. One concern is that the import knowledge may have a different impact on Domestic firms and Foreign firms (FDI) in China. This is because foreign firms might not have a comparative disadvantage in skill-intensive industries. Hence, my theory predicts that the productivity growth of foreign firms may not benefit from knowledge import. To address this concern, I separately estimate the impact of knowledge import on domestic firms and foreign-invested firms. The empirical result is consistent with what the theory predicts. Domestic firms exhibit significant productivity growth in skill-intensive industry, which also drives our aggregate pattern. Foreign-invested firms exhibit significant productivity growth in industries with strong knowledge import shock, but the impact on skill-intensive and low-skilled industries is not significant.

Another concern is that productivity growth might be faster in skill-intensive industries as these industries rely heavily on external finance and are capital intensive industries. The measure of skill-intensity may also capture an industry's demand for capital that is skill-biased (Manova, 2008; Manova et al., 2015). To resolve such concerns, I include both the interaction of an industry's capital-labour intensity with knowledge import and the interaction of an industry's reliance on external finance with knowledge import. Though China also exhibits a comparative dis-advantage in industries with a high capital-labour ratio and industries with a strong reliance on external finance, the results suggest that only industries with high skill-intensity have faster firm TFP growth.

This paper contributes to the literature by developing the causal relationship between import technology diffusion and productivity growth. The literature addresses the importance of R&D investment in affecting technology diffusion among firms(Bloom et al., 2013). Fons-Rosen et al. (2017) decomposes the impact of technology diffusion and competition of foreign direct investment (FDI) on local firms' productivity. Following their spirit, I develop a novel approach in measuring knowledge content in imports and use this measure to estimate knowledge diffusion via imports.

This paper is the first paper to address importance of knowledge import in affecting the productivity growth in a developing country and credibly estimating this effect. Grossman (1991); Keller (1997) used country and industry level data to estimate the impact of knowledge import among developed countries. Keller (2009) decomposed the competition and technology diffusion effect on local firms using firm-level data. The knowledge import in these studies is not random. To address this concern, my paper employs the 'Bartik' approach.

This paper also fits into the literature about globalization and skill-upgrading. Yeaple (2005), Bustos (2011), and Verhoogen (2008) show that exporting to larger markets or richer countries makes technology adoption more profitable, which increases the quality of the products. The demand for producing high-quality products to serve the markets induces firms in developing countries to adopt skill-biased technology. From an import perspective, Thoenig and Verdier (2003) shows that import competition encourages local firms to engage in skill-biased technological innovation, which leads to productivity growth. Complementing this literature, I evaluate a new channel from imports, through which local firms increase their productivity by increasing their exposure to new technology from imports.

2.2 Data Description and Historical Background

2.2.1 Data Description

In generating the motivating facts and the regression-based evidence, I use three datasets. First, I use the firm-level data from the Annual Survey of Industrial Firms (ASIF) in China. This dataset has been widely used in previous studies of the Chinese economy. Between 1998 and 2007, these surveys cover all state-owned enterprises, as well as large-sized private enterprises with more than five million RMB (around 770,000 US dollars under the current exchange rate) annual sales. This dataset contains rich firm-level information, including ownership structure, employment, capital stock, gross output, export value, firm identifier, etc.

Then, I use the universe of China's International Trade data at the transaction level between 2000 and 2006. Coded using an 8-digit classification based on the Harmonized System (HS), this data reports a firms' free-on-board value, price, amount, and unit of export and import across countries. Furthermore, it provides geographical information about each firm, such as its address and corresponding custom office where the individual transaction was processed.

Thirdly, I use Business Enterprise R&D expenditure from the OECD website, which is freely available.[5] This dataset contains the business R&D expenditure for all OECD countries by industry (ISIC rev 3.1) between 1987 to 2015.

The other Chinese data sources used in this study include the Chinese patent data from the State Intellectual Property Office (SIPO), which contains the patents granted to individuals and firms by the SIPO between 1990 and 2015.

2.2.2 Historical Background

In this section, I introduce the background, summarize the data and document the stylize facts.

[5]This dataset is freely available on http://www.oecd.org/innovation/inno/researchanddevelopmentstatisticsrds.htm

Productivity Growth across Industries in China

In recent decades, China has experienced substantial growth in the manufacturing industry, in particular, productivity growth. The average growth rate of productivity stood at around 7.96% between 1998 and 2007 (Brandt et al., 2013). Productivity growth and manufacturing production exhibit certain regularities across industries. To document this regularity, I first run a regression of firm-level productivity, measured by its TFP, labour productivity and sales per capita, on a year dummy for skill-intensive and low-skill industries[6]. In this regression, I also control the industry fixed effects, the ownership of the firms. I visualize the dynamic of firms productivity growth in Figure 2.1. This figure shows us the coefficients of the year dummy in these regressions. It shows that the coefficients increase over time, which implies the increase of TFP in this period, and more for skill-intensive industries.

To measure the dynamics for firm sizes and technology innovation/adoption activity of the local firms across industries, I run the following regression specification:

$$ln(y_{fi,t}) = \alpha + \beta_1 Skill_i + \delta_t + \sum_t \delta_t Skill_i + \delta_f + \epsilon_{fi,t}$$

where $y_{fi,t}$ can be the measures of firm sizes, such as firm-level sales, exports and value-added. $y_{fi,t}$ can be the measures of technology innovation/adoption, i.e, number of patents. $Skill_i$ is a dummy variable if the skill requirement of an industry is more than the medium. δ_f, δ_t represents firm and year fixed effects, respectively.

Columns (1) - (3) in Table 2.3 show the results for firm-level sales, value-added and exports, respectively. In this period, firm size increased, in terms of these three variables, and more in skill-intensive industry. The last three columns in this table display the results for the number of design patents, utility patents, and invention patents. They show similar patterns in the same period as the firm size. These growth patterns for firms are consistent with Che and Zhang (2018).

Knowledge Import in China

Accompanied by a substantial growth in sales, China is becoming increasingly integrated with the international markets. Between 1998 and 2007, China saw substantial increases in total knowledge import, from three leading countries: the United States, Germany and Japan(Eaton and Kortum, 1999, 2001) and Table 2.1

[6]Each industry is characterized by its skilled and unskilled labour ratio. An industry is defined as a skill-intensive if its skilled and unskilled labour ratio is above the medium.

shows that the average R&D expenses for these three countries are substantial, especially for the United States. This average R&D investment for the US is far higher than in Japan and Germany. Between 2000 and 2006, these three countries experienced more than a 50% increase in R&D expenditure.

In the same period, import value from these three countries in China is also enormous, and their total imports constitute nearly 40% of the aggregate imports for China. Figure 2.2 shows that the log value of aggregate import for China from these three countries increased at a similar pace.

Following the idea of Keller (2004), I construct the following variable to capture the knowledge import from these three countries:

$$Knowledge_{is,t} = Import_{is,t} \times \frac{\bar{rd}_{is,00-06}}{Y_{is,00-06}}$$

where $Import_{is,t}$ measures the import value of China from country $s \in \{US, Germany, Japan\}$ in industry i at time t. $\bar{rd}_{is,00-06}$ measures the average R&D expenses of country s in industry i between 2000 and 2006. $Y_{is,00-06}$ is the average gross output of country s in the industry i between 2000 and 2006. The knowledge import at the city-industry pair level is similarly constructed. This measure captures the total knowledge China is exposed to. The higher of this $Knowledge_{is,t}$ suggests that firms in China in industry i are more likely to be exposed to knowledge from these three countries. Figure 2.3 shows that knowledge import is strongest for both Japan and the United States and not so much for Germany. The relative larger value for both Japan and the US is because import for Japan is highest among all three countries, while the R&D investment for the US is the highest of the three countries. Table 2.2 suggests that knowledge import at the prefecture level tends on average to increase over these years, which is identical to the aggregate trend.

The knowledge import in China exhibits some geographic regularities, and in a later section, I will exploit this geographic variation to identify the impact of knowledge import. I exhibit regression results of Chinese city-industry pair's knowledge import on a city's location and an industry's skill intensity in Table 2.4. The first three columns in this table show that knowledge import increased gradually in skill-intensive industry between 2000 and 2006. This pattern is more intense for knowledge import from Japan and the United States than from Germany. The interaction term between year dummy and inverse distance to the nearest international ports shows that knowledge import in the coastal area does not change significantly over these years. This means that the geographic pattern is rather stable for knowledge import and import in this period. In terms of interaction between industry skill intensity and the inverse distance to the nearest international ports, we know that knowledge import in skill-intensive industry is mainly concentrated in the coastal area, and the extent of concentration is stronger than solely the import itself.

Does knowledge import generate technology spillovers for local companies in China? Rich anecdotal evidence focuses on the effect of foreign direct investment (FDI) on the performance of local firms. Less is known about the role of knowledge import.

Table 2.1: Innovation Investment of the US, Japan and Germany over time

year	USA	Japan	Germany
2000	8447.17	4441.8	1931.4
2001	8083.88	4390.0	2122.5
2002	7663.94	4706.5	3936.4
2003	8329.88	4808.2	2319.8
2004	10649.8	5137.7	3164
2005	11518.0	5775.4	2384.5
2006	12543.7	6274.8	3498.5
Total	9605.218	5081.471	2598.273

The number in the table measures the average innovation investment. The unit of measurement is in US millions of US dollars.

Source: OECD

Table 2.2: The Evolution of Average Import Knowledge across cities

Year	$ln(Knowledge_{c,DEU,t})$	$ln(Knowledge_{c,Jpn,t})$	$ln(Knowledge_{c,US,t})$
2000	7.07	8.52	7.94
2001	7.68	8.95	8.07
2002	7.85	9.35	8.20
2003	7.90	9.45	8.60
2004	7.17	9.31	8.50
2005	7.90	9.26	8.49
2006	7.29	9.24	8.68
Total	7.14	9.17	8.37

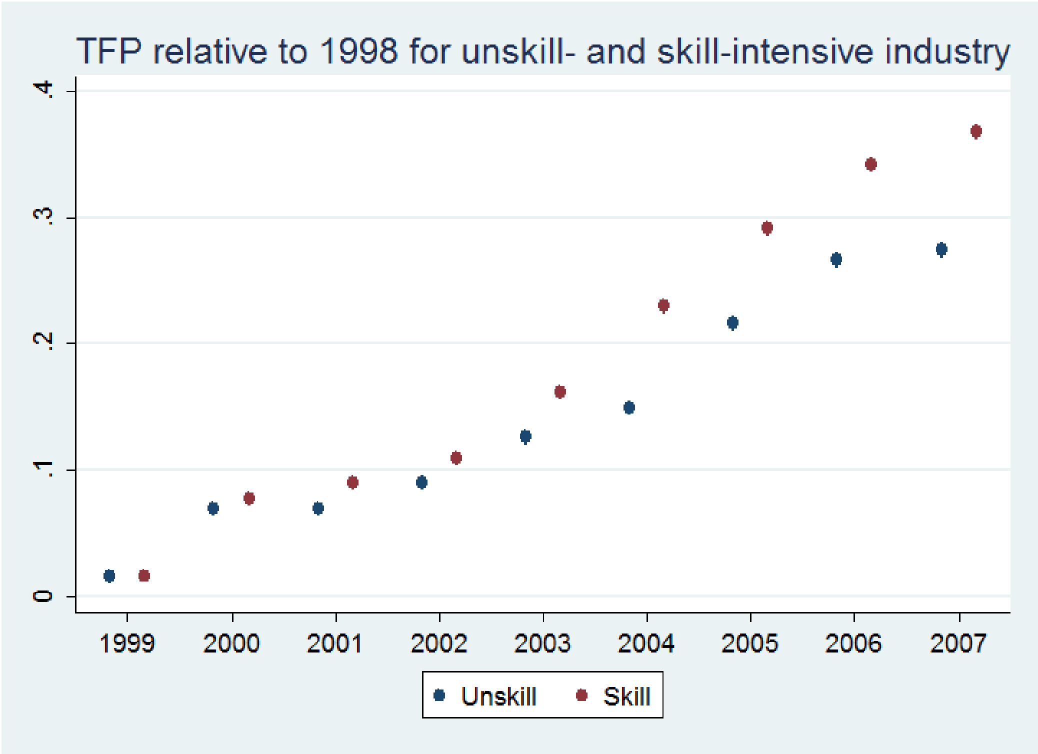

Figure 2.1: TFP relative to 1998 for low skill- and skill-intensive industry

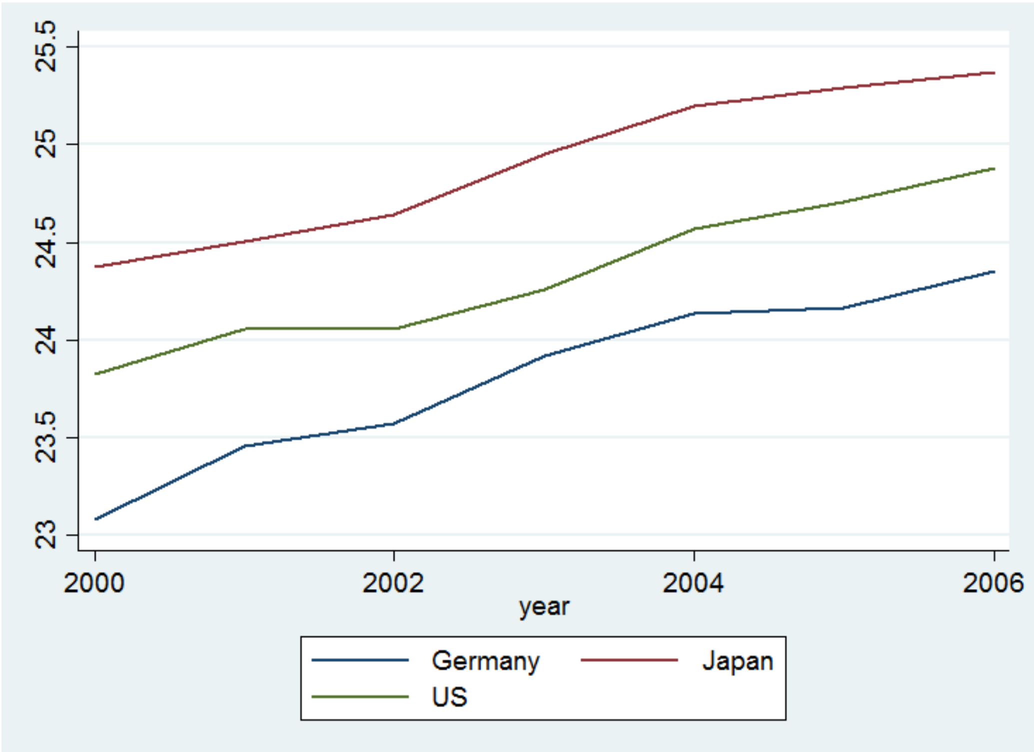

Figure 2.2: China's import value from US, Germany and Japan between 2000 and 2006

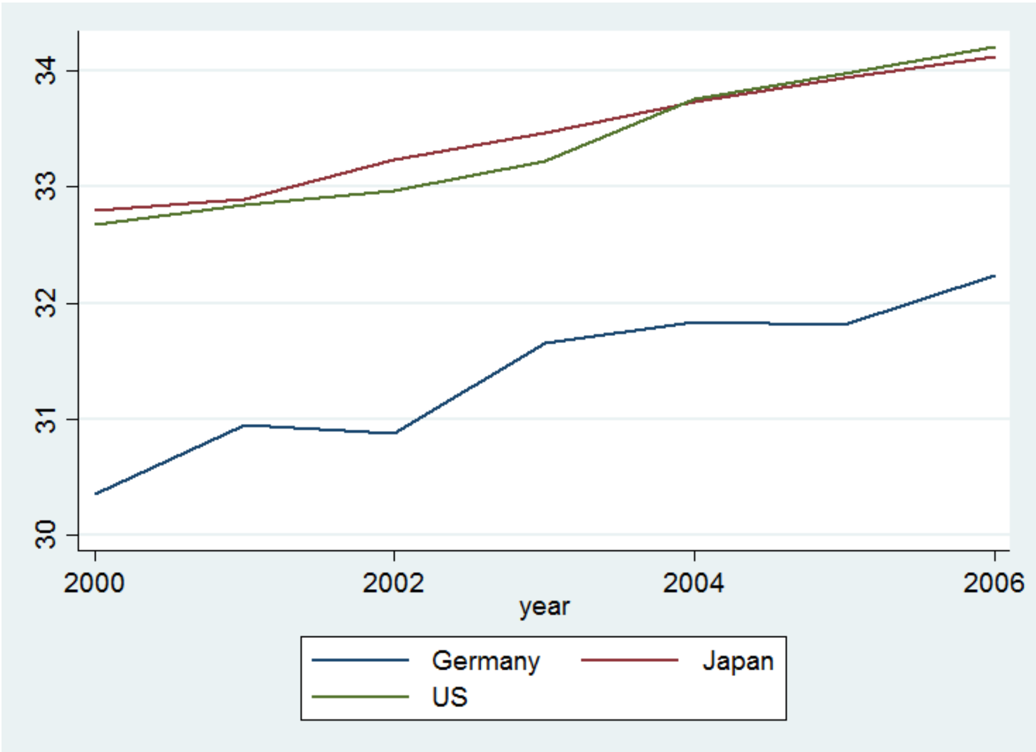

Figure 2.3: China's import value from US, Germany and Japan between 2000 and 2006

Table 2.3: The dynamic of sales, value-added and patent filing in skill-intensive industry between 1998 and 2007

	(1) $ln(Sales_{f,t})$	(2) $ln(V.A_{f,t})$	(3) $ln(Exports_{f,t})$	(4) $ln(design_{f,t})$	(5) $ln(utility_{f,t})$	(6) $ln(invent_{f,t})$
$Skill_i$	-0.0549***	-0.0511***	0.0269	-0.00737***	-0.0119***	-0.00938***
	(0.000)	(0.000)	(0.434)	(0.001)	(0.000)	(0.000)
$(Year = 1999)$	0.0313***	-0.0109**	-0.0496***	0.00153*	0.000884	0.000925***
	(0.000)	(0.045)	(0.000)	(0.074)	(0.130)	(0.005)
$(Year = 2000)$	0.0582***	0.0707***	0.0193	0.00315***	0.00329***	0.00256***
	(0.000)	(0.000)	(0.215)	(0.001)	(0.000)	(0.000)
$(Year = 2001)$	0.0934***	0.0884***	-0.0308*	0.00196*	0.00579***	0.00410***
	(0.000)	(0.000)	(0.074)	(0.070)	(0.000)	(0.000)
$(Year = 2002)$	0.204***	0.148***	0.0585***	0.00203*	0.00809***	0.00614***
	(0.000)	(0.000)	(0.001)	(0.091)	(0.000)	(0.000)
$(Year = 2003)$	0.299***	0.254***	0.140***	0.00188	0.00949***	0.00823***
	(0.000)	(0.000)	(0.000)	(0.133)	(0.000)	(0.000)
$(Year = 2004)$	0.300***	0.317***	0.453***	0.00311**	0.0109***	0.0107***
	(0.000)	(0.000)	(0.000)	(0.022)	(0.000)	(0.000)
$(Year = 2005)$	0.459***	0.524***	0.422***	0.00390***	0.0131***	0.0136***
	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)
$(Year = 2006)$	0.612***	0.706***	0.457***	0.00695***	0.0171***	0.0171***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$(Year = 2007)$	0.795***	0.922***	0.373***	0.00994***	0.0206***	0.0205***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Skill_i \times (Year = 1999)$	0.0256***	0.0145**	0.0184	0.00179	0.00228**	0.000594
	(0.000)	(0.035)	(0.268)	(0.113)	(0.012)	(0.249)
$Skill_i \times (Year = 2000)$	0.0219***	0.0102	-0.00954	0.00204	0.00186*	0.000685
	(0.000)	(0.181)	(0.614)	(0.115)	(0.071)	(0.281)
$Skill_i \times (Year = 2001)$	0.0348***	0.0314***	0.0371*	0.00478***	0.00389***	0.00166**
	(0.000)	(0.000)	(0.076)	(0.001)	(0.001)	(0.027)
$Skill_i \times (Year = 2002)$	0.0515***	0.0538***	-0.0131	0.00829***	0.00732***	0.00530***
	(0.000)	(0.000)	(0.555)	(0.000)	(0.000)	(0.000)
$Skill_i \times (Year = 2003)$	0.0605***	0.0547***	-0.0147	0.00890***	0.0117***	0.00941***
	(0.000)	(0.000)	(0.534)	(0.000)	(0.000)	(0.000)
$Skill_i \times (Year = 2004)$	0.0722***	0.0761***	-0.0721***	0.00850***	0.0128***	0.0111***
	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)
$Skill_i \times (Year = 2005)$	0.0327***	0.0481***	0.0692***	0.00989***	0.0160***	0.0144***
	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)	(0.000)
$Skill_i \times (Year = 2006)$	0.0285***	0.0298***	0.0847***	0.00987***	0.0213***	0.0195***
	(0.002)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
$Skill_i \times (Year = 2007)$	0.0436***	0.0313***	0.101***	0.00915***	0.0253***	0.0236***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.876	0.758	0.835	0.506	0.548	0.534

p-values in parentheses

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

$ln(design)$, $ln(utility)$ and $ln(invent)$ are three different types of patents.

Firm, industry and ownership fixed effects are controlled.

Table 2.4: The distribution of knowledge import across locations and industries

	(1) $ln(Knowledge_{DEU,t})$	(2) $ln(Knowledge_{JPN,t})$	(3) $ln(Knowledge_{US,t})$	(4) $ln(IM_{DEU,t})$	(5) $ln(IM_{JPN,t})$	(6) $ln(IM_{US,t})$
$Skill_j$	-4.066**	-4.558*	-8.935***	-5.088***	-2.788*	-5.442***
	(1.889)	(2.457)	(2.282)	(1.196)	(1.512)	(1.361)
$\frac{1}{Sea_i}$	0.335	1.270	2.598*	0.711	1.065	2.028**
	(1.360)	(1.616)	(1.495)	(1.042)	(1.087)	(1.028)
$\frac{Skill_j}{Sea_i}$	18.85***	17.04***	0.576	6.240**	12.54***	-0.210
	(4.484)	(4.882)	(4.483)	(2.979)	(3.139)	(2.969)
$Skill_j \times (year = 2001)$	3.341***	3.165***	1.549**	2.332***	1.478***	1.453***
	(0.692)	(0.880)	(0.785)	(0.427)	(0.531)	(0.475)
$Skill_j \times (year = 2002)$	-9.956***	3.928***	2.156**	2.962***	1.660***	1.710***
	(1.057)	(0.908)	(0.855)	(0.464)	(0.557)	(0.521)
$Skill_j \times (year = 2003)$	7.836***	6.721***	5.599***	4.836***	3.684***	3.774***
	(0.882)	(0.995)	(0.889)	(0.538)	(0.615)	(0.555)
$Skill_j \times (year = 2004)$	4.141***	6.330***	6.289***	5.934***	3.455***	4.181***
	(0.949)	(1.096)	(0.975)	(0.605)	(0.650)	(0.626)
$Skill_j \times (year = 2005)$	9.162***	6.550***	6.983***	6.258***	3.561***	4.558***
	(1.056)	(1.102)	(0.997)	(0.642)	(0.655)	(0.649)
$Skill_j \times (year = 2006)$	5.882***	7.233***	8.477***	6.920***	3.727***	5.166***
	(1.002)	(1.181)	(1.125)	(0.675)	(0.726)	(0.707)
$\frac{1}{Sea_i} \times (year = 2001)$	0.454*	0.0502	-0.436*	0.274**	-0.0783	-0.274*
	(0.251)	(0.268)	(0.246)	(0.127)	(0.157)	(0.148)
$\frac{1}{Sea_i} \times (year = 2002)$	-2.158***	0.128	0.0943	0.395**	-0.124	0.0780
	(0.489)	(0.261)	(0.318)	(0.200)	(0.160)	(0.176)
$\frac{1}{Sea_i} \times (year = 2003)$	0.724*	0.160	0.0364	0.498**	-0.0565	0.122
	(0.390)	(0.306)	(0.371)	(0.230)	(0.180)	(0.235)
$\frac{1}{Sea_i} \times (year = 2004)$	-0.277	0.587*	0.419	0.590**	0.165	0.300
	(0.419)	(0.311)	(0.400)	(0.234)	(0.213)	(0.258)
$\frac{1}{Sea_i} \times (year = 2005)$	0.960***	0.511	1.072***	0.576**	0.149	0.631***
	(0.354)	(0.327)	(0.395)	(0.229)	(0.204)	(0.236)
$\frac{1}{Sea_i} \times (year = 2006)$	-0.214	0.443	0.858*	0.682**	0.0774	0.469*
	(0.440)	(0.407)	(0.501)	(0.283)	(0.247)	(0.279)
Province-Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.347	0.417	0.375	0.397	0.442	0.391

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.3 A Model of Import-Driven Productivity Growth

2.3.1 Setup

This section presents a stylized, dynamic multi-industry model to help us think about how knowledge import affects the productivity growth rate across industries. In modelling technology diffusion, I follow the idea of Buera and Oberfield (2016). In the model, I consider a world economy comprising two countries, China (C) and Foreign (F). There are two industries, and each industry uses only skilled or unskilled labour to produce. Within each industry, there are two types of firms: importers and non-importers.[7] The key difference between importers and non-importers is that importers can interact with foreign sellers to have technology spillover, while the non-importers can not. There is no difference between importers and non-importers under autarky.

Within each industry, there is a continuum of goods indexed by $\omega \in \Omega$. Preferences are Cobb-Douglas across two industries, but Constant Elasticity of Substitution (CES) with the elasticity of substitution $\rho > 1$ within each industry. For simplicity, I allow equal share across industries in the utility function, while this assumption is without loss of generality.[8] China (Foreign country) is endowed with L_C (L_F) of unskilled labour and H_C (H_F) of skilled labour.

The consumer in country $k \in \{C, F\}$, decides how much to spend on each type of goods, according to the following preferences:

$$U_k = Q_{H,k}^{0.5} Q_{L,k}^{0.5}$$

where $Q_{H,k}$ is the aggregate consumption of H-type product:

$$Q_{H,k} = (\int_{\Omega_{H,k}} q_{H,k}(\omega)^{\frac{\rho}{\rho-1}} d\omega)^{\frac{\rho-1}{\rho}}$$

and $Q_{L,k}$ is the aggregate consumption of L-type product:

$$Q_{L,k} = (\int_{\Omega_{L,k}} q_{L,k}(\omega)^{\frac{\rho}{\rho-1}} d\omega)^{\frac{\rho-1}{\rho}}$$

[7]In my setting, I assume that the productivity growth of importers will be affected by foreign sellers, but that of non-importers will not. This setting can be complicated by allowing two regions in China, with different trade costs to the rest of the world. Firms located in the region, which is near the foreign country, can be considered as 'Importers'. Firms located in the region, that is far away from the foreign country, can be thought of as 'Non-importers.' This complication will make our model more realistic, but not tractable in deriving an analytical solution.

[8]This is because the expenditure share of an agent will always be a constant given that the preference is Cobb-Douglas across two industries.

where $\Omega_{_{H,k}}$ and $\Omega_{_{L,k}}$ measure the set of product varieties available in country k for industry H and L, respectively. $q_{m,k}(\omega)$ is the consumption of variety ω for type of goods $m \in \{H, L\}$, and $\rho > 1$ is the elasticity of substitution. Let the aggregate consumption expenditure in country k for good m be $X_{m,k}$. The demand for variety ω is:

$$q_{m,k}(\omega) = p_{m,k}(\omega)^{-\rho} \frac{X_{m,k}}{P_{m,k}^{1-\rho}}$$

where $P_{m,k}^{1-\rho} = \int_{\Omega_i} p_{m,k}(\omega)^{1-\rho} d\omega$

Technology

Following the idea of Buera and Oberfield (2016), technology diffusion is a process involving the random interaction among producers of different goods within the same industry. This process implies an interaction with more advanced individual results in more productive ideas, but it also allows for randomness in adapting techniques of others to alternative uses.

If technology is too diffuse across firms as in Buera and Oberfield (2016), the productivity draws should be Frechet distributed within each industry for both China and the foreign country:

$$z_{mv,k}^{(t)} \sim F_{mv,k}^{(t)} = \exp(-T_{mv,k}^{(t)} z^{-\theta}),$$

and the average productivity growth of a given type of firm within the industry depends on the productivity (x) of the interacted firms and their aggregate productivity ($G(x)$):

$$\frac{T_{mv,C}^{(t+1)}}{T_{mv,C}^{(t)}} = \int x^{\beta\theta} dG(x)$$

where $0 < \beta < 1$ captures the extent of diffusion, $z_{mv,k}^{(t)}$ is the productivity draw, $G(x)$ captures the source distribution, x captures the interacted producer's productivity, and $T_{mv,C}^{(t)}$ measures the average productivity of $v \in \{i, n\}$ type of firms (importers or non-importers).

Production

Within each industry, the firm uses either skilled-labour (H) or unskilled labour (L) to produce. The production function of importers within each industry $m \in \{H, L\}$ of country $k \in \{C, F\}$ in time t shows constant returns to scale and is given by:

$$q_{mv,k}^{(t)} = z_{mv,k}^{(t)} l_{vk}^{m}$$

where $z^{(t)}_{mv,k}$ is the production shifter for v type of firms in industry m and country k. l^m_{vk} is its factor usage.

2.3.2 Model Predictions

In this section, we use this model setup to show how productivity changes across different industries are affected by international trade. In particular, I compare the case of autarky and international trade openness. In my model, there are two types of firms, i.e., importers and non-importers, within each industry. The difference between the two will affect their productivity growth only when there is international trade.

Autarky

As in Eaton and Kortum (2002), the firms face perfect competition within each industry. This suggests that only the most productive, with the lowest marginal production cost, can sell in the market. Therefore, the probability of being the lowest cost producers between importers and non-importers is given by:

$$\frac{w_{m,C}}{z_{m,C}} = \min\left(\frac{w_{m,C}}{z_{mi,C}}, \frac{w_{m,C}}{z_{mn,C}}\right)$$

where $z^{(t)}_{m,C}$ is the higher productivity draw among importers and non-importers and $w_{m,C}$ is the wage value of the m-type factor. In particular, the aggregate productivity distribution within the same industry in China can be expressed as:

$$Prob(z^{(t)}_{m,C} < z) = \exp(-(T^{(t)}_{mi,C} + T^{(t)}_{mn,C})z^{-\theta})$$

This equation suggests that the aggregation of two Frechet distributions with the same dispersion parameter θ is still Frechet distributed under perfect competition.

Under autarky, importers can only learn from non-importers or themselves within each industry. Hence, productivity growth is the same for both importers and non-importers because they are facing the same groups of firms. Therefore, productivity growth is given by:

$$\frac{T^{(t+1)}_{mi,k}}{T^{(t)}_{mi,k}} = \frac{T^{(t+1)}_{mn,k}}{T^{(t)}_{mn,k}} = (T^{(t)}_{mi,C} + T^{(t)}_{mn,C})^{\beta} > \max((T^{(t)}_{mi,C})^{\beta}, (T^{(t)}_{mm,C})^{\beta})$$

This shows us that the productivity growth rate for both importers and non-importers is identical. Therefore, the aggregate productivity growth rate of an industry should also be equal to $(T^{(t)}_{mi,C} + T^{(t)}_{mn,C})^{\beta}$. More importantly, this equation shows us that allowing productivity diffusion between importers and non-importers within the same country, i.e., sharing the same labour market, enables faster productivity growth than not allowing it. The implication of this equation is that it is always better to have the opportunity of meeting more producers is always better of meeting more producers than not to, even if it means meeting someone with lower productivity.[9] Without diffusion across different types of firms, the productivity growth rate for importers and non-importers are $(T^{(t)}_{mi,C})^{\beta}$ and $(T^{(t)}_{mm,C})^{\beta}$, respectively

With the productivity growth of the two industries, the relative productivity growth rate between them is given by:

$$R^{(t)}_A = \frac{T^{(t+1)}_{Hi,k}/T^{(t)}_{Hi,k}}{T^{(t+1)}_{Li,k}/T^{(t)}_{Li,k}} = \left(\frac{T^{(t)}_{Hi,C} + T^{(t)}_{Hn,C}}{T^{(t)}_{Li,C} + T^{(t)}_{Ln,C}}\right)^{\beta}$$

$R^{(t)}_A$ captures the ratio of productivity growth between H- and L-industry under Autarky. Whether or not $R^{(t)}_A$ is larger or smaller than one depends on the absolute advantages. $R^{(t)}_A > 1$ as long as China had absolute productivity advantage in H-industry.

Trade Openness

So how is relative aggregate productivity growth affected under international trade? This depends on the expenditure share on foreign products in both industries and the comparative advantage of China relative to the foreign country. If China opens up to trade with countries exhibiting similar technology distribution across industries, trade openness will not make a big difference. To make our question more interesting, I allow a foreign country to have a comparative advantage in producing goods in H-industry. To put it more formally:

Assumption 1. The last period before opening to international trade ($t = 0$), the productivity level for both importers and non-importers is identical within the same industry.A foreign country has comparative advantages in H-industry.

$$\frac{T^{(0)}_{H,F}}{T^{(0)}_{L,F}} > \frac{T^{(0)}_{Hi,C}}{T^{(0)}_{Li,C}} = \frac{T^{(0)}_{Hn,C}}{T^{(0)}_{Ln,C}},$$

[9] The reason for this result is because the interaction between importers and non-importers bears no cost.

with $H_C = H_F$ and $L_C = L_F$.

Proposition 1. Given the Assumption 1, after trade openness (I refer to trade openness here as free trade.), which is $t > 1$, the relative productivity growth in the comparatively disadvantaged industry is higher for importers than for non-importers:

$$\frac{T_{H,F}^{(t)}/T_{H,F}^{(t-1)}}{T_{L,F}^{(t)}/T_{L,F}^{(t-1)}} = \frac{T_{Hi,C}^{(t)}/T_{Hi,C}^{(t-1)}}{T_{Li,C}^{(t)}/T_{Li,C}^{(t-1)}} > \frac{T_{Hn,C}^{(t)}/T_{Hn,C}^{(t-1)}}{T_{Ln,C}^{(t)}/T_{Ln,C}^{(t-1)}}$$

(Proof in Appendix)

Comparative advantage is critical in determining the relative growth rate between importers and non-importers between H- and L-industries. Importers should grow relatively faster than non-importers in H-industry than in L-industry, if foreign firms are comparatively more productive in H- than in L-industry.

Proposition 2. Given assumption 1, aggregate relative productivity growth rate for China between H-industry and L-industry in trade openness is higher than that in autarky, i.e, $R_T > R_A$.

(proof in Appendix)

In the Long Run.
In the previous section, I discussed how productivity growth changes from autarky to trade openness. However, this change in productivity growth for importers and non-importers may have long-run implications. Given that production is aggregated via CES within each industry, the difference in productivity growth rate leads to the expansion of one type of firm, importers or non-importers, at the expense of the shrinkage of the other type of firm. In the long run, importers or non-importers will exit the market.

If $T_{H,F}^{(0)} > T_{Hi,C}^{(0)} = T_{Hn,C}^{(0)}$, the aggregate distribution for sellers in H-industry as $t \to \infty$.

$$z \sim \exp(-(T_{Hi,C} + T_{H,F}(\tau \frac{w_{H,F}}{w_{H,C}})^{-\theta})z^{-\theta})$$

with $z = \min(\frac{1}{z_{Hi,C}}, \frac{w_{H,F}}{z_{Hi,C} w_{H,C}})$

If $T_{L,F}^{(0)} < T_{Li,C}^{(0)} = T_{Ln,C}^{(0)}$, the aggregate distribution for sellers in L-industry as $t \to \infty$

$$z \sim \exp(-(T_{Li,C} + T_{Ln,C})z^{-\theta})$$

The stylized model in this section shows us how knowledge import affects productivity growth across different industries. Under autarky, an industry's productivity growth is determined by the productivity growth of the importers and non-importers within the industry. Under trade openness, different industries are exposed differently to knowledge import. In particular, firms in comparative disadvantaged industries are exposed to a large share of foreign advanced technology, and hence, stronger technology diffusion than firms in industries with a comparative advantage.

2.4 Empirical Evidence

2.4.1 Empirical Strategy

In this section, I provide regression-based evidence to support the main prediction of my model. In particular, I use the measure of knowledge import to capture the size of technology diffusion via imports as in a previous section, and estimate its impact on manufacturing firms in China. The key idea is to compare firms' productivity of industry-city pairs with strong exposure to high knowledge import with that of industry-city pairs with low knowledge import. In particular, I use the following regression specification:

$$y_{icf,t} = \alpha + \beta ln(knowledge_{ic,t}^{diff}) + X_{f,t} + X_{ic,t} + \delta_i + \delta_c + \delta_f + \delta_t + \epsilon_{icf,t}$$

where $y_{icf,t}$ indicates the indicators at the firm-level, such as TFP, patent filings, and sales, etc. in city c industry i and year t, $knowledge_{ic,t}^{diff}$ measures the technology diffusion via import. $X_{f,t}$ captures the time-varying firm variables such as age square, export status, and ownership status. $\delta_i, \delta_c, \delta_f, \delta_t$ capture industry, city, firm and time fixed effect, respectively.

Key Variable and Controls

The key variables in this regression is technology diffusion via imports, which is defined as:

$$knowledge_{ic,t}^{diff} = \sum_s rd_{si,t} \times im_{sic,t}$$

where $rd_{si,t}$ is the R&D investment of country s for industry i at year t, $im_{sic,t}$ measure the import value of city c from country s in industry i. I use the R&D investment from the United States, Germany and Japan, and hence $s \in \{US, DEU, JPN\}$.

The more city c imports from goods from country-industry pair with higher investment in R&D, the stronger the diffusion of technology via import. The local firms from city c are more likely to be exposed to good ideas.

Table 2.2 shows the evolution of import knowledge diffusion from these three countries. In general, the import knowledge increases through on average, for all cities. The value for import diffusion is highest for Japan, partly because of its high import share in China's total import. Table 2.1 shows the average R&D investment of the three countries across industries between 2000 and 2006.

The effect of technology diffusion via import trade is easily contaminated by the import competition effects, since effects result in higher productivity across firms. To measure the import competition effects, I include the import tariff at the industry level. Also, I measure the import competition by including the average productivity of the import products.

The increase in productivity due to imports may also be driven by importing higher quality products. To address this concern, I control for the average import price of the products at the city-industry level.

Instrumental Variables for technology diffusion via import

To identify the import effect on a firm's productivity via imports, it is necessary to construct instrumental variables for import diffusion. The technology diffusion through imports at the city-industry pair level may not be random, and local productive firms may self-select to import large amounts of goods, which is R&D intensive. I follow the 'Bartik' approach in constructing the instrumental variables:

$$knowledge^{diff,iv}_{sic,t} = rd_{si,1980} \times Q_{si,t} \times Share_{sic,2000}$$

where $rd_{si,1980}$ captures the R&D expenditure of country s in industry i in 1980, $Q_{si,t}$ is the output of country s in industry i for time t, and $Share_{sic,2000}$ is the import share of products from industry from country s for city c in 2000.

$Share_{sic,2000}$ captures the import product structure at the initial period, and hence, my IV measures the technology diffusion of import trade via an intensive margin. $rd_{si,1980}$ captures the importance of R&D spending of industry i for country s, and the relative share of R&D spending across the industry within a country is fairly stable. The time-varying part of this IV comes from the $Q_{si,t}$, which may be driven by exogenous productivity shock, which is orthogonal to the economic activity in city c.

2.4.2 Results

This section reports the empirical results of the knowledge import on a firm's productivity. First, I show that my instrumental variables effectively predicted a city-industry pair's exposure to technology from imports. With these instrumental variables, I empirically show that the increase in knowledge from imports leads to an increase in a firm's productivity.

Results from First-Stage Regression

Table 2.5 shows us the first-stage regression of knowledge import on controls and the instruments. The result shows that the knowledge instruments from the U.S and Germany correlate positively and significantly with the knowledge import, while the instrument variable from Japan is not significant. The controlling variables are also significant and reasonable.

Results from firm's productivity

Table 2.6 reports the impact of technology diffusion on a local firm's productivity via product imports. Columns (1) to (4) show us the result at firm-level TFP(R), and Columns (5) to (8) represents the result of labour productivity. Column (1) shows that a one standard deviation increase in import technology diffusion leads to a 0.24% increase in a firm's TFP(R), and column (2) shows that a one standard deviation increase in import technology diffusion leads to an extra 0.25% increase in a firm's TFP(R). I also value-added per sec as an alternative means to measure a firm's productivity. Column (6) shows that one standard error increase in import technology diffusion in the more skill-intensive industry leads to a 1% increase in labour productivity. Additionally, I present the result using OLS in columns (3), (4), (7) and (8), and they show that import technology spillover is significantly correlated with firm's a TFP(R) and labour productivity.

Regarding the control variables, a reduction in import tariffs is associated with a higher firm-level TFP(R) as shown in Columns (1) - (4). This implies that stronger competition is associated with higher firm productivity. Firms that export are also associated with higher productivity.

2.4.3 Results from a Firm's Patent Application

To further understand the impact of technology diffusion via imports, I also test its effect on a firm's innovation activity, which I use the patent application number to index. Specifically, I observe the types of patents applied for by the individual

Table 2.5: The result for the First-Stage Regression

	(1)
	$knowledge^{diff}_{ic,t}$
$tariff_{i,t}$	-0.243***
	(0.0109)
$ln(age_{f,t})$	0.0559*
	(0.0333)
$Export_{f,t}$	0.0254
	(0.0280)
$ln(Pice_{Jpn,it})$	-0.00386
	(0.00508)
$ln(Pice_{Deu,it})$	-0.0322***
	(0.00555)
$ln(Pice_{US,it})$	0.00701
	(0.00590)
$ln(RD_{Jpn,it})$	0.0742***
	(0.00842)
$ln(RD_{Deu,it})$	-0.0552***
	(0.00532)
$ln(RD_{US,it})$	0.0374***
	(0.00993)
$ln(im_{Jpn,cit})$	0.0291***
	(0.00315)
$ln(im_{Deu,cit})$	0.00869***
	(0.00263)
$ln(im_{US,cit})$	0.0577***
	(0.00277)
$knowledge^{diff,iv}_{DEU,ic,t}$	0.0468***
	(0.00508)
$knowledge^{diff,iv}_{Jpn,ic,t}$	-0.00394
	(0.00616)
$knowledge^{diff,iv}_{US,ic,t}$	0.0177***
	(0.00501)
R^2	0.847
Firm-fixed	Yes
Industry-fixed	Yes
Year-fixed	Yes
Ownership-fixed	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: The technology diffusion effects on a firm's productivity via imports

	(1) $ln(tfp_{ft})$	(2) $ln(tfp_{ft})$	(3) $ln(tfp_{ft})$	(4) $ln(tfp_{ft})$	(5) $ln(va_{ft})$	(6) $ln(va_{ft})$	(7) $ln(va_{ft})$	(8) $ln(va_{ft})$
$ln(knowledge^{diff}_{cit})$	0.0024**	0.0019	0.0002**	-0.0001	-0.0049	-0.0062	0.0014***	-0.0002
	(1.97)	(1.63)	(2.40)	(-1.04)	(-0.73)	(-0.91)	(4.10)	(-0.20)
$ln(knowledge^{diff}_{cit}) \times Skill_i$		0.0025***		0.0022***		0.0107*		0.0114**
		(2.78)		(2.68)		(1.81)		(2.26)
$tariff_{i,t}$	-0.0005	-0.0005	-0.0005	-0.0005*	0.0262***	0.0261***	0.0263***	0.0261***
	(-1.57)	(-1.60)	(-1.62)	(-1.65)	(15.56)	(15.41)	(15.59)	(15.44)
$ln(age_{f,t})$	-0.0018**	-0.0019**	-0.0019**	-0.0019**	0.0496***	0.0500***	0.0497***	0.0501***
	(-2.03)	(-2.10)	(-2.07)	(-2.14)	(9.70)	(9.77)	(9.72)	(9.79)
$Export_{f,t}$	0.0106***	0.0105***	0.0107***	0.0106***	0.0460***	0.0456***	0.0459***	0.0456***
	(11.42)	(11.34)	(11.44)	(11.37)	(10.73)	(10.64)	(10.71)	(10.63)
$ln(Price_{Jpn,it})$	-0.0023***	-0.0023***	-0.0023***	-0.0024***	-0.0049***	-0.0049***	-0.0047***	-0.0047***
	(-18.67)	(-18.85)	(-20.55)	(-20.58)	(-6.95)	(-6.82)	(-7.02)	(-6.89)
$ln(Price_{Deu,it})$	-0.0009***	-0.0009***	-0.0009***	-0.0009***	0.0001	0.0001	0.0000	-0.0000
	(-8.01)	(-8.12)	(-7.80)	(-7.91)	(0.22)	(0.11)	(0.02)	(-0.06)
$ln(Price_{US,it})$	-0.0001	-0.0001	-0.0002*	-0.0002**	-0.0038***	-0.0038***	-0.0035***	-0.0035***
	(-0.73)	(-1.08)	(-1.86)	(-2.18)	(-5.12)	(-5.15)	(-5.32)	(-5.38)
$ln(RD_{Jpn,it})$	0.0006***	0.0006***	0.0007***	0.0007***	-0.0033**	-0.0034**	-0.0037***	-0.0038***
	(3.01)	(3.06)	(4.14)	(4.18)	(-2.43)	(-2.53)	(-2.89)	(-2.97)
$ln(RD_{Deu,it})$	-0.0011***	-0.0011***	-0.0007***	-0.0008***	0.0015	0.0015	0.0004	0.0003
	(-4.79)	(-4.88)	(-6.92)	(-7.28)	(1.11)	(1.04)	(0.60)	(0.39)
$ln(RD_{US,it})$	-0.0005***	-0.0005***	-0.0005**	-0.0005**	0.0029**	0.0032**	0.0027**	0.0030**
	(-2.68)	(-2.71)	(-2.37)	(-2.37)	(2.17)	(2.34)	(2.04)	(2.26)
$ln(im_{Jpn,cit})$	-0.0007	-0.0006	0.0007***	0.0007***	0.0050	0.0049	0.0011**	0.0012**
	(-0.95)	(-0.85)	(7.08)	(7.16)	(1.20)	(1.19)	(2.11)	(2.15)
$ln(im_{Deu,cit})$	-0.0003	-0.0003	0.0003***	0.0003***	0.0014	0.0013	-0.0002	-0.0002
	(-0.93)	(-0.83)	(3.17)	(3.19)	(0.79)	(0.77)	(-0.45)	(-0.44)
$ln(im_{US,cit})$	-0.0015**	-0.0014**	-0.0003***	-0.0003***	0.0046	0.0046	0.0013***	0.0014***
	(-2.26)	(-2.17)	(-3.59)	(-3.30)	(1.30)	(1.30)	(2.97)	(3.19)
Firm-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	OLS	OLS	IV	IV	OLS	OLS
Obs.	1335487	1335487	1335487	1335487	1335487	1335487	1335487	1335487
R-squre	0.6290	0.6290	0.6290	0.6290	0.7706	0.7700	0.7706	0.7706

Robust standard errors are in parentheses and are clustered at the firm level.
$tfp_{f,t}$ represents the TFP level of firm f at year t. $ln(va)$ represents the log value of the ratio between firm's value-added and employment
$tariff_{i,t}$ is China's import tariff at the 4-digit industry level, $age_{f,t}$ represents the firm's age, $Export_{f,t}$ is a dummy variable and represents the firm's export status at year t. $Price_{s,it}$, with $s \in \{Jpn, Deu, US\}$, represents the price of the import products at the industry level. $RD_{s,it}$, with $s \in \{Jpn, Deu, US\}$, represents the R&D investment of at the industry level of country s. $im_{s,cit}$, with $s \in \{Jpn, Deu, US\}$, represents the import value at the industry level of city c from country s.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

firm and construct two measures of patents[10]. The first one measures the good quality patents, which are the sum of 'invent' and 'utility' patents:

$$patent^{(1)}_{f,t} = invent_{f,t} + utility_{f,t}$$

The second one measures the total number of patents applied for by the firm, including the 'design' patents:

$$patent^{(2)}_{f,t} = invent_{f,t} + utility_{f,t} + design_{f,t}$$

I take the ratio between the first and the second measure to capture the firm's average patent quality:

$$ratio_{f,t} = \frac{patent^{(1)}_{f,t}}{patent^{(2)}_{f,t}}$$

Table 2.7 shows us the impact of import technology diffusion on a firm's patent application. Columns (3) to (6) show that on average technology diffusion via imports does not have a significant impact on a firm's patent application. However, column (3) shows that one standard deviation increase in import technology diffusion leads to a significant 0.33% increase in high quality patent applications in more skill-intensive industries. Column (5) shows that one standard deviation increase in import technology diffusion leads to a significant 0.37% increase in a firm's total patent applications in more skill-intensive industries. Column (1) shows that one standard deviation increase in import technology diffusion leads to a significant 0.14% increase in a firm's share of good patent applications in more skill-intensive industries. This result implies that import technology diffusion improves the quality of a firm's patents.

Results from Firm Size and Factor Usage

To further understand a firm's behaviour, I examine the impact of technology diffusion via trade on a firm's size, value-added, and factor usage. The results are

[10]In the data, there are three types of patents: 'invent,' 'utility' and 'design.' It takes around two years to obtain approval for the 'invent' and 'utility' patents, while less than one year for the 'design' patents after the application

Table 2.7: The technology diffusion effect on a firm's patent application

	(1)	(2)	(3)	(4)	(5)	(6)
	$ln(ratio_{f,t})$	$ln(ratio_{f,t})$	$ln(patent^{(1)}_{f,t})$	$ln(patent^{(1)}_{f,t})$	$ln(patent^{(2)}_{f,t})$	$ln(patent^{(2)}_{f,t})$
$ln(knowledge^{diff}_{cit})$	0.0000	0.0002	-0.0011	-0.0006	-0.0029	-0.0023
	(0.02)	(0.30)	(-0.73)	(-0.41)	(-1.54)	(-1.25)
$ln(knowledge^{diff}_{cit}) \times Skill_i$	0.0014*		0.0033**		0.0037**	
	(1.70)		(2.08)		(1.97)	
$tariff_{i,t}$	0.0008***	0.0009***	0.0025***	0.0027***	0.0026***	0.0027***
	(4.86)	(5.26)	(6.49)	(6.93)	(4.77)	(5.10)
$ln(age_{f,t})$	-0.0007	-0.0006	-0.0037***	-0.0036***	-0.0038***	-0.0037**
	(-1.24)	(-1.19)	(-3.23)	(-3.17)	(-2.61)	(-2.56)
$Export_{f,t}$	0.0026***	0.0026***	0.0079***	0.0079***	0.0111***	0.0111***
	(4.64)	(4.64)	(6.41)	(6.42)	(7.16)	(7.16)
$ln(Price_{Jpn,it})$	0.0002**	0.0002**	0.0008***	0.0008***	0.0007**	0.0007***
	(2.15)	(2.19)	(3.32)	(3.36)	(2.57)	(2.62)
$ln(Price_{Deu,it})$	0.0002	0.0002	0.0006***	0.0006***	0.0007***	0.0007***
	(1.58)	(1.56)	(2.93)	(2.92)	(2.88)	(2.87)
$ln(Price_{US,it})$	-0.0000	-0.0000	0.0000	0.0000	0.0001	0.0002
	(-0.19)	(-0.19)	(0.08)	(0.10)	(0.56)	(0.58)
$ln(RD_{Jpn,it})$	-0.0005***	-0.0005***	-0.0010**	-0.0010**	-0.0007	-0.0007
	(-2.67)	(-2.65)	(-2.34)	(-2.33)	(-1.38)	(-1.37)
$ln(RD_{Deu,it})$	0.0003*	0.0003*	0.0011***	0.0011***	0.0012***	0.0012***
	(1.84)	(1.81)	(3.13)	(3.10)	(2.73)	(2.70)
$ln(RD_{US,it})$	0.0002	0.0001	0.0002	0.0001	0.0002	0.0002
	(0.77)	(0.71)	(0.39)	(0.34)	(0.36)	(0.32)
$ln(im_{Jpn,cit})$	-0.0001	-0.0002	0.0003	0.0003	0.0014	0.0013
	(-0.29)	(-0.34)	(0.34)	(0.29)	(1.22)	(1.17)
$ln(im_{Deu,cit})$	-0.0001	-0.0001	0.0001	0.0000	0.0006	0.0006
	(-0.37)	(-0.40)	(0.15)	(0.11)	(1.21)	(1.17)
$ln(im_{US,cit})$	-0.0001	-0.0002	0.0002	0.0002	0.0013	0.0012
	(-0.36)	(-0.43)	(0.28)	(0.22)	(1.29)	(1.22)
Firm-Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year-Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Ownership-Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV	IV	IV
R-Square	0.4953	0.4953	0.6133	0.6132	0.6167	0.6167

Robust standard errors are in parentheses and are clustered at the firm level.
$patent^{(1)}_{f,t}$ measures the sum of firm f's 'utility' and 'invent' at year t. $patent^{(2)}_{f,t}$ measures the sum of all of firm f's three types of patents, which are 'utility', 'invent' and 'design' at year t. $ratio_{f,t} = \frac{patent^{(1)}_{f,t}}{patent^{(2)}_{f,t}}$ captures the quality of the patent application.
$tariff_{i,t}$ is China's import tariff at the 4-digit industry level, $age_{f,t}$ represents the firm's age, $Export_{f,t}$ is a dummy variable and represents the firm's export status at year t. $Price_{s,it}$, with $s \in \{Jpn, Deu, US\}$, represents the price of the import products at the industry level. $RD_{s,it}$, with $s \in \{Jpn, Deu, US\}$, represents the R&D investment at the industry level of country s. $im_{s,cit}$, with $s \in \{Jpn, Deu, US\}$, represents the import value at the industry level of city c from country s.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

shown in Table 2.8. Columns (1) and (2) show that technology diffusion via imports does not have a significant impact on a firm's value-added and total employment. Column (3) shows that one standard deviation increase in import technology spillover leads to a significant 1% increase in a firm's sales in more skill-intensive industries. Column (7) shows that one standard deviation increase in import technology spillover leads to a 0.58% increase in a firm's skill-labour ratio. This implies that firms demand a larger share of skilled labour with strong technology diffusion via imports.

2.4.4 Robustness Check

In this section, I conduct a robustness check for my baseline results using alternative regression specification. There are mainly two concerns for our baseline regression. The first one is that knowledge import may have different impacts on local firms depending on their ownership. The second concern is that the measure of an industry's skill intensity may capture the effect of capital intensity.

Ownership and Knowledge Import

The first concern specifies that firms with different ownerships may be affected differently under knowledge import within the same industry. Local Chinese firms exhibit comparative dis-advantages in skill-intensive industries, while foreign-invested firms exhibit comparative advantages in skill-intensive industries. This is because the productivity of foreign affiliates in China is heavily affected by the productivity of their parent firms in the source country. Therefore, the technology may diffuse via the linkage between parent-affiliate rather than via international trade, according to the prediction of our model.

To support this argument, I run my baseline regression specification with the samples of the same ownership. Columns (1) - (4) in Table 2.9 show that knowledge import has a significant impact on a privately-owned Chinese firm's TFP, but an insignificant impact on the productivity of a state-owned or foreign-owned firm. A one standard deviation in knowledge import leads to a 0.57% significant increase in a private firm's TFP. Columns (5) - (8) in this table show that knowledge import has a significant impact on Chinese privately-owned and state-owned firms' productivity growth, but its impact on foreign-owned firms is insignificant. This is mainly because the technology diffuses via parent and affiliate in foreign-owned firms in China, but not through international trade. A one standard deviation increase in knowledge import leads to a roughly 0.61% increase in privately-owned firms' productivity and a 0.73% increase in state-owned firms' productivity. These are consistent with the model prediction that if the foreign affiliates in China have

Table 2.8: The effect import technology diffusion on a firm's size and factor use

	(1) $ln(value_{f,t})$	(2) $ln(value_{f,t})$	(3) $ln(sales_{f,t})$	(4) $ln(sales_{f,t})$	(5) $ln(Employ_{f,t})$	(6) $ln(Employ_{f,t})$	(7) $Skill_{f,t}$	(8) $Skill_{f,t}$
$ln(Knowledge^{diff}_{cit})$	-0.0150	-0.0141	-0.0141	-0.0135	0.0006	0.0002	0.0002*	0.0007***
	(-1.32)	(-1.25)	(-1.57)	(-1.51)	(0.09)	(0.03)	(1.70)	(5.48)
$ln(Knowledge^{diff}_{cit}) \times Skill_i$	0.0085		0.0097*		-0.0014		0.0058***	
	(1.22)		(1.87)		(-0.37)		(14.25)	
$tariff_{i,t}$	0.0268***	0.0275***	0.0152***	0.0156***	-0.0000	0.0006	-0.0024***	-0.0022***
	(12.49)	(12.85)	(9.64)	(9.97)	(-0.03)	(0.47)	(-3.87)	(-3.53)
$ln(age_{f,t})$	0.2161***	0.2163***	0.1796***	0.1795***	0.1499***	0.1503***	-0.0040***	-0.0040***
	(34.23)	(34.28)	(39.75)	(39.77)	(43.46)	(43.63)	(-10.51)	(-10.68)
$Export_{f,t}$	0.2017***	0.2021***	0.1815***	0.1817***	0.1274***	0.1273***	-0.0062***	-0.0061***
	(36.73)	(36.80)	(47.34)	(47.40)	(43.02)	(43.01)	(-15.62)	(-15.34)
$ln(Price_{Jpn,it})$	-0.0035***	-0.0037***	-0.0050***	-0.0050***	0.0013***	0.0013***	0.0003***	0.0004***
	(-4.29)	(-4.50)	(-8.53)	(-8.57)	(2.88)	(2.92)	(3.46)	(4.28)
$ln(Price_{Deu,it})$	-0.0005	-0.0005	0.0001	0.0001	-0.0008*	-0.0008**	-0.0004***	-0.0004***
	(-0.62)	(-0.64)	(0.18)	(0.23)	(-1.92)	(-2.10)	(-3.54)	(-3.59)
$ln(Price_{US,it})$	-0.0042***	-0.0042***	-0.0055***	-0.0055***	-0.0005	-0.0006	0.0013***	0.0013***
	(-4.68)	(-4.73)	(-8.54)	(-8.55)	(-1.04)	(-1.20)	(12.08)	(12.07)
$ln(RD_{Jpn,it})$	-0.0009	-0.0003	-0.0004	-0.0002	0.0026***	0.0026***	-0.0050***	-0.0051***
	(-0.61)	(-0.19)	(-0.44)	(-0.20)	(3.23)	(3.25)	(-13.13)	(-13.71)
$ln(RD_{Deu,it})$	0.0050**	0.0050**	0.0050***	0.0052***	0.0016	0.0015	0.0013***	0.0017***
	(2.10)	(2.11)	(2.70)	(2.81)	(1.15)	(1.11)	(6.35)	(7.97)
$ln(RD_{US,it})$	-0.0033*	-0.0042**	-0.0034***	-0.0037***	-0.0038***	-0.0037***	0.0032***	0.0032***
	(-1.83)	(-2.30)	(-2.63)	(-2.92)	(-3.88)	(-3.84)	(10.44)	(10.51)
$ln(im_{Jpn,cit})$	0.0093	0.0094	0.0079*	0.0082*	-0.0003	-0.0002	-0.0007***	-0.0005***
	(1.58)	(1.61)	(1.70)	(1.76)	(-0.08)	(-0.05)	(-6.59)	(-4.89)
$ln(im_{Deu,cit})$	0.0039*	0.0039*	0.0040**	0.0041**	0.0011	0.0012	-0.0002***	-0.0001
	(1.72)	(1.75)	(2.25)	(2.33)	(0.82)	(0.86)	(-2.66)	(-1.40)
$ln(im_{US,cit})$	0.0093*	0.0094*	0.0083**	0.0086**	0.0005	0.0006	-0.0004***	-0.0003***
	(1.85)	(1.87)	(2.10)	(2.16)	(0.17)	(0.21)	(-4.92)	(-3.76)
Firm-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV	IV	IV	IV	IV
R-square	0.8334	0.8342	0.9015	0.9023	0.9135	0.9136	0.1899	0.1880

Robust standard errors are in parentheses and are clustered at the firm level.
$value_{f,t}$ represents the value-added of firm f at year t, $sales_{f,t}$ is a firm's sales, $Employ_{f,t}$ is firm f's total employment and $Skill_{f,t}$ is the skilled labor ratio of firm f.
$tariff_{i,t}$ is the China's import tariff at the 4-digit industry level, $age_{f,t}$ represents firm's age, $Export_{f,t}$ is a dummy variable and represents firm's export status at year t. $Price_{s,it}$, with $s \in \{Jpn, Deu, US\}$, represents the price of the import products at the industry level. $RD_{s,it}$, with $s \in \{Jpn, Deu, US\}$, represents the R&D investment of at the industry level of country s. $im_{s,cit}$, with $s \in \{Jpn, Deu, US\}$, represents the import value of at the industry level of city c from country s.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

similar productivity to their parent firms from the foreign countries, import knowledge would not have a significant impact on their productivity growth.

Different Measure of Industries

The other concern is that the measure of skill-intensity of an industry may partially capture the effect from capital-intensity because firms in capital-intensive industries need to hire skilled labour to operate the machines. Another reason is that China also exhibits a comparative disadvantage in capital intensive industries or industries reliant on external finance. To address this concern, I incorporate both the measures of an industry's capital-intensity and an industry's reliance on external finance in my baseline regression specification.

Table 2.10 shows that our result remains significant and robust, even if we include other measures of the industries. This suggests that skilled labour is critical in adopting technology via imports. The first three columns show that a one standard deviation increase in knowledge import in skill-intensive industries leads to a 0.39% increase in TFP. I also use labour productivity, which is the ratio between value-added per capita, to capture a firm's productivity. Columns (4) - (6) in this table show that a one standard deviation increase in knowledge import leads to an around 1.7% increase in labour productivity.

2.5 Conclusion

This paper extends the work of Buera and Oberfield (2016) into a multi-industry version, which allows for H-O Comparative Advantage. The tractability of the model enables me to derive two testable predictions: 1. knowledge import allows the productivity growth of importers relative to non-importers to be higher in skill-intensive industry. 2. Productivity growth is faster in unskilled industry than in skilled industry with trade openness.

To the best of my knowledge, this paper is the first to emphasize the importance of knowledge import for manufacturing firms in developing countries. in its efforts to complement the literature focused on international knowledge diffusion via FDI, this paper provides credible empirical evidence on how Chinese firms learn from the knowledge embodied in importing goods.

Table 2.9: The impact of import knowledge on productivity for firms with different ownership

	(1) State-owned	(2) Private	(3) HK-Owned	(4) Foreign-Owned	(5) State-owned	(6) Private	(7) HK-Owned	(8) Foreign-Owned
$ln(knowledge_{cit}^{diff})$	0.00168	0.00570*	-0.00207	-0.00430	0.00135	0.00454	-0.00336	-0.00267
	(0.00608)	(0.00269)	(0.00925)	(0.00776)	(0.00613)	(0.00367)	(0.00926)	(0.00786)
$ln(knowledge_{cit}^{diff}) \times Skill_i$					0.00734*	0.00615**	0.00590	-0.00715
					(0.00407)	(0.00242)	(0.00481)	(0.00538)
$tariff_{i,t}$	0.00151*	-0.00270***	-0.000956	0.000566	0.00140*	-0.00272***	-0.000905	0.000559
	(0.000838)	(0.000525)	(0.00102)	(0.00103)	(0.000842)	(0.000529)	(0.00102)	(0.00103)
$Export_{f,t}$	0.0172***	0.0213***	-0.00577***	-0.00785***	0.0171***	0.0211***	-0.00579***	-0.00782***
	(0.00315)	(0.00186)	(0.00183)	(0.00210)	(0.00315)	(0.00186)	(0.00183)	(0.00210)
$ln(age_{f,t})$	-0.00290	-0.00268**	0.0137***	-0.00245	-0.00290	-0.00270**	0.0137***	-0.00246
	(0.00365)	(0.00133)	(0.00370)	(0.00384)	(0.00367)	(0.00133)	(0.00370)	(0.00384)
$ln(Price_{Jpn,it})$	-0.00178***	-0.00301***	-0.00528***	-0.00220***	-0.00179***	-0.00299***	-0.00528***	-0.00218***
	(0.000337)	(0.000202)	(0.000393)	(0.000509)	(0.000342)	(0.000203)	(0.000396)	(0.000511)
$ln(Price_{Deu,it})$	-0.000167	-0.000837***	-0.00281***	-0.00242***	-0.000248	-0.000828***	-0.00279***	-0.00241***
	(0.000288)	(0.000182)	(0.000377)	(0.000399)	(0.000293)	(0.000183)	(0.000380)	(0.000401)
$ln(Price_{US,it})$	-0.00153***	-0.00186***	-0.00103**	-0.000125	-0.00162***	-0.00192***	-0.00108***	-0.000131
	(0.000300)	(0.000193)	(0.000410)	(0.000459)	(0.000305)	(0.000193)	(0.000413)	(0.000462)
$ln(RD_{Jpn,it})$	0.00179**	-0.000974*	-0.000544	0.000834*	0.00168**	-0.000873*	-0.000602	0.000814*
	(0.000800)	(0.000522)	(0.000590)	(0.000489)	(0.000817)	(0.000523)	(0.000593)	(0.000490)
$ln(RD_{Deu,it})$	-0.000843*	-0.000214	-0.000530	-0.000340	-0.000879**	-0.000202	-0.000525	-0.000360
	(0.000435)	(0.000275)	(0.000622)	(0.000549)	(0.000438)	(0.000275)	(0.000621)	(0.000552)
$ln(RD_{US,it})$	-0.000926	0.000943**	0.00292***	0.000791	-0.000776	0.000850*	0.00305***	0.000764
	(0.000711)	(0.000473)	(0.000627)	(0.000590)	(0.000734)	(0.000473)	(0.000633)	(0.000591)
$ln(im_{Jpn,cit})$	0.000639	-0.000986	0.00294	0.00334	0.000377	-0.000854	0.00317	0.00308
	(0.00217)	(0.00130)	(0.00332)	(0.00283)	(0.00218)	(0.00130)	(0.00332)	(0.00285)
$ln(im_{Deu,cit})$	-0.000218	-0.000532	0.00267*	0.00180	-0.000297	-0.000477	0.00277**	0.00168
	(0.000925)	(0.000583)	(0.00140)	(0.00122)	(0.000928)	(0.000583)	(0.00140)	(0.00123)
$ln(im_{US,cit})$	-0.000138	-0.00133	0.000818	0.000488	-0.000261	-0.00125	0.000960	0.000263
	(0.00156)	(0.000954)	(0.00238)	(0.00203)	(0.00157)	(0.000952)	(0.00238)	(0.00205)
Firm-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.593	0.635	0.620	0.591	0.593	0.635	0.620	0.591

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: Robustness Check for the impact of knowledge import on firm's productivity

	(1) $ln(TFP)$	(2) $ln(TFP)$	(3) $ln(TFP)$	(4) $ln(\frac{V.A}{Employment})$	(5) $ln(\frac{V.A}{Employment})$	(6) $ln(\frac{V.A}{Employment})$
$ln(knowledge_{cit}^{diff})$	0.0000236	0.000164	-0.0000826	-0.0184	-0.0150	-0.0183
	(0.00159)	(0.00158)	(0.00160)	(0.0121)	(0.0120)	(0.0122)
$ln(knowledge_{cit}^{diff}) \times Skill_i$	0.00390***	0.00400***	0.00345***	0.0167*	0.0248**	0.0172
	(0.000991)	(0.00117)	(0.00125)	(0.00867)	(0.0101)	(0.0110)
$ln(knowledge_{cit}^{diff}) \times Capital_i$	0.0000967		0.000162	0.00226**		0.00219
	(0.000103)		(0.000156)	(0.000963)		(0.00138)
$ln(knowledge_{cit}^{diff}) \times Finance_i$		-0.0000637	0.000174		-0.00342*	-0.000187
		(0.000194)	(0.000293)		(0.00191)	(0.00274)
$tariff_{i,t}$	-0.000716***	-0.000713***	-0.000715***	0.0164***	0.0165***	0.0164***
	(0.000218)	(0.000218)	(0.000218)	(0.00160)	(0.00160)	(0.00160)
$Export_{f,t}$	0.00707***	0.00707***	0.00707***	0.0576***	0.0576***	0.0576***
	(0.000665)	(0.000665)	(0.000665)	(0.00354)	(0.00354)	(0.00354)
$ln(age_{f,t})$	-0.00163**	-0.00163**	-0.00163**	0.0332***	0.0333***	0.0332***
	(0.000686)	(0.000686)	(0.000686)	(0.00435)	(0.00435)	(0.00435)
$ln(Price_{Jpn,it})$	-0.00137***	-0.00137***	-0.00137***	-0.00597***	-0.00596***	-0.00597***
	(0.0000769)	(0.0000769)	(0.0000769)	(0.000583)	(0.000583)	(0.000583)
$ln(Price_{Deu,it})$	0.000116*	0.000115	0.000115*	0.000531	0.000526	0.000532
	(0.0000697)	(0.0000697)	(0.0000697)	(0.000550)	(0.000550)	(0.000550)
$ln(Price_{US,it})$	-0.000934***	-0.000935***	-0.000936***	-0.00492***	-0.00492***	-0.00492***
	(0.0000721)	(0.0000721)	(0.0000722)	(0.000559)	(0.000559)	(0.000559)
$ln(Price_{Jpn,it})$	0.000142	0.000142	0.000141	-0.00350***	-0.00349***	-0.00350***
	(0.000161)	(0.000161)	(0.000161)	(0.00118)	(0.00117)	(0.00117)
$ln(Price_{Deu,it})$	-0.000424***	-0.000424***	-0.000424***	0.00150*	0.00150*	0.00150*
	(0.000110)	(0.000110)	(0.000110)	(0.000863)	(0.000862)	(0.000862)
$ln(Price_{US,it})$	0.000175	0.000176	0.000177	0.00365***	0.00363***	0.00365***
	(0.000156)	(0.000156)	(0.000156)	(0.00116)	(0.00116)	(0.00116)
$ln(im_{Jpn,cit})$	0.000291	0.000293	0.000295	0.00713*	0.00711*	0.00713*
	(0.000559)	(0.000559)	(0.000559)	(0.00424)	(0.00424)	(0.00424)
$ln(im_{Deu,cit})$	-0.000162	-0.000160	-0.000161	0.00383**	0.00384**	0.00383**
	(0.000241)	(0.000241)	(0.000241)	(0.00180)	(0.00180)	(0.00180)
$ln(im_{US,cit})$	0.0000992	0.000101	0.000102	0.00484	0.00482	0.00484
	(0.000408)	(0.000408)	(0.000408)	(0.00305)	(0.00305)	(0.00305)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Ownership-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV	IV	IV
R^2	0.657	0.657	0.657	0.848	0.848	0.848

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
$Skill_i$ measures the skill-intensity of an industry, $Capital_i$ is the capital-labor ratio, and $Finance_i$ is the reliance on external

2.6 Appendix

2.6.1 Proof for the proposition 1

Under free-trade, the wage ratio, for skilled or unskilled labor, between China and the foreign country of the same factor is given by:

$$\frac{w_{H,F}}{w_{H,C}} = (\frac{T_{H,F}}{T_{Hi,C}+T_{Hn,C}}\frac{H_C}{H_F})^{1/(1+\theta)} = (\frac{T_{H,F}}{T_{Hi,C}+T_{Hn,C}})^{1/(1+\theta)}$$

$$\frac{w_{L,F}}{w_{L,C}} = (\frac{T_{L,F}}{T_{Li,C}+T_{Ln,C}}\frac{L_C}{L_F})^{1/(1+\theta)} = (\frac{T_{L,F}}{T_{Li,C}+T_{Ln,C}})^{1/(1+\theta)}$$

The productivity growth rate of importers could be written as a function of the productivity growth of the non-importers within the same industry. In particular,

$$\frac{T_{mi,C}^{(t+1)}}{T_{mi,C}^{(t)}} = \frac{T_{mn,C}^{(t+1)}}{T_{mn,C}^{(t)}}\frac{1+(\frac{T_{m,F}^{(t)}}{T_{mi,C}^{(t)}+T_{mn,C}^{(t)}})^{\frac{1+\beta\theta}{1+\theta}}}{(1+(\frac{T_{m,F}^{(t)}}{T_{mi,C}^{(t)}+T_{mn,C}^{(t)}})^{\frac{1}{1+\theta}})^{1-\beta}}$$

To show that $\frac{T_{Hi,C}^{(t)}/T_{Hi,C}^{(t-1)}}{T_{Li,C}^{(t)}/T_{Li,C}^{(t-1)}} > \frac{T_{Hn,C}^{(t)}/T_{Hn,C}^{(t-1)}}{T_{Ln,C}^{(t)}/T_{Ln,C}^{(t-1)}}$, it is equivalent to show that

$$\frac{1+(\frac{T_{H,F}^{(t)}}{T_{Hi,C}^{(t)}+T_{Hn,C}^{(t)}})^{\frac{1+\beta\theta}{1+\theta}}}{1+(\frac{T_{L,F}^{(t)}}{T_{Li,C}^{(t)}+T_{Ln,C}^{(t)}})^{\frac{1+\beta\theta}{1+\theta}}} > \frac{(1+(\frac{T_{H,F}^{(t)}}{T_{Hi,C}^{(t)}+T_{Hn,C}^{(t)}})^{\frac{1}{1+\theta}})^{1-\beta}}{(1+(\frac{T_{L,F}^{(t)}}{T_{Li,C}^{(t)}+T_{Ln,C}^{(t)}})^{\frac{1}{1+\theta}})^{1-\beta}}$$

The LHS of the above inequality is always larger than the RHS. This is because if $\frac{T_{H,F}^{(t)}}{T_{Hi,C}^{(t)}+T_{Hn,C}^{(t)}} > \frac{T_{L,F}^{(t)}}{T_{Li,C}^{(t)}+T_{Ln,C}^{(t)}}$, the LHS is an increasing function of β and the RHS is a decreasing function of β. When $\beta = 0$, LHS = RHS. In this case, LHS reaches its lower bound, while the RHS reaches its upper bound.

Next, we need to show that $\frac{T_{H,F}^{(t)}}{T_{Hi,C}^{(t)}+T_{Hn,C}^{(t)}} > \frac{T_{L,F}^{(t)}}{T_{Li,C}^{(t)}+T_{Ln,C}^{(t)}}$ when $\beta \in (0,1]$ and $t > 0$.

When t = 0, $\frac{T_{H,F}^{(0)}}{T_{L,F}^{(0)}} > \frac{T_{Hi,C}^{(0)}}{T_{Li,C}^{(0)}} = \frac{T_{Hn,C}^{(0)}}{T_{Ln,C}^{(0)}}$ implies $\frac{T_{H,F}^{(0)}}{T_{Hi,C}^{(0)}+T_{Hn,C}^{(0)}} > \frac{T_{L,F}^{(0)}}{T_{Li,C}^{(0)}+T_{Ln,C}^{(0)}}$, and hence

$$\frac{T_{H,F}^{(1)}/T_{H,F}^{(0)}}{T_{L,F}^{(1)}/T_{L,F}^{(0)}} = \frac{T_{Hi,C}^{(1)}/T_{Hi,C}^{(0)}}{T_{Li,C}^{(1)}/T_{Li,C}^{(0)}} > \frac{T_{Hn,C}^{(1)}/T_{Hn,C}^{(0)}}{T_{Ln,C}^{(1)}/T_{Ln,C}^{(0)}}.$$

With this condition, we know $\frac{T_{H,F}^{(1)}}{T_{L,F}^{(1)}} > \frac{T_{Hi,C}^{(1)}}{T_{Li,C}^{(1)}} > \frac{T_{Hn,C}^{(1)}}{T_{Ln,C}^{(1)}}$. This implies that $\frac{T_{H,F}^{(1)}}{T_{Hi,C}^{(1)}+T_{Hn,C}^{(1)}} > \frac{T_{L,F}^{(1)}}{T_{Li,C}^{(1)}+T_{Ln,C}^{(1)}}$. For any $t > 1$, we will always have $\frac{T_{H,F}^{(t)}}{T_{Hi,C}^{(t)}+T_{Hn,C}^{(t)}} > \frac{T_{L,F}^{(t)}}{T_{Li,C}^{(t)}+T_{Ln,C}^{(t)}}$. ##

2.6.2 Proof of Proposition 2

Under free trade, an industry's productivity growth is the weighted-average of productivity growth for the importers and the non-importers. The contribution of importers or non-importers on aggregate industry's productivity growth depends also on its production share. In particular, the relative productivity growth of H-industry on L-industry under trade openness is given by:

$$R_T = \frac{(T_{Hi,C}^{(t)}/T_{Hi,C}^{(t-1)})^{\frac{T_{Hi,C}^{(t-1)}}{T_{Hi,C}^{(t-1)}+T_{Hn,C}^{(t-1)}}} + (T_{Hn,C}^{(t)}/T_{Hn,C}^{(t-1)})^{\frac{T_{Hn,C}^{(t-1)}}{T_{Hi,C}^{(t-1)}+T_{Hn,C}^{(t-1)}}}}{(T_{Li,C}^{(t)}/T_{Li,C}^{(t-1)})^{\frac{T_{Li,C}^{(t-1)}}{T_{Li,C}^{(t-1)}+T_{Ln,C}^{(t-1)}}} + (T_{Ln,C}^{(t)}/T_{Ln,C}^{(t-1)})^{\frac{T_{Ln,C}^{(t-1)}}{T_{Li,C}^{(t-1)}+T_{Ln,C}^{(t-1)}}}}$$

Therefore, the relative productivity growth across industries can be simplified as following:

$$R_T = \frac{(T_{Hi,C}^{(t)} + T_{Hn,C}^{(t)})/(T_{Hi,C}^{(t-1)} + T_{Hn,C}^{(t-1)})}{(T_{Li,C}^{(t)} + T_{Ln,C}^{(t)})/(T_{Li,C}^{(t-1)} + T_{Ln,C}^{(t-1)})}$$

As such, the range of R_T is given:

$$\frac{T_{Hn,C}^{(t)}/T_{Hn,C}^{(t-1)}}{T_{Ln,C}^{(t)}/T_{Ln,C}^{(t-1)}} < R_T < \frac{T_{Hi,C}^{(t)}/T_{Hi,C}^{(t-1)}}{T_{Li,C}^{(t)}/T_{Li,C}^{(t-1)}}$$

We could have: $R_T > R_A$ ##

Bibliography

Acharya, R. C. and Keller, W. (2007). Technology transfer through imports. Working Paper 13086, National Bureau of Economic Research.

Alfaro, L., Antrás, P., Chor, D., and Conconi, P. (2015). Internalizing global value chains: A firm-level analysis. Working Paper 21582, National Bureau of Economic Research.

Alvarez, F. E., Buera, F. J., and Lucas, Robert E, J. (2013). Idea flows, economic growth, and trade. Working Paper 19667, National Bureau of Economic Research.

Amiti, M. and Konings, J. (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *American Economic Review*, 97(5):1611–1638.

Antràs, P. and Chor, D. (2013). Organizing the global value chain. *Econometrica*, 81(6):2127–2204. From March 2013.

Antras, P., Chor, D., Fally, T., and Hillberry, R. (2012). Measuring the Upstreamness of Production and Trade Flows. *American Economic Review*, 102(3):412–416.

Antràs, P. and de Gortari, A. (2017). On the geography of global value chains. Number 23456 in Working Paper Series.

Baldwin, R. and Venables, A. J. (2013). Spiders and snakes: Offshoring and agglomeration in the global economy. *Journal of International Economics*, 90(2):245 – 254.

Baldwin, R. E. (2006). Multilateralising Regionalism: Spaghetti Bowls as Building Blocs on the Path to Global Free Trade. *The World Economy*, 29(11):1451–1518.

Baum-Snow, N. (2007). Did highways cause suburbanization? *The Quarterly Journal of Economics*, 122(2):775–805.

Baum-Snow, N., Brandt, L., Henderson, J. V., Turner, M. A., and Zhang, Q. (2017). Roads, Railroads, and Decentralization of Chinese Cities. *The Review of Economics and Statistics*, 99(3):435–448.

Bloom, N., Schankerman, M., and Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4):1347–1393.

Brandt, L. and Morrow, P. M. (2017). Tariffs and the organization of trade in china. *Journal of International Economics*, 104:85 – 103.

Brandt, L., Tombe, T., and Zhu, X. (2013). Factor Market Distortions Across Time, Space, and Sectors in China. *Review of Economic Dynamics*, 16(1):39–58.

Buera, F. J. and Oberfield, E. (2016). The Global Diffusion of Ideas. NBER Working Papers 21844, National Bureau of Economic Research, Inc.

Bustos, P. (2011). Trade liberalization, exports, and technology upgrading: Evidence on the impact of mercosur on argentinian firms. *The American Economic Review*, 101(1):304–340.

Che, Y. and Zhang, L. (2018). Human capital, technology adoption and firm performance: Impacts of china's higher education expansion in the late 1990s. *The Economic Journal*, 128(614):2282–2320.

Chor, D., Manova, K., and Yu, Z. (2016). The global production line position of chinese firms. In *Industrial Upgrading and Urbanization Conference, Stockholm*, volume 28, page 29.

Coe, D. T. and Helpman, E. (1995). International rd spillovers. *European Economic Review*, 39(5):859 – 887.

Costinot, A., Vogel, J., and Wang, S. (2013). An elementary theory of global supply chains. *Review of Economic Studies*, 80(1):109–144.

Duranton, G., Morrow, P. M., and Turner, M. A. (2014). Roads and trade: Evidence from the us. *The Review of Economic Studies*, 81(2):681–724.

Eaton, J. and Kortum, S. (1999). International technology diffusion: Theory and measurement. *International Economic Review*, 40(3):537–570.

Eaton, J. and Kortum, S. (2001). Trade in capital goods. *European Economic Review*, 45(7):1195 – 1235. International Seminar On Macroeconomics.

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5):1741–1779.

Faber, B. (2014). Trade integration, market size, and industrialization: Evidence from china's national trunk highway system. *The Review of Economic Studies*, 81(3):1046–1070.

Fally, T. (2012). Production Staging: Measurement and Factss.

Fons-Rosen, C., Kalemli-Ozcan, S., Sorensen, B. E., Villegas-Sanchez, C., and Volosovych, V. (2017). Foreign investment and domestic productivity: Identifying knowledge spillovers and competition effects. Working Paper 23643, National Bureau of Economic Research.

Garcia-Milà, T. and Montalvo, J. G. (2011). The impact of new highways on business location: new evidence from spain.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., and Topalova, P. (2010). Imported Intermediate Inputs and Domestic Product Growth: Evidence from India*. *The Quarterly Journal of Economics*, 125(4):1727–1767.

Grossman, Gene M.and Helpman, E. (1991). Quality ladders in the theory of growth. *The Review of Economic Studies*, 58(1):43–61.

Grossman, G. M. and Rossi-Hansberg, E. (2012). Task trade between similar countries. *Econometrica*, 80(2):593–629.

Head, K. and Ries, J. (2001). Increasing returns versus national product differentiation as an explanation for the pattern of u.s.-canada trade. *The American Economic Review*, 91(4):858–876.

Hummels, David L.and Schaur, G. (2013). Time as a trade barrier. *American Economic Review*, 103(7):2935–59.

Hyytinen, A. and Toivanen, O. (2011). Income inequality and technology diffusion: Evidence from developing countries*. *The Scandinavian Journal of Economics*, 113(2):364–387.

Johnson, R. C. and Noguera, G. (2012). Fragmentation and Trade in Value Added over Four Decades. (18186).

Johnson, R. C. and Noguera, G. (2017). A portrait of trade in value-added over four decades. *The Review of Economics and Statistics*, 99(5):896–911.

Kee, H. L. and Tang, H. (2016). Domestic value added in exports: Theory and firm evidence from china. *American Economic Review*, 106(6):1402–36.

Keller, W. (1997). Trade and transmission of technology. Working Paper 6113, National Bureau of Economic Research.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, 42(3):752–782.

Keller, W. (2009). International trade, foreign direct investment, and technology spillovers. Working Paper 15442, National Bureau of Economic Research.

Keller, W. and Yeaple, S. R. (2009). Multinational enterprises, international trade, and productivity growth: Firm-level evidence from the united states. *The Review of Economics and Statistics*, 91(4):821–831.

Koopman, R., Wang, Z., and Wei, S.-J. (2014). Tracing value-added and double counting in gross exports. *American Economic Review*, 104(2):459–94.

Krugman, P. R. (1987). Is free trade passe? *Journal of Economic Perspectives*, 1(2):131–144.

Lee, E. and Yi, K.-M. (2018). Global value chains and inequality with endogenous labor supply. Working Paper 24884, National Bureau of Economic Research.

Limao, N. and Venables, A. J. (2001). Infrastructure, geographical disadvantage, transport costs, and trade (english). *The World Bank economic review*, 15(3):451–479.

Lucas, Robert E, J. and Moll, B. (2011). Knowledge growth and the allocation of time. Working Paper 17495, National Bureau of Economic Research.

Manova, K. (2008). Credit constraints, heterogeneous firms, and international trade. Working Paper 14531, National Bureau of Economic Research.

Manova, K., Wei, S.-J., and Zhang, Z. (2015). Firm exports and multinational activity under credit constraints. *The Review of Economics and Statistics*, 97(3):574–588.

Matsuyama, K. (2000). A ricardian model with a continuum of goods under nonhomothetic preferences: Demand complementarities, income distribution, and north-south trade. *Journal of Political Economy*, 108(6):1093–1120.

Moxnes, A. and Johnson, R. C. (2016). Technology, trade costs, and the pattern of trade with multistage production.

Redding, S. J. and Turner, M. A. (2015). *Transportation Costs and the Spatial Organization of Economic Activity*, volume 5 of *Handbook of Regional and Urban Economics*, chapter 0, pages 1339–1398. Elsevier.

Thoenig, M. and Verdier, T. (2003). A theory of defensive skill-biased innovation and globalization. *American Economic Review*, 93(3):709–728.

Topalova, P. and Khandelwal, A. (2011). Trade liberalization and firm productivity: The case of india. *The Review of Economics and Statistics*, 93(3):995–1009.

Verhoogen, E. (2008). Trade, quality upgrading, and wage inequality in the mexican manufacturing sector. *The Quarterly Journal of Economics*, 123(2):489–530.

Yeaple, S. (2005). A simple model of firm heterogeneity, international trade, and wages. *Journal of International Economics*, 65(1):1–20.

Yi, K.-M. (2003). Can vertical specialization explain the growth of world trade? *Journal of Political Economy*, 111(1):52–102.

Yi, K.-M. (2010). Can multistage production explain the home bias in trade? *American Economic Review*, 100(1):364–93.

Yu, M. (2014). Processing trade, tariff reductions and firm productivity: Evidence from chinese firms. *The Economic Journal*, 125(585):943–988.