



Faculty of Economics and Business

**Impact of Global Value Chain and Industrial Agglomeration on China's
Automobile Industry Upgrading**

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Impact of Global Value Chain and Industrial Agglomeration on China's
Automobile Industry Upgrading

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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ABSTRACT

The automobile industry is a crucial component of China's national economy, serving as both a pillar and a leading sector. In the era of globalization, the trend of mergers and acquisitions has swept across the globe, making China's automobile industry a microcosm of the global automotive landscape. This industry is characterized by its high degree of interconnectedness, an extensive industrial chain, and a broad employment scope, all of which play a significant role in driving the growth of the national economy. Although China leads the world in automobile production, the Chinese automobile industry lacks competitiveness in the international market. The objective of this study is to investigate the factors influencing the upgrading of China's automobile industry and provide recommendations to enhance its competitiveness in the global market. Specifically, this thesis mainly studies the impact of industrial agglomeration and global value chain on the upgrading of China's automobile industry, and discusses whether government support plays a moderating role in the process of industrial agglomeration's impact on the upgrading of China's automobile industry, and whether foreign direct investment plays a moderating role in the process of global value chain's impact on the upgrading of China's automobile industry. Moreover, it analyses whether technological innovation plays a mediating role in the impact of global value chain on the upgrading of China's automobile industry. Finally, it examines whether human capital has a threshold effect in the impact of industrial agglomeration on the upgrading of China's automobile industry. It aims to contribute to the development of China's automobile industry and strengthen China's position in the global automobile market. This study selects a 21-year dataset from 28 provinces in China, spanning from 2000 to 2020, to ensure the availability and authenticity of the data. To measure industrial upgrading, total factor productivity (TFP) is chosen as the proxy variable. The TFP is calculated using the DEA-Malmquist method

with the Deap2.1 software. For estimation, System GMM and the dynamic panel threshold model are employed, with regression analysis conducted using Stata 17 software. The empirical results indicate that industrial agglomeration positively promotes the upgrading of China's automobile industry. However, embedding in the global value chain inhibits this upgrading. Government support does play a mediating role in the influence of industrial agglomeration on the upgrading of China's automobile industry. Similarly, foreign direct investment moderates the impact of global value chain on the upgrading of China's automobile industry, and technological innovation serves as a mediating factor in the effect of global value chain on the upgrading of China's automobile industry. Additionally, human capital acts as a threshold factor influencing the impact of industrial agglomeration on the upgrading of China's automobile industry, with a threshold value of 8.5099. Specifically, when human capital is below this threshold, industrial agglomeration does not significantly promote the upgrading of the industry. It is only when human capital exceeds the threshold that industrial agglomeration significantly enhances the upgrading of China's automobile industry. Based on these empirical analysis results, this study proposes recommendations for the upgrading of China's automobile industry.

Keywords: Global value chain, industrial agglomeration, data envelopment analysis, GMM, dynamic panel threshold

Kesan Rantaian Nilai Global dan Aglomerasi Industri terhadap Peningkatan Industri Automobil China

ABSTRAK

Industri automobil merupakan komponen penting dalam ekonomi negara China, berfungsi sebagai tonggak dan sektor utama. Dalam era globalisasi, trend penggabungan dan pengambilalihan telah melanda seluruh dunia, menjadikan industri automobil China sebagai mikrokosma landskap automotif global. Industri ini dicirikan oleh tahap saling berkaitan yang tinggi, rantaian perindustrian yang luas, dan skop pekerjaan yang luas, yang semuanya memainkan peranan penting dalam memacu pertumbuhan ekonomi negara. Walaupun China memimpin dunia dalam pengeluaran kereta, industri automobil China sering digambarkan sebagai "besar tetapi tidak kuat" dan tidak begitu kompetitif di pasaran antarabangsa. Objektif kajian ini adalah untuk menyiasat faktor-faktor yang mempengaruhi peningkatan industri automobil China dan memberikan cadangan untuk meningkatkan daya saingnya dalam pasaran global. Secara khusus, tesis ini terutamanya mengkaji kesan aglomerasi industri dan rantaian nilai global terhadap peningkatan industri automobil China, dan membincangkan sama ada sokongan kerajaan memainkan peranan penyederhanaan dalam proses kesan aglomerasi industri terhadap peningkatan industri automobil China, dan sama ada pelaburan langsung asing memainkan peranan penyederhanaan dalam proses kesan rantaian nilai global terhadap peningkatan industri automobil China. Selain itu, ia menganalisis sama ada rantaian nilai global mempengaruhi peningkatan industri automobil China melalui impak ke atas inovasi teknologi. Akhirnya, ia mengesahkan sama ada modal insan memainkan peranan ambang dalam mempengaruhi aglomerasi industri terhadap peningkatan industri automobil China. Ia bertujuan untuk menyumbang kepada pembangunan industri automotif China dan mengukuhkan kedudukan

China dalam pasaran automobil global. Kajian ini menggunakan set data 21 tahun dari 28 wilayah di China, yang merangkumi dari tahun 2000 hingga 2020, untuk memastikan ketersediaan dan kesahihan data. Untuk mengukur peningkatan industri, jumlah produktiviti faktor (TFP) dipilih sebagai pembolehubah proksi. TFP dikira menggunakan kaedah DEA-Malmquist dengan perisian Deap2.1. Untuk teknik penganggaran, Sistem GMM dan model ambang panel dinamik digunakan, dengan analisis regresi yang dijalankan menggunakan perisian Stata 17. Hasil empirikal menunjukkan bahawa aglomerasi industri secara positif menggalakkan peningkatan industri automobil China. Walau bagaimanapun, rangkaian nilai global menghalang peningkatan ini. Sokongan kerajaan memainkan peranan mengawal selia dalam proses pengaruh aglomerasi industri terhadap peningkatan industri automobil China. Begitu juga, pelaburan langsung asing menyederhanakan kesan rangkaian nilai global terhadap peningkatan industri automobil China, dan rangkaian nilai global menghalang peningkatan industri automobil China dengan menyekat inovasi teknologi. Di samping itu, modal insan bertindak sebagai ambang dalam pengaruh aglomerasi industri mengenai peningkatan industri automobil China, dengan nilai ambang 8.5099. Iaitu, apabila modal insan berada di bawah ambang, aglomerasi perindustrian tidak menggalakkan peningkatan industri automobil China dengan ketara. Walau bagaimanapun, apabila modal insan melebihi ambang, aglomerasi industri dengan ketara menggalakkan peningkatan industri automobil China. Berdasarkan keputusan analisis empirikal ini, kajian ini mencadangkan langkah-langkah untuk menaik taraf industri automobil China.

Kata kunci: *Rangkaian nilai global, aglomerasi perindustrian, analisis penyampulan data, GMM, ambang panel dinamik*

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LIST OF ABBREVIATIONS

GVC	Global Value Chain
TFP	Total Factor Productivity
FDI	Foreign Direct Investment
DEA	Data Envelopment Analysis
GMM	Generalized Method of Moments
OEA	Original Equipment Assembly
OEM	Original Equipment Manufacturer
ODM	Original Design Manufacturer
OBM	Original Brand Manufacturer
HC	Human Capital
AGG	Agglomeration
R&D	Research and Development
CRS	Constant Returns to Scale
VRS	Variable Returns to Scale
TEC	Technical Efficiency Change
TC	Technological Change
PTEC	Pure Technical Efficiency Change
SEC	Scale Efficiency Change
UNIDO	United Nations Industrial Development Organization

CHAPTER 1

INTRODUCTION

1.1 Introduction

Against the backdrop of economic globalization, an increasing number of multinational corporations are engaging in production and operational activities on a global scale. This shift has altered the traditional patterns of world trade flow and benefit distribution, resulting in market integration and production regionalization. This emerging global economic phenomenon is called the global value chain (Kano et al., 2020). The global value chain (GVC) encompasses all activities that firms and workers undertake to bring a product from conception to end use, including design, production, marketing, and after-sales service, with these activities frequently distributed across different countries (Gereffi & Fernandez-Stark, 2016). How to further reshape the level of China's manufacturing resources within the framework of the global value chain (GVC) has become a common concern for all countries. Few industries match the size and influence of the automobile industry, which is arguably the largest manufacturing sector in the world (Thirupathi et al., 2019). As the leading industry of manufacturing, the impact of the global value chain on the automobile industry is worth studying.

Industrial agglomeration is the organic integration of industry and region. It refers to the phenomenon where regionally distributed and networked businesses, specialist vendors, service providers, producers from associated sectors, and pertinent organizations come together in a highly concentrated manner within a specific industry and field (Yu et al., 2022). Industrial agglomeration exhibits both industrial and regional characteristics, representing the clustering of industries within a specific area. This phenomenon offers more advantages

than the development of individual enterprises, as it leverages the cooperation among businesses to create an agglomeration effect. Industrial agglomeration can enhance the competitiveness of a region or a country (Bhawsar & Chattopadhyay, 2018).

Industrial agglomeration is an effective strategy for developing the automobile industry. Japanese automobiles dominate Southeast Asia by implementing a regionalized production and management model. This approach has significantly contributed to the rapid growth of the Japanese automobile market (Fujikawa, 2022). This development model is rooted in industrial agglomeration, highlighting its effectiveness in fostering competitiveness within the automobile market. Similarly, China's automobile industry has also grown rapidly through industrial agglomeration. There are six major automobile industry clusters in China: the Yangtze River Delta automobile industry cluster, the Pearl River Delta automobile industry cluster, the Beijing-Tianjin-Hebei automobile industry cluster, the Northeast automobile industry cluster, the Central China automobile industry cluster, and the Sichuan-Chongqing automobile industry cluster (Min et al., 2022). The rapid development of these six automobile clusters has propelled the growth of the entire Chinese automobile industry.

Influenced by the wave of industrial transfer, China's automobile industry has gradually embedded itself into the global value chain through the upstream and downstream extension of the production chain and the value chain integration. Although this integration demonstrates a certain level of openness, challenges remain. These include relatively weak international competitiveness, primarily engaging in low-value-added segments of the value chain, and dependence on developed countries (Chen et al., 2019).

Therefore, this research focuses on how global value chains and industrial agglomeration influence the upgrading of China's automobile industry. It aims to promote

the development of China's automobile industry and strengthen China's position in the global automobile market.

1.2 Background of the Study

1.2.1 Development of China's Automobile Industry

1.2.1.1 Automobile Production and Sales in China

China is the world's largest automobile production plant. According to the China Association of Automobile Manufacturers (2024), China's total automobile production and sales have ranked first worldwide for 15 consecutive years. In 2023, China's automobile production and sales accounted for 32.2% of the global total, reflecting a significant contribution to the worldwide market. Despite facing numerous difficulties in recent years, such as a shortage of chips and rising prices for raw materials used in power batteries, the Chinese automobile industry demonstrated remarkable resilience in 2023. Specifically, automobile production reached 30.161 million units, representing an 11.6% year-on-year increase, while sales reached 30.094 million units, marking a 12% increase compared to the previous year. Table 1.1 presents a comprehensive overview of China's automobile production and sales data from 2009 to 2023.

In terms of production, as shown in Table 1.1, China's automobile production grew steadily from 2009 to 2017, reaching a record high of 29.0154 million units in 2017. However, production declined from 2018 to 2020, dropping from 27.8002 million units to 25.225 million units. Production began to rebound in 2021, with 2023 seeing production levels reach 30.161 million units. Regarding sales, there was continuous growth from 2009 to 2017, increasing from 13.6448 million units sold in 2009 to 28.8789 million units sold in 2017. Sales declined in 2018 and continued to decrease through 2020, eventually reaching

25.311 million units. Sales increased from 2020 to 2023, reaching 30.094 million vehicles in 2023.

Table 1.1: Production and Sales Data of China's Automobiles from 2009 to 2023

Year	Production		Sales	
	Automobile (10,000 units)	Year-on-year growth	Automobile (10,000 units)	Year-on-year growth (%)
2009	1379.10	47.6	1364.48	45.5
2010	1826.47	32.4	1806.19	32.4
2011	1841.89	0.8	1850.51	2.5
2012	1927.18	4.6	1930.64	4.3
2013	2211.68	14.8	2198.41	13.9
2014	2372.29	7.3	2349.19	6.9
2015	2450.33	3.3	2459.76	4.7
2016	2811.88	14.8	2802.82	13.9
2017	2901.54	3.2	2887.89	3.0
2018	2780.02	-4.2	2808.06	-2.8
2019	2572.07	-7.5	2576.87	-8.2
2020	2522.50	-2.0	2531.10	-1.9
2021	2608.20	3.4	2627.50	3.8
2022	2702.06	3.4	2686.37	2.1
2023	3016.10	11.6	3009.40	12

Source: China Association of Automobile Manufacturers (2010-2024)

From 2018 to 2020, China's automobile production and sales experienced slight declines, primarily due to the impact of export trade restrictions imposed by developed countries and reduced subsidies for new energy vehicles. In January 2018, removing the

preferential policy on passenger vehicle purchase taxes and a decline in both domestic and international macroeconomic conditions led to a downturn in the national automobile industry's production and sales. In 2018, automobile production and sales were 27.8002 million and 28.0806 million units, respectively, marking 4.2% and 2.8% annual decreases. This was the first decline in recent years. As the number of vehicles in society increased and public transportation resources became more developed, a gentle decline in vehicle production and sales ensued, which is considered a normal trend.

Table 1.2: Production and Sales of New Energy Vehicles in China from 2012 to 2023

Year	Production		Sales	
	New Energy Vehicles (10000)	Year-on-year Growth	New Energy Vehicles (10000)	Year-on-year Growth
2012	1.26	50.0	1.28	56.1
2013	1.75	38.9	1.76	37.5
2014	7.85	348.6	7.48	325.0
2015	34.04	333.6	33.11	342.6
2016	51.70	51.9	50.70	53.1
2017	79.40	53.6	77.70	53.3
2018	125.41	57.9	123.99	59.6
2019	123.93	-1.2	120.40	-2.9
2020	136.60	7.5	136.70	10.9
2021	354.50	159.5	352.10	157.6
2022	703.04	97.1	685.81	93.7
2023	958.70	35.8	949.50	37.9

Source: China Association of Automobile Manufacturers (2013-2024)

It is worth noting that China's new energy vehicles have developed rapidly in recent years. In this study, the term "new energy vehicles" (NEVs) refers explicitly to the classification used in China, which encompasses a variety of vehicle types including battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell vehicles (FCVs), as outlined by the State Council of China (2020). This particular classification is more comprehensive than the term "electric vehicle" (EV), which is generally understood to include only battery electric vehicles (BEVs). As shown in Table 1.2, 3.545 million new energy vehicles were produced in 2021, representing a year-on-year increase of 159.5%. By 2023, production reached 9.587 million units, with a year-on-year increase of 35.8%. In 2021, new energy vehicle sales were 3.521 million units, reflecting a year-on-year increase of 157.6%. By 2023, sales had risen to 9.495 million units, with a year-on-year increase of 37.9%.

1.2.1.2 Automobile Import and Export in China

In 2023, China's automobile exports achieved a historic breakthrough, exceeding 4 million units for the first time and reaching 4.91 million units. This marks a year-on-year increase of 57.9 percent. Figure 1.1 illustrates the export of automobiles in China from 2013 to 2023. The graph reveals a decline in exports from 2013 to 2015, with a sharp drop in 2015 reflecting challenges in the industry. However, a recovery began from 2016 to 2019, with steady growth culminating in a peak in 2021. The most notable aspect is the dramatic surge in exports in 2022 and 2023, where the growth rate reached an exceptional 57.9%, highlighting the robust expansion of China's automotive sector in the global market.

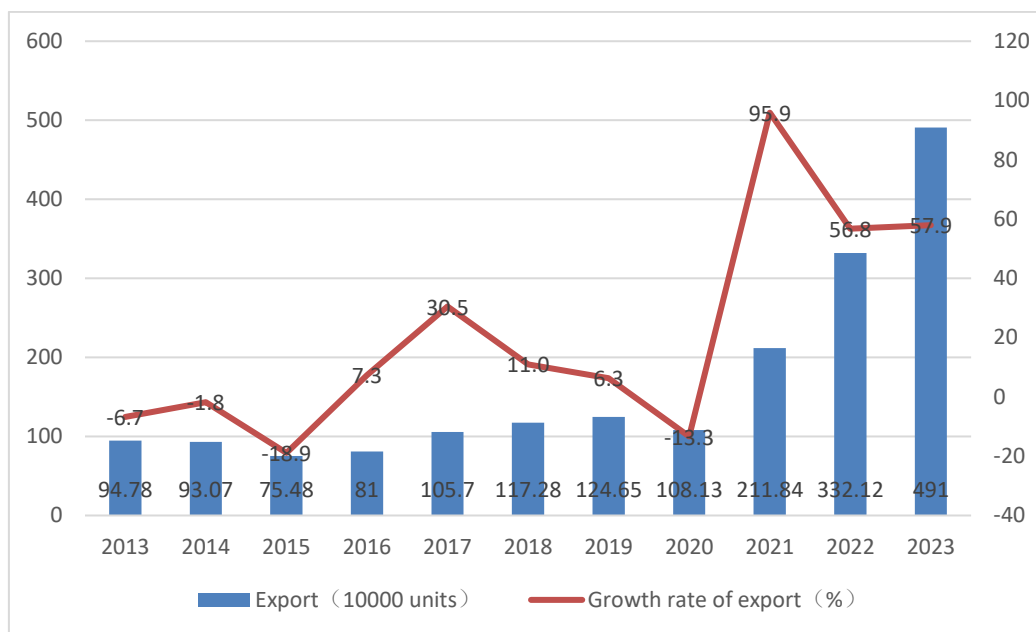


Figure 1.1: Export of Automobiles in China from 2013 to 2023

Source: China Association of Automobile Manufacturers (2014-2024)

Influenced by multiple factors such as the COVID-19 pandemic and the chip shortage, the scale of China's imported vehicle market continued to remain low in 2022, staying below the level of 1 million units for three consecutive years since 2020, as a result of these combined factors, automobile imports in 2022 fell to the lowest level since 2011. According to the Statista Database (2023), China imported 878,000 automobiles in 2022, marking a year-on-year decrease of 6.5%. The import value was 53.24 billion US dollars, reflecting a year-on-year reduction of 1.2%. Figure 1.2 illustrates the import of automobiles in China from 2007 to 2022.

From 2014 to 2022, China's automobile imports exhibited a consistent decreasing trend, while the country's automobile exports steadily increased yearly. A significant turning point occurred in 2018 when the volume of automobile exports surpassed imports for the first time, shifting the trade balance from a deficit to a surplus. Since this pivotal moment, the automobile trade surplus has expanded progressively. In 2022, the import volume was

878,000 units, while the export volume reached 3,321,200 units, indicating a substantial surplus. In 2021, China's automobile export volume stood at 2.1184 million vehicles, marking a 95.9 percent increase compared to 2020. The export volume continued to rise in 2023, reaching 4.91 million vehicles, representing a 57.9 percent increase compared to 2022.

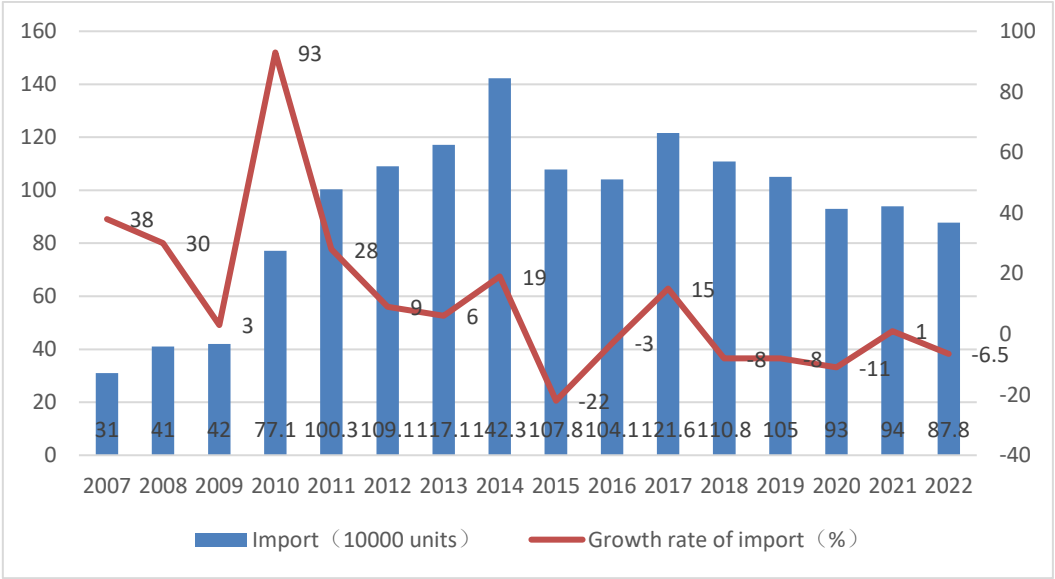


Figure 1.2: Import of Automobiles in China from 2007 to 2022

Source: Statista Database (2023)

From the perspective of major exporters, China's key automobile enterprises have experienced rapid export growth. According to China Automotive Industry Yearbook (2023), among the top 10 automobile export companies in 2022, SAIC Motor and Chery exceeded export scales of 900,000 and 450,000 units, respectively, for the first time. Additionally, Chang'an and Dongfeng each surpassed 200,000 units in annual exports for the first time. The top ten export companies' year-on-year growth rate achieved double-digit increases. Table 1.3 illustrates the exports of major automobile companies in China in 2022.

Table 1.3: Exports of Major Automobile Companies in China (2022)

Ranking	Automobile Companies	Export Volume (10000 units)	Year-on-year Growth (%)
1	SAIC Motor Corporation Limited	90.63	51.5
2	Chery Holding	45.17	67.7
3	Tesla (Shanghai) Co., Ltd	27.11	65.9
4	Chongqing Chang'an Automobile Company	24.92	56.6
5	Dongfeng Motor Corporation	24.23	57.4
6	Zhejiang Geely Holding Group	19.82	72.4
7	Great Wall Motor Company Limited	17.32	21.3
8	Anhui Jianghuai Automobile Group Corp., Ltd	11.46	55.7
9	BAIC Motor Corporation, Ltd	10.95	35.0
10	CNHTC	8.28	48.6
11	BYD Company Limited	5.87	261.1
12	Daqing Volvo Car Manufacturing Co., Ltd	3.65	-3.7
13	China FAW Group Corporation	3.57	48.6
14	Shaanxi Automobile Holding Group Co., Ltd	3.44	80.3
15	Guangzhou Automobile Group Co., Ltd	3.30	59.5
16	BMW Brilliance Automotive Ltd	3.00	37.6
17	Brilliance Xinyuan Chongqing Automobile Co., Ltd	1.91	74.8
18	Xiamen Kinglong Motor Group Co., Ltd	1.50	-14.3
19	ZX AUTO	0.82	40.0
20	Yutong Bus Co., Ltd	0.57	15.6

Source: China Automotive Industry Yearbook (2023)

From the perspective of export markets, countries such as Belgium, the United Kingdom, and Mexico are emerging as significant growth areas for China's automobile

exports. According to China Automotive Industry Yearbook (2023), the top 10 countries for China's automobile exports in 2022 were Mexico, Saudi Arabia, Chile, Belgium, Russia, Australia, the United Kingdom, the Philippines, Malaysia, and the United Arab Emirates. Notably, the markets in the United Arab Emirates and Mexico demonstrated strong performance, with year-on-year growth rates of 2.69 times and 1.69 times, respectively. Among these top 10 countries, Mexico held the largest share, with exports reaching 254,500 units. These export destinations include both developing and developed countries, collectively accounting for 48.5% of China's total automobile exports, nearly half. Additionally, China's automobile exports to the U.S. increased, moving it up to 15th place, up two positions from 2021. Table 1.4 showcases China's automobile exports by country in 2022.

Table 1.4: China's Automobile Exports by Country in 2022

Ranking	Country	Export Volume (10000 units)	Year-on-Year Growth (%)	Export Amount (billion dollars)	Year-on-year Growth (%)
1	Mexico	25.45	169.2	2.809	200.1
2	Saudi Arabia	22.24	67.1	3.144	71.2
3	Chile	21.18	10.7	2.456	32.9
4	Belgium	20.70	86.6	5.581	81.1
5	Russia	16.21	33.4	4.026	103.3
6	Australia	15.97	66.7	3.003	82.8
7	UK	14.75	87.9	4.294	91.5
8	Philippines	14.55	148.8	1.327	43.7
9	Malaysia	9.57	113.5	0.854	94.8
10	U.A.E	9.32	269.2	20.45	348.8

Table 1.4 continued

11	Thailand	8.80	81.5	0.702	239.4
12	Peru	7.63	29.9	0.819	32.1
13	Vietnam	6.90	19.8	1.358	5.8
14	Ecuador	6.76	47.5	0.706	46.0
15	USA	6.64	52.7	1.555	53.1
Other Totals		125.63	38.1	25.487	65.1
Total		332.30	56.9	60.166	74.7

Source: China Automotive Industry Yearbook (2023)

In 2022, Germany, Japan, and the United States were the top three countries from which China imported automobiles, maintaining the same ranking as in 2021. China imported 259,000 units from Germany, 254,000 units from Japan, and 138,000 units from the United States in 2022. In terms of unit price, Austria had the highest unit price among the top 10 countries by import volume, reaching 107,000 US dollars per vehicle. In contrast, Hungary and Japan had less than 40,000 US dollars per vehicle unit prices. Table 1.5 illustrates China's automobile imports by country in 2022.

Although China's automobile export volume continues to grow and achieve historic milestones, the primary export destinations are not countries with established automobile industries such as Japan, Germany, and the United States. However, from the perspective of automobile imports, China predominantly imports vehicles from Germany, Japan, and the United States. This indicates that while China's automobile industry has made significant strides, it still does not dominate the global market. Japan, Germany, and the United States have not yet become major buyers of Chinese automobiles, whereas China continues to rely on imports from these countries. Therefore, to further enhance its international

competitiveness and strengthen its position in the global automobile market, China's automobile industry needs further development and upgrading.

Table 1.5: China's Automobile Imports by Country in 2022

Ranking	Country of Origin	Import Volume (10000 units)	Import Amount (billion dollars)	Average Unit Price (10000 dollars/unit)
1	Germany	25.9	17.40	6.7
2	Japan	25.4	9.73	3.8
3	USA	13.8	9.90	7.2
4	Slovakia	8.1	6.19	7.7
5	UK	5.7	4.37	7.7
6	Sweden	2.4	1.17	4.8
7	Austria	1.7	1.79	10.7
8	Hungary	1.2	0.37	3.1
9	Italy	1.1	1.04	9.3
10	Thailand	0.7	0.54	7.9
11	Netherlands	0.6	0.19	3.0
12	Mexico	0.5	0.18	3.7
13	Korea	0.3	0.10	3.7
14	China	0.2	0.02	1.1
15	Belgium	0.1	0.03	6.2

Source: China Automotive Industry Yearbook (2023)

1.2.1.3 Automobile Brands in China

Although China is the world's most significant automobile production and sales country, many of the leading brands in the Chinese market are joint venture brands. Table 1.6 highlights the top 20 automobile brands by sales in China in 2022.

Table 1.6: Top 20 Automobile Brands by Sales in China (2022)

Ranking	Company	Brand	Sales (unit)
1	SAIC-GM-Wuling	Wuling Hongguang mini	554071
2	Tesla (Shanghai)	Model Y BEV	455091
3	SAIC Volkswagen	New Lavida	376627
4	BYD	Song DM 1.5T	349338
5	Great Wall Motors	Haval H6	288083
6	FAW Toyota	Corolla 1.2L	257751
7	Tesla (Shanghai)	Model 3	255774
8	GAC Toyota	Camry 2.0L	249839
9	FAW-Volkswagen	Sagitar 1.2T	236142
10	Guangqi Honda	Accord 1.5T	233887
11	Dongfeng Nissan	New Sylphy 1.6	221032
12	Dongfeng Honda	CR-V 1.5T	737679
13	GAC Toyota	Levin 1.2T	213426
14	FAW-Volkswagen	Bora 1.2T	211103
15	BYD	Dolphin BEV	205417
16	BYD	Yuan PLUS BEV	202058
17	Dongfeng Nissan	Sylphy 1.6L	196905
18	BYD	Qin PLUS DM-i 1.5L PHEV	195349
19	SAIC Volkswagen	New Passat 1.4T	190629
20	Chongqing Changan	CS75 plus 2.0T	187473

Source: China Automotive Industry Yearbook (2023)

As clearly illustrated in Table 1.6, the top 20 brands by sales in China in 2022 are mainly from joint ventures. Brands such as SAIC General Motors, Tesla (Shanghai), SAIC Volkswagen, FAW Toyota, GAC Toyota, FAW Volkswagen, GAC Honda, Dongfeng

Nissan, and Dongfeng Honda are all joint venture brands. In China, 14 out of the top 20 brands by sales are joint ventures, accounting for 70% of the market. BYD Auto, an independent Chinese vehicle brand, has achieved significant sales, primarily due to its strong performance in the new energy vehicle market, which has garnered substantial consumer support. However, other domestic brands continue to lag behind. The influence of brand value on sales is evident, as a strong brand image can significantly boost market share (Chakraborty & Bhat, 2018). Chinese consumers tend to favor joint venture brands over independent domestic brands, highlighting the disadvantages of brand influence faced by Chinese auto-independent brands.

Looking at the international market, this brand issue is gradually expanding. According to Statista's database (2024), the top ten most valuable brands in the global automobile industry in 2023 are, in order: Tesla, Toyota, Mercedes-Benz, BMW, Porsche, BYD, Ford, Audi, Honda, and Ferrari, as shown in Figure 1.3.

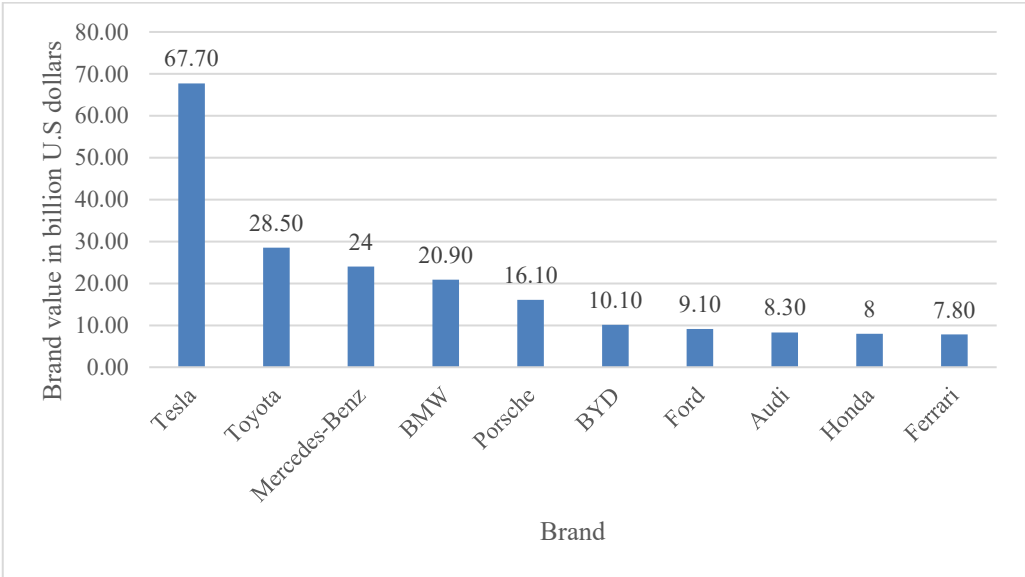


Figure 1.3: Most Valuable Automobile Brands Worldwide by Brand Value in 2023

Source: Statista Database (2024)

As evident from Figure 1.3, Tesla ranks first with an automobile brand value of 67.70 billion U.S. dollars, significantly higher than other automobile brands. The second and third positions are held by Japan's Toyota and Germany's Mercedes-Benz, with brand values of 28.50 billion U.S. dollars and 24 billion U.S. dollars, respectively. The United States, Japan, and Germany still dominate the world's most valuable automobile brands. Only one Chinese automaker, BYD Auto, ranked 6th with a brand value of 10.10 billion U.S. dollars. However, BYD still has a noticeable gap compared to other top-ranked automobile companies. American, Japanese, and German brands remain dominant in the global automobile market.

According to Fortune (2023), 34 vehicles and parts companies worldwide made the list; the total operating income of these 34 companies was 306.84 billion US dollars in 2022, accounting for 7.47% of the total operating income. Table 1.7 shows major automobile enterprises' ranking, operating income, and profit in the world's top 500 in 2022. As can be seen from Table 1.7, Volkswagen ranks first, followed by Toyota and Stellantis, with operating income of \$293.6847 billion, \$274.4914 billion, and \$188.8875 billion, respectively. The profits of the three companies were \$15.2232 billion, \$18.11 billion, and \$17.6685 billion, respectively. Notably, BMW and Tesla demonstrate exceptional profitability, with BMW generating 18.8696 billion in profit from 149.9913 billion in operating income and Tesla achieving 12.556 billion in profit from 81.462 billion in operating income, the highest margin among all listed automakers. Most top automakers are from Japan, Germany, and the United States. The only Chinese automaker in the top ten vehicle and parts companies on the list is SAIC, ranking ninth among the 34 automobile and parts enterprises, with operating income of \$110.6123 billion and profit of \$2.396 billion, which is still a big gap compared with well-known vehicle companies in Japan, Germany and the United States.

Table 1.7: 2023 Fortune 500 Major Automakers Ranking

Ranking	Full Ranking	Company name	Operating Income (US\$ million)	Profit (US\$ million)	Country
1	15	Volkswagen Company	293,684.7	15,223.2	Germany
2	19	Toyota Motor	274,491.4	18,110	Japan
3	31	Stellantis	188,887.5	17,668.5	Netherlands
7	57	BMW Group	149,991.3	18,869.6	Germany
9	84	SAIC Motor	110,612.3	2,396	China
13	152	Tesla	81,462	12,556	The United States

Source: Fortune (2023)

1.2.1.4 Automobile Research and Development in China

The essential technologies for the growth of the automobile sector typically include generators, steering devices, and vehicle chassis systems. China has made significant progress in recent years, with its domestic and international market share gradually increasing. However, its capacity for independent research and development remains insufficient. The parts market is still dominated by enterprises from developed countries such as ZF, Japan's Aisin and Jatco, and the United States' GM. Consequently, Chinese automobile companies often rely on technology introductions, lacking strong research and development capabilities. Moreover, Chinese automobile companies have a noticeable gap in R&D investment compared to well-known foreign automobile companies (Liu et al., 2023). Table 1.8 shows the ranking of R&D investment of global automobile companies in 2022.

Table 1.8: R&D Expenses and Intensity of Automobile Companies Worldwide 2022

Automobile Companies	R&D Expenses (million euros)	R&D Intensity(%)	Country
Volkswagen	18908	6.8	Germany
General Motor	9188.08	6.3	The United States
Toyota Motor	8776.13	3.3	Japan
Mercedes-Benz	8509	5.7	Germany
Ford Motor	7312.96	4.9	The United States
BMW	7178	5	Germany
Stellantis	6720	3.7	Netherlands
Honda Motor	6220.86	5.2	Japan
Nissan Motor	3691.01	4.9	Japan
Tesla	2882.99	3.8	The United States
SAIC Motor	2800.36	3	China
BYD	2547.29	4.7	China
Hyundai Motor	2468.42	2.3	Korea
Renault	2259	4.8	France
Volvo	2199.29	5.2	Sweden
Tata Motors	2087.05	5.4	India

Source: Statista database (2023)

As shown in the table above, Germany, the United States, Japan, and China had the highest R&D spending in 2022. Volkswagen led the pack with an R&D expenditure of €18.908 billion, accounting for 6.8% of its sales revenue. Following Volkswagen are GM and Toyota. Chinese automakers SAIC and BYD ranked 11th and 12th, with R&D investments of €2.8 billion and €2.547 billion, respectively, representing 3% and 4.7% of their sales revenue.

1.2.2 Development of China's Automobile Industry Agglomeration

There is a specific agglomeration phenomenon in China's automobile industry. China has formed six automobile industry clusters, including the Yangtze River Delta automobile industry cluster, the Pearl River Delta automobile industry cluster, the Northeast automobile industry cluster, the Beijing-Tianjin-Hebei automobile industry cluster, the Central China automobile industry cluster, and the Sichuan-Chongqing automobile industry cluster. Figure 1.4 shows the distribution map of China's six major automobile industry clusters.

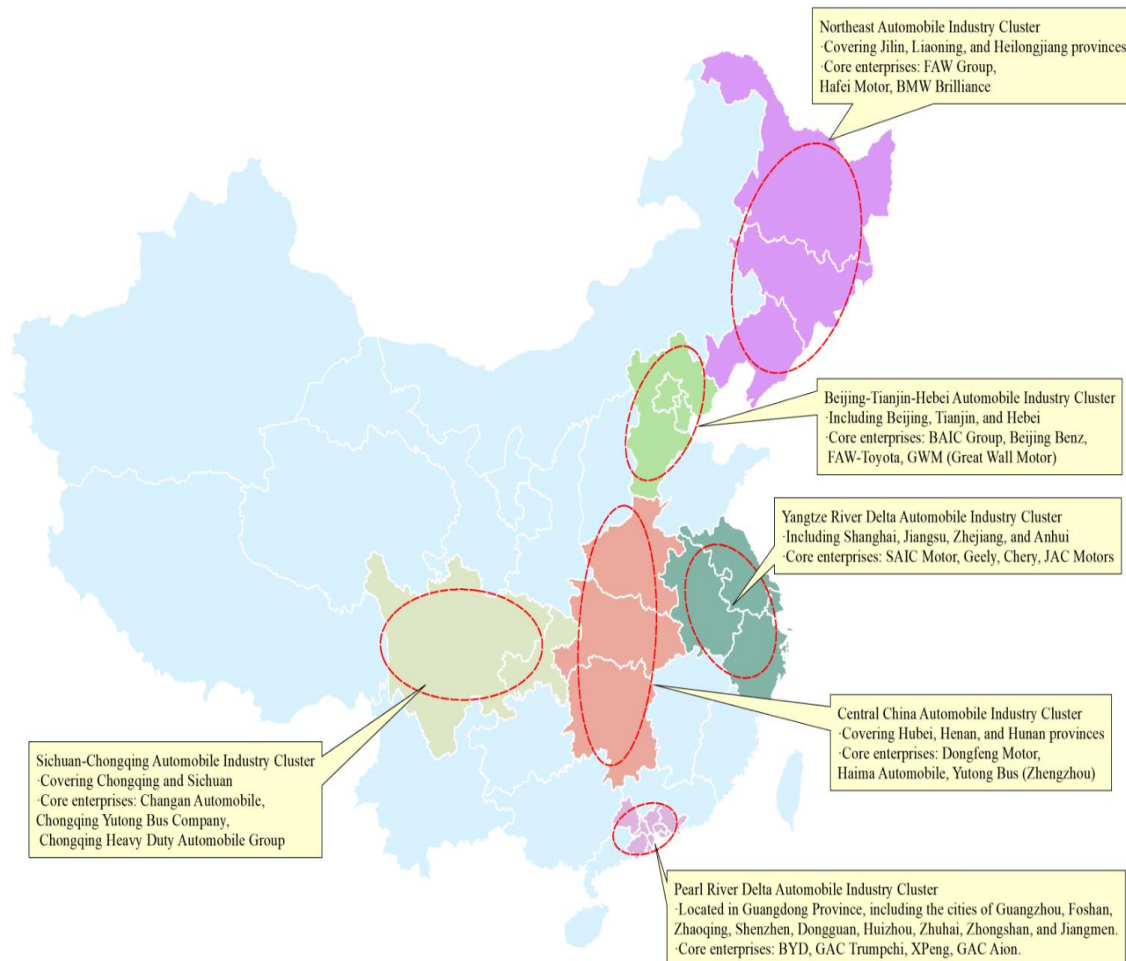


Figure 1.4: Distribution Map of the Six Major Automobile Industry Clusters in China

1.2.2.1 Yangtze River Delta Automobile Industry Cluster

The Yangtze River Delta (YRD) automobile industry cluster includes three provinces and one city, namely Shanghai City, Jiangsu Province, Zhejiang Province, and Anhui Province. According to the China Automotive Industry Yearbook (2023), the total output of the YRD automobile industry cluster in 2022 was 8.0081 million units. Specifically, the automobile outputs for Shanghai, Jiangsu, Zhejiang, and Anhui were 3.0245 million units, 1.643 million units, 1.5937 million units, and 1.7469 million units, respectively. Throughout 2022, the total automobile production in China was 27.0206 million units, with the Yangtze River Delta region contributing 29.64 percent of the country's total production.

Table 1.9: Automobile Production and Revenue in the Yangtze River Delta in 2022

Index Region	Production (10000 units)	Main Business Income (billion yuan)
Shanghai	302.45	962.391
Jiangsu	164.3	928.36
Zhejiang	159.37	749.7
Anhui	174.69	384.54
All of China	2702.06	9289.99

Source: China Automotive Industry Yearbook (2023)

In terms of main business income, the automobile main business income of the YRD in 2022 was 3,024.991 billion yuan. The main business income from automobiles for Shanghai, Jiangsu, Zhejiang, and Anhui was 962.391 billion yuan, 928.36 billion yuan, 749.7 billion yuan, and 384.54 billion yuan, respectively. The annual main business income from automobiles in 2022 was 9,289.99 billion yuan. The Yangtze River Delta's automobile main business income accounted for 32.56% of the national total. This demonstrates that the

Yangtze River Delta automobile industry cluster is the largest in China. Table 1.9 details the production and main business income of the YRD automobile cluster in 2022.

The Yangtze River Delta automobile industry cluster has gradually developed a strong industrial synergy. Supported by robust vehicle production, enterprises engaged in parts manufacturing, research and development, and design within this cluster are thriving. The ongoing implementation of policies promoting new energy vehicles has further improved the efficiency of the automotive industry's transformation and upgrade. Since 2020, the Yangtze River Delta industrial cluster has consistently demonstrated its agglomeration effect. The establishment of significant vehicle projects, such as the Shanghai Tesla Gigafactory and the Volkswagen (Anhui) Plant, has further solidified the leading position of the Yangtze River Delta industrial cluster (Min,2022).

Shanghai hosts China's largest vehicle production base and is home to SAIC Motor Group, one of the country's three major automobile groups. It also accommodates China's largest Sino-German vehicle joint venture, Shanghai Volkswagen, and the Sino-US vehicle joint venture, Shanghai GM. Additionally, the Shanghai International Automobile City Auto Parts Park has attracted numerous parts suppliers. In Zhejiang Province, the growth of the automotive sector primarily depends on private enterprises. The province boasts major vehicle manufacturers like Geely Group Co., Ltd., along with numerous strong auto parts companies, such as Wanxiang Group and Huaxiang Group. Jiangsu Province's automobile industry is also progressing rapidly. Some brand vehicles produced here not only have a significant market in China but also enjoy a strong reputation abroad. Notable examples include Fiat in Nanjing and Dongfeng Yueda Kia in Yancheng. Nanjing is also the second production base for Changan Ford, where Ford partnered with Mazda, leading to the creation

of two core host companies in Jiangsu, including Nanjing Fiat. This collaboration has spurred the development of industrial clusters in the region (Guo et al., 2023).

Anhui Province's automobile industry includes well-known enterprises such as Jianghuai Automobile and Chery Group. Hefei, the provincial capital of Anhui province, is one of the first cities in China to pilot the promotion of new energy vehicles and was approved in 2015 to build a provincial-level major emerging industry base for new energy vehicles. In recent years, Hefei has placed significant emphasis on developing new energy vehicles and intelligent networked vehicles, leading to continuous improvements in both output scale and technical level. The city has attracted more than 120 industrial chain enterprises, forming a comprehensive industrial chain encompassing complete vehicles, key components, applications, and supporting facilities (Huang, 2022).

1.2.2.2 Pearl River Delta Automobile Industry Cluster

Located in Guangdong Province, the Pearl River Delta predominantly includes nine cities: Guangzhou, Foshan, Zhaoqing, Shenzhen, Dongguan, Huizhou, Zhuhai, Zhongshan, and Jiangmen. According to China Automotive Industry Yearbook (2023), in 2022, Guangdong Province's total automobile production reached 4.1537 million units, representing 15.37% of the national automobile output. The production of new energy automobiles in Guangdong province totaled 1.2973 million units, contributing 18.45% to the national new energy vehicle output. The main business income in 2022 amounted to 1,198.743-billion-yuan, accounting for 12.9% of the national total. In recent years, the number and scale of automobile manufacturing enterprises in Guangdong have experienced steady growth. Companies like BYD and GAC-Tranqi have successfully developed their brands, while new energy vehicle manufacturers such as Xiaopeng Automobile and GAC

AION have gradually emerged. This growth has contributed to developing an automotive industry cluster in the Pearl River Delta.

The Pearl River Delta automobile industry cluster is centered in Guangzhou. In recent years, Guangzhou Automobile has promptly adjusted its strategic policy and established three major automobile production bases: Huangpu, Huadu, and the Nansha Development Zone. In Huadu, Dongfeng Motor Co., Ltd. and Nissan Motor Company jointly invested in the construction of the Huadu Passenger Vehicle Plant, which led to the creation of Guangzhou Huadu Auto City, centered around Dongfeng Passenger Vehicle Company. This expansive automobile city encompasses major sectors, including automobile production, parts production, logistics, trade services, export processing, automobile culture, and entertainment (Jiang, 2023).

1.2.2.3 Northeast Automobile Industry Cluster

The Northeast Automobile Industry Cluster encompasses the three provinces of Jilin, Liaoning, and Heilongjiang. According to the China Automotive Industry Yearbook (2023), Jilin Province produced 1.335 million vehicles and sold 1.368 million units in 2022. The province's vehicle output value reached 282.89 billion yuan, while the value of parts and components was 157.4 billion yuan. Liaoning Province produced 766,000 vehicles in 2022, with the automobile industry generating an annual operating income of 381.35 billion yuan and a total profit of 55.47 billion yuan. Heilongjiang Province produced 82,600 vehicles in 2022, achieving a main business income of 42.34 billion yuan and a total profit of 1.83 billion yuan. The Northeast automobile industry cluster has established an overall development pattern with Jilin Province as the core, Liaoning Province as the support, and Heilongjiang Province as the supplement.

The three northeastern provinces each have their core automobile enterprises and industrial parks. In Jilin, there is the FAW Group, one of the three major automobile groups in China. According to the China Automobile Industry Yearbook (2022), Jilin Province initiated a total of 175 key projects for upgrading the automotive sector, with an overall investment amounting to 105.6 billion yuan in 2021. Liaoning Province is home to three major vehicle brands: Zhonghua, BMW, and Cruz. The province has developed a relatively complete automobile production system that includes complete vehicles, engines, and parts. Key industrial parks in Liaoning, such as Jinpu New District and the Dandong Automotive and Parts Industry Cluster, host prominent automakers like BMW Brilliance and SAIC-GM (Bai & Zhu, 2020). In Heilongjiang, there is Hafei Automobile, an independently developed Chinese brand. Key vehicle production enterprises in the province include Daqing Volvo Vehicle Manufacturing Co., Ltd., and FAW Harbin Light Duty Vehicle Co. The three northeastern provinces also lead the country in automobile scientific research and talent training. The School of Automotive Engineering at Jilin University is a significant base for automotive talent development in China. Additionally, the Laboratory of Electrochemistry and the Changchun Institute of Applied Chemistry are important centers for scientific research (Ou, 2020).

1.2.2.4 Beijing-Tianjin-Hebei Automobile Industry Cluster

The Beijing-Tianjin-Hebei automobile industry cluster encompasses Beijing, Tianjin, and Hebei provinces. According to China Automobile Industry Yearbook (2023), vehicle production in 2022 was as follows: 1,517,876 units in Beijing, 792,643 units in Tianjin, and 905,535 units in Hebei. Together, these figures represent 11.90% of the national automobile production.

Beijing has developed an industrial agglomeration centered around vehicle manufacturers like Beijing Hyundai, BAIC Foton, Beijing Benz, and BAIC Co., Ltd. This agglomeration is also dominated by large bus manufacturing, special-purpose vehicles, and parts manufacturing. The city boasts enterprises involved in various segments of the industrial chain, including basic chips, operating systems, and software algorithms. Additionally, Beijing is home to several automobile-related research institutes, colleges and universities, and service and trade enterprises, creating a robust and comprehensive automobile industry system (Lu & Jiang, 2021).

The Tianjin automobile industry has refined its system around vehicle manufacturing, new energy core parts and components, automotive electronics, powertrains, chassis, and body manufacturing. Leading enterprises such as FAW Toyota, FAW-Volkswagen, and Great Wall Haval play a pivotal role in this system. The industry focuses on enhancing the influence of these leading vehicle manufacturers, accelerating the development of eco-friendly enterprises, and fostering collaboration between upstream and downstream companies to drive innovation. By integrating the development of large, medium, and small enterprises, Tianjin aims to cultivate automobile and new energy automobile industry clusters with international influence and competitiveness, thereby advancing the construction of these industry clusters (Shi, 2022).

Hebei Province has capitalized on the Beijing-Tianjin-Hebei coordinated development strategy, creating a favorable environment for the automobile industry, primarily driven by Great Wall Motor. Currently, the automobile industry in Hebei Province encompasses a wide range of products, including engines, new energy vehicles, and buses, with significant competitive advantages. The regional industrial cluster in Hebei's automobile sector is beginning to take shape, featuring 11 industrial clusters, such as the

Baoding Great Wall Automobile cluster, the Zhuozhou Songlindian industrial area for parts, and the Dingxing automobile and parts gathering area (Lu & Jiang, 2021).

1.2.2.5 Central China Automobile Industry Cluster

The central automobile cluster consists of the provinces of Hubei, Henan, and Hunan. According to China Automotive Industry Yearbook (2023), Hubei produced 18.96 million vehicles, Hunan manufactured 9.53 million units, and Henan contributed 5.86 million units in 2022. The total vehicle production from the central China automobile industry cluster collectively accounted for 12.71% of the national automobile output.

With the growth of Dongfeng Honda and Dongfeng Nissan, as well as the entry of SAIC-GM and GAC, and the establishment of new energy automobile manufacturers such as Xiaopeng and Xinghui, Hubei province has cultivated a diverse development pattern encompassing both independent and joint venture brands. Hubei boasts a new energy automobile industry base centered in Wuhan, with an increasingly comprehensive industrial chain. Dongfeng Motor Company serves as the core enterprise, driving significant production capacity. Additionally, an extensive auto parts industry belt stretches from Wuhan to Xiangfan and Shiyan, spanning thousands of miles (Fan & Duan, 2020).

By the end of 2021, Hunan Province had clustered 449 key Telematics enterprises, strongly driving the local Telematics industry to achieve domestic leadership. The automotive industry in Hunan Province has formed a pattern with the three cities of ChangZhuTan as the core and the cities of Hengyang, Yongzhou, and Changde as the synergistic development. Among them, ChangZhuTan has more than 300 above-scale automobile industry enterprises, representing 72% of the overall count of large-scale automobile firms in the province (Min,2022).

Vehicle development in Henan Province showcases a trend of balanced growth led by Zhengzhou, with support from Kaifeng and Luoyang. As the automobile industry in Henan continues to expand, numerous key parts manufacturers have established a presence in the region. Zhengzhou stands out as the most significant automobile production base in the province, hosting major manufacturers like Zhengzhou Yutong, Zhengzhou Nissan, and Haima Automobile. In recent years, with the ongoing acceleration of enterprise investment and enhanced production capacity, Zhengzhou has attracted over 100 major parts and components enterprises (Zhu, 2023).

1.2.2.6 Sichuan-Chongqing Automobile Industry Cluster

The Sichuan-Chongqing automobile industry cluster, encompassing Chongqing City and Sichuan Province, has seen remarkable growth, with the number of enterprises increasing from fewer than 100 to over 2,000. According to the China Automotive Industry Yearbook (2023), Chongqing produced 2.09 million vehicles in 2022, while Sichuan Province produced 1.10 million vehicles in 2022, bringing their combined total to 3.19 million vehicles, which accounts for 11.81% of the national automobile production. The total output value of the automobile industry in Sichuan and Chongqing exceeded 500 billion yuan.

Chongqing serves as the central hub for automobile industry development in the Sichuan-Chongqing region, hosting significant companies such as Chang'an Automobile Group, Chongqing Yutong Bus Company, and Chongqing Heavy Duty Automobile Group. The presence of these enterprises exerts a substantial influence on Chongqing's economy. The automobile industry is the cornerstone of Chongqing's economic structure. Within the city, there is a versatile “Ten Mile Auto City” centered around Changan Ford vehicles. This

area integrates automobile production, research and development, trade, culture, education, and tourism into a cohesive development model (Chen et al., 2022).

Sichuan has established an automobile industry cluster centered around Chengdu, driven by vehicle production and supported by specialized industrial parks. Notable developments include the Chengdu Economic and Technological Development Zone and the Sichuan Mianyang Anzhou Industrial Park. In alignment with the Chengdu-Chongqing region, Sichuan Province serves the national auto parts parks and the parts sales market. Furthermore, colleges and universities in Chongqing and Sichuan collaborate with leading enterprises, creating an alliance that integrates automotive industry and education in the Chengdu-Chongqing area (Wang et al., 2023).

1.2.3 China's Automobile Industry in the Global Value Chain

1.2.3.1 Value Distribution of Automobile Industry in Global Value Chain

The value distribution of the automobile industry in the global value chain encompasses five major processes: research and development, production, assembly, marketing, and branding. The automobile industry experiences significant disparities in profitability due to varying technological requirements and factor conditions at each step. In this value chain, the segments involving research and development, key parts production, marketing, and branding generate substantial profits. In contrast, the general parts production and assembly segments yield relatively low earnings (Wei et al., 2020).

In the value distribution of the automotive industry's value chain, the research and development process demand the highest levels of capital and technology and is situated in the upstream, high-value-added segment of the chain. The product research and development phase is crucial for establishing a company's product brand. Auto parts production occurs in the middle of the global value chain, requiring substantial labor but with lower demands for

technology and capital. The production and assembly processes are positioned at the lowest segment of the value chain and are influenced by both upstream and downstream activities, resulting in the lowest added value. Conversely, the brand and marketing processes are located in the value chain's high-value-added segment, with significant technology and capital requirements (Lu et al., 2015). Figure 1.5 shows the global value chain's value distribution of the automobile industry.

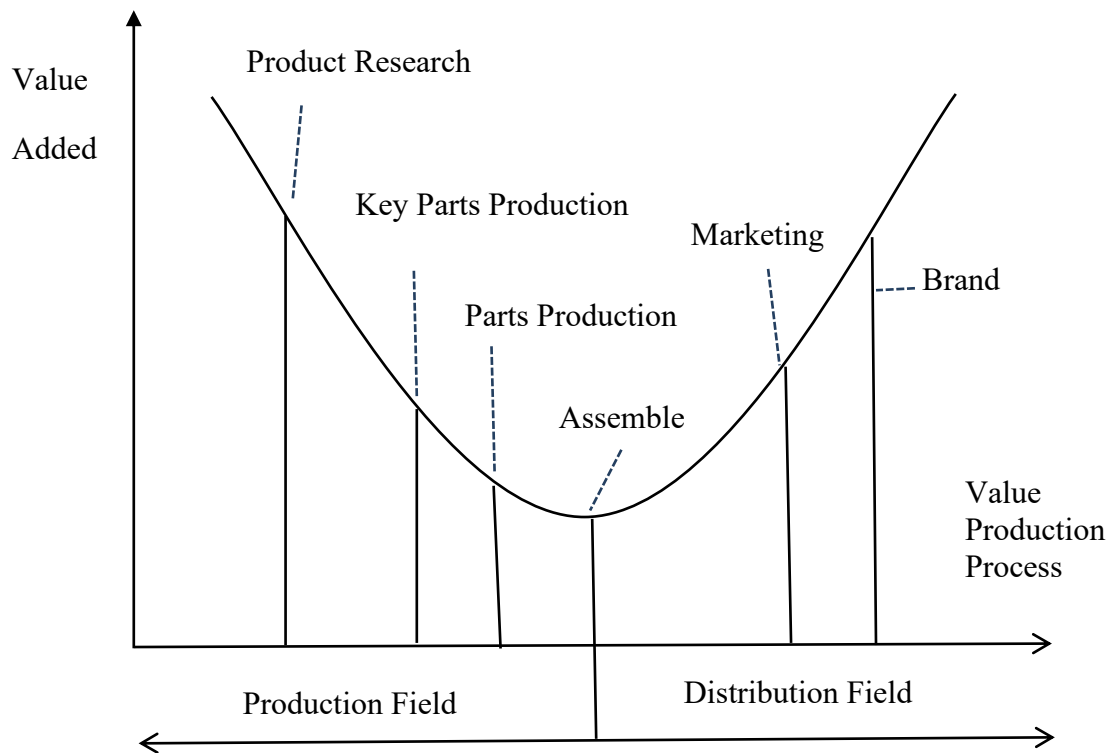


Figure 1.5: Value Distribution of Automobile Industry in Global Value Chain
Source: Song (2012)

1.2.3.2 The Global Distribution of Different Processes in the Automobile Value Chain

The global distribution of the various processes that constitute the automobile industry value chain is primarily as follows: low-value-added processes, such as assembly, are predominantly carried out in developing countries, while core production technologies, research and development (R&D), and design are controlled by large multinational automobile enterprises. Most of the world's automobile R&D and design is conducted by the

facilities of major multinational corporations like Toyota, Ford, Hyundai, Honda, BMW, Volkswagen, Mazda, and Nissan. In recent years, China has gradually increased its investment in research and development within the automotive sector. Currently, many developing countries participate in the automobile value chain, but their involvement is primarily limited to manufacturing and processing, which have lower technological content. The fundamental strategic activities in the automobile industry's value chain remain under the control of developed nations, compelling developing nations to participate mainly in low-end value processes such as manufacturing and processing (Wang et al., 2020). Assembly and component manufacturers in developing countries must seize the opportunity to upgrade their technological capabilities and enhance their competitiveness.

The transfer of specific R&D and design activities and manufacturing processes is a primary manifestation of the fragmentation within the global automotive value chain. The overall pattern is characterized by large multinational automobile enterprises controlling R&D, design resources, and advanced core production technologies. In contrast, most developing countries are involved in low-value-added processes, primarily focusing on manufacturing (Fuente & Lampón, 2020).

The position of different countries and regions in the global automobile value chain is illustrated in Figure 1.6. Global automobile R&D and design are primarily conducted by major companies such as Toyota, Volkswagen, General Motors, Ford, Honda, Nissan, and BMW. The R&D and core technology for global auto parts are controlled by renowned multinational groups like Cummins, Deere, Delphi, Bosch, and Michelin. Manufacturing within the automotive value chain is relatively fragmented, with participation from numerous developing countries. However, most of this involvement is in manufacturing processing, embedded within the producer-driven global automobile value chain. Brand

manufacturers are central and dominant in the global automotive value chain, acting as its governors. Large enterprises in developed countries control the strategic processes of the value chain and occupy the high end of the entire automotive industry value chain. In contrast, many developing countries are limited to engaging in low-value-added processes such as low-end manufacturing and assembly (Li et al., 2020).

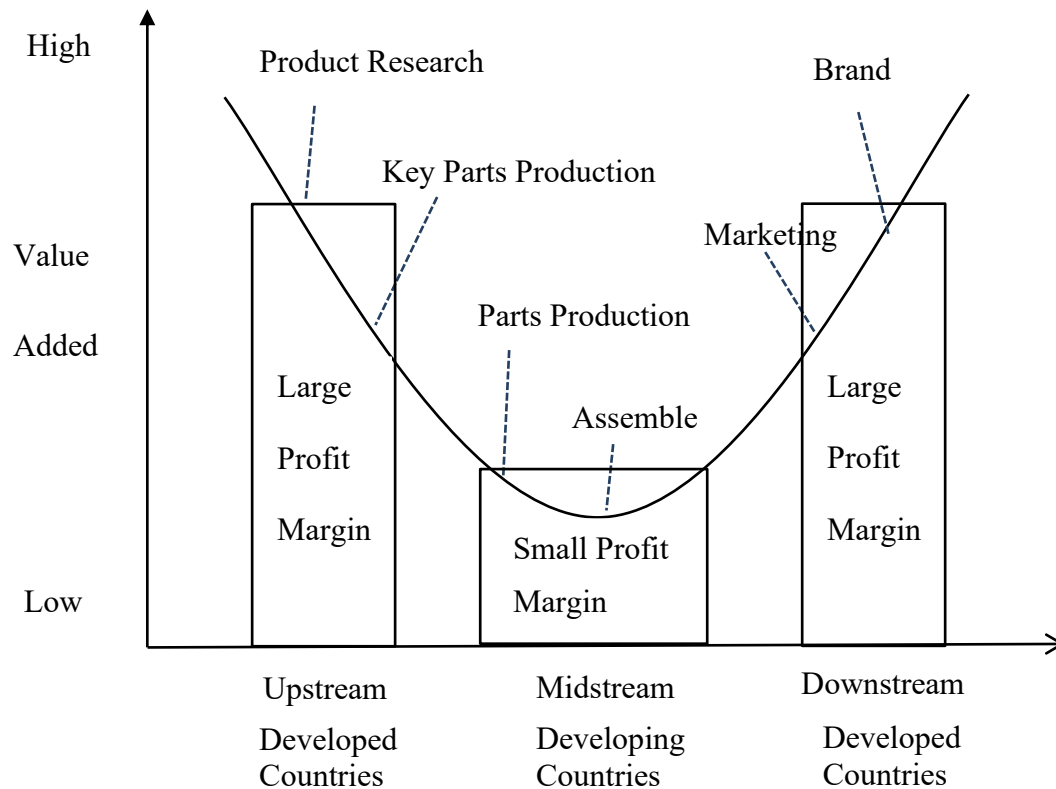


Figure 1.6: The Position of Different Countries and Regions in the Global Automobile Value Chain

Source: Tang (2020)

1.2.3.3 The Positioning of China's Automobile Industry in the Global Value Chain

Industrialized nations like Germany and the United States dominate the most strategically crucial global automobile value chain link. These countries leverage their high-end technical expertise, strong economic foundations, and extensive sales networks to achieve high profits in development, sales, and service. The technology and capital intensity

of the automobile industry result in enterprises in developing countries being highly dependent on developed nations when entering the industry. Consequently, these developing countries often engage in low-tech, relatively simple manufacturing and assembly processes, which yield low profits (Pla-Barber & Villar, 2019).

From the global value chain of China's automobile industry, the upstream research and development design, the production of key parts, and the downstream sales and brand segments are still controlled by automobile multinational companies from developed countries. These segments have high added value. China primarily engages in the production and assembly of basic components. Most parts exported by China are low-value-added drive systems, electrical and electronic products, body parts, and accessories, which are mainly used in the aftermarket. In contrast, China imports parts from Japan, Germany, and Korea, predominantly high-tech engines and transmission systems. This indicates that large foreign automobile multinational companies dominate key parts, while China focuses on producing basic parts (Wei et al., 2020).

1.2.4 Importance of Upgrading for Automobile Industry

Put simply, industrial upgrading is the process of optimizing and enhancing the industrial structure to improve industry efficiency and quality. From the perspective of individual enterprises and specific production, industrial upgrading means improving production efficiency and product quality. This can be reflected in advancements in production technology, better personnel and supply chain management, and the enhancement of final product quality (Li et al., 2010).

The automobile industry is a quintessential example of a capital- and technology-intensive sector. As a leading sector within the manufacturing industry, the automobile industry is characterized by substantial investment requirements, high technical demands,

and complex products. Furthermore, it encompasses a wide range, achieving significant economies of scale and acting as a foundation for stable economic growth. Upgrading the automobile industry will directly and indirectly influence other industrial sectors, creating a multiplier effect on the overall macroeconomic environment. This highlights the crucial significance of upgrading within the automobile industry (Jing, 2019).

For China's automobile industry, micro-level upgrading involves enhancing the value created by automobile manufacturers across various value creation links. These links include but are not limited to the research and development and design of vehicles and key auto parts, manufacturing and assembly of cars and core components, establishing independent brands and market operations, and developing a robust product after-sales service system and at the mesoscopic level, upgrading fosters a favorable external environment for developing automobile industry clusters. This encompasses institutional, cultural, and economic environments. In turn, fostering such an environment will generate economies of scale and promote the overall production efficiency of the industry (Ding & Wu, 2009). At the macro level, the upgrading of China's automobile industry involves advancing towards more profitable segments and obtaining higher added value. Additionally, it encompasses fostering efficient cooperation and collective upgrading across all links in the upstream and downstream segments of the automobile industry's supply chain (Wang & Liu, 2018).

Kaplinsky et al. (2002) proposed the path of industrial upgrading that includes process upgrading, product upgrading, functional upgrading, and chain upgrading. Process upgrading involves enhancing industrial performance by improving the production efficiency of a specific link in the global value chain, which enterprises can achieve by adopting new technologies to boost efficiency and become more competitive. Product upgrading entails improving existing products or creating new ones, continuously

introducing innovations to enhance features or quality, thereby outpacing competitors. Functional upgrading refers to the recombination of value chain activities to achieve value addition, specifically by shifting from low-value tasks like assembly to high-value activities like R&D, design, marketing, and sales. Finally, chain upgrading is how enterprises transform their production and operation methods, moving from one industrial chain to another, leveraging existing competitive advantages to enter industries unrelated to their current one.

The concept of industrial upgrading is not unified and can be viewed from various levels. At the micro enterprise level, it encompasses efficiency improvement and technological innovation. At the mesoscopic level, it involves creating a favorable external environment for industrial clusters. At the macro level, it entails the entire industry moving towards more profitable segments. From the value chain perspective, industrial upgrading is divided into process upgrading, product upgrading, functional upgrading, and chain upgrading.

Upgrading China's automobile industry can enhance its competitiveness and promote better development. As one of the pillar industries of China's national economy, its upgrading plays a decisive role in guiding the future development of the country's industrial system. The automobile industry significantly impacts China's economy due to its strong industrial relevance, ability to open up new markets, promotion of related technological advancements, and improvement of labour productivity. Additionally, it plays a crucial role in improving consumers' income and consumption levels, thereby contributing to the stable development of the national economy. Therefore, upgrading China's automobile industry is paramount (Zhou, 2018).

1.2.5 Government Support of China's Automobile Industry

During 2021 and 2022, China's vehicle production and sales achieved substantial growth, partially offsetting the adverse impacts of the global COVID-19 pandemic, energy crisis, and supply chain constraints. This success is closely tied to the effective supervision of the Chinese government. The government actively enhanced the support policy system, improved regulations and standards, provided guidance to industry players, and effectively addressed new challenges and problems faced by the industry. According to the China Association of Automobile Manufacturers (2023), in 2022, China's automobile output reached 27.0206 million vehicles, marking a 3.4 percent year-on-year increase, while sales reached 26.8737 million vehicles, a 2.1 percent increase. Through these efforts, the Chinese government has helped the country's automobile industry end its three consecutive years of decline since 2018.

The Chinese government has issued a series of policies and regulations in industrial development, investment management, and fiscal and tax incentives to stimulate healthy and rapid growth of China's automotive industry. In terms of industrial development, the Ministry of Industry and Information Technology (MIIT) issued the Automotive Semiconductor Supply and Demand Matchmaking Handbook, which focuses on building a platform for supply and demand matchmaking and establishing a robust industrial chain, thereby fostering high-quality development in the automotive sector. Regarding investment management, the Ministry of Commerce introduced the “14th Five-Year Plan for the Utilisation of Foreign Investment,” which outlines guidance for foreign-invested enterprises in the automotive, chemical, and equipment manufacturing sectors to expand into research and development, design, marketing, and maintenance fields. Additionally, in terms of fiscal policy, the Ministry of Finance and the Ministry of Transport released the Interim Measures

for the Administration of Local Funds Subsidised by Revenue from Vehicle Purchase Tax. Under these measures, the central government subsidises local funds through the revenue generated from vehicle purchase tax to support the construction of highways and other transportation infrastructures (China Automotive Industry Yearbook, 2022).

In terms of local policies and regulations, Chinese local governments have updated and issued a series of automotive-related policies in 2021, primarily covering smart internet-connected vehicles, new energy vehicles, and automotive consumption. Among the local provinces and cities, Beijing, Shanghai, Guangzhou, and Shenzhen have played a leading role by issuing several policies and regulations to fill gaps in industry management. For intelligent networked vehicles, Beijing released the Overall Implementation Plan for Beijing Intelligent Networked Vehicle Policy Pioneer Zone; Shanghai issued the Measures for the Administration of Intelligent Networked Vehicle Testing and Application to promote the healthy and orderly development of the intelligent networked vehicle industry; and Guangzhou issued the Opinions on the Gradual Sub-Regional Early and Pilot Demonstration and Operation Policies for the Application of Intelligent Networked Vehicles in Different Mixed-Mode Environments, aiming to explore the application of self-driving vehicles in mixed-mode operation. Shenzhen has formulated the Regulations on the Management of Intelligent Networked Vehicles in the Shenzhen Special Economic Zone (Draft for Opinion) from a legislative perspective, covering road testing, access and registration, use management, road transport, traffic accidents and violations, and legal liability. This is the first instance of specialized legislation in intelligent networked vehicles in a Chinese local area, marking a significant exploratory effort. In terms of new energy vehicles, Shanghai, Shenzhen, and other considerable regions have issued several guidance and support documents focusing on the promotion and application of new energy vehicles, fuel cell

vehicles, and charging and switching infrastructure. Regarding automotive consumption, local provinces and municipalities, notably Guangdong Province, have introduced various initiatives to promote consumption, such as trade-ins, promoting automobiles in rural areas, and offering preferential treatment.

Local governments also provide strong support for the automobile industry. According to China Automotive Industry Yearbook (2022), the Hefei Municipal Government in Anhui Province invested 7 billion yuan in NIO Inc. (NIO) to help the company overcome difficulties and successfully go public, positioning it among the leading new forces in vehicle manufacturing and giving it a first-mover advantage in the new energy vehicle industry. In February 2021, the Hefei Municipal People's Government and NIO signed a framework agreement to deepen cooperation and jointly build the Xinqiao Intelligent Electric Vehicle Industrial Park. In April 2021, Volkswagen's new plant in Anhui Province commenced construction. By the end of 2021, Hefei had initiated more than 50 significant projects in the new energy vehicle industry, with a total investment exceeding 50 billion yuan. The cooperative enterprises involved include Volkswagen, JAC, NIO, Guoxuan Hi-Tech, and Huating Power.

1.2.6 Foreign Direct Investment of China's Automobile Industry

According to the National Bureau of Statistics of China (2023), the amount of foreign investment attracted by China exceeded the trillion-yuan mark in 2022, with the actual use of foreign investment surpassing 1.2 trillion yuan for the first time, equivalent to US\$ 189.13 billion, marking an 8% increase. This achievement maintains China's position among the top countries in the world for attracting foreign investment. Specifically, in 2022, China's manufacturing industry utilized 323.7 billion yuan of foreign investment, representing a 46.1%

increase. Notably, the comprehensive liberalization of foreign investment access restrictions led to a significant 263.8% rise in investment in the automobile manufacturing industry.

Foreign capital has fully entered China's automobile market, with mainstream multinational companies having largely completed their strategic layout. In the automotive sector, China is one of the most crucial markets for foreign-funded enterprises. These companies have established a comprehensive presence covering the entire industrial and supply chains, including vehicles, parts, and materials. Their investment areas span the entire industry, encompassing manufacturing, R&D and design, sales and service, and infrastructure. In response to the global shift towards electrification, foreign enterprises increasingly focus their investments on China, leading to deeper cooperation between Chinese and foreign companies (Dong & Mah, 2020).

As of the end of 2022, 45 Sino-foreign joint ventures and wholly foreign-owned vehicle manufacturers were listed in the Announcement on Road Motor Vehicle Manufacturers and Products. According to data from the China Automobile Industry Yearbook (2023), sales of foreign-owned brand passenger vehicles totaled 11.797 million units in 2021, accounting for 50.1% of total passenger vehicle sales. This represents a year-on-year decrease of 5.5 percentage points.

The continuous expansion of foreign direct investment (FDI) has brought significant opportunities for developing China's automobile industry. Since the reform and opening up, China has actively promoted “bringing in” and “going out,” making concerted efforts to integrate into the international market. This has involved not only reducing numerous restrictions on foreign direct investment but also introducing a series of policies to encourage foreign investment. In 1994, the Industrial Policy for the Automobile Industry was officially promulgated and implemented, marking the first policy regulation of China's automotive

sector. The policy stated that “the state encourages automobile industry enterprises to use foreign capital to develop China's automobile industry,” establishing a legal framework for foreign brands to directly invest in China, albeit with a 50% foreign shareholding limit. On November 11, 2001, China officially signed the protocol to join the World Trade Organization (WTO), reaffirming that automobiles are a pillar industry and encouraging consumer demand (Ilia, 2021). This ushered in a boom in the automobile market. Following China's accession to the WTO, the pace of foreign investment in China's auto industry accelerated significantly

On April 17, 2018, the National Development and Reform Commission (NDRC) announced that the automobile industry would gradually remove all restrictions on foreign ownership. The restrictions on foreign ownership of special vehicles and new energy vehicles were lifted in 2018, for commercial vehicles in 2020, and for passenger vehicles in 2022, with the stipulation that no more than two joint ventures would be allowed. In 2020, China enacted the Foreign Investment Law of the People's Republic of China, further opening up the country's automobile industry (Sang, 2022). This law has facilitated an increase in foreign direct investment in China's auto market while providing a fair and competitive platform for both foreign and local auto companies, thereby promoting the development of the automobile industry.

More and more R&D centers of multinational automobile companies in China are opening up to the outside world. The policy environment, legal framework, market conditions, and business climate for foreign investment in China continue to improve. As a result, many multinational automobile companies and parts groups have accelerated their entry and increased their R&D investments. According to China Automotive industry Yearbook (2022), Companies such as General Motors, Ford, Honda, Toyota, Hyundai,

Mercedes-Benz, Audi, Bosch, and Faurecia have all established R&D centers in China. In 2022, international parts companies increased the number of R&D centers in China and began undertaking more substantive development tasks. This is especially true in intelligent networked vehicles, where there is a growing emphasis on localized R&D. For instance, GM's upgraded and expanded China Forward-Looking Design Technology Center was officially put into use. Similarly, Tesla's Shanghai R&D Innovation Center and Shanghai Gigafactory Data Center were completed and put into operation. Additionally, the new Daimler China R&D Technology Center was officially opened in Beijing.

1.3 Problem Statement

The Chinese automobile industry stands at a critical juncture in its development. As the nation's largest economic pillar, generating 11 trillion yuan in output value and accounting for 10% of China's GDP in 2023, it has now surpassed real estate in economic significance (China Auto Chongqing Summit, 2024). Despite this domestic dominance, the industry's global competitiveness reveals significant gaps. Among the world's top 10 automakers by revenue, only one Chinese company (SAIC) appears, ranking ninth with 110.6123 billion in revenue and 2.396 billion in profit, far behind industry leaders like Volkswagen (293.6847 billion in revenue) and Toyota (18.110 billion in profit) (Fortune, 2023). This shows that the international competitiveness of China's automobile industry needs to be improved and China's automobile industry requires further upgraded (Tang, 2020; Wang & Liu, 2018).

A primary concern lies in the industry's positioning within global value chains (GVCs). China's auto sector remains concentrated in low-value-added activities such as parts assembly and manufacturing, while developed economies control high-value segments like R&D and brand management. The relationship between GVC participation and

industrial upgrading remains ambiguous, particularly regarding how technological innovation might mediate this process and whether foreign direct investment (FDI) could mitigate existing constraints. Existing studies have yet to establish whether deeper GVC integration facilitates or hinders China's move up the value chain.

Equally pressing is the question of industrial agglomeration's effectiveness. While China has developed six major automobile clusters, their contribution to upgrading appears inconsistent. Research suggests these agglomerations only yield productivity gains when regional human capital surpasses a critical threshold (Cui et al., 2013; Li et al., 2021; Ni & Li, 2017). The role of government support in optimizing these clusters remains underexplored, particularly in addressing market failures and facilitating knowledge spillovers (Brezna, 2019; Hu et al., 2021; Michael E. Porter, 1990).

Compounding these challenges is the lack of consensus on measuring industrial upgrading. Scholars have employed divergent metrics, including labour productivity, profit rates, and total factor productivity, leading to fragmented policy recommendations. This measurement ambiguity obscures the evaluation of China's industrial policies and their effectiveness in fostering genuine upgrading.

This study seeks to resolve these ambiguities by examining three interconnected dimensions. Firstly, the direct impacts of GVC embeddedness and industrial agglomeration on upgrading. Secondly, the moderating role of government support in the relationship between industrial agglomeration and upgrading, and the moderating role of FDI in the relationship between GVC embeddedness and upgrading. Thirdly, the mediating role of technological innovation in channeling GVC participation into industrial upgrading and the threshold effects of human capital in determining when agglomeration yields upgrading benefits. The findings will provide much-needed clarity for policymakers navigating China's

transition from manufacturing scale to manufacturing sophistication, addressing the core challenge of enhancing international competitiveness in the automobile industry.

1.4 Research Questions

- i. How can the upgrading of China's automobile industry be measured and the impacts of industrial agglomeration and the global value chain (GVC) on this upgrading be elucidated?
- ii. Does government support moderate the impact of industrial agglomeration on upgrading, and does FDI moderate the effect of GVC on upgrading?
- iii. Does technological innovation mediate the relationship between GVC and upgrading, and does human capital serve as a threshold for industrial agglomeration to promote upgrading?

1.5 Research Objectives

The general objective of this research is to explore the multifaceted determinants and underlying mechanisms that drive the upgrading of China's automobile industry. By examining various factors such as industrial agglomeration, global value chain (GVC), government support, foreign direct investment, technological innovation, and human capital, this study aims to provide a comprehensive understanding of how these elements interact and influence the industry's upgrading.

- i. To evaluate the upgrading of China's automobile industry using the DEA-Malmquist total factor productivity index, and the direct impacts of industrial agglomeration and global value chain (GVC) on the upgrading.
- ii. To examine the moderating effects of government support in the relationship between industrial agglomeration and upgrading, and foreign direct investment in the relationship between GVC and upgrading.

- iii. To examine the mediating role of technological innovation in the relationship between GVC and upgrading, and the threshold effect of human capital in the relationship between industrial agglomeration and upgrading.

1.6 Scope of the Study

The scope of this study is defined by several key dimensions, including geographical, temporal, and thematic boundaries, which collectively frame the investigation of the impact of industrial agglomeration and global value chain (GVC) on the upgrading of China's automobile industry.

Geographically, this research focuses on the automobile industry across 28 provinces in China, including major automotive production hubs such as Shanghai, Jilin, Zhejiang, Beijing, and Hubei. These provinces are selected due to their significant contributions to the automotive sector's production, research, and development. Focusing on these regions, the study aims to capture a comprehensive and representative analysis of the factors influencing industrial upgrading within China's diverse automotive landscape.

The study analyzes data from 2000 to 2020. These 21 years are chosen to reflect the rapid development and transformation of China's automobile industry, including the effects of globalization, policy changes, and economic reforms. By utilizing this timeframe, the research aims to provide insights into long-term trends and patterns in industrial upgrading.

The research's thematic scope includes an examination of various factors such as industrial agglomeration, GVC embeddedness, government, foreign direct investment (FDI), technological innovation, and human capital, all of which play critical roles in the context of industry upgrading. The total factor productivity (TFP) used to measure industrial upgrading is calculated using the DEA-Malmquist method, ensuring a robust analytical framework.

1.7 Significance of the Study

1.7.1 Contribution to Literature

This study makes significant theoretical contributions by bridging the Global Value Chain governance framework with regional agglomeration theory to examine industrial upgrading in China's automotive sector. While existing literature has predominantly focused on manufacturing industries, this research provides novel insights into the automobile industry's unique characteristics, including its modular production networks and technology spillover mechanisms.

A key methodological advancement involves analyzing comprehensive provincial-level data from 2000 to 2020, which provides systematic evidence of regional upgrading patterns across China's automotive industry. This provincial perspective enables a more nuanced examination of spatial dynamics compared to conventional national-level analyses. Furthermore, the development of an integrated DEA-Malmquist and threshold regression model offers a robust approach to capture the nonlinear effects of industrial agglomeration, addressing a critical limitation in prior studies that assumed linear relationships.

By focusing specifically on China's automobile industry, this research fills an important gap in the current understanding of how global value chain integration and regional clustering jointly influence industrial upgrading. The findings contribute to broader theoretical discussions in international division of labor and industrial economics while providing industry-specific evidence that challenges conventional assumptions about developing economies' position in global production networks.

1.7.2 Contribution to Practice

The practical implications of this research stem from the automobile industry's pivotal role in national economic development. As an industry with extensive supply chain

linkages and significant employment generation capacity, the automotive sector upgrading has multiplier effects across the entire manufacturing ecosystem (Tai, 2016).

The study yields several important policy recommendations. First, provincial governments should strengthen industrial agglomeration by optimizing cluster planning, improving industrial park infrastructure, and leveraging leading firms like FAW and SAIC to drive innovation and supply chain integration. Second, foreign direct investment policies should prioritize high-quality technology transfer through strategic partnerships with tier-one global suppliers, supported by rigorous screening and evaluation mechanisms. Third, targeted human capital development is essential, including enhanced university-industry collaboration and specialized training programs to meet regional industry needs and overcome skill thresholds for effective technology absorption.

These findings provide empirical support for China's current industrial policy framework. By quantifying the synergistic effects of global value chain participation and industrial agglomeration, the research offers actionable insights for achieving the nation's strategic objectives and manufacturing competitiveness. The results will help policymakers optimize resource allocation and institutional design to accelerate China's transition to automotive industry leadership.

1.8 Organization of Thesis Chapters

This research focuses on the impact of the global value chain and industrial agglomeration on the upgrading of China's automobile industry. Furthermore, it examines whether government support moderates the relationship between the level of industrial agglomeration and the upgrading of the automobile industry. The study also investigates whether foreign direct investment influences the relationship between the global value chain and the industry's upgrading. Additionally, it explores whether global value chains affect the

upgrading of China's automobile industry by influencing technological innovation, as well as whether human capital serves as a threshold factor in the impact of industrial agglomeration on this upgrading process. It is hoped that through this analysis, the upgrading of China's automobile industry will be promoted and China will truly build strength in the automobile industry. The thesis consists of five chapters.

Chapter 1 begins by establishing the research background, examining the development status of China's automobile industry, its position in global value chains, and the fundamental characteristics of industrial agglomeration (1.2 Background of the Study). It then identifies and analyzes the key challenges hindering industrial upgrading (1.3 Problem Statement), formulates precise research questions (1.4 Research Questions), and defines the study's objectives (1.5 Research Objectives). The chapter clarifies the research scope and boundaries (1.6 Scope of the Study), highlights the academic and practical significance of the investigation (1.7 Significance of the Study), and concludes with an overview of the thesis structure (1.8 Organization of Thesis Chapters).

Chapter 2 systematically reviews core concepts including industrial agglomeration, global value chains, and industrial upgrading (2.2 Definition of Industrial Agglomeration, Global Value Chain and Industry Upgrading). It traces the theoretical evolution of agglomeration economics and GVC governance frameworks (2.3 Theories of Industrial Agglomeration and Global Value Chain), while critically evaluating empirical findings on upgrading pathways, measurement approaches, and determinant factors (2.4 Empirical Studies on Industrial Upgrading). Building on identified research gaps (2.5 Literature Gap), the chapter presents the study's conceptual framework (2.6 Conceptual Framework) and develops testable hypotheses (2.7 Hypotheses Development).

Chapter 3 details the research methodology, beginning with an introduction (3.1 Introduction) and outlining the overall research design (3.2 Research Design). It specifies the model specification, including baseline, moderating effect, mediating effect, and dynamic threshold models (3.3 Model Specification). The chapter then describes the data requirements and processing procedures for the analysis (3.4 Data Description), including the measurement of dependent, independent, control, and moderating variables. Finally, it provides comprehensive explanations of the estimation techniques used: descriptive statistics (3.5.1 Descriptive Statistics), data envelopment analysis (3.5.2 Data Envelopment Analysis), the generalized method of moments (3.5.3 Generalised Method of Moments), and the dynamic threshold model (3.5.4 Dynamic Threshold Model), concluding with a summary (3.6 Summary).

Presenting the empirical findings, Chapter 4 opens with an introduction (4.1 Introduction) and provides descriptive statistics of key variables (4.2 Descriptive Statistics). The chapter then details the results of total factor productivity analysis (4.3). It presents baseline analysis results of industrial agglomeration and global value chain on industry upgrading (4.4), moderating effect results of government support on industrial agglomeration and industry upgrading (4.5), mediating effect results of technological innovation on global value chain and industry upgrading (4.6), and dynamic threshold analysis results of human capital on industrial agglomeration and industry upgrading (4.7). The chapter also includes the results of robustness tests (4.8) and concludes with a summary (4.9).

Chapter 5 synthesizes major findings regarding agglomeration effects, GVC impacts, and human capital thresholds (5.1 Summary of Results). It derives targeted policy recommendations for cluster development, FDI management, and governance improvement

(5.2 Policy Implications) while acknowledging methodological limitations and suggesting future research directions (5.3 Limitations of the study and 5.4 Suggestions for Future Research).

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the definitions and theories of industrial agglomeration and global value chain. It sorts out the definition, paths, influencing factors, and measurement indicators of automobile industry upgrading to better understand the relevant literature and establish the theoretical framework of this thesis. Therefore, this chapter will compile the previous literature, further elaborate on the variables involved and research gaps, and finally present a hypothetical model.

2.2 Definition of Industrial Agglomeration, Global Value Chain and Industry Upgrading

2.2.1 Definition of Industrial Agglomeration

The concept of industrial agglomeration has undergone significant development since the seminal work of Marshall (1890), with contemporary scholars building upon and challenging foundational concepts through various analytical lenses. Marshall's original formulation identified three key benefits of spatial clustering, including labour market pooling, intermediate input specialization, and knowledge spillovers, which established the basis for subsequent theoretical advancements. The location theory of Weber (1929) expanded this framework by incorporating cost minimization principles, examining how transportation costs and factor inputs influence agglomeration patterns, though his model has been critiqued for underestimating the role of institutional and knowledge factors.

The cluster theory of Porter (1990) marked a paradigm shift by introducing competitive advantage as the central driver of agglomeration, emphasizing how

geographically proximate firms and institutions create mutually reinforcing value through collaboration and competition. This perspective has proven particularly relevant for analyzing China's automotive industry clusters, where the co-location of OEMs, suppliers, and research institutions exemplifies Porter's conceptualization. However, later scholars have challenged the universality of Porter's framework, with Baptista (2000) and Otsuka and Goto (2015) demonstrating how agglomeration dynamics vary significantly across developmental contexts and industry types.

Recent concept developments have increasingly integrated global value chain perspectives with traditional agglomeration theory. Wang et al. (2010) and Ren (2016) extended Marshall's knowledge spillover concept by showing how agglomeration facilitates learning effects and scale economies in emerging industries, while De Marchi and Grandinetti (2017) introduced a governance dimension by examining how CSR pressures in global supply chains reshape agglomeration patterns. This evolution reflects the growing complexity of industrial organization, where spatial proximity interacts with global production networks in ways that Marshall and Weber could not have anticipated.

Theoretical tensions persist regarding the primary mechanisms driving agglomeration benefits. While Wang and Gu (2002) emphasize knowledge sharing and trust as surpassing market mechanisms, empirical studies of Chinese automotive clusters reveal how both formal market relationships and informal knowledge flows jointly contribute to upgrading outcomes. This synthesis suggests that contemporary agglomeration theory must account for Marshallian externalities and intentional coordination mechanisms, particularly in technology-intensive sectors where innovation systems depend on planned collaboration as much as spontaneous spillovers.

2.2.2 The Importance of Industrial Agglomeration

Industrial agglomeration's significance extends far beyond Marshall's (1890) foundational framework of external economies, with contemporary research revealing complex mechanisms through which spatial clustering influences economic development. While Marshall's three key benefits, including knowledge spillovers, shared inputs, and labor market pooling, remain theoretically relevant, empirical studies demonstrate these advantages manifest differently across industries and developmental contexts. The automobile industry, with its intricate supply chains and technological intensity, presents a particularly revealing case for examining these dynamics.

Schmitz and Nadvi (1999) collective efficiency framework fundamentally challenged the passive view of agglomeration benefits by demonstrating how active collaboration among clustered firms creates competitive advantages that individual enterprises cannot achieve independently. This perspective proves especially pertinent to China's automotive sector, where government-led industrial parks actively foster inter-firm cooperation while simultaneously creating potential path dependencies. Subsequent research by Dupont (2007) further complicated this picture by revealing how tacit knowledge circulation within clusters follows distinct patterns in capital-intensive versus labor-intensive industries, suggesting that Marshallian spillovers require specific institutional conditions to materialize in advanced manufacturing sectors.

The productivity impacts of agglomeration exhibit similar contextual variations. Combes et al. (2012) found that inter-industry agglomeration outperforms intra-industry clustering in productivity gains, which has important implications for automotive hubs. In these hubs, the co-location of parts suppliers, material scientists, and engineering services may be more significant than the simple concentration of assemblers. This observation aligns

with the systems view of industrial districts presented by Bergman and Feser (2020), which emphasizes the combinatorial innovation potential that arises from strategic interdependencies among heterogeneous firms. This phenomenon is observable in China's Yangtze River Delta automotive cluster.

Urban and regional development scholars have progressively reconceptualized agglomeration as a dynamic rather than a static advantage. The research of Wang (2023) on innovation ecosystems illustrates how mature clusters evolve through phases of knowledge exploration, exploitation, and recombination, with distinct policy requirements at each stage. This evolutionary perspective helps explain why some automotive clusters successfully upgrade while others remain locked in low-value activities, suggesting that the mere presence of agglomeration provides no guarantee of development outcomes.

2.2.3 Definition of Global Value Chain

The concept development of global value chain (GVC) analysis has evolved through several distinct phases, reflecting broader shifts in global production organization. The initial value chain framework was proposed by Porter (1985), which focused on firm-level activities, established critical foundations through its distinction between primary and support activities, a conceptual dichotomy that continues to inform contemporary GVC analysis. However, this micro level perspective proved limited in explaining the emerging transnational production networks of the late 20th century, which prompted Kogut (1985) crucial theoretical intervention. His value-added chains concept introduced essential spatial and organizational dimensions that anticipated and helped shape current GVC debates, particularly concerning how nations and regions develop specialized roles within specific chain segments.

The emergence of global commodity chain theory (Gereffi, 1999) marked a significant theoretical advancement by systematically examining four key dimensions of transnational production networks. This multidimensional approach proved valuable for analyzing industries like automobiles, where input-output structures, territorial configurations, governance modes, and institutional frameworks interact complexly. The producer-driven/buyer-driven typology offered initial tools for understanding power asymmetries in GVCs, though later scholarship would reveal more nuanced governance patterns in technology-intensive sectors.

The consolidation of GVC theory in the early 2000s (Kaplinsky & Gereffi, 2001) represented a maturation of this intellectual trajectory, synthesizing previous concepts into an integrated analytical framework. This theoretical systematization enabled researchers to examine both the structural characteristics of GVCs and their dynamic evolution - a dual perspective essential for understanding upgrading processes in developing economies. The United Nations Industrial Development Organization (2002) expanded this further by emphasizing the networked nature of value creation and the importance of inter-firm relationships, while somewhat underplaying the role of state actors that later research would highlight as crucial in industries like China's automotive sector.

2.2.4 Definition of Industry Upgrading

Industrial upgrading is a fundamental and significant concept in industrial economics. Its connotation can be defined at macro, meso, and micro levels, and based on the form of upgrading, it can also be categorized into inter-industry upgrading and intra-industry upgrading. However, scholars have not yet reached a unified definition of this concept.

Ernst et al. (1998) were the first to introduce the concept of industrial upgrading. Through their study of international trade theory, they highlighted, from the perspective of

industrial comparative advantage, that industrial upgrading was the process by which a product from a country's industry transitioned from low-value-added attributes to high-value-added attributes.

Liu and An (2002) argued that industrial upgrading was not merely an increase in output, but a process of industrial transformation from a lower to a higher level. In this process, the rationalization of industrial structure should be enhanced, the upgrading of industrial structure should be promoted, and the internal utilization of resources in enterprises should be transformed from low output and low efficiency to high output and high efficiency.

Li et al. (2010) believed that industrial upgrading meant improving product quality, enhancing production structure, and strengthening the ability to obtain profits. This transformation and upgrading facilitated the coordinated development of industries, thereby promoting overall economic growth. At the same time, the industrial structure also changed correspondingly, shifting from labor-intensive to capital-intensive and technology-intensive development. Specifically regarding the product itself, it was the transformation process of the added value contained in the product from low to high (Poon, 2004).

Fu (2012) argued that with technological advancements, industrial upgrading can no longer be defined by the traditional categories of labor-intensive, capital-intensive, or technology-intensive industries. Traditional manufacturing industries may also incorporate high and new technologies and achieve high production efficiency, while high-tech manufacturing industries may eventually become traditional manufacturing sectors. Therefore, she proposed that industrial upgrading can be defined from two new dimensions. On one hand, it can refer to the process of enhancing the industry's innovation capability, and on the other hand, it can also refer to the process of improving production efficiency.

Park et al. (2013) argued that industrial upgrading refers to the process whereby market entities, such as enterprises and countries, enhance output by increasing the input of factors and technologies within the specialized division of labor. This process aims to enhance industrial added value and achieve sustainable profit maximization.

Gereffi (1999) divided industrial upgrading into intra-industry upgrading and inter-industry upgrading. Intra-industry upgrading refers to the enhancement of products through improvements in research and development levels and manufacturing processes, or the transformation of low-value-added manufacturing departments into higher value-added departments, which is also known as intra-sector upgrading. Inter-industry upgrading, on the other hand, refers to shifting from labor-intensive sectors to those that are capital- or technology-intensive, also known as inter-sector upgrading.

Humphrey and Schmitz (2002) argued that industrial upgrading included process upgrading, product upgrading, function upgrading, and chain upgrading. Process upgrading involved surpassing competitors in specific value chain links by improving input-output efficiency. Product upgrading was achieved by enhancing existing products or developing new ones with better quality and faster update cycles. Function upgrading entailed participating in higher value-added activities, such as design and marketing, within the value chain. Chain upgrading refers to transitioning to a new, more profitable value chain. They pointed out that process upgrading, product upgrading, and function upgrading were methods of intra-industry upgrading, while cross-industry upgrading was a method of inter-industry upgrading.

In summary, industrial upgrading is a multifaceted concept integrating various dimensions of economic development, innovation, and structural transformation. Despite the

lack of a unified definition, the contributions of various scholars provide a robust framework for understanding the processes and implications of upgrading within and across industries.

2.3 Theories of Industrial Agglomeration and Global Value Chain

2.3.1 Evolution of Industrial Agglomeration Theories

2.3.1.1 Industrial Zone Theory

The theoretical foundations of industrial agglomeration have evolved significantly since Marshall's (1890) seminal work, with successive scholars building upon and challenging his original conceptions. Marshall's identification of industrial districts as concentrations of specialized small and medium enterprises established the crucial link between spatial proximity and economic externalities. His framework highlighted three primary mechanisms, including labor market pooling, input sharing, and knowledge spillovers, which continue to inform contemporary agglomeration research. However, this early formulation has been substantially refined through subsequent theoretical developments that address its limitations in explaining modern industrial clustering patterns.

The new economic geography of Krugman (1991) marked a pivotal theoretical advancement by formalizing the relationship between scale economies, transportation costs, and agglomeration dynamics. His center-periphery model provided rigorous analytical tools to explain why certain regions develop persistent industrial advantages, addressing a key gap in Marshall's more descriptive approach. This theoretical progression proves particularly relevant for analyzing China's automotive clusters, where both Marshallian externalities and Krugman's scale effects interact with state-led development policies.

2.3.1.2 Industrial Location Theory

The development of industrial location theory represents a significant evolution in understanding spatial economic organization. Weber's (1929) foundational work established

core principles that continue to inform contemporary agglomeration research. Weber's dichotomous framework distinguished regional factors (transportation costs and labor) and agglomeration factors, providing crucial insights into how cost minimization drives enterprise clustering. However, this classical formulation has been substantially refined through subsequent theoretical extensions that address its limitations in explaining modern industrial geography, particularly in policy-driven economies like China.

Later scholars such as Fetter (1924) and Hoover (1948) significantly expanded Weber's model by incorporating demand-side considerations and multidimensional cost analyses. Fetter's trade boundary theory introduced the critical role of market access and consumption patterns in location decisions, while Hoover's comprehensive framework integrated institutional and infrastructural factors that Weber's original manufacturing-focused approach had overlooked. These theoretical advancements prove particularly valuable for analyzing China's automotive industry clusters, where state-led development policies interact with traditional agglomeration economics in complex ways. The coexistence of these factors helps explain why certain regions like the Pearl River Delta have successfully emerged as automotive hubs despite not necessarily possessing classical location advantages.

2.3.1.3 New Industrial Zone Theory

The study of new industrial regions began in the late 1970s, when Italian sociologist Bagnasco (1977) focused on the development of northeastern and central Italy and introduced the concept of "Third Italy." Bagnasco compared Third Italy to the "industrial areas" studied by Marshall, noting that while these regions shared significant similarities with Marshall's industrial areas, they also exhibited new characteristics. As a result, these regions were termed new industrial areas. Bagnasco was a pioneer in studying new industrial

areas, focusing on the development of northeastern and central Italy. His work laid the groundwork for further exploration in this field. Scott (1988) and Storper (1992) also contributed significantly to the study of new industrial areas. Their research and insights have helped shape the “new industrial area theory.” The combined efforts of these scholars have expanded and refined our understanding of new industrial regions.

The New Industrial Zone Theory differs from the Marshall Industrial Zone Theory by emphasizing two main factors in the formation of industrial agglomeration. Firstly, it highlights the importance of a stable localized cooperation network, characterized by the flexibility of enterprise operation mechanisms, the specialization of enterprise division of labor, and the stability of collaboration. This flexible specialization enables small and medium-sized enterprises to better compete with larger firms, thereby enhancing regional competitiveness. Secondly, the theory underscores the rootedness of enterprises, where economic activities are deeply embedded in various social relations within the industrial zone. Economic interactions and information technology flows rely on the shared cultural and institutional background of the local area. This common cultural framework reduces friction in cooperation between enterprises, further solidifies the establishment of localized cooperation networks, enhances the stability of industrial agglomeration, and mitigates the impact of changes in the external environment on enterprises.

2.3.1.4 Diamond Model

The study of industrial agglomeration has been significantly advanced by Michael E. Porter’s diamond model, which identifies four interdependent determinants of national industrial competitiveness: factor conditions such as human capital and infrastructure, demand conditions, related and supporting industries, and firm strategy, structure, and rivalry—additionally, two other variables, government and chance events, further shape this

dynamic system. Porter (1990) posits that geographic concentration amplifies synergies among these factors, fostering innovation and upgrading. Crucially, he highlights human capital as a pivotal element of factor conditions, emphasizing that labor skills, knowledge, and innovation capacity, rather than just workforce size, determine industrial competitiveness. High-quality human capital enhances productivity and facilitates the interplay of all determinants, while governments provide indirect support to clusters through policies, infrastructure, and education rather than direct intervention.

Building on Porter's work, Padmore and Gibson (1998) introduced the GEM model to evaluate cluster competitiveness systematically. Their framework categorizes influencing factors into six dimensions: resources, infrastructure, suppliers/related enterprises, firm structure/strategy, local markets, and external markets. This adaptation refines Porter's theory by delineating more granular drivers of cluster performance, particularly the roles of regional and global market dynamics. By incorporating these dimensions, the GEM model provides a more comprehensive understanding of how various elements interact to influence competitive advantage. Table 2.1 is a summary of industrial agglomeration theory.

Table 2.1: Industrial Agglomeration Theory

Theory Name	Research Focus	Representative Scholars
Industrial Zone Theory	External Economics	Marshall (1890); Krugman (1991)
Industrial Location	Aggregation Economy	Weber (1929); Fetter (1924); Hoover (1948)
New Industrial Zone Theory	New Industrial Space	Bagnasco (1977); Scot (1988); Storper (1992)
Diamond Model	Cluster Competitiveness	Porter (1990); Padmore and Gibson (1998)

2.3.2 Theories of Global Value Chain

2.3.2.1 Drivers of Global Value Chain

The global value chain (GVC) framework highlights how different actors control and coordinate international production networks. Gereffi (1994) established the fundamental distinction between producer-driven and buyer-driven value chains: producer-driven chains are dominated by large manufacturers or branded enterprises (e.g., Toyota, Intel) that control technology, capital, and production processes, particularly in capital-intensive industries like automotive and electronics, where firms maintain oversight of R&D and core manufacturing while outsourcing peripheral activities. Through overseas investment or outsourcing, producers relocate some production to regions with lower costs or specific technological advantages; conversely, buyer-driven chains prevail in labor-intensive sectors like apparel and consumer goods, where retailers and brand owners (e.g., Nike, Walmart) leverage market access rather than production assets, focusing on design and distribution while relying on contracted manufacturers in low-cost regions for physical production.

While later scholars like Zhang (2006) identified hybrid forms that combine elements of both: the increasing complexity of global production has given rise to value chains that blend these logics, as seen in electronics where companies like Dell combine proprietary marketing (buyer-driven trait) with selective product development control (producer-driven trait), requiring nuanced upgrading strategies as value creation disperses across knowledge-intensive and market-oriented activities. The global value chain is categorized into three driving types: producer-driven, buyer-driven, and hybrid-driven. Table 2.2 illustrates a comparison of the differences among the value chains associated with these three driving modes.

Table 2.2: Comparison of Producer, Buyer and Mixed-driven Global Value Chain

Item	Producer Driven Model	Buyer Driven Model	Hybrid Drive Mode
Source of Motivation	Industry Capital	Commercial Capital	Both
Core Competencies	Research and Development Capacity; Production Capacity	Brand Building and Marketing Ability	Both
Barriers to Entry	Economy of Scale	Economy of Scope	Both
Representative of Industry	Automobile, Aircraft Manufacturing, Electronics etc	Clothing, Footwear, Toys, Household Goods etc	Computer, etc.
Leader	Large Multinational Manufacturers	Large Retailers, Brand Manufacturers	Both
Ownership	Multinational Companies in Developed Countries	Regional Industrial Clusters in Developing Countries	Both
Leading Industry Structure	Vertical Integration	Horizontal Integration	Both
Major Network Relationships	Focus on Investment	Focus on Trade	Both
Typical Multinational Corporation	Toyota, Boeing, etc	Adidas, Carrefour, etc	Ford, Dell, etc

Source: Gereffi (1994) and Zhang (2006)

2.3.2.2 The Governance Model of Global Value Chain

The growing complexity of the international division of labor has elevated the importance of global value chain (GVC) governance, which Gereffi et al. (2005) conceptualize as a spectrum of coordination mechanisms ranging from market-based to

hierarchical control. Market governance facilitates decentralized transactions through price mechanisms at one end, which is ideal for standardized commodities requiring minimal coordination. Progressing along the continuum, modular governance enables operational independence among suppliers while maintaining technical compliance, as seen in electronics manufacturing. The middle range features relational governance, where trust-based partnerships foster knowledge sharing in industries like high-end fashion design. In contrast, captive governance creates power asymmetries, with dominant buyers controlling dependent suppliers in outsourced manufacturing arrangements. The spectrum culminates in hierarchical governance, vertical integration, and direct control in complex sectors like automotive production. These models frequently intersect and evolve dynamically in practice, reflecting the adaptive nature of global production networks.

The governance framework reveals essential insights about power dynamics in global production networks. While market and modular governance maintain relatively balanced power relationships, captive governance exhibits significant asymmetry. Relational governance creates interdependence, whereas hierarchical governance concentrates power within a single firm. These coordination intensity and power distribution differences directly impact how value chains respond to disruptions and where value gets captured along the chain. Table 2.3 systematically compares these governance models across key dimensions, including coordination complexity, power distribution, and typical industry applications.

The global value chain governance model provides the foundational framework for this study by offering a structured approach to analyze the interplay between industrial agglomeration, FDI, and upgrading dynamics in China's automobile industry. Unlike network theory, which emphasizes decentralized collaboration or stakeholder theory and focuses on diverse interest groups, the GVC governance model elucidates how hierarchical

and modular relationships within production networks shape upgrading pathways. This theoretical lens proves particularly suitable for China's automotive sector, where lead firms (e.g., joint venture OEMs) and domestic suppliers interact within clearly defined power asymmetries that influence technology transfer and value capture.

Table 2.3: Comparison of Five Governance Models of Global Value Chain

Governance Model	Governance Coordination Mechanism	Transaction Complexity	Transaction Codifiability	Supplier Capabilities
Market	Market Price	Low	High	High
Modular	Product Quality Standard	High	High	High
Relational	Reputation and Trust	High	Low	High
Captive	Buyer's Overall Control over Supplier	High	High	Low
Hierarchical	Control and Management	High	Low	Low

Source: Gereffi et al. (2005)

The model's focus on five governance types: market, modular, relational, captive, and hierarchy, provides a robust analytical tool for examining how various agglomeration patterns influence upgrading outcomes. A prime example can be seen in China's automotive clusters, where captive governance arrangements often serve as initial conduits for knowledge transfer from foreign OEMs to domestic suppliers. In contrast, relational governance structures tend to be more pivotal in fostering indigenous innovation during advanced upgrading phases. This governance framework offers particular explanatory power

regarding foreign direct investment by differentiating between market-seeking investments that may perpetuate low value chain positions and technology-focused investments that actively support functional upgrading. Such distinctive analytical capabilities establish the GVC governance model as particularly well suited for investigating industries like automobile manufacturing, where strategic positioning within global production networks profoundly shapes regional development pathways.

2.3.3 Theoretical Framework

This study integrates multiple theoretical frameworks to examine the impacts of industrial agglomeration and global value chains (GVC) on industrial upgrading. Each theoretical perspective is a robust foundation for the research, elucidating its application through specific mechanisms and contextual analyses. The subsequent sections provide a detailed account of how these theories are applied and integrated into the overall framework of this study.

Firstly, the direct impacts of industrial agglomeration and global value chains (GVC) on industrial upgrading are examined through established theoretical frameworks. The theory of industrial agglomeration, particularly Marshall's Industrial Zone Theory, elucidates how industrial clusters facilitate upgrading through three primary mechanisms: labor market pooling, input sharing, and knowledge spillovers. These mechanisms enhance skill levels, reduce production costs, and promote innovation among firms within the cluster, ultimately driving the industrial upgrading process. On the other hand, the GVC captive governance theory highlights how foreign lead firms within global value chains can restrict local firms to low-value tasks, as evidenced in the Chinese automotive industry, where local suppliers are often locked into assembly roles. This limitation hinders their ability to move up the value chain and achieve higher levels of industrial upgrading.

Secondly, the moderating effects of government on the relationship between industrial clusters and upgrading and foreign direct investment (FDI) in the relationship between GVC and upgrading are pivotal in this research. Utilizing Porter's Diamond Model, the study explores how government interventions, such as policy support, infrastructure development, and talent cultivation, can enhance the competitive advantages of industrial clusters and facilitate their upgrading. Similarly, the Producer-driven global value chain theory provides insights into how FDI introduces advanced technologies and management practices, thereby boosting the technological capabilities of local firms.

Thirdly, the role of technological innovation as a mediator in the relationship between GVC and upgrading and the threshold effect of human capital in the relationship between industrial agglomeration and upgrading are essential components of this investigation. The governance structures within GVCs, particularly captive governance, constrain local firms' innovative capacities, limiting their competitiveness in the global market. Conversely, technological innovation is a driving force for industrial upgrading, enabling firms to enhance their product offerings and market positions. Regarding human capital, Porter's Diamond Model emphasizes its critical role in fostering competitive advantages within industrial clusters. High-quality talent boosts innovation and attracts investment and resources, creating a virtuous cycle that facilitates industrial upgrading. This comprehensive analysis aims to provide a nuanced understanding of the interplay between these factors and their implications for industrial evolution.

2.4 Empirical Studies on Industrial Upgrading

2.4.1 Industrial Upgrade Path

The theoretical literature on industrial upgrading presents diverse perspectives, with scholars developing distinct analytical frameworks based on different research contexts.

Zhang (2005) proposed the sequential OEA-OEM-ODM-OBM upgrading path, which provides an essential reference for understanding manufacturing development in East Asia by emphasizing the gradual transformation of firms' roles in global value chains. However, this linear model shows limitations in explaining the leapfrogging development of specific Chinese industries, such as Huawei's rapid transition from OEM to OBM through independent innovation.

The second influential framework was proposed by Humphrey and Schmitz (2002). They introduced the concepts of process upgrade, product upgrade, function upgrade, and chain upgrade. Process upgrade refers to improving the efficiency of production processes, such as enhancing raw material utilization rates. Product upgrade involves improving existing products or introducing new ones. Functional upgrade focuses on enhancing the overall competitive advantage of the global value chain (GVC) by restructuring its components. Chain upgrading refers to adding or migrating production activities to another value chain. For example, in Taiwan, the production shifted from transistors to radios, calculators, TVs, and computers. As the production chain evolved, the value chain also transformed, resulting in chain upgrades.

Fernandez-Stark et al. (2014) expanded the theoretical understanding of industrial upgrading by examining key aspects, including value chain entry barriers, backward linkage upgrading, and end-market upgrading. Their work underscores the various obstacles developing country firms encounter when entering global value chains, particularly technical standards and certification systems that often pose significant challenges. This perspective is valuable in analyzing Chinese manufacturers' difficulties during their initial integration into global production networks. However, the framework's predominant focus on multinational corporations leaves the specific upgrading pathways of small and medium

enterprises relatively unexplored, representing an essential limitation in its application to more diverse industrial contexts.

Recent studies on technology-driven upgrading and industrial agglomeration effects have introduced new theoretical insights. Huang et al. (2019) and Zhang and Xu (2020) identified technological innovation as the core driver of industrial upgrading, arguing that mere participation in global value chains does not automatically lead to upgrading. The study of Han (2024) on manufacturing agglomeration in Anhui Province revealed that spatial clustering significantly promotes regional industrial upgrading through knowledge spillovers and economies of scale. These studies demonstrate the multidimensional nature of upgrading determinants, though they have yet to connect technological, spatial, and institutional factors systematically.

The automobile industry is a critical case study for examining industrial upgrading dynamics within global value chain (GVC). Scholars have approached this sector from multiple theoretical angles, revealing convergent and divergent pathways for developing economies. The foundational work of Humphrey and Memedovic (2003) established that developing-country automotive sectors require both market liberalization and strategic policy support to achieve functional upgrading, particularly for component suppliers. This policy-centric view finds empirical validation in China's experience, where, as Sturgeon and Van Biesebroeck (2011) demonstrate, initial foreign direct investment dependence gradually gave way to greater autonomy through market expansion and strategic acquisitions, suggesting that GVC integration strategies must evolve with industrial maturity.

The technological dimension of upgrading emerges as another crucial theoretical thread. Ma (2015) confirmed that upgrading typically originates with sectoral leaders through R&D-intensive innovation, aligning with the broader literature on technological

capability accumulation. This perspective has been extended by Liu et al. (2018) and Wang (2019), who introduce digital transformation as a contemporary upgrading vector. Their work bridges traditional upgrading theories with the Fourth Industrial Revolution paradigm, emphasizing how smart manufacturing and big data applications create new upgrading pathways that complement conventional process and product improvements.

Recent theoretical developments, exemplified by Lampón et al. (2022), advocate for hybrid upgrading strategies that combine traditional GVC participation with knowledge partnerships. Their supplier collaboration model addresses a key critique of earlier frameworks regarding overemphasizing complete autonomy or full dependence by proposing intermediate cooperation modes. This evolution in theoretical thinking mirrors the automotive industry's transformation, where upgrading increasingly involves simultaneous engagement with multiple technological paradigms and governance modes.

2.4.2 Methods for Measuring Industrial Upgrading

The measurement of industrial upgrading remains a contested terrain in academic research, with scholars adopting diverse approaches that reflect distinct theoretical perspectives and empirical challenges. While no universally accepted metric exists, existing studies broadly cluster around five methodological paradigms, each with specific strengths and limitations.

A dominant strand of literature equates industrial upgrading with increases in domestic value creation within global production networks. Kaplinsky and Readman (2005) use industrial efficiency to measure industrial upgrading, and the added value of products is one of the measurement indicators of industrial upgrading. Kowalski et al. (2015) defined upgrading as a product's domestic value-added share to empirically analyze the impact of participation in global value chains on the national economy. Taglioni and Winkler (2016)

measured upgrades using domestic value added, level of domestic value added, and productivity in total exports. However, this method struggles to isolate genuine productivity gains from exogenous factors (e.g., commodity price fluctuations), making it less suitable for assessing automobile industry upgrading, where production efficiency and innovation are paramount.

Analyzing factor intensity shifts through input-output ratios represents another approach to measuring industrial upgrading, focusing specifically on changes in production patterns through capital deepening or skill intensification. Pavlínek and Ženka (2011) and Guo and Lu (2015) used the change of factor input ratio to reflect industrial upgrading. While these methods effectively track structural transformations in manufacturing processes, they exhibit significant limitations in distinguishing between different types of technological advancement.

Based on the premise that higher value-chain positions typically yield greater profitability, industrial profit rates have been employed as an upgrading indicator by scholars like Sheng (2014) and Ji and Zhang (2017). However, this approach faces significant limitations in China's automotive sector, where government subsidies, regional protectionism, and market cyclicity frequently distort profit metrics. While offering some value for cross-sector comparisons, profit rates prove inadequate for accurately assessing genuine upgrading dynamics due to their susceptibility to external market and policy influences.

Labor productivity has long served as a fundamental metric for assessing industrial upgrading. Grossman and Helpman (1993), Milberg and Winkler (2011), and Li and Yan (2018) used labor productivity to measure industrial upgrading. While applicable across different economies, this approach has limitations in capital-intensive industries like

automobile manufacturing. Its focus on output-per-worker ratios fails to account for automation and equipment investments crucial in modern production systems, potentially overlooking the impact of technological advancements and capital investments that significantly enhance overall productivity and efficiency in these industries.

Table 2.4: Methods for Measuring Industrial Upgrading

Measurement Indicators	Representative Scholars
Domestic Added Value of Products	Kaplinsky and Readman (2005); Kowalski et al. (2015); Taglioni and Winkler (2016)
Factor Input-Output Ratio	Pavlínek and Ženka (2011); Guo and Lu (2015)
Industrial Profit Rate	Sheng (2014); Ji and Zhang (2017)
Labor Productivity	Grossman and Helpman (1993); Milberg and Winkler (2011); Li and Yan (2018)
Total Factor Productivity	Sun and Xi (2015); Liu et al. (2017); Yu and Li (2019); Wang and Lu (2019); Xu (2020)

Total factor productivity (TFP) offers a more comprehensive alternative, especially for technology-driven sectors. Sun and Xi (2015), Liu et al. (2017), Yu and Li (2019), Wang and Lu (2019), Xu (2020) all took the total factor productivity of manufacturing industry as an indicator to measure the upgrading level of manufacturing industry in their empirical studies. Sun and Xi (2015) showed that TFP captures input efficiency and technological and managerial advances. Subsequent China studies confirmed its effectiveness in analyzing automotive sector upgrading, where it reflects multiple production factors and aligns with

national quality-growth strategies. TFP's multidimensional approach makes it superior to simpler productivity metrics. Table 2.4 is a summary of the measurement methods for industrial upgrading.

2.4.3 Influencing Factors for Industrial Upgrading

2.4.3.1 The Level of Industrial Agglomeration

The impact of industrial agglomeration externalities on regional innovation has been widely studied. Marshall (1890) first proposed the concept, arguing that agglomeration fosters external economies that facilitate knowledge and technology spillovers among firms. Subsequent research in economic geography has emphasized industrial agglomeration as a key driver of regional innovation (Lee & Sohn, 2019). Krugman (2011) further suggested that agglomeration enhances regional innovation capacity by accelerating the flow of innovation-related resources, highlighting the importance of spatial concentration for knowledge sharing and collaborative iteration.

Beyond innovation, industrial agglomeration also reduces R&D costs, catalyzing regional economic growth (Dalum et al., 2005). Clustered firms benefit from shared infrastructure, talent, and technology, lowering barriers to innovation (Boix & Galletto, 2009). Muro and Katz (2011) added that agglomeration accumulates critical innovation resources, such as skilled labour, capital, and technology, boosting regional innovation performance.

Human capital plays a threshold role in moderating agglomeration effects. Cui et al. (2013) found that industrial agglomeration significantly enhances total factor productivity only after human capital surpasses a certain threshold, with more potent effects at higher levels. Similarly, Ni and Li (2017) and Yang (2020) confirmed that agglomeration's positive

impact on innovation depends on local human capital, with regional variations across China. Capozza et al. (2018) noted that agglomeration further stimulates innovation by fostering the growth of innovative enterprises.

Recent studies have expanded on agglomeration's spatial spillovers. Aritenang (2021) demonstrated its role in local economic growth using Indonesia as a case study. Guo and Sun (2023) found that manufacturing agglomeration not only boosts local economies but also generates cross-regional spillover effects, though with regional heterogeneity.

Table 2.5: Summary of the Impact of Industrial Agglomeration on Industrial Upgrading

The Direction of Effects	Representative Scholars
Positive Effect	Marshal (1890); Dalum et al. (2005); Boix and Galletto (2009); Muro and Katz (2011); Cui et al. (2013); Ni and Li (2017); Capozza et al. (2018); Yang (2020); Aritenang (2021); Guo and Sun (2023)
Negative Effect	Alejandro (2005); Wang (2012); Cerina and Mureddu (2014); Hardjoko et al. (2021)

According to some research, industrial agglomeration impedes economic expansion. Alejandro (2005) based on the fitting of agglomeration and productivity in 32 Mexican states, concluded that the effect of agglomeration on productivity was not significant, or even negative. Wang (2012) found that there is a threshold value for agglomeration scale, beyond which the “crowding effect” becomes evident. Cerina and Mureddu (2014) argued that industrial agglomeration negatively impacts the growth rate of real income, both at the regional and overall levels. Hardjoko et al. (2021) analyzed the panel data of East Java, Indonesia, from 2011 to 2019 and concluded that industrial agglomeration slows down local

economic growth and synergistic development. Table 2.5 summarizes the impact of industrial agglomeration on industrial upgrading.

2.4.3.2 Global Value Chain

The relationship between global value chain (GVC) participation and industrial upgrading has generated considerable debate among scholars, with substantial evidence suggesting potential negative consequences for developing economies. Gereffi et al. (2005) pioneered this critical perspective by arguing that excessive reliance on GVCs might undermine domestic innovation capabilities. Subsequent research has consistently reinforced these concerns: Liu and Zhang (2009) found limited technology spillovers for Chinese firms in GVCs; Cui (2013) revealed how developed countries strategically constrain innovation pathways through their dominant positions; and Huang (2015) documented structural power asymmetries in GVC governance. Empirical evidence at both macro and micro levels further substantiates these findings - Fagerberg et al. (2018) observed no growth advantage for GVC-participating countries, with particularly detrimental effects on smaller economies, while Wang and Lu (2019) demonstrated how GVC embeddedness reduces firms' incentives for independent R&D, ultimately hindering industrial upgrading. The most comprehensive support comes from Mao (2022), whose survey of 63 nations recommended that emerging economies reduce dependence on foreign-dominated value chains to protect their development trajectories.

Contrasting this pessimistic view, another group of scholars emphasizes the potential benefits of GVC participation. Grounded in the early work of Grossman and Helpman (1993) on "learning by doing" and technology spillovers, this perspective has been developed through studies like Kaplinsky (2000) of strategic technology utilization and Criscuolo and Timmis (2017), who identified multiple productivity-enhancing mechanisms in GVCs.

Recent empirical research by Yanikkaya and Altun (2020) and Fu (2023) has provided macroeconomic and sector-specific evidence supporting the positive relationship between GVC participation and industrial upgrading, particularly in the context of China's manufacturing sector. Table 2.6 summarizes the impact of global value chain on industrial upgrading.

The apparent contradiction between these perspectives becomes clearer when examining the contextual factors that shape GVC outcomes. Several critical variables mediate the relationship between GVC participation and industrial upgrading, including how deeply a country integrates into GVCs, the strength of domestic institutional support for innovation, and unique sector-specific characteristics. Passive, low-value participation often results in the captive relationships identified by more pessimistic scholars. In contrast, strategic engagement with GVCs, especially with robust domestic policy support, creates meaningful upgrading opportunities. This more nuanced perspective helps bridge the gap between opposing views in the literature and establishes a more complete analytical framework for understanding GVC impacts.

Table 2.6: Summary of the Impact of Global Value Chain on Industrial Upgrading

The Direction of Effects	Representative Scholars
Positive Effect	Kaplinsky (2000); Criscuolo and Timmis (2017); Yanikkaya and Altun (2020); Fu (2023)
Negative Effect	Liu (2009); Huang (2015); Fagerberg et al. (2018); Mao (2022)

2.4.3.3 Government Support

The government's role in shaping industrial competitiveness has been conceptualized and examined through multiple theoretical lenses, with scholars progressively refining our understanding of effective policy interventions. The foundational "diamond" model of Porter (1990) established government as a pivotal actor capable of influencing all determinants of industrial competitiveness, from factor conditions to firm strategy. This theoretical framework has been empirically validated and expanded in subsequent research. For instance, De Cos et al. (2009) demonstrated through their study of California clusters that effective governance extends beyond infrastructure to include institutional support for knowledge exchange and market standardization, directly addressing coordination failures that Porter's model implicitly acknowledges.

Contemporary studies have further nuanced this perspective by examining the limits and modalities of government intervention. Breznau (2019) provided an analysis of market failures that offers a critical justification for state involvement, while Damstra et al. (2021) caution against overreach by examining national industry policies. Their work reveals an emerging consensus: governments function most effectively as adaptive regulators and enablers rather than dominant directors of industrial development. This evolution in thought mirrors the practical challenges observed across different developmental contexts, where successful industrial policies (e.g., East Asia's export-oriented growth) have balanced strategic intervention with market signals. In contrast, less successful attempts (e.g., import-substitution in some Latin American economies) often overemphasized state control.

2.4.3.4 Foreign Direct Investment

The impact of foreign direct investment (FDI) on industrial upgrading remains a subject of ongoing scholarly debate, with empirical evidence revealing both catalytic and

inhibitory effects depending on contextual factors. The optimistic perspective, rooted in the seminal work of Dunning (1998) on multinational corporations, suggests that FDI can stimulate industrial upgrading through multiple channels, including technology transfer, efficiency gains from agglomeration economies, and strategic asset acquisition. This view finds empirical support in the longitudinal study of Pavlínek et al. (2009) on Central Europe's automotive sector, which demonstrated that FDI inflows between 1990 and 2006 significantly contributed to industrial modernization. More recent analyses by Buzdugan and Tüselmann (2018) along with research by Wang et al. (2020) further substantiate these findings, particularly in the Chinese context. However, the latter study importantly qualifies this by noting the limited spatial spillover effects of FDI. The reciprocal relationship between FDI and economic growth, as demonstrated through analysis of Indian data by Kumari et al. (2023), adds another dimension to this positive assessment.

However, a substantial body of research challenges this optimistic narrative by highlighting the potential negative consequences of FDI. Early warnings emerged from the study conducted by Aitken and Harrison (1999) on Venezuelan manufacturing, which revealed negative productivity spillovers from foreign investment. Subsequent research carried out by Djankov and Hoekman (2000) in the Czech Republic and by Ahmed (2012) in Malaysia similarly found FDI to be negatively correlated with domestic productivity. In the Chinese context, analysis at the enterprise level by Fan and Hu (2007) uncovered a paradoxical situation where FDI increased industry-level R&D while depressing it at the firm level. More concerning findings appear in work by Yuan and Xie (2014) and Chen and Li (2019), who argue that FDI may hinder industrial restructuring and lower domestic industries' global value chain position. Lu et al. (2017) argued that the influx of foreign capital intensifies market competition, squeezing the living space of local enterprises and

causing a decline in their profitability (Xu, 2017). The most comprehensive critique comes from the Vietnamese study by Nguyen (2022), which suggests that while FDI may boost short-term growth, it could undermine long-term economic development.

2.4.3.5 Human Capital

Some scholars believe that human capital influences the direction of industrial structure evolution in a country or region and determines the ultimate degree of industrial upgrading. Lorentzen (2007) studied human capital and regional economic growth, arguing that investment in human capital promotes technology absorption, which fosters economic growth and industrial upgrading. Zhang et al. (2011) examined the impact of human capital on industrial structure upgrading using China's panel data from 1978 to 2008, showing that human capital significantly affects industrial upgrading, which is heterogeneous. Zhou (2018) highlighted that human capital in the tertiary industry facilitates industrial upgrading. Additionally, the level of institutional development regulates how human capital influences industrial upgrading. Noura and Saafi (2022) verified whether human capital affects economic growth by using dynamic panel regressions for 56 countries over the period 1995-2015. They concluded that human capital promotes economic growth.

2.4.3.6 Technological Innovation

The role of technological innovation in facilitating industrial upgrading has been extensively examined across different economic contexts and methodological approaches. A consistent finding emerging from this body of research is that innovation is a critical mechanism for reallocating production factors toward more productive uses. The foundational analysis conducted by Peneder (2003) using data from 28 OECD economies established this relationship by demonstrating how technological progress enables the transfer of resources from low-efficiency to high-efficiency sectors, thereby raising

aggregate productivity. This macroeconomic perspective finds micro-level validation in the sector-specific study of Spanish shipping completed by Flor and Oltra (2004), which revealed similar upgrading dynamics at the industry level.

The mechanisms through which innovation drives structural transformation have been further elaborated in subsequent research. Ngai and Pissarides (2007) theorized that technological change facilitates upgrading by altering production functions across sectors, while research by Aboal et al. (2015) emphasized its dual role in both directly transforming industries and indirectly reshaping entire economic systems through demand-side adaptations. Recent empirical work has added geographical and temporal dimensions to this understanding, illustrating how local contexts and historical trajectories can influence the pace and nature of industrial transformation. This multifaceted perspective underscores the complexity of innovation's impact on economic development.

The spatial econometric analysis of Ji and Li (2015) using Chinese provincial data demonstrated that regional innovation capabilities significantly influence industrial upgrading patterns, suggesting the importance of local innovation ecosystems. This spatial perspective was extended through the longitudinal study of 108 cities in the Yangtze River Economic Belt conducted by Liu et al. (2023), which confirmed the persistent effect of technological progress on industrial transformation over 12 years, highlighting the dynamic interplay between regional policies, innovation activities, and economic performance in driving sustainable industrial development. Table 2.7 summarizes the influencing factors of industrial upgrading.

Table 2.7: Summary of Influencing Factors Related to Industrial Upgrading

Influencing Factors	Authors (year)	Findings
Industrial Agglomeration	Krugman (2011)	Industrial agglomeration has the potential to greatly increase an area's total capacity for innovation by speeding up the movement of innovation elements within the region.
	Capozza et al. (2018)	Industrial agglomeration raises the degree of regional innovation by quickening the emergence, growth, and improvement of innovative businesses within an area.
	Guo and Sun (2023)	Manufacturing agglomeration can promote high-quality economic development in the region.
	Cerina and Mureddu (2014)	Industrial agglomeration negatively impacted the growth rate of real income at the regional and overall levels.
	Hardjoko et al. (2021)	Industrial agglomeration slowed down local economic growth and synergistic development.
Global Value Chain	Liu and Zhang (2009)	The technology spillover effect of Chinese firms participation in the global value chain was small, which was not conducive to the upgrading of manufacturing industry.
	Fagerberg et al. (2018)	Countries that participated in GVCs were growing no faster than others. For small countries, participation in global value chains was detrimental to their own countries.
	Yanikkaya and Altun (2020)	High participation in global value chains led to higher output and total factor productivity in the manufacturing sector.
	Fu (2023)	Both forward and backward participation in the global value chain were conducive to the upgrading of China's manufacturing industry.

Table 2.7 continued

Government Support	Porter (1990)	The government can influence the basic factors of diamond model, and can have a positive or negative impact on any of them, thus affecting the competitiveness of industry.
	Breznau (2019)	The implementation of policies and measures by the government can intervene and regulate the market economy and solve the problem of market failure.
	Damstra et al. (2021)	The government can implement reasonable measures to promote the market according to the actual situation of industrial development.
Foreign Direct Investment	Pavlínek et al. (2009)	Pavlínek concluded that FDI has a very important role in the upgrading of the automotive industry.
	Buzdugan and Tüselmann (2018)	They found that it is of great significance that FDI can promote industrial development, give full play to the potential of FDI, and deepen industrial upgrading.
	Lu et al. (2017)	They believed that foreign investment has intensified market competition, squeezed the living space of local enterprises, and led to a decline in their profitability.
	Nguyen (2022)	FDI can promote economic growth in the short term, but in the long term, FDI may damage economic growth.
Human Capital	Lorentzen (2007)	He believed that investment in human capital promotes technology absorption, economic growth, and industrial upgrading.
	Zhang et al. (2011)	They found that human capital has a significant impact on industrial upgrading, and this impact is heterogeneous.
	Zhou (2018)	He pointed out that the human capital of the tertiary industry has a role in promoting industrial upgrading.
	Nouira and Saafi (2022)	They pointed out that human capital promotes economic growth under certain threshold conditions.

Table 2.7 continued

Technological Innovation	Peneder (2003)	He pointed out that technological innovation can improve labor productivity and accelerate industrial upgrading.
	Ngai and Pissarides (2007)	They believed that technological innovation can promote the upgrading of industrial structure to a certain extent.
	Aboal et al. (2015)	They believed that technological change affected not only the adjustment of industrial structure but also the entire economic system based on changes in social needs.
	Liu et al. (2023)	They concluded that technological progress has a significant impact on industrial transformation and upgrading.

2.5 Literature Gap

The existing literature has made significant contributions to the definitions and theories surrounding industrial agglomeration and global value chains and the various aspects of industrial upgrading, including its definitions, pathways, measurements, and influencing factors. These foundational studies have paved the way for more in-depth explorations into the impact of global value chain embeddedness and the industrial agglomeration level on the upgrading of specific sectors, such as China's automobile industry. However, despite the wealth of relevant research, several notable gaps and shortcomings remain:

Firstly, much of the existing research has predominantly centered on the manufacturing industry, analyzing the influencing factors or pathways of industrial upgrading across China's manufacturing sector. This broad focus has overlooked the unique dynamics of the automobile industry, a critical sector in China's economy. Consequently, there is a lack of targeted studies investigating the interplay between global value chains and

industrial agglomeration, specifically within the context of the automobile industry. This research aims to fill this gap by concentrating on how the degree of global value chain embeddedness and the level of industrial agglomeration specifically influence the upgrading of China's automobile sector.

Secondly, while previous literature has explored the impact mechanisms of industrial upgrading, there has been limited consideration of government support and foreign direct investment (FDI) as moderating variables. This study addresses this oversight by incorporating government and FDI as moderating factors to provide a more comprehensive understanding of the impact mechanisms at play. Specifically, it will explore whether government support can moderate the relationship between industrial agglomeration and the upgrading of China's automobile industry, and whether FDI can moderate the impact of global value chains on industrial upgrading. This approach aims to enrich the current understanding of the dynamics that drive this sector's upgrading process.

Thirdly, previous investigations into the effects of global value chains on industrial upgrading have rarely utilized technological innovation as a mediating variable. This research addresses this gap by introducing technological innovation to examine whether embedding in global value chains influences the upgrading of China's automobile industry by affecting technological advancements. By doing so, this study seeks to enhance the understanding of how global value chains facilitate industrial upgrading through technological innovation.

Lastly, although there has been research on the influence of industrial agglomeration on industrial upgrading, the threshold role of human capital has not been adequately explored. This study introduces human capital as a threshold variable in analyzing the effect of industrial agglomeration on the upgrading of China's automobile industry. It will investigate

whether the impact of industrial agglomeration on upgrading is contingent upon human capital reaching a certain threshold level. This approach aims to provide deeper insights into the mechanisms through which industrial agglomeration influences industrial upgrading, emphasizing human capital's critical role in this process.

In summary, this research seeks to address these identified gaps by focusing on the automobile industry, incorporating moderating and mediating variables, and exploring the threshold effects of human capital. This comprehensive approach aims to contribute significantly to the understanding of the mechanisms of industrial upgrading in China's automobile sector.

2.6 Conceptual Framework

This research aims to analyze the impact of the level of global value chain (GVC) embeddedness and the level of industrial agglomeration on the upgrading of China's automobile industry. The core independent variables in this study are the level of GVC embeddedness and industrial agglomeration. These variables are crucial as they influence how effectively the automobile industry can adapt and advance within a competitive global landscape. In addition to the primary independent variables, this research incorporates human capital and technological innovation as control variables. Human capital refers to the skills and expertise of the workforce, which play a significant role in the industry's ability to innovate and upgrade. Technological innovation encompasses developing and implementing new technologies, which are vital for maintaining competitiveness and facilitating industry upgrades.

To provide a deeper understanding of the dynamics at play, government support and foreign direct investment (FDI) are introduced as moderating variables. The government support can influence the relationship between industrial agglomeration and upgrading by

implementing policies that support collaboration and growth within the industry. Similarly, FDI can moderate the relationship between GVC embeddedness and upgrading by bringing in additional resources, technology, and market opportunities, thereby enhancing the industry's upgrading potential.

Furthermore, technological innovation is proposed as a mediating variable in the framework. This indicates that the influence of GVC embeddedness on upgrading is likely to occur through its impact on technological innovation. Additionally, this research examines human capital as a threshold variable that may affect the relationship between industrial agglomeration and upgrading. It seeks to determine whether the positive effects of industrial agglomeration on upgrading are realized only when human capital reaches a certain level.

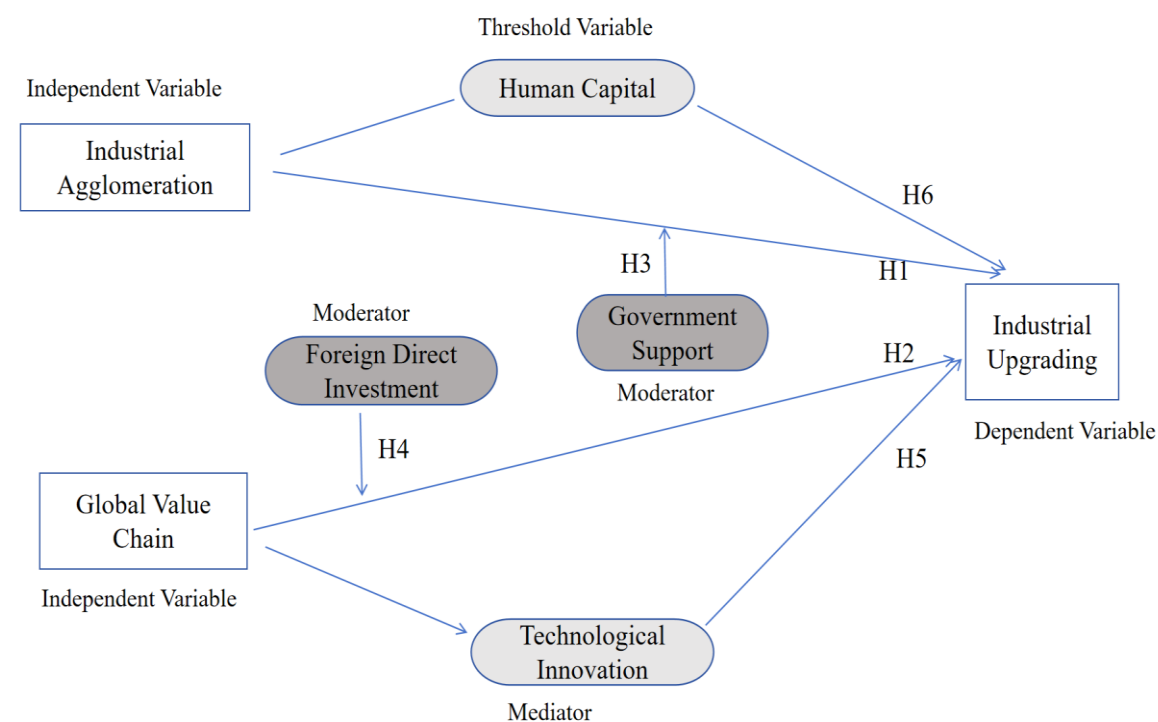


Figure 2.1: Conceptual Framework

In summary, this conceptual framework provides a comprehensive overview of the key variables and their interactions, guiding the exploration of how global value chain

embeddedness and industrial agglomeration contribute to the upgrading of China's automobile industry. By illustrating these relationships, the framework lays a foundation for understanding the complex mechanisms influencing industrial growth and transformation in this vital sector. The conceptual framework is shown in the above figure.

2.7 Hypotheses Development

Based on the literature review and the previous discussion, this thesis proposes six hypotheses.

2.7.1 The Relationship between Industrial Agglomeration and the Upgrading of China's Automobile Industry

Desmet and Fafchamps (2005) constructed an econometric model based on industrial data from county-level units in the United States to empirically examine the impact of productive service agglomeration on the structural upgrading of the manufacturing industry. Their findings confirmed that the productive service industry's agglomeration significantly promotes the manufacturing sector's structural optimization. Hu et al. (2010), starting from the perspective of agglomeration economic zones, circles, and belts, pointed out that industrial agglomeration in a broad area and the diversified cluster industries formed within it are crucial for a country (or region) to enhance its international competitiveness. Poon et al. (2013) employed a spatial autoregressive method to analyze the influence of enterprise agglomeration on technological innovation, discovering that knowledge sharing among enterprises in agglomeration areas fosters industrial transformation and upgrading. Han (2020) found that the specialized agglomeration of industries can significantly promote the upgrading of the manufacturing structure in and around the local area through economies of scale and technology spillover effects. Therefore, this thesis presents the following hypothesis:

H1: There is a significant and positive relationship between industrial agglomeration and the upgrading of China's automobile industry.

2.7.2 The Relationship between Global Value Chain and the Upgrading of China's Automobile Industry

Some scholars argue that participation in global value chains can promote industrial upgrading. Lemoine and Ünal-Kesenci (2004) focused on China's manufacturing industry and found that the division of labor in the global value chain has promoted the technological upgrading of China's manufacturing processing industry. Tian et al. (2022) examined the impact of forward and backward participation in global value chains on industrial upgrading, products, and skills. They concluded that backward participation in GVCs is more favorable to industrial upgrading in developing countries, while forward participation is more advantageous for developed countries. Their study highlights that participation in GVCs is an essential route to industrial upgrading, with backward GVC participation favoring developing countries and forward GVC participation favoring developed countries.

However, many researchers contend that engagement in global value chains does not support the upgrading of industry in emerging economies. Liu and Zhang (2008) argued that multinational enterprises from developed countries capture the production capabilities of multinational enterprises in developing countries through hierarchical governance models. This leads to the entrenchment of developing countries' multinational enterprises in processing and manufacturing roles, making it difficult for them to pursue industrial upgrading. Herrera and Schroth (2011) argued that it is challenging for industries to transform and upgrade across different value chains continuously. While embedding in the global value chain can enhance manufacturing capacity in developing countries, industries positioned at the low end of the value chain face pressure from enterprises at the high end.

This creates development bottlenecks and further limits the technological innovation of firms' capabilities at the lower end.

Huang and Zhang (2015) found that developed countries continuously consolidate their leading positions in the global value chain through their technological and capital advantages, making it difficult for developing countries to move beyond low-end manufacturing roles and restricting their industrial upgrading potential. Fagerberg et al. (2018) noted that the economies of countries involved in global value chains (GVCs) do not experience faster growth than those that do not participate. Being part of GVCs can be harmful for smaller and less capable countries. Volkova (2021) argued that involvement in global value chains can result in the excessive exploitation of low-skilled workers, causing problems such as insufficient wages, lack of social stability, and gender disparities, which are detrimental to economic upgrading.

This thesis leans more towards the latter viewpoint, suggesting that integration into the global value chain may inhibit the upgrading of China's automobile industry. Developed countries strictly regulate the transfer and diffusion of core industrial technologies to maintain their industrial advantages and control. As a result, they often position developing countries primarily as production bases, preventing them from establishing and maintaining technological linkages necessary for rapid industrial transformation. Consequently, while the industry in developing countries undergoes high-speed transformation, it remains highly dependent on the technological output of developed nations. Moreover, developed countries rigorously control the spillover of their core and cutting-edge technologies and continually raise technological and industrial standards to achieve industrial control. Based on this understanding, the following hypotheses are proposed in this thesis:

H2: There is a significant negative relationship between global value chain and the upgrading of China's automobile industry.

2.7.3 The Moderating Effect of Government Support on the Relationship between Industrial Agglomeration and the Upgrading of China's Automobile Industry

Porter (1990) introduced the diamond model in his book “The Competitive Advantage of Nations,” asserting that the competitiveness of a country's industry is influenced by four key aspects: factor conditions, demand conditions, related and supporting industries, and firm strategy, structure, and rivalry. He considered government and chance as external variables to these four factors, emphasizing that government intervention can enhance the effectiveness of the diamond system. Similarly, Bagnasco (1977) proposed the theory of new industrial areas, highlighting that regional industrial agglomerations are formed through a highly specialized division of labor among agglomerated enterprises and are deeply rooted in their locales. He noted that an enterprise's competitiveness is influenced by the national environment and regional and local contexts, with economic activities inherently tied to the local social and cultural environment. Singh (2003) examined the practices of government support in South Africa, Scandinavia, India, Chinese Taipei, Canada, and other regions in fostering industrial agglomeration areas. He suggested that governments should act as “middlemen,” “service providers,” “initiators,” “participants,” and “listeners” in industrial agglomeration production activities to attract partners and create a sense of urgency for action, as well as conduct ongoing industrial clusters assessments to ensure global competitiveness.

Wu (2018) studied the development of industrial agglomeration areas in the United States, France, and the Netherlands, summarizing the impact of government policies on industrial advancement and pointing out that appropriate regulation and prudent

administration in areas such as risk prevention, infrastructure development, scientific research and technology promotion, social service systems, and market order maintenance can expedite the growth of industrial clusters. Hu et al. (2021) found in the survey and research based on industrial clusters in Zhejiang, China, that although market competition can stimulate the creativity of enterprises, it cannot promote the innovation and development of high-quality products. The public goods provided by the government in the crisis can help enterprises overcome the disadvantages of externalities and promote the development of industrial innovation. Building on these previous studies, this research hypothesizes that government support may moderate the relationship between the level of industrial agglomeration and the upgrading of China's automobile industry. Therefore, this study proposes the following hypothesis:

H3: Government support has a significant moderating effect on the relationship between industrial agglomeration and the upgrading of China's automobile industry.

2.7.4 The Moderating Effect of Foreign Direct Investment on the Relationship between Global Value Chain and the Upgrading of China's Automobile Industry

Foreign direct investment has a long-term dynamic effect on host countries, enabling them to accumulate technology and knowledge. This accumulation facilitates value chain upgrading or industrial upgrading by integrating the host countries into higher value chains (Zhang, 2022). Anderson and Sutherland (2015) selected Canada for analysis and testing. After collecting relevant data on introducing foreign capital in the country, they conducted an empirical study. They found that foreign investment can improve Canada's economic level and optimize its domestic industrial structure. This, in turn, effectively enhances Canada's position in the international value chain. Additionally, a country's direct investment

in industries involving multiple value chain activities inevitably leads to the scale expansion and technological advancement of related upstream and downstream supporting industries. The resulting industrial linkage effect promotes significant improvements in the overall technological level of the sector (Zhang, 2013).

By providing manufacturing and assembly services to multinational companies in advanced economies, foreign direct investment OEMs access a wealth of learning opportunities, advanced technologies, and R&D skills. This access enables them to develop the ability to adapt and integrate the latest and secondary technologies (Chin, 2013). Staritz and Morris (2013) pointed out that foreign direct investment (FDI) serves as a means for many low-income countries to integrate into global value chains. FDI facilitates functional and process upgrading, and consequently industrial upgrading, by influencing the ownership patterns, governance structures, and markets within value chains. Stephenson (2024) asserted that FDI contributed to diversification and industrial upgrading. He argued that linkages between foreign and domestic companies might be the most effective way to transfer knowledge and technology, driving upgrading, particularly in the automotive industry. Based on this, the following hypothesis is proposed in this thesis.

H4: There is a significant moderating effect of foreign direct investment on the relationship between global value chain and the upgrading of China's automobile industry.

2.7.5 The Mediating Effect of Technological Innovation on the Relationship between Global Value Chain and the Upgrading of China's Automobile Industry

Schmitz (2004) and Gereffi et al. (2005) pointed out that the dependence of developing countries on the GVC system has a certain negative impact on their ability to innovate independently. For example, when developing countries try to upgrade their status of value chain through independent innovation in the global value chain system, developed

countries block the advanced technologies of developing countries or exploit the profit margins of processing trade enterprises, and control the access of contract manufacturing enterprises in developing countries to independent innovation and research and development channels. Cui (2013) pointed out that developed countries, as the dominant players in the value chain, use their advantages in market and technology to seize the limited high-end market of developing countries, thus fundamentally cutting off the endogenous channel for developing countries to improve their industrial innovation capacity. The "capture" relationship and benefit distribution pattern of developed countries to developing countries are solidified in GVC, thus suppressing the industrial upgrading of developing countries based on internal demand innovation and the learning effect.

Zhang and Zheng (2017) found that since China participated in the division of labor in the value chain, only a few enterprises have completed the transformation and upgrading through technological progress. More enterprises are at the low end of the value chain for production activities and cannot improve their technical level. Wang and Lu (2019) pointed out that the embedding of global value chains led to the decline of independent innovation ability. The embedding of global value chains reduces the incentive for enterprises to independently research and develop new technologies and products, which leads to the decline of independent innovation capability and hinders China's industrial upgrading. Shen and Zheng (2020) believed that the low-end embedding of global value chains negatively affects technological innovation in developing countries. Based on this understanding, the following hypotheses are proposed in this thesis:

H5: There is a significant negative relationship between global value chain and the technological innovation of China's automobile industry, which inhibits its upgrading.

2.7.6 The Threshold Effect of Human Capital on the Relationship between Industrial Agglomeration and the Upgrading of China's Automobile Industry

Human capital is a necessary production factor for industrial agglomeration to promote the economic growth of agglomeration areas. When the human capital level of an enterprise cannot match the production level of the enterprise, the lack of human capital elements will lead to the idle productivity of the enterprise, which is not conducive to the optimal allocation of resources within the enterprise. The higher the human capital, the stronger their ability to process information and accept new knowledge, the easier it will be to innovate, thus reducing the production cost of enterprises and improving productivity (Dai, 2014). Human capital is an essential carrier of knowledge transfer and technology absorption. Industrial agglomeration forms an increasing return to scale effect through knowledge spillover and human capital flow, effectively enhancing the driving force of economic growth (Krugman, 1991).

Cui et al. (2013) verified the threshold effect of spatial agglomeration on total factor productivity growth under different human capital conditions. The empirical results showed that industrial agglomeration has no impact on the development of total factor productivity under low human capital. When human capital crosses the “threshold value”, industrial agglomeration significantly promotes total factor productivity growth. The promotion effect is strengthened considerably with the further improvement of human capital. Ni and Li (2017) believed that industrial agglomeration's promotion of regional innovation may be restricted by the change of human capital threshold structure, and the interaction between industrial agglomeration and human capital can help improve regional innovation ability. Li et al. (2021) argued that human capital in different regions creates new demand for high-tech agglomeration, and merely pursuing industrial agglomeration cannot drive innovation

benefits. Therefore, it is essential to reasonably guide and maintain the free flow and effective allocation of high-end labor to harness the positive role of human capital in high-tech industrial agglomeration. Based on this, the following hypothesis is proposed in this thesis.

H6: There is a significant threshold effect of human capital on the relationship between industrial agglomeration and the upgrading of China's automobile industry.

2.8 Summary

Chapter 2 provides a thorough literature review on industrial agglomeration, global value chains, and industry upgrading, beginning with definitions and their significance in economic development. It explores relevant theoretical frameworks and empirical studies, highlighting various pathways to industrial upgrading and the factors that influence them. The chapter identifies existing gaps in the literature, introduces a conceptual framework to synthesize key insights, and concludes by developing hypotheses to guide further research. This comprehensive overview sets a solid foundation for understanding the interconnected themes vital to the study.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter focuses on the research design, data description, estimation techniques, and models. The research design section delves into the research methodology, data sources, and data collection methods. The data description section details the indicators used to measure the independent, dependent, moderating, and control variables. The section on estimation models and techniques discusses the DEA, GMM, and threshold models utilized in this thesis, providing the research formulas and analytical methods employed.

3.2 Research Design

This study employs quantitative analysis methods to investigate the impact of the global value chain and industrial agglomeration on the upgrading of China's automobile industry. Quantitative analysis is a structured, deductive, predictive, and explanatory approach emphasizing statistical analysis. It quantifies problems and phenomena, then analyses, tests, and interprets them to derive significant research methods and processes. Quantitative analysis is more intuitive, objective, and accurate than qualitative analysis, yielding effective results (Mackenzie & Knipe, 2006).

In terms of variables, the independent variables are the level of industrial agglomeration and the global value chain. The moderator includes province governance and foreign direct investment, while the control variables encompass human capital and technological innovation. The dependent variable is industrial upgrading. Total factor productivity, calculated using the DEA method, is used as an indicator to measure industrial upgrading.

For data selection and collection, the sample consists primarily of the provinces defined by China's administrative regions, with 28 provinces included due to missing data from three provinces. The research period spans from 2000 to 2020, covering 21 years of panel data. Since this study uses the GMM model, which is appropriate for short-term panel data, it is crucial to ensure the reliability of the effect by increasing the gap between N and T. Therefore, the 21 years are divided into seven segments, with the average data for every three years treated as one year, effectively making T equal to 7, thus enhancing the reliability of the results.

The study period of 2000-2020 was selected due to its significance in China's automotive industry development. This timeframe captures critical transformations, including China's WTO accession in 2001, which reshaped global value chain participation through increased foreign investment and joint ventures, rapid market expansion that propelled industry upgrading through changing consumer demands, and significant technological advancements, particularly in electric vehicle development. Furthermore, this period benefits from the relative completeness and availability of relevant data, which provides a solid foundation for our quantitative analysis. This comprehensive understanding of the dynamics within the selected timeframe supports our exploration of the relationships between industrial agglomeration, GVC participation, and industrial upgrading, ultimately enhancing the robustness of our research conclusions.

The data utilized in this study are secondary data. Data on the agglomeration level of China's automobile industry are sourced from the China Automotive Industry Yearbook (2001-2021), the China Statistical Yearbook (2001-2021), and the China Industrial Statistical Yearbook (2001-2021). Data on the degree of global value chain embeddedness are obtained from the OECD-TIVA 2023 version database, the China Automotive Industry

Yearbook (2001-2021), and the China Statistical Yearbook (2001-2021). Data on government support comes from the China Statistical Yearbook (2001-2021). FDI data are sourced from the China Statistical Yearbook (2001-2021) and the China Automotive Industry Yearbook (2001-2021). When using DEA to calculate total factor productivity for measuring the upgrading of the automobile industry, the input and output data are derived from the China Automotive Industry Yearbook (2001-2021) and the China Industrial Statistical Yearbook (2001-2021). The data only extends to 2020 because the latest OECD-TIVA database, the 2023 version, is updated to 2020.

In terms of research techniques, this study uses Stata software. The measurement of industrial upgrading uses the DEA-Malmquist total factor productivity. Baseline analysis, moderating effect, and mediating effect regression were performed using the GMM model. Since individual effects can cause endogeneity problems in dynamic panel models, the GMM model can solve the endogeneity problems by introducing a one-stage lag to estimate the model (Baum et al., 2003). The threshold effect was examined using a dynamic panel threshold model.

In this study, the DEA-Malmquist method is utilized to measure dynamic productivity changes, as it effectively decomposes total factor productivity into technological progress and technical efficiency. This approach allows for nuanced insights into the upgrading process in the automotive sector. The System GMM technique addresses potential endogeneity issues, particularly reverse causality, using lagged variables as instruments. This method enhances the robustness of the estimates and ensures that valid conclusions can be drawn regarding the relationships between industrial agglomeration, GVC participation, and industrial upgrading. Additionally, the dynamic panel threshold regression technique enables the identification of non-linearities and critical thresholds that

influence the relationships under examination, such as the impact of human capital on upgrading. These methodologies align closely with the research objectives, providing a comprehensive framework for analyzing the complex dynamics of upgrading in China's automotive industry.

3.3 Model Specification

3.3.1 Baseline Model

This chapter establishes a baseline analysis model to examine the effects of the global value chain and industrial agglomeration on the upgrading of China's automobile industry. It also explores the moderating roles of government support and foreign direct investment (FDI) to determine whether government support influences the relationship between the level of industrial agglomeration and the upgrading of the automobile industry and whether FDI moderates the effects of the global value chain on industry upgrading. Additionally, this study investigates whether technological innovation mediates the relationship between the global value chain and the upgrading of China's automobile industry. Lastly, the thesis assesses the threshold effect of human capital on the impact of industrial agglomeration on the upgrading of China's automobile industry.

This thesis employs a panel data model for analysis in the model setup. This approach captures the dynamic changes in the selected data and allows for a multi-perspective examination of the indicators. In the practical application of the panel model, this study focuses on two dimensions: cross-section and time. The time series spans from 2000 to 2020, while the cross-sectional dimension is derived from data collected across 28 provinces in China. The 28 provinces are Beijing, Tianjin, Hebei, Shanxi, InnerMongolia, LiaoNing, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, GuangXi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi,

Gansu and Xinjiang. To enhance the effectiveness of the GMM model, this research averages the data over three years to represent a single year, resulting in a total of 7 years of data. This adjustment increases the gap between the number of provinces (N) and the time periods (T), thereby ensuring the accuracy of the short-term panel GMM model's outcomes.

This research considers industrial agglomeration as an independent variable to investigate its effect on the upgrading of China's automobile industry. If the coefficient for industrial agglomeration is significant and positive, it will indicate a positive impact on the industry's upgrading. The other independent variable is the global value chain, which is examined to determine its influence on the upgrading of China's automobile industry. If the coefficient for the global value chain is significant and negative, this would demonstrate a negative impact on the industry's upgrading.

In order to verify the relationship between industrial agglomeration, global value chain, and the upgrading of China's automobile industry, the baseline analysis model 1 is set up as follows:

$$Upgrade_{i,t} = \alpha_0 + \alpha_1 Upgrade_{i,t-1} + \alpha_2 GVC_{i,t} + \alpha_3 AGG_{i,t} + \alpha_4 HC_{i,t} + \alpha_5 TI_{i,t} + \alpha_6 GOV_{i,t} + \alpha_7 FDI_{i,t} + \varepsilon_{i,t} \quad \text{Equation 3.1}$$

In the model, i is province, t is time, $Upgrade_{i,t}$ is the dependent variable of the model, which represents the upgrading of China's automobile industry, $Upgrade_{i,t-1}$ represents the lag of the dependent variable by one period; and the independent variable is $AGG_{i,t}$, which represents the level of industrial agglomeration of China's automobile industry in the year t and the province i . The other independent variable is $GVC_{i,t}$, which represents the level of global value chain embeddedness. $HC_{i,t}$ represents the human capital situation of province i of China's automobile industry in year t , $TI_{i,t}$ represents the technological innovation situation of province i of China's automobile industry in year t . $GOV_{i,t}$ represents

the degree of government support of province i of China's automobile industry in year t . $FDI_{i,t}$ represents the foreign direct investment situation of province i of China's automobile industry in year t . $\varepsilon_{i,t}$ is the perturbation term that changes with the change of individuals and time.

The coefficient α_3 indicates the direction of the influence of industrial agglomeration level on the upgrading of automobile industry, if α_3 is significant and positive, it means that the industrial agglomeration level positively influences the upgrading of automobile industry. This can be used to test H1. The coefficient α_2 indicates the direction of the influence of global value chain on the upgrading of automobile industry, if α_2 is significant and negative, it means that global value chain negatively influences the upgrading of automobile industry. This can be used to test H2.

3.3.2 Moderating Effect Model

This research uses government support as a moderator to study the moderating effect of government support on the relationship between industrial agglomeration level and the upgrading of China's automobile industry. The moderating effect model needs to introduce the interaction term of government support and industrial agglomeration level. If the coefficient of the interaction term is significant, then it can be proved that government support moderates the impact of industrial agglomeration level on the upgrading of China's automobile industry. This research uses foreign direct investment (FDI) as a moderator to study the moderating effect of foreign direct investment on the relationship between global value chain and the upgrading of China's automobile industry. In order to test the moderating effect, it is necessary to introduce the interaction term between FDI and the global value chain, and if the coefficient of the interaction term is significant, then foreign direct

investment moderates the impact of the global value chain on the upgrading of China's automobile industry. The moderating effect model 2 is set as follows:

$$Upgrade_{i,t} = \beta_0 + \beta_1 Upgrade_{i,t-1} + \beta_2 AGG_{i,t} + \beta_3 GVC_{i,t} + \beta_4 HC_{i,t} + \beta_5 TI_{i,t} + \beta_6 GOV_{i,t} + \beta_7 FDI_{i,t} + \beta_8 GOV_{i,t} * AGG_{i,t} + \beta_9 FDI_{i,t} * GVC_{i,t} + \varepsilon_{i,t} \quad \text{Equation 3.2}$$

In the model 2, moderating variables are $GOV_{i,t}$ and $FDI_{i,t}$. $GOV_{i,t}$ represents the degree of government support of province i of China's automobile industry in year t. $FDI_{i,t}$ represents the foreign direct investment situation of province i of China's automobile industry in year t. $\varepsilon_{i,t}$ is the perturbation term that changes with the change of individuals and time. $GOV_{i,t} * AGG_{i,t}$ denotes the interaction term of government support and industrial agglomeration. $FDI_{i,t} * GVC_{i,t}$ denotes the interaction term of foreign direct investment and global value chain embeddedness.

The coefficient β_8 represents the interaction term between government support and industrial agglomeration. If the coefficient of this interaction term is significant, it indicates a moderating effect of government support on the relationship between the level of industrial agglomeration and the upgrading of China's automobile industry (He & Li, 2021), thus allowing for the testing of hypothesis H3. Similarly, the coefficient β_9 reflects the interaction term between foreign direct investment and the global value chain. If this coefficient is significant, it suggests that foreign direct investment moderates the relationship between global value chain embeddedness and the upgrading of China's automobile industry (Yang et al., 2023), which can be used to test H4.

3.3.3 Mediating Effect Model

In this thesis, the control variable of technological innovation is treated as a mediator to investigate its mediating effect on the relationship between the global value chain and the

upgrading of China's automobile industry. The objective is to determine whether global value chains hinder the upgrading of China's automobile industry through their influence on technological innovation. The mediating effect model 3 is established as follows:

$$Upgrade_{i,t} = \theta_0 + \theta_1 Upgrade_{i,t-1} + \theta_2 GVC_{i,t} + \theta_3 AGG_{i,t} + \theta_4 HC_{i,t} + \theta_5 GOV_{i,t} + \theta_6 FDI_{i,t} + \varepsilon_{i,t} \quad \text{Equation 3.3}$$

$$TI_{i,t} = \gamma_0 + \gamma_1 TI_{i,t-1} + \gamma_2 GVC_{i,t} + \gamma_3 AGG_{i,t} + \gamma_4 HC_{i,t} + \gamma_5 GOV_{i,t} + \gamma_6 FDI_{i,t} + \varepsilon_{i,t} \quad \text{Equation 3.4}$$

$$Upgrade_{i,t} = \omega_0 + \omega_1 Upgrade_{i,t-1} + \omega_2 GVC_{i,t} + \omega_3 TI_{i,t} + \omega_4 AGG_{i,t} + \omega_5 HC_{i,t} + \omega_6 GOV_{i,t} + \omega_7 FDI_{i,t} + \varepsilon_{i,t} \quad \text{Equation 3.5}$$

In the above model, TI represents the mediator, which stands for technological innovation. The constants are denoted by θ_0 , γ_0 and ω_0 , while θ_1 - θ_6 , γ_1 - γ_6 and ω_1 - ω_7 represent the estimated parameters. This study refers to the mediation model method of Li et al. (2022) and Yang et al. (2023) to analyze the mediation effect. Importantly, θ_2 signifies the total effects, while γ_2 and ω_3 reflect the indirect effects of the mediator (TI) on the relationship between the global value chain (GVC) and industry upgrading. Mediating effects are confirmed when θ_2 , γ_2 , and ω_3 are all significant, indicating that technological innovation indeed has a mediating effect in the impact of global value chain on the upgrading of China's automobile industry. If θ_2 is significantly negative, γ_2 is significantly negative, and ω_3 is significantly positive, this suggests that the global value chain inhibits the upgrading of China's automobile industry through its influence on technological innovation. This relationship can be used to test hypothesis H5.

3.3.4 Dynamic Threshold Model

To investigate the threshold effect of human capital on the impact of industrial agglomeration on the upgrading of China's automobile industry, this thesis employs the panel threshold model. Additionally, to address endogeneity concerns and potential estimation biases inherent in traditional static threshold models, this study uses a dynamic panel threshold model following the framework developed by Seo et al. (2019). The dynamic threshold model is specified below:

$$Upgrade_{i,t} = \theta_0 + \theta_1 Upgrade_{i,t-1} + \theta_2 AGG_{i,t} \cdot I(HC_{i,t} \leq c) + \theta_3 AGG_{i,t} \cdot I(HC_{i,t} > c) + \theta_4 X_{i,t} + \varepsilon_{i,t} \quad \text{Equation 3.6}$$

In the equation above, i denotes the province, t refers to the year. $Upgrade_{i,t}$ represents dependent variable, which is the upgrading of China's automobile industry. $Upgrade_{i,t-1}$ denotes the first lag term of $Upgrade_{i,t}$. $AGG_{i,t}$ is independent variable, denoting the level of industrial agglomeration. $HC_{i,t}$ represents the threshold variable, namely human capital. The indicator function is denoted by $I(\cdot)$ and c represents the threshold value. $X_{i,t}$ includes global value chain (GVC), technological innovation (TI), government support (GOV), foreign direct investment (FDI). $\varepsilon_{i,t}$ is the perturbation term that changes with the change of individuals and time. If industrial agglomeration exerts differential impacts on the upgrading of China's automobile industry across varying levels of human capital, this would statistically validate the threshold effect hypothesized in H6, suggesting that human capital serves as a critical threshold variable in this relationship.

The dynamic panel threshold model presented by Seo et al. (2019) and the System Generalised Method of Moments (System GMM) form the foundation of this study's approach. As this thesis needs to deeply consider the lagged effects of the dependent variable and the endogeneity of the threshold variable, the traditional static panel regression model

obviously cannot meet the analytical needs of this study. Seo et al. (2019) developed a dynamic threshold model based on the theoretical framework developed by Seo and Shin (2016). Seo et al. improved the asymptotic variance estimator and the generalised method of moments (GMM) estimator based on the research of Seo and Shin. These instructions considerably simplify the application of the model and result interpretation by offering not just strong analytical tools but also commands for determining whether threshold effects occur.

When it comes to consistent asymptotic normalcy estimations, the `xthenreg` command outperforms the original `xthreg` command. With this enhancement, we can now get estimates that are more trustworthy when working with intricate data structures. Furthermore, a more effective bootstrap approach for linear testing was suggested by Seo et al. (2019). This approach successfully increases the accuracy and robustness of statistical inference while also outperforming the original nonparametric independent identically distributed bootstrap technique suggested by Seo and Shin (2016).

3.4 Data Description

3.4.1 Measurement of Dependent Variable Industrial Upgrading

As analyzed above, many scholars use total factor productivity (TFP) to measure industrial upgrading. Following the practices of Sun and Xi (2015), this research also selects TFP to assess the upgrading of China's automobile industry. This is because TFP provides a relatively comprehensive measure of industrial upgrading.

Total factor productivity represents the combined productivity of a production unit, encompassing various factors within a system, distinguishing it from individual factor productivity (such as technological productivity). TFP is a comprehensive measure of enterprise technology upgrading, management model improvement, product quality

enhancement, and enterprise structure upgrading. In essence, any realistic productivity is, in fact, total factor productivity. TFP can also be referred to as system productivity. The improvement of TFP signifies the development of industrial upgrading and overall productivity (Chang, 2012). Total factor productivity is considered to represent an increase in output resulting from changes that are not directly observable, such as technological progress or institutional improvements (Solow, 1957). Consequently, many recent studies have utilized TFP to measure industrial upgrading.

There are two main methodologies for measuring total factor productivity: parametric methods and non-parametric methods. The parametric methods, which include the residual production function and stochastic frontier analysis, are also known as econometric methods and involve estimating capital, labor, and related parameters to calculate TFP under certain functional forms, random error distributions, and other relevant assumptions. In contrast, the non-parametric methods primarily consist of index numbers and data envelopment analysis (DEA). The index method involves a series of index measurement techniques for statistical data analysis that can be calculated directly according to index theory. Data envelopment analysis is similar to stochastic frontier analysis in the parametric method, but with a key difference: DEA does not require the specification of a functional form and instead uses linear programming to solve the problem (Van Beveren, 2012).

The residual production function method was one of the earliest approaches widely used for calculating total factor productivity. The calculation process involves several steps: First, appropriate function forms, such as the Cobb-Douglas production function, Translog function, or constant elasticity of substitution production function, are selected. Then, measurement software is used to fit the chosen production function to the sample data,

yielding specific parameter values within the production function. Subsequently, by deriving, adding, and subtracting within these specific production functions, the residual value obtained from the output growth rate, after excluding the quantitative accumulation contribution of various production factors, is considered the increase in total factor productivity (McCombie, 2000). Although the total factor productivity obtained using different production function forms varies in magnitude, the methods applied by the residual production function approach are essentially based on the Solow residual framework. Solow (1957) published “Technical Change and the Aggregate Production Function,” which first introduced a neoclassical production function assuming steady returns to scale and Hicks-neutral technological advancement. In this work, he estimated the technological progress of the United States from 1909 to 1949.

The Solow residual production function method has advantages and drawbacks in estimating total factor productivity. It offers two main advantages: it allows for using a wide range of data, including time series, cross-sectional, and panel data, and is based on the growth model, which is well-suited for long-term economic forecasts. But this method also presents several challenges. Firstly, the model relies on strong and somewhat unrealistic assumptions, such as exogenous technical advancement, constant returns to scale, and Hicks-neutral technological progress. Consequently, economists continuously refine the production function to mitigate these assumptions and select the function forms that best align with the reality of the research subject to improve the fitting results. Secondly, the measurement of factor inputs is often insufficient. For instance, the labor force is typically treated as homogeneous despite varying education levels, and there are issues in calculating the depreciation rate when measuring capital stock. Over- or underestimating factor inputs can affect the final residual value, leading to estimation errors. Thirdly, the estimated total factor

productivity growth rate cannot be further decomposed, making it difficult to investigate the underlying reasons for changes in productivity (Hartley, 2000).

The concept of stochastic frontier analysis was first put forth independently by Aigner et al. (1977), Meeusen and van Den Broeck (1977). The outcome determined by the stochastic frontier production function is, strictly speaking, efficiency rather than total factor productivity in the classic sense. The stochastic frontier production function consists of the frontier production function part and the non-efficiency part. The general process of calculating total factor productivity using the stochastic frontier production function method is as follows: first, the parameters to be estimated in the stochastic frontier production function are estimated using the observed samples. Then, according to the method proposed by Kumbhakar et al. (2000), the total factor productivity is decomposed into four parts: technological progress, technical efficiency, allocation efficiency, and scale efficiency, and finally, the total factor productivity is calculated. It is worth mentioning that, in the initial setting of the frontier production function form, there are mainly two choices: the Cobb-Douglas production function and the Translog function. Comparatively, the transcendental production function form relaxes the elastic assumption of constant substitution and incorporates endogeneity to a certain extent, although it involves many parameters and the quadratic term lacks clear economic meaning.

Stochastic frontier analysis divides the production function into two parts: the frontier production function and the non-efficiency component. This method eliminates the influence of random factors on the frontier production function to some extent, while still considering their impact on economic growth, thereby providing a better fit for real economic situations. Additionally, by examining the impact of specific policies and measures on non-efficiency items, it is possible to indirectly assess their effects on total

factor productivity, offering valuable insights for policy formulation and implementation. Despite these advantages, several issues require attention in the application of stochastic frontier analysis. Firstly, the choice of the specific production function form is crucial. Secondly, the distribution assumption for non-efficiency items is often too subjective; its true distribution form is difficult to identify and can directly affect the efficiency estimation results (Kumbhakar & Lovell, 2003).

In essence, the index method is a statistical approach that involves obtaining a statistical index by comparing the total output of a production unit over a certain period with the total input, and then deriving the total factor productivity index by comparing the statistical indices across two different periods to measure the growth rate of total factor productivity. In the actual economy, there are various input elements and output products rather than just one straightforward scenario, and the rates and directions of change in the quantities of these input factors and output products can differ. Therefore, when measuring the overall input index and the total output index, it is necessary to use a comprehensive index form to capture such complex changes. The variety of index forms includes the Paasche index, Laspeyres index, Divisia index, Fisher index, Tornqvist index, and Malmquist index (See & Li, 2015).

The index method measures total factor productivity, and its advantage lies in its simplicity, intuitive approach, and clear economic meaning. However, the biggest shortcoming of this method is its strict requirements for the comprehensiveness and authenticity of the price and quantity indices and its neglect of the impact of random factors on total factor productivity. Nonetheless, the Malmquist index within the index method can be combined with stochastic frontier analysis and data envelopment analysis to form a precise measure of total factor productivity (Bjurek, 1996).

DEA theory, first developed by Charnes et al. (1978), is based on the deterministic parameter-less frontier concept proposed by Farrell (1957). This theory is based on relative efficiency and employs convex analysis and linear programming as its tools. This model is known as the CCR model to honor its founders' academic contributions. DEA utilizes mathematical programming models to evaluate the relative efficiency of Decision-Making Units (DMUs) with multiple inputs and outputs. By carefully examining each decision unit's inputs and outputs, the analysis builds an effective production frontier by utilising the best decision units. Next, it determines if a unit's input-output data falls on the efficient production frontier to determine if it is DEA efficient. A decision-making unit's relative efficiency is determined by its distance from the efficient production frontier (Wei, 2001).

It is impossible to calculate total factor productivity using the DEA method alone; it must be combined with the Malmquist index construction method to achieve this. Therefore, it is called the DEA-Malmquist index method. Using the data envelopment analysis method to measure the change in total factor productivity primarily involves solving the distance function. This is because the Malmquist total factor productivity index and its decomposition rely heavily on measuring a series of distance functions. The process begins by comparing production units to each other to identify the “best practices” production units that constitute the production frontier (these best practices must be on the production frontier), and then “envelopes” all other data points (Lothgren & Tambour, 1999). To judge the performance or efficiency of a production unit, one examines the degree to which the unit deviates from the production frontier or best practices. The greater the deviation, the lower the technical efficiency.

Since the DEA method is non-parametric, it does not require specifying a particular functional form or error distribution. Instead, it is entirely driven by the data to compare the

relative efficiency levels of production units. Therefore, using DEA to solve the distance function is particularly suitable for the measurement and decomposition research of total factor productivity compared to other methods (Cooper et al., 2011). This thesis employs the DEA-Malmquist method to measure and analyze the upgrading of the automobile industry across China's provinces.

In the measurement of total factor productivity, the two major variables of input and output are generally used, and selecting these variables is crucial. The quality of the indicators chosen directly affects whether the measurement can accurately reflect the actual economic development of the automobile industry. According to relevant economic theories and data availability, when empirically analyzing the total factor productivity level of China's automobile industry, determining the output and input indicators is of utmost importance.

3.4.1.1 Selection of Input Indicators for DEA- Malmquist Analysis

The input factors of China's automobile industry primarily include labor input and capital investment. Labor typically refers to the actual amount of worker input. This encompasses the number of employees, labor intensity, working hours, total wages, and labor quality. Strictly speaking, the contribution of labor input factors to total output growth should be measured by total working hours (Wang et al., 2020). However, there is a lack of relevant statistics in China. In a market economy, workers' wages can also scientifically reflect changes in labor input. But due to the lack of market mechanism adjustments in China's distribution system, labor income does not effectively capture changes in labor input. Over the long term, the quality of labor has improved due to technological advances and increased investment in education. Simultaneously, the time and intensity of labor have decreased due to social progress. Therefore, it is reasonable to use the number of laborers as

a substitute for the labor input index. Therefore, following the practices of Lu and Xia (2014), Jiang et al. (2018), and Qu and Meng (2022), this research selects the number of workers as an indicator of labor input. Specifically, the number of employees in the automobile manufacturing industry at the end of the year is used as the labor input data for each region. The data, measured in units of 10,000 people, comes from the China Industrial Statistical Yearbook (2001-2021). Since the China Industrial Statistical Yearbook did not distinguish between other transportation equipment manufacturing and automobile manufacturing from 2000 to 2011, this research adopts the approach of Chen (2011) and Sun and Liu (2016) to split the transportation equipment manufacturing industry from 2000 to 2011 according to the proportions observed when the distinction began in 2012, and obtained the data for the automobile manufacturing industry. To be precise, the proportion of automobile manufacturing data relative to the total transportation manufacturing data for 2012 is first calculated. Subsequently, all transportation manufacturing data from 2000 to 2011 is multiplied by this proportion to derive the automobile manufacturing data for the same period.

Capital refers to factors of production such as funds, equipment, raw materials, etc.; capital stock refers to the existing resources of a production unit, which can be used to illustrate the current scale of production and the level of technology of the production unit, and capital stock exists in the form of assets and is therefore also known as asset stock (Pang, 2009). Since there is no data on the capital stock in China, there is a lack of industry capital. When calculating total factor productivity, Wu and Chen (2011) used the original value of fixed assets; Qian (2015) used the net value of fixed assets, and Fu (2020) used the original value of fixed assets plus total current assets to represent the amount of capital investment. Referring to the previous research on total factor productivity, this research selects the total

capital investment of “original value of fixed assets” and “total current assets” to measure capital investment, to fully reflect the capital investment of the automobile industry as much as possible. Data comes from the China Industrial Statistical Yearbook (2001-2021), the unit of 100 million yuan, and the year 2000 is used as the base period for deflating. Similar to the above, referring to the practices of Chen (2011) and Sun and Liu (2016), the transportation equipment manufacturing industry from 2000 to 2011 was split according to the proportion of the time when the distinction began in 2012.

3.4.1.2 Selection of Output Indicators for DEA- Malmquist Analysis

Some economists choose industrial added value or net output value in output indicators (Bhanumurthy & Das, 2006), but industrial added value lacks the transfer value of intermediate goods that can reflect scale conservation and resource allocation efficiency, so it is inaccurate to replace total output with industrial added value. The use of net output value indicators instead of output indicators also has shortcomings (You & Yan, 2011), and the inconsistency of its accounting scope and value composition will lead to changes in the function of total factor productivity indicators, so Pang (2009); Lu and Wen (2018) choose gross output value as output indicators when analyzing total factor productivity in various industries. This research also selects the total industrial output value of the automobile industry from 2000 to 2020 instead of the output. Data comes from the China Automotive Industry Yearbook (2001-2021), the unit is 100 million yuan, and the year 2000 is used as the base period for deflating. Figure 3.1 is an illustration of the DEA to calculate total factor productivity.

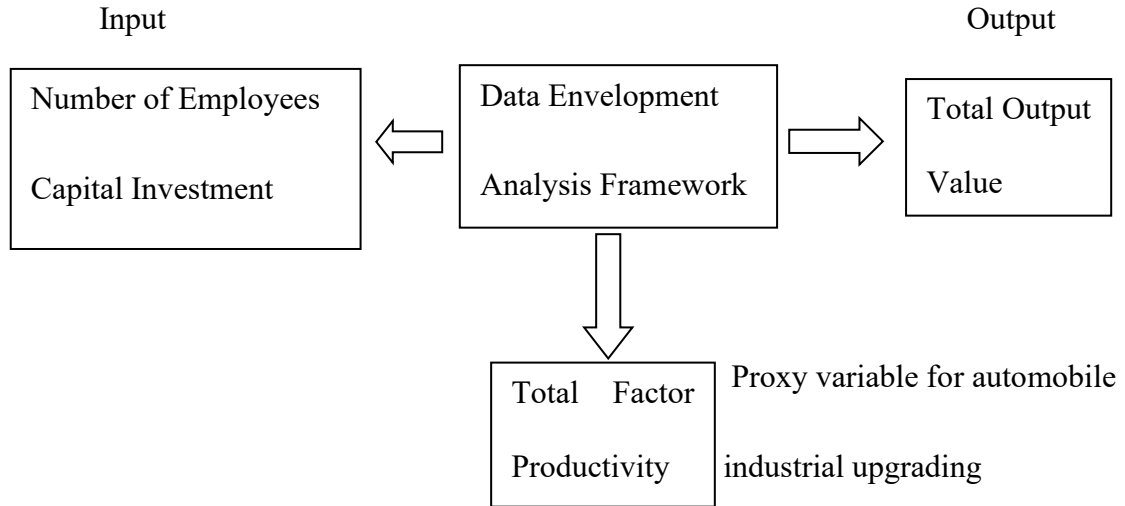


Figure 3.1: Illustration of DEA to Calculate Total Factor Productivity

The total factor productivity index is calculated by the Malmquist index under the DEA model. Then, according to the practice of Qiu et al. (2008), Cheng and Lu (2014), L. Li et al. (2020), Du and Liu (2023). The TFP value in the base period year 2000 is set to 1, and the TFP value in 2001 is obtained by multiplying the Malmquist index value in 2001 and the TFP value in 2000, and so on for subsequent years.

3.4.2 Measurement of Independent Variables

3.4.2.1 Measurement of Industrial Agglomeration Level

There are many ways to measure industrial agglomeration, mainly the location entropy index, the spatial Gini coefficient, the industry concentration index, the EG index, and the Hirschmann-Heffendahl index (Nakamura & Paul, 2019). The location entropy index method was first proposed by Haggett (1977) and applied to location analysis, which can effectively remove the different factors between regions and truly reflect the distribution of factors in a certain area. This research refers to the measurement methods of scholars such as Liu et al. (2016) and Han and Li (2019) and uses the location entropy index method to measure the automobile industry agglomeration in 28 provinces in China from 2000 to 2020. The detailed calculation formula is as follows: the larger the location entropy value, the more

mature the automobile industry is in this region, and it has more scale advantages and comparative advantages.

$$AGG_i = \frac{AS_i / S_i}{AS / S} \quad \text{Equation 3.7}$$

AGG_i represents the degree of automobile industry agglomeration in province i , AS_i represents the total output value of the automobile industry in province i , S_i is the industrial output value of province i , AS is the output value of the national automobile industry, and S represents the total industrial output value of the country. When $AGG_i > 1$, it means that i province has a comparative advantage of automobile industry in the country. If $AGG_i < 1$, it means that the specialisation level of the industry in province i is lower than the national average level and has disadvantages. Data obtained from the China Automotive Industry Yearbook (2001-2021), the China Industrial Statistical Yearbook (2001-2021), and the China Statistical Yearbook (2001-2021). Since the China Industrial Statistical Yearbook no longer publishes the gross industrial output value of each province since 2012, only the industrial sales output value of each province is published, this research refers to the practice of Yang (2009) and Fu and He (2021) to divide the industrial sales output value of each province by the product sales rate to replace the gross industrial output value. The output value data are deflated for the base year 2000.

3.4.2.2 Measurement of Global Value Chain

From the viewpoint of international division of labor, the index of a country's position in the global value chain of a certain industry measures the country's position in the international division of labor network. The deeper the degree of global value chain division, the stronger the industry upgrading effect, indicating a comparative advantage in international competition (Yang et al., 2020). Therefore, this research incorporates the index of the position in the global value chain division into the econometric model, aiming to

analyze the impact of the degree of global value chain embeddedness on the upgrading of China's automobile industry.

Koopman et al. (2010) further presented the global value chain position index as a clear indication to measure the position of a country's industry in the global division of labor network in accordance with the total trade accounting model. The formula for its calculation is as follows:

$$GVC-Position_{ir} = \ln(1 + \frac{IV_{ir}}{E_{ir}}) - \ln(1 + \frac{FV_{ir}}{E_{ir}}) \quad \text{Equation 3.8}$$

$GVC-Position_{ir}$ represents the global value chain position index of the i industry in country r . IV_{ir} represents the indirect value-added exports of the i industry of country r , that is, the intermediate goods trade volume exported by the i industry of country r to other countries; The FV_{ir} represents the value of foreign imported intermediate goods included in the export of final products of the i industry in country r ; E_{ir} represents the total export value added of the i industry in r countries. The larger the GVC position index, it indicates that a particular industry in the country is in the upstream position of the GVC division of labor system, which means that the country's industry has a higher status in the international division of labor network, and its impact on the world economy is also stronger. The smaller the GVC position index, it indicates that a country's industry is in the division of labor's downstream position in the global value chain. Generally, a country can achieve a dominant position in international competitiveness if it possesses a higher GVC position index within its global value chain.

When analyzing the positions of different provinces in the Chinese automobile industry within the global value chain, this study follows the approach of Yu and Gu (2016) and Fu and He (2021) to consider regional differences within the country and industry-specific factors within regions in the national-level industrial division of labor. The levels of

the provinces' positions in the global value chain are calculated accordingly. In considering industry-specific factors, this research references the methodology of Gonzalez et al. (2015), which treats the total foreign value added of each industry in a country as the sum of the contributions from corresponding industries across various regions within that country. The contribution of a particular region and industry to the export value added of that industry in the country is then measured by the proportion of the output of that industry in the region to the total output of the industry in the country. When considering regional differences, Liu and Wu (2013) found that their research findings can be used to adjust the actual value-added contributions of industries within regions based on the proportion of each region's exports to the country's total exports. After considering both regional and industry-specific differences, the index of the global value chain position of industry i in province j of country r can be expressed as:

$$GVC-Position_{ijr} = \ln \left(1 + \frac{IV_{ir}V_{aij}/V_{air}}{E_{ir}T_j/T_r} \right) - \ln \left(1 + \frac{FV_{ir}V_{aij}/V_{air}}{E_{ir}T_j/T_r} \right) \quad \text{Equation 3.9}$$

Where $GVC-Position_{ijr}$ represents the global value chain position index of industry i in province j of country r . V_{aij} and V_{air} respectively represent the output of industry i in province j and the overall output of industry i in country r . T_j and T_r represent the total exports of province j and country r , respectively. IV_{ir} , FV_{ir} , and E_{ir} denote the indirect value added, foreign value added, and total value added of industry i in the exports of country r , respectively.

The data for IV_{ir} , FV_{ir} , and E_{ir} in this thesis are sourced from the OECD-TiVA 2023ed database. The industry i refers to the automobile industry, which is classified as C29 in the database. The country r is China. The latest data in OECD-TiVA 2023ed database is updated until 2020. IV_{ir} corresponds to the EXGR_IDC indicator (Indirect domestic value

added content of gross exports) in the database, FV_{ir} corresponds to the EXGR_FVA indicator (Foreign value added content of gross exports) in the database, and E_{ir} corresponds to the EXGR indicator (Gross exports) in the database. The data for T_j and T_r are sourced from the China Statistical Yearbook (2001-2021), while the data for V_{aij} and V_{air} are sourced from the China Automotive Industry Yearbook (2001-2021) and the China Statistical Yearbook (2001-2021).

3.4.3 Measurement of Control Variables

3.4.3.1 Measurement of Human Capital

Human capital is a key factor of production, and investing in economic activities can lower production costs and enhance the efficiency of the production sector. Continuous improvement and human capital accumulation are essential for gradually achieving the rationalization and advancement of China's industry, encouraging industrial upgrading (Wu et al., 2021). Wu and Chen (2011) empirically analyzed total factor productivity and its influencing factors in the Chinese automobile industry. They found that human capital contributes significantly to total factor productivity, technological progress, and technical efficiency growth. They represented human capital using the average years of education across provinces. Similarly, Barro and Lee (2001), Tong (2016), Shi et al. (2020), and Liu et al. (2023) have also used the average years of education to represent human capital. Considering data availability, this research also uses the average years of education to represent human capital. The approach follows: Considering China's national conditions, primary school education is set at 6 years, while junior high school education is set at 9 years. Similarly, the duration for high school education is 12 years, and for college and above, it is 16 years. Utilizing this framework, the proportion of the population aged six and above, categorized by their educational attainment at the levels of primary school, junior high

school, high school, and college or above, is weighted according to the respective years of education. The aggregate of these weighted proportions yields the average years of education per capita, expressed in terms of education years per person. The data is from the China Statistical Yearbook (2001-2021).

3.4.3.2 Measurement of Technological Innovation

Technological innovation plays a crucial role in driving industrial upgrading, significantly enhancing the position of the manufacturing sector within the value chain. This advancement is vital for fostering the sustainable development of the manufacturing industry (Gao et al., 2023; Wu & Liu, 2021). The measurement of technological innovation varies among different scholars. Zhou and Lin (2024) measured it through indicators such as the number of patent grants, intensity of research and development (R&D) investment, and intensity of scientific and technological investment. Zhou and Song (2015), Yu et al. (2023), Wang et al. (2024) measured the level of technological innovation in enterprises by using internal R&D expenditure of industrial firms beyond a particular scale in each province. Considering data availability, this research also uses internal R&D expenditure to measure technological innovation. This study uses the practice of Shen (2017) to convert the proportion of internal R&D expenditure in GDP of each province by multiplying the total output value of the automobile industry of each province by the technological innovation of the automobile industry. The data is sourced from the China Statistical Yearbook (2001-2021) and the China Automobile Industry Yearbook (2001-2021).

3.4.4 Measurement of Moderating Variables

3.4.4.1 Measurement of Government Support

Schmitz (1995) suggested that the government should first play a mediating role to accelerate the collaboration of industrial clusters, and then cultivate the leading enterprises

to play the demonstration role and guide the cluster enterprises to develop together. Zhen and Liang (2016) believed the government has significantly promoted industrial upgrading. The government can encourage enterprises to participate in international competition, reshape their competitive advantages, help enterprises integrate into the global market, and promote industrial upgrading. Lee et al. (2020) pointed out that government efficiency and the rule of law can stimulate innovation, promote economic growth, reduce information asymmetry, and facilitate the upgrading of firms and industries. Gong and Yin (2015), Li et al. (2021), and Li and Liu (2024) measured government support by the proportion of general public budget expenditure to GDP at the regional government level. This research also adopts this approach to measure the level of government support in each province. The data is sourced from the China Statistical Yearbook (2001-2021).

3.4.4.2 Measurement of Foreign Direct Investment

Foreign direct investment significantly influences industrial upgrading through several key aspects. Firstly, FDI injects capital into a host country, fostering regional economic growth; this influx of funds enables regions to allocate more resources towards research and development (R&D), enhancing their innovative capacities and ultimately leading to industrial upgrading (Liao et al., 2021). Secondly, the presence of foreign direct investment can substantially alter the local industrial framework, as the introduction of high-tech industries may spur regional development and facilitate a transformation in the industry. Lastly, FDI has the potential to directly introduce advanced technologies, enhancing traditional regional technologies and bolstering industrial technological innovation capabilities, thereby contributing to the overall industrial upgrading (Wang et al., 2020). Taking into account the data availability and fundamental facts, the input of foreign direct investment is based on the scale of past industries and potential future output. Following the

approach suggested by Shen (2017), the annual automobile output value of each province is taken as a percentage of regional GDP and multiplied by the total foreign direct investment in the entire industry to obtain the FDI data. The data is sourced from the China Automotive Industry Yearbook (2001-2021) and China Statistical Yearbook (2001-2021).

Table 3.1: List of Variables, Indicator Abbreviations and Data Sources

Variable Properties	Variable Name	Indicator Abbreviation	Data Source
Dependent Variable	Industrial Upgrading	Upgrade	China Automotive Industry Yearbook (2001-2021); China Industrial Statistical Yearbook (2001-2021)
Independent Variables	Industry Agglomeration	AGG	China Automotive Industry Yearbook (2001-2021); China Industrial Statistical Yearbook (2001-2021); China Statistical Yearbook (2001-2021)
	Global Value Chain	GVC	OECD-TIVA database 2023ed; China Automotive Industry Yearbook (2001-2021); China Statistical Yearbook (2001-2021)
Moderating Variables	Government Support	GOV	China Statistical Yearbook (2001-2021)
	Foreign Direct Investment	FDI	China Automotive Industry Yearbook (2001-2021); China Statistical Yearbook (2001-2021)

Table 3.1 continued

Control Variables	Human Capital	HC	China Statistical Yearbook (2001-2021)
	Technological Innovation	TI	China Automobile Industry Yearbook (2001-2021); China Statistical Yearbook (2001-2021)

In this study, the upgrading of China's automobile industry is the dependent variable, industrial agglomeration and global value chain are the core independent variables, government support and foreign direct investment are the moderating variables, and human capital and technological innovation are the control variables. To present the measurement methods for the dependent variables, independent variables, moderating variables, and control variables in this thesis more clearly, Table 3.1 has been compiled. This table includes the variable names, abbreviations, and data sources for each type of variable examined in this study. This table clearly shows each variable and its source, which is crucial for the transparency and reliability of the research. Additionally, it provides a foundation for subsequent analysis and discussion, making the research findings easier to understand and verify.

3.5 Estimation Techniques

3.5.1 Descriptive Statistics

Descriptive statistics refer to a set of quantitative techniques used to summarize and characterize the fundamental features of a dataset. It includes a range of tools and techniques that describe data distribution by calculating measures of central tendency, such as the mean, median, and mode, and measures of dispersion like range, variance, and standard deviation.

Additionally, descriptive statistics involves constructing frequency distributions to show how often each value occurs, with common visual representations including histograms and bar charts. These methods help researchers understand the data clearly without making inferences about a larger population.

The primary purpose of descriptive statistics is to provide a simple and effective summary of the dataset, making it easier to comprehend and interpret. By condensing large amounts of data into manageable summaries, descriptive statistics facilitates the effective communication of research findings and helps identify trends and patterns within the data. It also supports graphical representations that make key features of the data more intuitive. Ultimately, descriptive statistics is a foundation for further analysis, helping researchers discover potential hypotheses or areas of interest, thereby advancing more in-depth data analysis and research.

3.5.2 Data Envelopment Analysis

This research employs total factor productivity to assess industrial upgrading, utilizing the Malmquist productivity index calculated through the Data Envelopment Analysis approach. Data Envelopment Analysis, also known as the DEA method, was first proposed by the famous American operations researchers Charnes et al. (1978), one of the applications of the linear programming model. This method assesses effectiveness based on observed values of various inputs and multiple outputs. DEA is a crucial tool in economic research for estimating the production frontier in multi-input, multi-output scenarios. This research utilizes total factor productivity to assess industrial upgrading, which is measured using the DEA-Malmquist approach. Under the condition of constant returns to scale (CRS), the Malmquist productivity index of period t can be expressed as:

$$M_i^t = D_i^t(x^{t+1}, y^{t+1}) / D_i^t(x^t, y^t) \quad \text{Equation 3.10}$$

Among them, M_i^t denotes the Malmquist productivity index for the i region during period t , while $D_i^t (x^{t+1}, y^{t+1})$ indicates the technical efficiency level for the i region in period $t+1$, using the technical level from period t as the reference. It can also be seen that technical efficiency changes from period t to period $t+1$ when using the technical level of period $t+1$ as the reference. As shown in Equation 3.5:

$$M_i^{t+1} = D_i^{t+1} (x^{t+1}, y^{t+1}) / D_i^{t+1} (x^t, y^t) \quad \text{Equation 3.11}$$

In order to exclude the arbitrariness of period selection, we usually use the geometric mean of M_i^t and M_i^{t+1} to calculate the change of total factor productivity over two time periods, and the mathematical formula is expressed as follows:

$$TFP = M_i (x^t, y^t, x^{t+1}, y^{t+1}) = \sqrt{M^t \times M^{t+1}} = \sqrt{\frac{D_i^t (x^{t+1}, y^{t+1})}{D_i^t (x^t, y^t)} \times \frac{D_i^{t+1} (x^{t+1}, y^{t+1})}{D_i^{t+1} (x^t, y^t)}} \quad \text{Equation 3.12}$$

If the result of this equation is greater than 1, it indicates that total factor productivity (TFP) has increased from period t to period $t+1$. Conversely, if the result is less than 1, it signifies a decrease in TFP during the same period.

In addition, Fare et al. (1994) proposed to decompose the Malmquist index into two parts: the technological progress index and the comprehensive technological efficiency change index, which can be expressed by the following mathematical formula:

$$\begin{aligned} M_i (x^t, y^t, x^{t+1}, y^{t+1}) &= \frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)} \times \sqrt{\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^t, y^t)}} \\ &= TEC (x^t, y^t, x^{t+1}, y^{t+1}) \times TC (x^t, y^t, x^{t+1}, y^{t+1}) \end{aligned} \quad \text{Equation 3.13}$$

$$TEC (x^t, y^t, x^{t+1}, y^{t+1}) = D_i^{t+1} (x^{t+1}, y^{t+1}) / D_i^t (x^t, y^t) \quad \text{Equation 3.14}$$

$$TC(x^t, y^t, x^{t+1}, y^{t+1}) = \sqrt{\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^t, y^t)}} \quad \text{Equation 3.15}$$

In the above three formulas, TEC is the abbreviation of technical efficiency change, TC is the abbreviation of technological change. TEC reflects the degree to which each observation object catches up to the production frontier from period t to period $t+1$, representing the change in technical efficiency of the enterprise over this time frame. It highlights the strengths and weaknesses of the enterprise's management practices and the quality of decisions made by its leaders. If the TEC is greater than 1, it indicates an improvement in the industry's technical efficiency, suggesting that the enterprise's decision-making and management methods are effective. Conversely, if the TEC is less than 1, it signifies a decline in technical efficiency, implying that the enterprise's decision-making and management practices may be inadequate.

TC indicates the shift in the enterprise's production frontier from period t to period $t+1$, reflecting the degree of change in technological advancements. This indicator measures the extent of innovation or technological progress within production activities. If the TC is greater than 1, it signifies that the production boundary has expanded outward, suggesting progress in the industry's technical level. Conversely, if the TC is less than 1, it indicates a contraction of the production boundary towards the origin, which reflects an overall decline in industrial technology.

Under variable returns to scale (VRS), technical efficiency change (TEC) can be further composed of two parts: pure technical efficiency change (PTEC) and scale efficiency change (SEC). The following decomposition form of the Malmquist index is obtained:

$$TEC(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_i^{t+1}(x^{t+1}, y^{t+1})_{VRS}}{D_i^t(x^t, y^t)_{VRS}} \times \frac{\frac{D_i^{t+1}(x^{t+1}, y^{t+1})_{CRS}}{D_i^{t+1}(x^{t+1}, y^{t+1})_{VRS}}}{\frac{D_i^t(x^t, y^t)_{CRS}}{D_i^t(x^t, y^t)_{VRS}}}$$

$$= PTEC(x^t, y^t, x^{t+1}, y^{t+1}) \times SEC(x^t, y^t, x^{t+1}, y^{t+1})$$

Equation 3.16

$$M_i(x^t, y^t, x^{t+1}, y^{t+1}) = PTEC(x^t, y^t, x^{t+1}, y^{t+1}) \times TC(x^t, y^t, x^{t+1}, y^{t+1}) \times SEC(x^t, y^t, x^{t+1}, y^{t+1})$$

Equation 3.17

It can be derived that $TFP = PTEC \times TC \times SEC$. If SEC is greater than 1, it indicates that period t+1 is closer to constant returns to scale (CRS) compared to period t. Conversely, when SEC is less than 1, it signifies that period t+1 is further away from CRS relative to period t. If PTEC is greater than 1, it suggests that efficiency (pure technical efficiency) has improved under variable returns to scale (VRS); otherwise, efficiency has declined. The Malmquist index measures the dynamic change in TFP from period t to period t+1. A value greater than 1 indicates an improvement in TFP from period t to period t+1, while a value less than 1 signifies a decrease in TFP. When M_i equals 1, it indicates that TFP remains unchanged.

3.5.3 Generalised Method of Moments

Generalised method of moments (GMM) is a semi-parametric estimation technique widely utilized in statistics and econometrics. Developed by Hansen (1982), it builds upon the method of moments introduced by Pearson (1894). GMM is particularly useful when the stringent assumptions of the least squares method do not hold, such as when independent variables are correlated with the error term or when the distribution of the information is unknown, making maximum likelihood estimation impractical. The relaxed assumptions inherent in GMM have contributed to its extensive adoption in econometrics. This estimation method possesses several desirable properties, including consistency, asymptotic normality, and efficiency.

Traditional econometric estimation methods, such as the ordinary least squares (OLS) method, instrumental variable method, and maximum likelihood method, each have their limitations. Specifically, the reliability of parameter estimators depends on certain assumptions, such as the random error term of the model following a normal distribution or being from a known distribution. In contrast, heteroskedasticity and serial correlation are permitted in the random error term using the Generalised Method of Moments (GMM), and it does not require precise knowledge of the distribution of the error term. As a result, the parameter estimates obtained through GMM tend to be more accurate than those generated by other estimation techniques. Consequently, GMM has become a widely adopted method for model parameter estimation (Baum et al., 2003).

The Generalised Method of Moments (GMM) is particularly effective in addressing the endogeneity problem often encountered in dynamic panel data analysis. This issue arises when independent variables are correlated with disturbance terms, which can occur due to omitted variables, bidirectional causality, or measurement errors. A fundamental requirement for valid ordinary least squares (OLS) estimates is that the independent variables must be uncorrelated with the disturbance term; otherwise, OLS estimates will be biased and inconsistent, a consequence of the endogeneity problem (Bond et al., 2001). Dynamic panel data models typically include lagged values of the dependent variables as independent variables. Even when employing fixed-effects models through within-group deviations or first-order differencing to eliminate individual effects, the endogeneity problem in dynamic panel models persists. However, the GMM approach, which utilizes instrumental variables, effectively addresses this endogeneity issue and results in more reliable estimations.

Understanding the underlying mechanisms and influencing elements of industrial upgrading is critical since it is a dynamic and complicated process. In order to better accurately reflect its dynamic properties, this study thus chooses to include the lag term of industrial upgrading into the model. In order to thoroughly investigate the link between several influencing factors and industrial upgrading from a dynamic perspective, this thesis built a dynamic panel regression model using this approach.

Although the addition of the dependent variable's lagged term can more accurately capture the dynamic process of industrial upgrading, it also invariably creates the endogeneity issue. This study uses the generalised method of moment estimation (GMM), a statistical approach created especially to handle the endogeneity problem, to successfully solve this obstacle. The systematic GMM and differential GMM techniques are the two fundamental components of the GMM approach. To mitigate the potential disruptions stemming from fixed effects within the fundamental differential GMM model, Arellano and Bond (1991) propose employing a collection of lagged independent variables as instrumental factors for the corresponding variables.

It is noteworthy that Arellano and Bond (1998) draw attention to the possibility that, in some circumstances, differential GMM estimators might be vulnerable to weak instrumental variables. To increase the validity and robustness of the estimates, they consequently put forth a systematic GMM technique. As a result, this study chooses to use the system GMM approach, which, by choosing the lagged term of the independent variable as an instrumental variable in the dynamic GMM framework, can better address the endogeneity issue and improve the explanatory and predictive power of the model.

To ensure the accuracy and reliability of the model, two critical diagnostic tests are essential. The first test evaluates the autocorrelation of the residuals, ensuring that there are

no excessive restrictions on the moment conditions and that the model does not have more instrumental variables than endogenous variables. In this context, it is expected that the model's perturbation terms exhibit significant first-order correlation while showing insignificant second-order autocorrelation. To assess this, the Arellano-Bond tests are conducted for both first-order and second-order serial correlation on the first-differenced residuals. Specifically, the criteria to be satisfied are that the p-value of AR(1) should be below 0.1, indicating significant first-order correlation, while the p-value of AR(2) should exceed 0.1, indicating no significant second-order autocorrelation.

The second test focuses on over-identifying restrictions, which is crucial for determining the overall validity of the instrumental variables used in the system GMM estimation. This can be assessed using either Sargan's test or Hansen's test. The null hypothesis for these tests posits that all instrumental variables are exogenous. If the instrumental variables are valid, the null hypothesis should not be rejected. For the Sargan test or Hansen test, a p-value greater than 0.10 is typically required to fail to reject the null hypothesis, thereby supporting the validity of the instruments (Roodman, 2009). A thorough understanding of these tests is essential for researchers, as it provides insights into the reliability and effectiveness of the methodological approach employed. Incorporating these diagnostic analyses enhances the robustness of the GMM model and ensures the reliability of its results.

3.5.4 Dynamic Threshold Model

Hansen (1999) introduced the static panel threshold model to explore the nonlinear relationships among variables, which has since been widely adopted by researchers globally for analyzing such relationships. However, this model necessitates that all variables be exogenous, making it unsuitable for addressing endogeneity issues. In response to this

limitation, Caner and Hansen (2004) developed a panel threshold model incorporating endogenous variables, building upon the static threshold model. In their approach, they performed least squares regression on the instrumental variables for the endogenous variables, replaced the endogenous variables with fitted proxy variables to identify threshold values, and subsequently grouped samples based on these threshold values for GMM regression. This effectively addresses the endogeneity of the independent variables. Furthermore, Dang et al. (2012) and Kremer et al. (2013) further advanced the threshold model, extending the static panel threshold model to a dynamic framework by incorporating the lagged term of the dependent variable and proposing a forward orthogonal transformation approach to eliminate fixed effects. Despite these advancements, the stringent exogeneity requirements for the threshold variables remained unmet.

To address the endogeneity issue commonly associated with the regression of macroeconomic variables, Seo and Shin (2016) and Seo et al. (2019) introduced a dynamic threshold model based on GMM estimation. This model effectively accounts for the endogeneity of both threshold variables and other regressors, making it more reflective of real-world conditions. Consequently, this thesis will employ this model for the empirical research conducted in the study.

The dynamic panel threshold regression model offers several distinct advantages over traditional linear regression models. Firstly, it accommodates nonlinear relationships among variables, effectively addressing endogeneity issues. Secondly, by allowing for shifts in the relationship between variables based on a threshold variable, this model can capture complex interdependencies that linear models may not adequately represent. Thirdly, it enables the depiction of varying relationships between variables for different entities within the panel, which is particularly beneficial for capturing heterogeneity among entities such as

firms or countries. Additionally, the model supports a range of functional forms for modeling relationships, enhancing its adaptability to complex data patterns. However, a notable limitation of the current algorithm for this model is its inability to handle multiple thresholds within the analytical framework (Seo et al., 2019).

To ensure the validity of the dynamic panel threshold model results, rigorous diagnostic tests must be conducted. Firstly, the threshold effect must be validated through the bootstrap likelihood ratio test ($p=0.000$), which strongly rejects the linear model and supports the threshold specification, effectively identifying the threshold's existence and confirming the model's nonlinear characteristics. Secondly, the 95% confidence interval for the threshold should be examined to assess the precision of its estimate; a narrower confidence interval indicates a more reliable threshold estimate, while a wider interval may suggest instability in the model or the influence of data noise. Thirdly, it is essential to analyze the significant differential effects across different regimes, as the independent variable may show no significance when below the threshold, but its positive relationship may become significantly stronger once it surpasses the threshold. This differential examination reveals the model's dynamic characteristics under varying conditions and the impact of institutional changes on the results. Collectively, these diagnostic procedures ensure the reliability of the nonlinear relationships identified in the threshold regression analysis, assisting researchers in accurately interpreting the results and providing a solid foundation for subsequent policy recommendations; thus, conducting systematic diagnostic tests is an indispensable part of analyzing the dynamic panel threshold model.

3.6 Summary

This chapter presents a comprehensive overview of the methodology employed in the research. It begins with an introduction to the research design, outlining its overall

approach and rationale. Following this, the chapter details the model specifications, including the baseline model, moderating effect model, mediating effect model, and dynamic threshold model, highlighting the unique features and applications of each. A thorough description of the data used in the analysis, including the measurement of dependent, independent, control, and moderating variables, ensuring clarity on how each variable is quantified and integrated into the models. Additionally, the estimation techniques employed, such as descriptive statistics, data envelopment analysis, the generalized method of moments, and the dynamic threshold model, are outlined, emphasizing their significance in validating the robustness of the findings.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the findings of the entire thesis. The analysis was conducted using Deap 2.1 and Stata 17 software. Specifically, Deap 2.1 was employed to analyze the results of the Data Envelopment Analysis (DEA) Malmquist index, while Stata 17 facilitated descriptive statistical analysis, as well as the implementation of the Generalised Method of Moments (GMM) and the dynamic threshold model. Section 4.2 provides the results of the descriptive statistical analysis for each variable included in this study. Section 4.3 details the findings related to the upgrading of China's automobile industry, specifically the total factor productivity results for 28 provinces calculated using the DEA-Malmquist index. Section 4.4 presents the GMM analysis results, encompassing the baseline analysis and the examination of moderating and mediating effects. Finally, Section 4.5 outlines the findings from the dynamic threshold model analysis.

4.2 Descriptive Statistics

Descriptive statistics refer to the statistical summary of the relevant data from all variables within the sample, offering a preliminary insight into the fundamental characteristics and distribution of the data. This includes key metrics such as the total number of observations, mean, standard deviation, minimum value, and maximum value. Table 4.1 presents the results of the descriptive statistical analysis for all variables examined in this research.

Table 4.1: Descriptive Statistics

Variable	Details of Variable	Obs	Mean	Std.de	Min	Max
Upgrade	Industrial Upgrading	196	3.0704	2.3097	0.2768	15.1788
AGG	Industrial Agglomeration	196	1.1627	1.4262	0.0119	8.5466
GVC	Global Value Chain	196	0.5830	0.2819	0.0132	1.3025
HC	Human Capital	196	8.6542	1.0744	6.0535	12.5817
TI	Technological Innovation	196	2.5193	5.1349	0.0006	29.2029
GOV	Government	196	0.1937	0.0770	0.0757	0.4575
FDI	Foreign Direct Investment	196	2.8040	4.4684	0.0002	27.3320

The dependent variable, Upgrade, reflects the upgrading of China's automobile industry, measured by the total factor productivity calculated using the DEA-Malmquist index, with a maximum value of 15.1788, a minimum value of 0.2768, and a standard deviation of 2.3097. These results indicate significant variations in total factor productivity across different years and provinces. The core independent variable, AGG, represents the level of agglomeration in China's automobile industry, quantified using the locational entropy index, which has a maximum value of 8.5466, a minimum value of 0.0119, and a standard deviation of 1.4262. This highlights disparities in industrial agglomeration across provinces; for instance, Jilin Province exhibits a strong agglomeration phenomenon with the highest locational entropy index. Gansu Province shows minimal signs of agglomeration, with a low index of 0.0119. Another core independent variable, GVC, indicates the extent of China's automobile industry's integration into the global value chain, showing a mean value of 0.5830 and a standard deviation of 0.2819, which suggests a low degree of dispersion and minimal differences across the overall data.

TI and FDI represent the technological innovation and foreign direct investment data of China's automobile industry, respectively. As shown in Table 4.1, the standard deviation of TI is 5.1349, with a minimum value of 0.0006 billion yuan and a maximum value of 29.2029 billion yuan. For FDI, the standard deviation is 4.4684, with a minimum value of 0.0002 billion yuan and a maximum value of 27.332 billion yuan. Notably, the maximum TI of 29.2029 billion yuan is associated with Beijing during year 7 (2018-2020), while the minimum TI of 0.0006 billion yuan corresponds to Xinjiang in year 2 (2003-2005). Similarly, the maximum FDI of 27.332 billion yuan is linked to Shanghai in year 5 (2012-2014), whereas the minimum FDI of 0.0002 billion yuan corresponds to Gansu in year 7 (2018-2020).

Foreign direct investment (FDI) in western regions such as Xinjiang, Yunnan, Guizhou, and Gansu is notably low. In contrast, the utilization of foreign investment in more developed eastern areas, including Shanghai, Guangdong, Jiangsu, Anhui, and Beijing, constitutes most of the country's total FDI, closely reflecting prevailing trends. The western automobile industry lagged in its development, with insufficient supporting facilities, making it challenging to attract foreign investment. Conversely, the eastern automobile industry, which developed earlier, benefits from well-established supporting infrastructure and favorable geographical conditions, facilitating the attraction of foreign capital. This disparity is also reflected in research and development (R&D), which serves as a measure of technological innovation (TI) in this thesis. Central automobile provinces such as Shanghai, Beijing, Tianjin, Chongqing, Jilin, Guangdong, and Hubei allocate substantial resources for R&D. In contrast, regions with less developed economies, such as Guizhou, Gansu, and Yunnan, which launched their automobile industries later, demonstrate significantly lower levels of R&D.

The variable HC represents human capital, with a standard deviation of 1.0744, an average value of 8.6542, a minimum value of 6.0535, and a maximum value of 12.5817. This data indicates that the differences in average years of schooling across various regions of China are not particularly pronounced. This uniformity can be attributed to the increasing improvement in China's higher education system, facilitated by the widespread implementation of nine-year compulsory education. Consequently, this finding aligns well with the actual quality of the Chinese labor force. In terms of government support, the standard deviation of GOV (government support) is 0.0770, indicating a low degree of dispersion in government support across different provinces in China.

4.3 Result of Total Factor Productivity

This research utilizes total factor productivity (TFP) to assess the upgrading of China's automobile industry. The TFP for automobiles is based on panel data regarding inputs and outputs from 28 provinces in China, covering the period from 2000 to 2020. Following the methodology outlined by Gu and Feng (2018), this study employs the output-oriented DEA-Malmquist index method with constant returns to scale to calculate TFP. The calculations for the DEA-Malmquist index are performed using DEAP 2.1 software.

4.3.1 Overall Analysis of Total Factor Productivity in China's Automobile Industry

The results obtained from the DEAP 2.1 software indicate the rate of change in total factor productivity (TFP). Table 4.2 presents the TFP change rates for the automobile industry across 28 provinces in China from 2000 to 2020. A value greater than 1 indicates an increase in the corresponding total factor productivity, while a value less than 1 signifies a decrease.

Table 4.2: Total Factor Productivity Change for China's Automobile Industry, 2000-2020

Province	2000/2001	2001/2002	2002/2003	2003/2004	2004/2005	2005/2006	2006/2007	2007/2008	2008/2009	2009/2010	2010/2011	2011/2012	2012/2013	2013/2014	2014/2015	2015/2016	2016/2017	2017/2018	2018/2019	2019/2020
Beijing	1.081	1.631	2.291	1.154	1.089	0.976	1.046	1.001	1.333	1.11	1.056	0.872	1.208	1.056	1.097	1.316	0.963	1.023	1.2	1.126
Tianjin	0.924	1.814	0.655	1.025	3.062	1.339	0.949	0.988	1.116	1.058	0.963	0.871	0.965	0.995	0.692	1.858	0.817	1.045	1.076	1.109
Hebei	1.031	1.639	1.331	0.995	0.979	0.935	1.075	0.901	1.377	1.085	0.917	0.687	0.953	0.911	1.881	1.315	0.996	0.788	1.219	1.096
Shanxi	0.917	1.292	0.8	1.341	0.823	0.635	1.285	1.255	1.097	0.762	1.703	1.034	0.826	0.922	1.212	1.12	1.65	1.011	1.04	1.163
InnerMongolia	1.468	1.209	1.505	1.756	0.683	1.072	1.241	0.976	1.184	1.142	1.001	0.989	1.235	1.018	0.945	0.996	1.122	0.675	1.833	1.231
Liaoning	1.358	1.37	1.341	0.628	1.245	1.389	1.032	0.641	1.462	0.98	0.69	1.095	1.258	0.974	0.879	2.618	0.952	1.053	1.06	1.036
Jilin	1.294	1.522	1.211	1.262	0.471	1.213	1.266	1.114	1.165	1.018	1.278	0.959	0.922	1.012	0.685	1.55	1.047	1.086	0.912	1.157
Heilongjiang	1.22	1.369	1.234	0.895	1.048	1.186	0.901	0.914	1.043	0.943	0.699	1.061	0.768	0.896	1.027	2.579	1.385	1.042	1.594	0.469
Shanghai	1.174	1.382	1.386	0.751	0.823	1.311	1.058	0.739	1.424	1.285	1.071	1.082	1.201	1.11	0.717	1.257	1.042	0.986	0.951	1.091
Jiangsu	1.116	1.448	0.867	0.844	1.333	1.135	0.795	0.614	0.977	1.069	0.925	0.926	0.865	0.971	2.815	1.61	0.815	0.88	0.982	1.008
Zhejiang	1.001	1.202	1.01	0.92	0.939	1.166	0.851	1.331	1.003	0.984	0.953	0.886	0.999	0.925	1.05	2.101	0.869	0.917	0.965	1.007
Anhui	1.32	1.731	1.057	0.976	1.005	1.124	1.099	0.81	1.338	1.19	0.783	1.012	0.856	1.072	1.014	1.556	1.178	1.176	1.285	0.701
Fujian	1.432	1.057	1.26	0.59	1.075	0.845	1	0.836	1.128	1.046	0.422	1.028	1.357	1.037	1.363	1.769	0.99	0.951	0.961	0.774
Jiangxi	1.041	1.308	1.006	1.232	0.705	0.993	0.987	1	0.97	1.07	0.754	1.069	0.962	0.883	2.535	1.01	0.996	1.087	1.044	0.897

Table 4.2 continued

Province	2000/2001	2001/2002	2002/2003	2003/2004	2004/2005	2005/2006	2006/2007	2007/2008	2008/2009	2009/2010	2010/2011	2011/2012	2012/2013	2013/2014	2014/2015	2015/2016	2016/2017	2017/2018	2018/2019	2019/2020
Shan dong	1.17	1.462	1.122	1.142	0.947	1.219	1.027	0.769	1.569	1.042	0.897	1.027	0.864	0.919	0.842	1.356	1.23	1.188	0.834	1.375
Henan	1.085	1.552	1.189	0.948	1.33	1.066	1.083	1.206	0.997	0.85	0.711	0.909	1.105	0.872	1.164	2.077	1.012	1.194	0.666	1.082
Hubei	1.588	1.401	1.335	0.864	0.588	1.297	1.103	0.866	1	1.072	1.335	1.263	1.083	1.027	0.738	1.474	1.093	0.943	1.189	0.883
Hunan	1.114	1.601	1.132	1.349	0.671	1.243	0.886	1.635	1.142	0.514	1.018	0.83	0.882	0.925	0.894	1.804	1.189	1.088	0.904	0.776
Guang dong	1.237	1.242	1.052	1.095	1.721	1.024	0.973	0.867	1.168	0.983	1.068	1.174	0.842	0.743	1.252	1.682	0.89	1.072	0.876	1.148
Guangxi	1.201	1.619	0.898	1.029	1.143	1.112	1.106	0.885	1.293	0.917	0.51	1.124	1.045	0.974	1.114	2.406	1.03	0.901	0.943	0.781
Hainan	2.089	2.005	1.904	0.113	7.625	0.865	1.003	0.621	1.271	1.242	0.884	0.979	1.114	1.006	0.625	1.361	0.905	0.653	0.245	2.752
Chong qing	1.416	0.919	5.608	0.986	0.977	1.132	1.056	0.872	1.074	0.966	0.71	1.001	0.906	1.272	1.14	1.265	0.935	0.797	0.935	1.099
Xichuan	1.089	1.403	0.132	1.351	1.308	1.173	1.179	0.908	1.338	0.708	0.879	0.92	1.228	0.983	1.031	2.861	0.954	0.933	0.987	1.036
Guizhou	1.057	0.872	1.228	1.074	1.173	0.969	0.879	1.341	1.061	1.136	0.922	0.955	1.025	0.888	1.399	2.055	0.89	0.566	0.906	1.399
Yunnan	1.176	0.782	0.881	1.645	1.489	1.018	0.935	1.08	1.387	0.965	1.166	1.026	1.005	0.935	1.019	1.234	1.063	0.939	0.784	0.68
Shaanxi	1.344	1.443	1.08	1.455	0.641	1.803	1.49	1.141	1.24	1.045	0.804	1.052	1.162	0.985	0.608	1.637	0.995	1.3	1	1.032
Gansu	0.9	1.059	1.239	1.729	0.386	3.694	1.289	0.864	1.101	2.236	0.308	1.619	1.407	1.663	0.512	1.276	1.148	0.541	0.609	0.089
Xinjiang	1.727	1.189	0.808	1.467	1.756	0.967	2.256	1.33	0.533	1.114	0.7	0.812	1.061	0.707	2.105	1.272	1.417	0.958	0.925	1.115

As shown in Table 4.2, the rate of change in total factor productivity (TFP) varies across provinces. In a given year, some provinces exhibit a TFP change rate greater than 1, indicating an increase, while others have a rate less than 1, signifying a decrease. For instance, between 2019 and 2020, traditional automobile provinces such as Beijing, Tianjin, Liaoning, Jilin, Shanghai, Jiangsu, Zhejiang, Guangdong, and Sichuan experienced TFP change rates exceeding 1, reflecting an increase in their total factor productivity. In contrast, provinces like Gansu, Guizhou, Yunnan, Guangxi, and Hunan reported TFP change rates below 1, indicating negative growth in their automobile sectors. This decline can be attributed to the slower development of the automobile industry in these regions and the absence of well-known automobile companies.

Further analysis of these results reveals that a variety of factors influences the total factor productivity across different provinces. For instance, economic development levels, policy support, market demand, and technological advancements can significantly affect the changes in TFP. Traditional automobile provinces attract more investment and innovation due to their strong industrial foundations, facilitating productivity improvements.

Similarly, the total factor productivity (TFP) of automobiles within the same province can fluctuate between increases and decreases across different years. For instance, in a major automobile hub like Shanghai, which is home to the well-known enterprise SAIC, the corresponding TFP does not exhibit consistent annual growth. In some years, such as 2003-2004, 2004-2005, 2007-2008, 2014-2015, 2017-2018, and 2018-2019, the automobile TFP recorded negative growth, with values less than 1, indicating a decline. This volatility is influenced by factors such as the international market environment and China's automobile policies.

Overall, the TFP change rates for automobiles across various provinces in China are predominantly greater than 1 in different years, indicating that most provinces have experienced growth in total factor productivity within the automobile industry during most of those years. However, there are still instances in certain provinces and specific years where TFP has declined, underscoring the necessity for further upgrades and enhancements in the industry.

4.3.2 Annual Mean Total Factor Productivity of China's Automobile Industry

To analyze the annual change rate of total factor productivity of China's automobile industry more intuitively, this research uses Deap2.1 software to obtain the annual means total factor productivity change rate and its decomposition index of China's automobile industry from 2000 to 2020. The results are presented in Table 4.3.

Tfpch represents the total factor productivity change, Techch indicates technological change, and Effch denotes technical efficiency change, reflecting the change rates of total factor productivity, technological progress, and technical efficiency, respectively. The data shows that from 2000 to 2020, the average growth rate of total factor productivity (TFP) in China's automobile industry was 6.3%. Technical efficiency and technological progress exhibit growth rates of 2.8% and 3.4%, respectively, indicating an overall upward trend. Notably, the growth rate of technological progress exceeds that of technical efficiency, suggesting that technological progress contributes more to TFP growth than technical efficiency. Thus, it can be concluded that the growth of TFP is primarily driven by technological progress.

Table 4.3: Change and Decomposition of Annual Mean Total Factor Productivity in China's Automobile Industry, 2000-2020

Year	Effch	Techch	Tfpch
2000-2001	1.068	1.134	1.211
2001-2002	0.968	1.39	1.346
2002-2003	1.381	0.812	1.121
2003-2004	0.849	1.183	1.005
2004-2005	1.418	0.753	1.069
2005-2006	1.011	1.135	1.148
2006-2007	1.127	0.956	1.078
2007-2008	0.812	1.176	0.955
2008-2009	0.982	1.172	1.151
2009-2010	1.217	0.842	1.025
2010-2011	0.798	1.068	0.852
2011-2012	1.038	0.961	0.997
2012-2013	1.005	1.022	1.026
2013-2014	0.982	0.995	0.977
2014-2015	1.141	0.926	1.057
2015-2016	1.218	1.306	1.591
2016-2017	1.057	0.985	1.042
2017-2018	0.864	1.084	0.937
2018-2019	0.723	1.315	0.95
2019-2020	1.229	0.763	0.938
Mean (2000-2020)	1.028	1.034	1.063

Notes: 1.Techch is the technological change; 2.Effch is the technical efficiency change; 3.Tfpch is the total factor productivity change.

Analysing the specific annual mean data, total factor productivity experienced negative growth during the years 2007-2008. This decline can be attributed to several factors. In August 2007, the global economic crisis triggered by the subprime mortgage crisis in the United States led to a worldwide economic slowdown, which significantly impacted exports from China's automobile industry. Additionally, implementing a series of tight fiscal policies at the macroeconomic level, along with a general rise in raw material prices, resulted in increased manufacturing costs for automobiles. Furthermore, the chain reaction of the economic crisis also caused a slump in consumer demand within the automobile market (Qu & Meng, 2022).

TFP exhibited negative changes during the periods of 2010-2011, 2011-2012, and 2013-2014. The data from the table indicates that while the growth rate of TFP turned positive as early as 2009-2010, it was a modest 2.5%. Similarly, although the growth rate shifted from negative to positive in 2012-2013, it remained weak at just 2.6%. During this timeframe, China's technical efficiency and technological progress experienced negative growth, contributing to the overall decline in TFP. The primary reason for this trend is the low production efficiency in China during these years, coupled with insufficient support for research and development within enterprises (Guo, 2016).

The negative growth of total factor productivity in the automobile industry from 2017 to 2020 can be attributed to the complete elimination of vehicle purchase tax incentives in 2018, as well as a decline in the macroeconomic environment both domestically and internationally (Shi, 2022). These factors have hindered the growth of total factor productivity in the automobile industry. The removal of vehicle purchase tax incentives has diminished consumer demand among vehicle buyers, which in turn affects the production

output of enterprises. This decline in output subsequently impacts the financial performance of these companies, further leading to a decrease in their total factor productivity.

In other years, total factor productivity in China's automobile industry has shown an upward trend. Notably, the periods of 2015-2016 and 2001-2002 experienced the fastest growth in total factor productivity, with growth rates of an impressive 59.1% and 34.6%, respectively. During these same periods, the growth rates of technological progress were 30.6% and 39%, respectively. It is clear that advancements in technological progress during these times played a crucial role in driving the growth of TFP within the automobile industry.

4.3.3 Mean Total Factor Productivity by Province in China's Automobile Industry

To facilitate a more intuitive analysis of the changes in total factor productivity within China's automobile industry across various provinces, this study employs Deap 2.1 software to calculate the mean change rates of total factor productivity for the automobile industry in 28 provinces. The results are presented in Figure 4.1.

In the figure below, Tfpch represents the change in total factor productivity. Analyzing the data from each province reveals an overall upward trend in total factor productivity across China's automobile industry. Specifically, the average annual growth rate of total factor productivity in this sector is 6.3%. However, certain provinces, such as Gansu, exhibited a slight decline. In contrast, the total factor productivity indices for other regions were above 1. Overall, while the total factor productivity of China's automobile industry demonstrates an increasing trend, there are notable disparities in regional development, indicating an imbalance in growth across different areas.

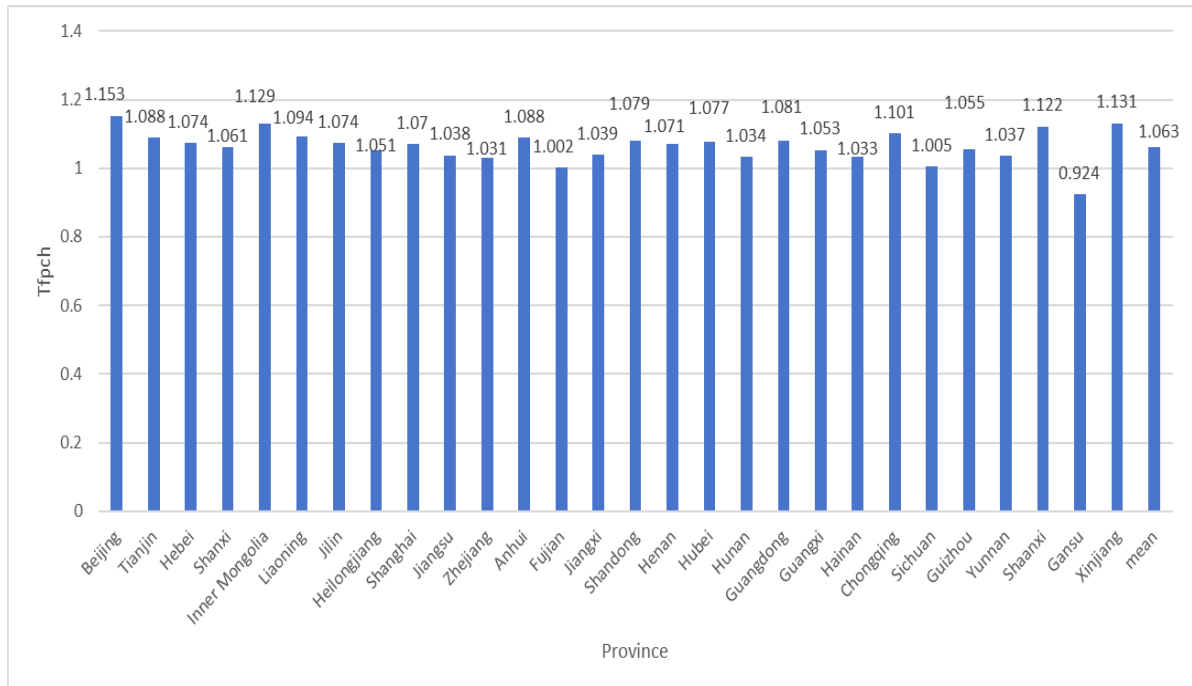


Figure 4.1: Change in Total Factor Productivity of the Means of 28 Provinces in China's Automobile Industry

The data presented in Figure 4.1 indicates that the increase in the automotive sector's total factor productivity is outpacing the national average in several regions, including Beijing, Tianjin, Hebei, Inner Mongolia, Liaoning, Jilin, Shanghai, Anhui, Shandong, Henan, Hubei, Guangdong, Chongqing, Shaanxi, and Xinjiang. Notably, half of these areas are traditional key bases for China's automobile industry, housing major enterprises such as the FAW Group in Jilin, Dongfeng Group (formerly known as the “Second Automobile” Group) in Hubei, SAIC in Shanghai, BAIC Group in Beijing, Changcheng Automobile in Hebei, Sinotruk in Shandong, Chery Group and Jianghuai Automobile in Anhui, GAC Group and BYD in Guangdong, Changan Automobile in Chongqing, Shaanxi Automobile Group in Shaanxi, and Tianjin FAW in Tianjin.

As significant hubs for the automobile industry, these regions benefit from substantial scales of operation and a concentration of capital, technological expertise, and policy resources. Furthermore, the automobile industry has a long-standing presence in these

areas and receives robust support from the state, resulting in a well-developed and relatively mature industrial ecosystem (Lai et al., 2023). These regions are also noteworthy for attracting foreign investment in China's automobile sector. Consequently, they excel in various aspects such as vehicle sales, research and development capabilities, management practices, product marketing, and brand promotion, aligning the observed growth in total factor productivity with the actual economic development trends within China's automobile industry.

Among the regions exhibiting high total factor productivity (TFP) growth rates, some areas often go overlooked. Inner Mongolia and Xinjiang, which are non-traditional key regions in the automobile industry, have experienced significant TFP growth, mainly due to the rise of the new energy vehicle sector that China has been actively promoting (Zhao, 2014). For instance, Inner Mongolia has made substantial strides in developing new energy vehicles in recent years. This progress has been facilitated by factors such as the relatively small scale of its original automobile industry and minimal fluctuations in industrial renewal, resulting in a remarkable improvement in the total factor productivity of its automobile sector.

Similarly, Xinjiang has also witnessed accelerated growth in TFP, driven by its auto parts industry's rapid development and adjustment tailored for new energy vehicles. The region's TFP growth is further bolstered by the state's differentiated industrial policies, which have attracted numerous well-known domestic and international automobile manufacturers to Xinjiang for investment and factory establishment. Companies such as SAIC Volkswagen, GAC Trumpchi, Dongfeng, and Shaanxi Automobile have collaborated to form a modern automobile industry system in the Urumqi Economic and Technological Development Zone, leveraging strengths in passenger and heavy commercial vehicles.

The regions where the growth rate of total factor productivity (TFP) in the automobile sector exceeds the national average either started their development early, progressed rapidly, maintained large-scale operations, or exhibited highly mature management practices. Alternatively, some of these areas have seen significant advancements later on and have gained recognition from the state. These factors collectively contribute to the rapid TFP growth observed in these regions.

Overall, it is evident that the total factor productivity, technological progress, and technical efficiency of the automobile industry across China are on an upward trend. While traditional automobile manufacturing shows consistent growth, certain non-traditional regions have experienced notable increases in productivity. However, despite this positive overall trend, there are still instances of negative TFP growth in specific years and provinces. This indicates considerable potential for further development within China's automobile industry. Therefore, it is essential to enhance the total factor productivity of the sector comprehensively to facilitate an overall upgrade of China's automobile industry.

4.4 Baseline Analysis Results of Industrial Agglomeration and Global Value Chain on Industry Upgrading

Industrial upgrading is a dynamic evolutionary process. In other words, the adjustment and optimization of the industry in the current period depend on the industry in the previous period, that is, the industry upgrading in the last period is the basis of the industrial upgrading in the current period, and the upgrading of the industry in the current period is the continuation of the industry in the previous period (Wang, 2014). Therefore, to more accurately investigate the impact of global value chain embeddedness and industrial agglomeration on industrial upgrading, this research takes the lag term of industrial upgrading as one of the independent variables to reflect the endogeneity problem. In order

to solve the endogeneity problem, this research uses the dynamic panel GMM regression model for estimation. The system GMM estimate approach uses the lag term of the dependent variable's first-order difference as the instrumental variable. It integrates the benefits of differential and horizontal GMM, which have a smaller bias and higher efficiency than the differential GMM and horizontal GMM. Therefore, in this research, system GMM is used for regression analysis. The GMM results of dynamic panel systems for baseline analysis, moderating effect, and mediating effect are analyzed separately below.

In accordance with Model 1, a regression analysis is conducted to examine the direct effects of global value chain embeddedness and the level of industrial agglomeration on China's automobile industry, employing Stata 17 software and the system GMM methodology. The results of the baseline analysis are presented in Table 4.4.

From the results of baseline analysis, the P value of AR(1) is 0.036, which is less than 0.1, and the P value of AR(2) is 0.453, which is greater than 0.1, so the disturbance term does not have an autocorrelation issue. In addition, the P-value of the Hansen test is 0.172, which is greater than 0.1, indicating that there is no over-identification problem of instrumental variables, indicating that the setting of the dynamic model is reasonable and the estimation effect is relatively good.

As can be seen from Table 4.4, in the dynamic panel model constructed by adding the first-order lag term of the dependent variable (Upgrade), the coefficient value of the first-order lag term of China's automobile industry upgrading (L1.Upgrade) has passed the significance level of 1% and is greater than 0, indicating that the upgrading of China's automobile industry is a continuous process of continuous advancement, and the industrial upgrading has been continuously enhanced through the passage of time. The automobile industry in the previous period improved, and the automobile industry in the current period

will improve further. The deterioration of the automobile industry in the previous period will intensify the deterioration of the automobile industry in the current period.

Table 4.4: Baseline Analysis Results

Variable	Model 1
	Upgrade
L1.Upgrade	0.7311*** (0.0279)
AGG	0.6123*** (0.0225)
GVC	-1.3075*** (0.3742)
TI	0.1364*** (0.0206)
HC	0.3632*** (0.1208)
GOV	2.6732*** 0.6983
FDI	-0.1319*** 0.0202
Constant	-2.4283* (0.8509)
Number of groups	28
Number of instruments	27
AR(1)	0.036
AR(2)	0.453
Hansen	0.172

Notes: 1. Figures in parentheses are standard errors. 2. ***, ** and * indicates significant at 1% 、 5% and 10% level of significance.

The coefficient for the core independent variable AGG is 0.6123, which is statistically significant at the 1% level. This indicates that industrial agglomeration

positively influences the upgrading of China's automobile industry. As industrial agglomeration increases, the automobile industry in the region is likely to continue upgrading. This finding supports the validity of hypothesis H1. The researcher believes that industrial agglomeration leverages its external effects to enhance the development and technological innovation of domestic enterprises while fostering effective competition among businesses. This dynamic facilitates the upgrading of China's automobile industry.

Compared to existing literature, which often emphasizes the role of industrial agglomeration in developed economies, our findings illustrate a unique context in China, where state policies and market dynamics significantly shape industrial outcomes. While studies such as Zhang et al. (2022) suggest that agglomeration can lead to diminishing returns in some sectors, our results indicate a robust positive influence resulting from China's ongoing industrial transformation and the growing emphasis on high-tech industries.

Its impact is primarily observed through three mechanisms: division of labor and specialization, economies of scale and externalities, and knowledge and technology spillovers. The division of labor and specialization foster close connections between enterprises, forming an industrial chain that consolidates resources, intensifies competition, boosts labor productivity, and drives regional economic growth. Additionally, industrial agglomeration promotes economies of scale, compelling companies to enhance their competitiveness by scaling up production, which leads to increased efficiency and greater benefits. Enterprises also consider external factors when making strategic decisions, often opting for regions with external economies to capitalize on their advantages. Lastly, industrial agglomeration attracts talent and skilled labor through knowledge and technology spillover effects, enabling local enterprises to enhance technological innovation, advance the regional economy, and contribute to industrial upgrading (Li, 2020).

To leverage the research findings, policymakers should guide the clustered development of China's automobile industry to accelerate upgrading. Establishing industrial clusters that enhance face-to-face communication and resource flow is crucial. Improving industrial park planning to ensure proximity between production links will boost efficiency. Additionally, engaging key enterprises like FAW, Dongfeng, and SAIC in core technology R&D, while collaborating with small and medium-sized firms, will strengthen the supply chain and foster innovation within the industry.

The coefficient of GVC, another core independent variable, is -1.3075, which passes the significance level of 1%, and the negative coefficient indicates that embedding in the global value chain will have a negative effect on the upgrading of China's automobile industry, thus verifying that the hypothesis H2 is valid. This finding diverges from some existing literature that posits participation in GVCs can enhance competitiveness and stimulate industrial upgrading (Gereffi & Fernandez-Stark, 2016). However, in the context of China, the results suggest that the dynamics of GVCs operate differently due to the unique challenges faced by Chinese enterprises.

There are two primary reasons why embedding in global value chains (GVCs) can inhibit industrial upgrading. Firstly, participation in GVCs may reduce the capacity for independent innovation among Chinese enterprises. By embedding in GVCs, these companies can easily import high-quality intermediate goods from abroad, diminishing their incentive to invest in independent research and developing new technologies and products. As a result, their ability to innovate independently declines. Furthermore, the control of core technologies by developed countries further constrains the innovative activities of Chinese enterprises, exacerbating the reduction in their capacity for independent innovation (Arkolakis et al., 2018; Shen & Zheng, 2020). Secondly, embedding in GVCs may result in

a low-end lock-in effect, as Chinese automobile enterprises predominantly operate within the low-value-added segments of the GVC while the high-value-added segments of the automobile value chain are largely controlled by developed countries. This positioning exposes Chinese firms to the risk of “low-end lock-in” within GVCs, thereby limiting their potential for upgrading and value creation (Chen et al., 2023; Wei et al., 2020).

Given these findings, policymakers should consider strategies that encourage independent innovation and facilitate the ascent of Chinese automobile enterprises within the global value chain. This can be achieved by promoting investment in R&D and providing incentives for companies to develop proprietary technologies. To mitigate the low-end lock-in effect, policies should also support the diversification of production into higher value-added segments of the value chain, such as electric vehicles and advanced automotive technologies. By creating a conducive environment for innovation and enabling firms to move up the value chain.

Regarding the control variables, the coefficient for technological innovation (TI) is 0.1364, which is statistically significant at the 1% level, indicating that technological innovation positively influences the upgrading of China's automobile industry. On one hand, technological innovation helps avoid dependence on developed countries (Xu & Zhang, 2016), as enterprises in developing nations often rely on technology introduction and imitation. Only through technological innovation can they effectively catch up with their developed counterparts (Dobrzanski, 2018). On the other hand, technological innovation fosters industrial economic development (Guo, 2020). It is a direct driving force for industrial upgrading (Gao et al., 2023), injecting vital momentum into the industry (Ye, 2015).

The coefficient for human capital (HC) is 0.3632, which is statistically significant at the 1% level, indicating that human capital positively influences the upgrading of China's automobile industry. This underscores that continuous human capital optimization can lead to industrial upgrading. On one hand, human capital accelerates research and development (R&D) and innovation, significantly advancing the technological progress of the industry and subsequently facilitating industrial upgrading (Zheng & Liu, 2021). On the other hand, human capital fosters knowledge spillover and dissemination, which contributes to the overall upgrading and development of the industry (Hu, 2021).

4.5 Moderating Effect Results: Government Support on Industrial Agglomeration and Industry Upgrading, FDI on Global Value Chain and Industry Upgrading

A regression analysis based on Model 2 was conducted to examine the moderating effects. This analysis aims to determine whether foreign direct investment moderates the relationship between the global value chain and the upgrading of China's automobile industry and whether government support moderates the impact of industrial agglomeration on this upgrading. The results of the moderating effect analysis are presented in Table 4.5.

The findings reveal that the p-value for AR(1) is 0.048, which is below 0.1, indicating the presence of autocorrelation in the first-order perturbation term. Conversely, the p-value for AR(2) is 0.243, exceeding 0.1, suggesting that there is no autocorrelation issue in the second-order perturbation term. Furthermore, Hansen's test yields a p-value of 0.133, which is also greater than 0.1, confirming that there are no over-identification problems with the instrumental variables. This indicates that the model is appropriate and the estimation results are relatively reliable.

Table 4.5: Moderating Effect Results

Variable	Upgrade
L1.Upgrade	0.6438*** (0.0384)
AGG	1.7320*** (0.1598)
GVC	-3.4576*** (0.5795)
FDI_GVC	0.8259*** (0.0979)
GOV_AGG	-5.7495*** (1.1674)
TI	0.0659** (0.0298)
HC	0.2387* (0.1323)
GOV	4.1865*** (0.9113)
FDI	-0.4608*** (0.0704)
Constant	-0.6093 (1.0330)
Number of groups	28
Number of instruments	27
AR(1)	0.048
AR(2)	0.243
Hansen	0.133

Notes: 1. Figures in parentheses are standard errors. 2. ***, ** and * indicates significant at 1% 、 5% and 10% level of significance. 3.FDI_GVC is the interaction term between FDI and GVC, and GOV_AGG is the interaction term between GOV and AGG.

As shown in Table 4.5, the coefficient for the interaction between government support and the degree of industrial agglomeration (GOV_AGG) is negative (-5.7495),

contrasting with the positive sign of the coefficient for industrial agglomeration (AGG), and is statistically significant at the 1% level. This indicates that government support moderates the relationship between industrial agglomeration and the upgrading of China's automobile industry. The negative coefficient for GOV_AGG suggests that the government support level of the Chinese government is not high (Bao, 2014; Wei, 2017; Wu, 2022). This finding is consistent with previous research indicating that insufficient government support can hinder the potential benefits of industrial agglomeration, particularly in developing economies (Chen & Zhang, 2023). The low governance of the Chinese government weakens the influence of the degree of industrial agglomeration on the upgrading of China's automobile industry. Therefore, it is necessary to improve the level of Chinese government support, and then strengthen the role of industrial agglomeration in promoting the upgrading of China's automobile industry.

In the context of the Chinese automobile industry, this situation is particularly pronounced. The rapid development of this sector has been accompanied by increasing competition both domestically and globally. While industrial agglomeration can lead to enhanced collaboration and innovation, the insufficient government support constrains the ability of local firms to transition from low-cost manufacturing to high-value innovation.

The government plays a vital role in moderating the upgrading of China's automobile industry in industrial agglomeration. On one hand, the government addresses market failures that can arise during industrial agglomeration, thereby facilitating further industrial upgrading. Market mechanisms often fail to resolve these issues, and government intervention can be decisive (Kuchiki, 2021). By implementing various policies and measures, the government can effectively regulate the market economy, remedy market failures, and ensure its regular operation (Breznau, 2019). The government's involvement is

particularly significant in transforming and upgrading industrial clusters (Lv et al., 2018), especially in regions with weak industrial foundations and fragmented authority. In such areas, local governments and market participants can leverage each other's strengths, paving the way for high-quality innovation and regional industrial development, ultimately contributing to economic catch-up (Liu & Zhou, 2020b).

On the other hand, the government can create a favorable environment for industrial agglomeration, which enhances its impact on industrial upgrading. It plays various roles in this process, including infrastructure development, provision of strategic information, planning, establishment of communication platforms, and support for research institutions, all of which contribute to fostering a conducive environment for industrial agglomeration (Liu & Zhou, 2020a). The government's functions in promoting industrial cluster development include improving governance capabilities, providing public goods and services, building social service systems, and formulating and implementing relevant policies. These actions collectively create a supportive environment for entrepreneurship and industrial growth. Jin (2022) also emphasizes that the proactive role of government functions in the market contributes to an optimal operating environment for developing industrial clusters.

To strengthen the link between industrial agglomeration and the upgrading of China's automobile industry, improving government effectiveness is essential. Weak government action can undermine the benefits of agglomeration, so it must actively address market failures. Increasing financial investment in science and technology for the automotive sector and providing research funding for universities will enhance innovation. Additionally, fostering collaboration platforms within industrial clusters can promote partnerships among enterprises, academia, and research institutions. Finally, optimizing the business

environment and improving infrastructure will enhance logistics efficiency and reduce costs, further supporting the industry's upgrade.

Table 4.5 also shows that the coefficient for the interaction between foreign direct investment (FDI) and global value chain (GVC) embeddedness (FDI_GVC) is 0.8259. This positive coefficient, which differs from the sign of the GVC coefficient and is statistically significant at the 1% level, indicates that FDI does indeed moderate the relationship between GVC embeddedness and the upgrading of China's automobile industry. This finding reflects the unique context of China's automobile industry, where substantial foreign investment has played a crucial role in shaping industry dynamics (Chen et al., 2024).

The reason why the coefficient of FDI_GVC is positive indicates the high level of foreign direct investment in the automobile industry in China. Since China acceded to the World Trade Organization, the scale of foreign direct investment in China has increased yearly over the past two decades. According to the United Nations Conference on Trade and Development (2021), total global FDI in 2020 was about \$859 billion, a decrease of 42% compared with 2019. China bucked the trend with a 4% rise in FDI to \$163 billion, overtaking the US as the world's largest recipient of foreign capital. The same pattern was observed in Chinese FDI in the automotive sector. According to the National Bureau of Statistics of China (2023), China's use of foreign investment exceeded 1.2 trillion yuan in 2022 for the first time, reaching \$189.13 billion in US dollar terms, marking an increase of 8%. The scale of foreign investment in China remained among the top in the world. In 2022, China's manufacturing industry utilized 323.7 billion yuan of foreign investment, an increase of 46.1%. Notably, thanks to the comprehensive liberalization of foreign investment access restrictions, investment in the automobile manufacturing industry increased significantly by 263.8%.

The high level of foreign direct investment in China's automobile industry has significantly influenced the inhibitory effect of global value chain embedment on industrial upgrading. This investment not only provides essential capital and access to advanced technologies but also enhances the competitive positioning of domestic firms within the global market. As foreign-invested enterprises typically feature superior management practices and innovative capabilities, they help elevate the overall efficiency and productivity of the sector. Moreover, with the growing global demand for electric vehicles and innovative driving technologies, FDI facilitates technology spillovers that enable local companies to rapidly assimilate and implement cutting-edge innovations, thereby accelerating their upgrade processes. Ultimately, FDI plays a critical moderating role, alleviating the negative impacts of global value chain embedment and fostering sustainable growth in China's automotive industry.

The most direct effect of foreign direct investment (FDI) is its ability to alleviate the capital shortage faced by enterprises (Manova et al., 2015; Zhang & Wu, 2022). FDI enriches the capital resources available for independent innovation and research and development within manufacturing firms, providing local enterprises with a solid foundation for growth. This financial support allows them to focus on reform and innovation instead of merely worrying about survival and funding issues, significantly enhancing their independent innovation capabilities and technical proficiency. Additionally, FDI strengthens these companies' ability to invest in foreign technologies, high-tech capital goods, and intermediate inputs necessary for innovative research and development. Given that research and development, design, and high-tech production in the upstream of the global value chain often demand substantial capital, FDI offers crucial financial backing for companies aiming to ascend the global value chain (Tang & Zhang, 2018). This support directly addresses the

issue of low-end lock-in within the global value chain and fosters the overall upgrading of the domestic industry.

In addition, foreign direct investment (FDI) can significantly enhance the productivity of domestic enterprises (Mao & Fang, 2020; Sugiharti et al., 2022). Generally, the productivity of foreign-owned firms surpasses that of the manufacturing industry as a whole, and those with higher productivity are often engaged in more value-added segments of the global value chain (Ma et al., 2017). FDI fosters the gradual establishment of comparative advantages in the trade of capital- and technology-intensive products while promoting the accumulation of high-tech human capital (Emako et al., 2023; Liang, 2017). These factors are conducive to the upgrading of manufacturing enterprises. Consequently, firms with higher productivity are more likely to ascend the global value chain, indicating that FDI propels firms upward in the global value chain by enhancing productivity, thus helping them overcome the low-end lock-in effect.

To maximize the benefits of foreign direct investment (FDI) in upgrading China's automobile industry, it is crucial to attract high-quality investments that meet local needs. Promoting collaboration between local firms and foreign enterprises, alongside a rigorous screening process for incoming FDI, will ensure that investments provide significant technological and service advantages. Establishing a tracking mechanism will further enhance the quality of these investments, thereby strengthening FDI's moderating role and helping to overcome low-end lock-in effects.

4.6 Mediating Effect Results of Technological Innovation on Global Value Chain and Industry Upgrading

A regression analysis was conducted based on Model 3 (equations 3.3-3.5) to examine the mediating effect of technological innovation on the relationship between the

global value chain and the upgrading of China's automobile industry. This analysis aimed to determine whether the global value chain inhibits the upgrading of China's automobile industry by influencing technological innovation. Table 4.6 displays the results of the regression estimation regarding the mediating effect.

According to the results of the mediating effect, the P value of AR(1) is less than 0.1, and the P value of AR(2) is greater than 0.1, indicating that there is no autocorrelation problem in the perturbation term. In addition, the P value of Hansen's test is greater than 0.1, indicating that there is no problem with over-identification of instrumental variables; that is, the mediating model is valid.

In this thesis, the results were analyzed concerning the mediating effect analysis method of Li et al. (2022) and Yang et al. (2023). In Table 4.6, Column (1) is the result of the benchmark regression of the mediating effect as we can see from Column (1) that GVC decreases the upgrading of China's automobile industry by 1.2088% when GVC is increased by 1%, proving the total effect of GVC on the upgrading of China's automobile industry. Column (2) verifies whether GVC affects TI. In column (2), the coefficient of GVC is significantly negative (-4.6132), indicating that the increase of GVC can reduce the technological innovation of China's automobile industry. Column (3) verifies whether TI can significantly affect the upgrading of China's automobile industry. The results of Column (3) show that the coefficient of TI is significantly positive (0.1364), suggesting that the rise of technological innovation enhances the upgrading of China's automobile industry. The above results confirm that GVC can inhibit the upgrading of China's automobile industry by inhibiting technological innovation.

Table 4.6: Mediating Effect Results

Variable	Upgrade	TI	Upgrade
	Column (1)	Column (2)	Column (3)
L1.Upgrade	0.7903*** (0.0299)		0.7311*** (0.0279)
L1.TI		0.9458*** (0.0592)	
GVC	-1.2088*** (0.3798)	-4.6132*** (1.1745)	-1.3075*** (0.3472)
TI			0.1364*** (0.0206)
AGG	0.5736*** (0.0245)	0.2963** (0.1242)	0.6123*** (0.0225)
HC	0.4880*** (0.0880)	1.1292*** (0.3273)	0.3632*** (0.1208)
GOV	2.2982*** (0.7074)	-5.1680** (2.4694)	2.6732*** (0.6983)
FDI	-0.0106 (0.0217)	0.2910*** (0.0717)	-1.1319*** (0.0202)
Constant	-3.6033*** (0.6466)	-6.3508** (2.9543)	-2.4283*** (0.8509)
Number of groups	28	28	28
Number of instruments	27	16	27
AR(1)	0.036	0.096	0.036
AR(2)	0.387	0.845	0.453
Hansen	0.173	0.112	0.172

Notes: 1. Figures in parentheses are standard errors. 2. ***, ** and * indicates significant at 1% 、 5% and 10% level of significance.

This study finds that participation in global value chains inhibits the upgrading of China's automobile industry by restricting technological innovation. A reasonable

explanation for this is that China's automobile industry, when embedded in global value chains, is often controlled by developed countries in terms of independent research and development channels, thereby remaining locked in lower-end segments. Additionally, reliance on global value chains diminishes the drive for technological innovation within China's automotive sector. Both factors contribute to stifling technological innovation (Gereffi et al., 2005; Shen & Zheng, 2020; Wang & Lu, 2019).

Technological innovation is a crucial positive factor that promotes industrial upgrading (Aboal et al., 2015; X. Liu et al., 2023). In the context of China's unique industrial environment, characterized by rapid development yet severe global competition, the lack of domestic innovation is particularly detrimental. In the Chinese automotive industry, the rise of electric vehicles exemplifies this trend. Domestic manufacturers have embraced advancements in battery technology and intelligent driving systems, significantly enhancing vehicle performance and energy efficiency. This shift not only boosts the competitiveness of Chinese automakers in the global market but is also vital for the upgrading of the Chinese automotive industry. Consequently, the embedding in global value chains inhibits technological innovation, which, in turn, hampers industrial upgrading. This underscores the important mediating role of technological innovation within the relationship between global value chains and the upgrading of China's automobile industry. Specifically, given China's distinct economic landscape, which is marked by a burgeoning market and a high dependency on foreign technologies, the failure to cultivate a strong domestic innovation ecosystem could limit the automotive sector's ability to upgrade effectively.

4.7 Dynamic Threshold Analysis Result of Human Capital on Industrial Agglomeration and Industry Upgrading

To verify the threshold effect of human capital on the influence of industrial agglomeration on the upgrading of China's automobile industry, this study employs the dynamic threshold panel regression model proposed by Seo et al. (2019) to analyze panel data from 28 provinces in China. The analysis investigates how industrial agglomeration impacts the upgrading of China's automobile industry at different levels of human capital. Based on Model 4, regression analysis was conducted, and the dynamic panel threshold model's results in this thesis are presented by referring to the presentation of threshold effect results of Cao et al. (2023) and Lee et al. (2023), as shown in Table 4.7:

The primary regression findings indicate a nonlinear relationship between industrial agglomeration (AGG) and China's automobile industry upgrading (Upgrade) when the human capital (HC) threshold is considered. The threshold value of HC is 8.5099, which falls within a significant 95% confidence interval ranging from 7.9338 to 9.0859. This suggests the existence of a threshold effect in the relationship. Additionally, the p-value from the linearity test is statistically significant at the 1% level, confirming the validity of the threshold relationship.

As observed in Table 4.7, AGG positively influences Upgrade when HC is less than 8.5099, but this effect is not statistically significant. In contrast, when HC exceeds 8.5099, AGG significantly enhances Upgrade. Specifically, at HC levels above 8.5099, the coefficient for AGG is 0.8348, which is significant at the 1% level. This indicates that the impact of AGG on Upgrade is both positive and significant only when the HC variable surpasses the threshold.

Table 4.7: Dynamic Panel Threshold Results

Variable	Upgrade	Upgrade
	Lower Regime	Upper Regime
Threshold value	8.5099*** (0.2939)	
L1.Upgrade	0.2360*** (0.0329)	-0.1921*** (0.0312)
AGG	0.0466 (0.0683)	0.8348*** (0.1133)
HC	-0.0513 (0.2890)	2.6228*** (0.3673)
Constant		-23.6507*** (3.0658)
Number of provinces	28	
Bootstrap p-value for linearity	0.000	
95% confidence interval	[7.9338, 9.0859]	

Notes: 1. Figures in parentheses are standard errors. 2. ***, ** and * indicates significant at 1% 、 5% and 10% level of significance.

This finding reinforces the arguments made by scholars such as Zhang and Guo (2025) who emphasize the critical role of skilled human capital in facilitating the benefits of industrial agglomeration in China. In the context of the Chinese automobile industry, the significance of human capital becomes even more apparent. As the industry transitions towards electric vehicles and intelligent manufacturing, the demand for highly skilled workers who can innovate and implement new technologies is paramount.

Industrial agglomeration can promote the dissemination of knowledge and technology among enterprises, but such dissemination requires a certain level of skilled

human capital as a basis. If the level of human capital in the region is not enough to understand and apply such knowledge and technology, the promotion effect of industrial agglomeration on industrial upgrading will be limited. Moreover, the improvement of human capital can improve labor productivity, thereby reducing production costs, improving product quality, and enhancing the competitiveness of enterprises. If the level of skilled human capital is low, enterprises may not be able to effectively improve production efficiency, which will affect industrial upgrading (Dai, 2014; Li et al., 2021; Xie, 2018). Therefore, under the low level of skilled human capital, industrial agglomeration does not significantly promote the upgrading of China's automobile industry. Under a high level of human capital, industrial agglomeration can significantly promote the upgrading of China's automobile industry.

The findings clearly indicate that enhancing skilled human capital is crucial for maximizing the benefits of industrial agglomeration on the upgrading of China's automobile industry. To achieve this, policymakers should prioritize investments in talent development, particularly in research and development. Strengthening partnerships between universities and automobile firms can facilitate the cultivation of innovative talent equipped with high-end technical skills. Additionally, actively recruiting top-tier talent from abroad and providing ongoing training for the current workforce will ensure that employees remain adept in the latest technologies. By fostering a skilled labor force, China can unlock the full potential of industrial agglomeration, driving significant advancements in the automobile industry.

4.8 Results of Robustness Tests

The reliability and robustness of the empirical findings were systematically verified through a comprehensive series of sensitivity analyses employing alternative model specifications and variable combinations, with the key results summarized in Table 4.8.

Initially, the baseline model was re-estimated, excluding the moderating variables (government and FDI) while retaining the core control variables of human capital and technological innovation. As presented in Column 1, both industrial agglomeration and GVC maintain their statistical significance and expected signs, with coefficients approximating the baseline estimates. This consistency confirms that the core findings remain robust regardless of the inclusion of moderating variables.

The analysis was extended by incorporating environmental regulation as an additional control variable alongside human capital and technological innovation, while maintaining the exclusion of moderating variables. Environmental regulation was measured by the ratio of industrial pollution control investment to industrial value-added. The results in Column 2 show that after incorporating environmental regulation as an additional control variable, both industrial agglomeration and GVC maintain their direction and statistical significance consistent with the baseline model.

A more comprehensive robustness check was conducted by estimating a full model that incorporated both moderating variables (government intervention and FDI) along with all three control variables (human capital, technological innovation, and environmental regulation). The results presented in Column 3 continue to support the main conclusions; the inclusion of moderating variables and additional control variables did not materially alter the primary relationships.

Table 4.8: Robustness Tests Results

Variable	Column 1	Column 2	Column 3	Column 4	Column 5
	Excluding Moderating Variables	Adding Environmental Regulation	Full Model	Fixed Effects	Random Effects
L1.Upgrade	0.7116*** (0.0299)	0.6684*** (0.0405)	0.8322*** (0.0447)		
AGG	0.8234*** (0.0701)	0.8715*** (0.0847)	0.5103*** (0.0892)	0.6735*** (0.1328)	0.5257*** (0.1241)
GVC	- 3.4255***	-3.0567*** (0.4442)	-1.5858*** (0.4945)	-2.2932*** (0.7423)	-1.9514*** (0.6654)
TI	0.1819*** (0.0176)	0.1940*** (0.0189)	0.1095*** (0.0168)	0.0516 (0.0436)	0.0982** (0.0429)
HC	0.3592*** (0.0935)	0.4107*** (0.0994)	0.3089* (0.1558)	1.0564*** (0.2578)	0.7675*** (0.1978)
ER		0.0750** (0.0340)	0.1645*** (0.0152)		
GOV			- 3.7571**	6.1778** (3.0207)	9.1875*** (2.2701)
FDI			-0.0528* (0.0286)	-0.0285 (0.0583)	-0.0624 (0.0568)
Constant	-1.3579* (0.7774)	-1.4011* (0.7762)	-2.0897* (1.1867)	-9.8347*** (1.8667)	-7.1727*** (1.5177)
Number of groups	28	28	28		
Number of instruments	26	26	27		
AR(1)	0.044	0.070	0.042		
AR(2)	0.549	0.516	0.525		
Hansen	0.165	0.163	0.164		
Hausman Test				0.0000	

Notes: 1. Figures in parentheses are standard errors. 2. ***, ** and * indicates significant at 1% 、5% and 10% level of significance.

Potential estimation issues were examined through the comparison of fixed-effects and random-effects specifications. While the Hausman test strongly favored the fixed-effects model ($p < 0.01$), Column 4 and Column 5 demonstrate that both estimation approaches produced qualitatively similar results for key variables. This methodological consistency across different estimation techniques further strengthens confidence in the empirical findings.

4.9 Summary

Chapter 4 provides a comprehensive analysis of all the results in this study. The chapter begins with an introduction that sets the context for the analysis, followed by descriptive statistics that provide an overview of the dataset. The chapter delves into a detailed analysis of TFP through the application of Data Envelopment Analysis (DEA), revealing overall trends, annual variations, and regional disparities. Furthermore, the results from the Generalized Method of Moments (GMM) analysis validate the significant influence of industrial agglomeration and global value chains on the upgrading of China's automobile industry. The study also investigates the moderating roles of government support and foreign direct investment and the mediating effect of technological innovation, thereby enhancing the understanding of these dynamic relationships. Additionally, the threshold analysis examines how the impact of industrial agglomeration on the upgrading of China's automobile industry varies across different levels of human capital. Collectively, these findings provide practical implications for policymakers and underscore the study's uniqueness within the context of China's economic landscape.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Results

This section summarizes the key conclusions of the study, organized according to the main objectives outlined in Chapter 1. In 5.2.1, the results regarding total factor productivity (TFP), measured using the DEA-Malmquist index, are presented to assess the upgrading of China's automobile industry. Section 5.2.2 discusses the impact of industrial agglomeration on the upgrading of the automobile industry, while Section 5.2.3 focuses on the effects of the global value chain on this process. Additionally, 5.2.4 examines how government support moderates the relationship between industrial agglomeration and upgrading. In 5.2.5, the findings related to the moderating effect of foreign direct investment (FDI) on the relationship between the global value chain and the industry's upgrading are analyzed. Section 5.2.6 explores the mediating role of technological innovation in the influence of the global value chain on upgrading, and finally, Section 5.2.7 details the threshold effect of human capital in the connection between industrial agglomeration and the upgrading of China's automobile industry.

5.1.1 Results of Total Factor Productivity as an Indicator for the Upgrading China's Automobile Industry

This research assesses the upgrading of China's automobile industry using total factor productivity (TFP), measured through the DEA-Malmquist index with panel data from 28 provinces between 2000 and 2020. The average TFP growth rate for the industry during this period is 6.3%, although negative growth was observed in specific years: 2007-2008, 2010-2011, 2011-2012, 2017-2018, 2018-2019, and 2019-2020. The decline in 2007-2008 can be

attributed to the global economic crisis, while the reductions in 2010-2012 were likely due to low production efficiency and insufficient R&D support. The negative growth from 2017 to 2020 was linked to the removal of vehicle purchase tax incentives in 2018 and unfavorable economic conditions. Conversely, TFP growth was notably high in 2015-2016 and 2001-2002, with rates of 59.1% and 34.6%, respectively.

Regionally, while TFP in the automobile industry has generally increased, some provinces, like Gansu, saw slight declines, with most others surpassing 1% growth. Provinces such as Beijing, Tianjin, Hebei, and Guangdong, which host major automobile manufacturers, recorded TFP growth above the national average. Inner Mongolia and Xinjiang achieved higher growth rates mainly due to advancements in the new energy vehicle sector. In summary, although China's automobile industry shows positive progress, instances of negative TFP highlight the need for continued development to support industry upgrading.

5.1.2 Impact of Industrial Agglomeration on the Upgrading of China's Automobile Industry

This research investigates the impact of industrial agglomeration on the upgrading of China's automobile industry, with the degree of agglomeration measured by the location entropy index. The empirical findings demonstrate that industrial agglomeration plays a significant role in promoting the upgrading of China's automobile industry; specifically, a higher degree of agglomeration is more conducive to this upgrading process. Industrial agglomeration facilitates the division of labor and specialization, leading to economies of scale and external benefits for enterprises. Additionally, it fosters knowledge and technology spillovers, which further enhance the upgrading of the automobile industry.

5.1.3 Impact of Global Value Chain on the Upgrading of China's Automobile Industry

This research examines the impact of global value chain on the upgrading of China's automobile industry, with the degree of embeddedness in the GVC assessed through the global value chain status index. Empirical results indicate that a higher degree of embeddedness significantly inhibits the upgrading of China's automobile industry. This negative relationship arises because such embeddedness often leads to dependence on the GVC system, adversely affecting firms' capacity for independent innovation and the development of new technologies and products. Furthermore, it may result in a "low-end lock-in" effect, where developing countries, lacking core technologies, become confined to low-profit manufacturing processes dictated by developed nations, thus hindering industrial upgrading.

5.1.4 Result of Moderating Effect of Government support on the Relationship Between Industrial Agglomeration and Upgrading of China's Automobile Industry

This research investigates the moderating effect of government support on the relationship between industrial agglomeration and the upgrading of China's automobile industry. Empirical findings indicate that government support plays a significant moderating role; specifically, insufficient government support diminishes the positive impact of industrial agglomeration on upgrading. To enhance the role of industrial agglomeration in facilitating growth, it is essential to elevate government support levels in China. Strong government support can address market failures during industrial agglomeration and create a favorable environment, amplifying its positive effects on industrial upgrading. The government's moderating influence can be summarized as improving market mechanisms,

providing public goods and services, formulating and implementing industrial cluster policies, and fostering an environment conducive to industrial advancement.

5.1.5 Result of FDI Moderating Effect on the Connection Between Global Value Chain and the Upgrading of China's Automobile Industry

This research examines the moderating effect of foreign direct investment (FDI) on the relationship between global value chain and the upgrading of China's automobile industry. The calculation method for FDI data is multiplying the proportion of each province's automobile output in GDP by the total amount of foreign direct investment in the entire industry. Empirical results indicate that FDI significantly moderates this relationship; specifically, high levels of FDI in China's automobile sector mitigate the negative effects of GVC on industrial upgrading. FDI helps address the capital shortage faced by local enterprises, providing essential funding for independent innovation and research and development. Additionally, it enhances these firms' capacity to acquire the intermediate inputs necessary for adopting foreign technologies, ultimately aiding in overcoming the low-end lock-in issue within the global value chain. This influx of capital and resources promotes the upgrading of China's automobile industry.

5.1.6 Result of Technological Innovation Mediating the Impact of Global Value Chain on the Upgrading of China's Automobile Industry

This thesis investigates the mediating effect of technological innovation on the relationship between global value chain (GVC) and the upgrading of China's automobile industry. Empirical results indicate that technological innovation significantly mediates this relationship. Specifically, the GVC inhibits industrial upgrading by suppressing technological innovation. When embedded in the GVC, Chinese enterprises are often controlled by dominant firms in developed countries, limiting their access to new

technologies and confining them to low-end segments. Furthermore, deep integration into the GVC fosters dependence on foreign technology, diminishing motivation for independent research, development, and innovation. As a result, this dependence stifles technological innovation, which is essential for industrial upgrading. Thus, the analysis concludes that embedding in global value chains impedes technological innovation and, consequently, the upgrading of China's automobile industry.

5.1.7 Result of the Threshold Effect of Human Capital in the Impact of Industrial Agglomeration on the Upgrading of China's Automobile Industry

This research examines the threshold effect of human capital on the relationship between industrial agglomeration and the upgrading of China's automobile industry. The findings reveal that human capital is a crucial threshold factor: industrial agglomeration promotes upgrading when it is below 8.5099, but this effect is not significant. Conversely, when human capital exceeds this threshold, the impact becomes significant. Agglomeration fosters knowledge dissemination and technology sharing, benefiting from sufficient human capital for effective absorption. Insufficient human capital limits these benefits, while enhanced human capital improves employee skills and production efficiency. In agglomerated environments, skilled workers better utilize advanced machinery to improve product quality. Therefore, industrial agglomeration has limited effects on upgrading at low human capital levels, with significant enhancements occurring only at higher levels.

5.2 Policy Implications

5.2.1 Strengthening the Agglomeration of the Automobile Industry

Both theoretical and empirical research indicate that industrial agglomeration can drive industrial upgrading. To accelerate the upgrading of China's automobile industry, promoting clustered development within the sector by establishing industrial clusters with

positive interactions and clear competitive advantages is essential. Leveraging China's geographical benefits can create a conducive environment for face-to-face communication among enterprises, reducing communication barriers and facilitating the free flow of resources. This approach will lower transportation costs, expand knowledge spillover effects, and enhance resource utilization, ultimately driving industrial upgrading.

Additionally, improving the planning and construction of industrial parks is vital for guiding cluster development. Special attention should be given to aligning and coordinating the industrial chain by positioning upstream and downstream production links to enhance efficiency. Moreover, capitalizing on the leading roles of key enterprises, such as FAW, Dongfeng, and SAIC, can further foster innovation. These firms should focus on breakthrough R&D in core technologies while outsourcing parts production and assembly processes to small and medium-sized companies, thus integrating more supporting enterprises into a cohesive supply chain. This strategy will improve capabilities and efficiency across the entire industrial chain, unleashing significant potential for collaborative production and innovation.

5.2.2 Attract Foreign Direct Investment into the Country

Foreign direct investment (FDI) is crucial for moderating the global value chain's impact on the upgrading of China's automobile industry. High levels of FDI can mitigate negative effects and enhance industry advancement by addressing capital shortages in local enterprises. This fosters independent innovation and strengthens their positions within the global value chain, helping to overcome low-end lock-in issues. Therefore, attracting high-quality foreign investment and promoting technical exchanges between local firms and foreign-funded companies is essential.

To optimize FDI benefits, the introduction process should involve careful screening to align incoming investments with the specific characteristics of enterprises. This approach can enhance the inflow of foreign capital in technology and services while establishing a comprehensive database of investment projects. Additionally, implementing a tracking and evaluation mechanism will help ensure investment quality. By prioritizing superior foreign capital, the automobile industry can maximize the positive impact of FDI on its upgrading efforts.

5.2.3 Enhancing Government Support for the Automobile Industry

The government plays a crucial role in moderating the relationship between industrial agglomeration and the upgrading of China's automobile industry. Low government support can diminish the positive effects of agglomeration on industry advancement, making it essential to enhance government support to leverage this moderating effect fully. The government must actively foster industrial agglomeration to effectively address market failures, as reliance on market mechanisms alone is insufficient.

Increased investment is necessary, particularly in science and technology, to enhance financial support for the automotive sector and provide dedicated research funding to universities and research institutions. Additionally, the government should facilitate establishing an automobile innovation system by creating platforms for cooperation within industry clusters, promoting an enterprise-centered collaboration system that integrates industry, academia, and research. Optimizing the business environment and promoting coordinated regional development are also vital. This can be achieved by improving infrastructure, enhancing public goods supply, and facilitating the unification of regional factor and automobile product markets.

5.2.4 Increase Skilled Human Capital

Human capital exhibits a threshold effect on the impact of industrial agglomeration on the upgrading of China's automobile industry. When human capital is at a low level, industrial agglomeration does not significantly promote the upgrading of the industry. It is only at a high level of human capital that industrial agglomeration can meaningfully enhance the upgrading of China's automobile industry. Therefore, improving the human capital level within this sector is essential.

To achieve this, increased investment in the development of innovative talent is crucial. Strengthening the R&D talent pool is a key strategy for Chinese automobile enterprises. Collaborations between academic institutions and businesses, along with skills training through automotive R&D centers, can enhance talent cultivation, particularly in high-end technical expertise. This approach will empower research teams within automobile enterprises to drive technological innovation. Additionally, intensifying the recruitment of high-level talent is important. Domestic enterprises should establish long-term partnerships with overseas industry associations and international automobile companies to attract top-tier professionals. Finally, enhancing the education and training of current employees is essential to ensure their skills remain aligned with the latest industry technologies, thereby advancing the overall capabilities of the workforce and the industry as a whole.

5.3 Limitations of the Study

This research examines the impact of industrial agglomeration and the global value chain on the upgrading of China's automobile industry. It assesses the role of government support as a moderator in the relationship between industrial agglomeration and the upgrading of the automobile industry in China, as well as the moderating effects of foreign direct investment (FDI) on the relationship between the global value chain and the upgrading of the industry. Furthermore, the study explores whether the global value chain inhibits the

upgrading of China's automobile industry by affecting technological innovation. Additionally, it explores whether human capital serves as a threshold variable in the process by which industrial agglomeration impacts the upgrading of the automobile industry. Utilizing panel data from 28 provinces across China, this research employs GMM and dynamic panel threshold models for comprehensive analysis. Despite obtaining significant results through empirical analysis and proposing recommendations based on these findings, there are still some limitations in this study that require further improvement:

On one hand, in terms of data scope, due to availability, Tibet, Qinghai, and Ningxia are partially missing, so Tibet, Qinghai, and Ningxia are not included in the study. This exclusion may introduce a geographical bias in the analysis, as these regions may have unique characteristics that could affect the results. In terms of data coverage, since the latest version of the OECD-TiVA database is the 2023 version, and the data is only updated to 2020, the data range used in this paper can only be 2000-2020, which is a shortcoming of this study as it does not capture the most recent developments in the industry.

On the other hand, this research is based on a relatively macro perspective, which studies the situation of the automobile industry in China's provinces and cities, and does not study the situation of a prefecture-level city in depth, nor does it analyze the situation at the level of automobile enterprises from the perspective of enterprises, that is, it does not study at the micro level. This macro focus limits the ability to capture the nuances of local market dynamics and the specific strategies employed by individual firms, which could provide additional insights into the upgrading process.

5.4 Suggestions for Future Research

Building on the limitations identified in this study, future research should aim to address the geographical bias by including data from all regions of China, including those

currently excluded. This would provide a more comprehensive understanding of the national dynamics of industrial agglomeration and global value chain in the automobile industry. Additionally, extending the data range to include more recent years would allow for an analysis of the industry's current trends and challenges.

Moreover, future studies could benefit from adopting a multi-level approach, combining macro and micro perspectives. This could involve in-depth case studies of specific prefecture-level cities or enterprises to explore how local conditions and firm strategies interact with broader industrial trends. Such an approach would enrich the understanding of the complex processes driving the upgrading of China's automobile industry.

Furthermore, future research should explore additional moderators and threshold variables to refine the theoretical framework linking industrial agglomeration, global value chain (GVC) participation, and industrial upgrading. Similarly, threshold variables such as environmental regulations and green technology adoption may influence how GVC integration facilitates or hinders upgrading. Investigating these elements would provide deeper insights into the dynamics of industrial upgrading, especially in light of China's dual carbon goals and the global shift toward sustainable manufacturing. This extension would enhance the model's explanatory power and offer more nuanced policy implications for promoting high-quality industrial development.

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