A Quantitative Analysis of Global Value Chains: Focusing on the Chinese Economy

by

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Chapter 1 General Introduction

1.1 Background

The emergence and development of global value chains (GVCs) have dramatically changed the organization of global production in recent decades, making a deep and lasting impact on international trade patterns and labor market structures. With the reduction of transportation and communication costs, the acceleration of technological improvements, and the fall of political and economic barriers to trade, an increasing number of firms now organize production activities on a global scale. The production process of goods has been split into multiple stages and relocated to various countries. Nowadays, most products are more likely to be labelled as “Made in the World” rather than made in a specific country. A variety of terms has been used to refer to this phenomenon: “production fragmentation,” “vertical specialization,” “foreign outsourcing,” and “offshoring.” The expansion of GVCs is probably the most remarkable feature of globalization.

The prevalence of production fragmentation has boosted the trade of intermediate goods. According to UNCTAD 2015, the trade of intermediate goods rose from $4 trillion in 2004 to almost $8 trillion in 2014, with an average annual growth rate of 8 percent. The increased trade of intermediate goods reflects the fact that GVCs have become more complex. Trade flows can be amplified because the value of parts and components that cross national borders multiple times for further processing will be counted several times by traditional trade statistics. In addition, production activities in many countries are increasingly dependent on imported intermediate inputs. There is a growing awareness that traditional trade statistics may not accurately capture how a country participates in GVCs. Misleading results may arise because traditional trade statistics are designed to measure the gross trade flows of final products, while the trade of intermediate goods is now expanding at a faster rate. Different from the traditional conceptualizations of international trade, which focus on bilateral transactions that involve only two countries (an exporting country and an importing country), production processes within GVCs often span more than two countries.

The performance of firms within GVCs is also a dominant issue in the study of international trade. In the real world, the firms directly take part in international trade rather than countries and industries. International trade research has begun to put more focus on firms and products than on industries and countries. As a wide range of micro-level data becomes available, it has become feasible for empirical studies to investigate the performances of firms within GVCs. Many studies find that firms participating in international trade are larger, are more productive, are more skill- and capital-intensive, and they pay higher wages than do non-trading firms. These empirical findings are explained by the theoretical work of Melitz (2003), who provides remarkable insights into firm heterogeneity in international trade, arguing that firms with high productivity are more likely to survive and increase their exports. On the other hand, firms with low productivity shrink or exit.

China has increasingly participated in GVCs, and it has been recognized as an important manufacturing center and exporter in the world. China's World Trade Organization (WTO) entry in 2001 provided the country with a good opportunity to be integrated into the global economy. China has become the largest exporter of goods in the world since 2009. The surging trade flows have been accompanied by the upgrading of China's export structure, with increased export shares in electrical machinery products and decreased shares in agricultural and apparel products. However, Koopman, Wang, and Wei (2008) document that China's production and exports rely heavily on imported intermediate inputs from other countries. Even though China seems to have changed its comparative advantage dramatically on the surface, a closer examination reveals that it still specializes in labor-intensive goods (Amiti and Freund 2008). The production fragmentation is posing new challenges to the analysis of international trade in the context of GVCs. Measuring the impacts of China's participation in GVCs has drawn considerable attention in empirical studies.

In addition, the rise of GVCs affects the labor market. A large body of empirical studies has found that international sourcing or imported content has an adverse impact on local labor market outcomes (e.g., Feenstra and Hanson 1997). The increased foreign contents embedded in the production of GVCs reflect the fact that many multinational firms offshore some production activities that were previously performed at home to take advantage of low labor costs. These products are subsequently shipped back home in the form of imported intermediate inputs. The employment reduction is more pronounced in some sectors that intensively require less skilled labor. Recent studies have begun to turn their attention to the effects of imported inputs on the skill structure of labor demand. Timmer et al. (2014) find a declined value-added share of low-skilled labor and an increased value-added share of high-skilled labor in many countries. This trend aligns with the circumstance that firms in advanced countries tend to concentrate on skill- and capital-intensive production activities while sending labor-intensive production processes to developing countries. Because less skilled labor-intensive industries still account for a large part of industrial activities, offshoring may decrease the demand for domestic labor. Nowadays, the prevalence of GVCs has led to an ongoing debate about the impact of import competition from developing countries on the labor market of advanced countries (e.g., Autor, Dorn and Hanson 2013; Pierce and Schott 2016).

In brief, GVCs have played an important role in international trade, global production, and the labor market. Studying GVCs provides insights into how a country participates in international trade and gives us a deeper understanding of the relationship between a firm's performance and the labor market.

1.2 Outline

The rest of this thesis proceeds as follows. Chapter 2 provides an overview of the emergence and development of GVCs and the factors that contribute to the prevalence of GVCs. Previous studies have used various empirical approaches to measure how a country participates in GVCs. First, using gross trade statistics from the UN Comtrade database, we illustrate the development of the electrical machinery industry in East Asia because this industry is a typical example of production fragmentation. Second, we explore the status of production fragmentation in China's electrical machinery industry by measuring the exports and imports of intermediate goods in electrical machinery industry. Third, case studies of Chinese electronics firms are presented. Fourth, we provide an outline of how to apply input–output tables in the measure of value-added content in trade. Finally, we summarize how firm-level data are used in the previous literature to measure the performance of firms in GVCs.

Chapter 3 addresses the question of whether the existing evidence based on traditional trade statistics describes the actual state of China's exports. This study measures the domestic value-added (DVA) of China's exports following Koopman, Wang, and Wei (2014). Previous studies calculate the DVA of exports for specific benchmark years. Using the World Input–Output Database, our results reveal the long-run trend in the DVA of China's exports during the period 2000–2014. We calculate the DVA share to examine the gap between the DVA and gross exports across industries. The result reveals that the DVA share of China's high technology manufacturing exports is lower than that of other industries. The next question this chapter addresses is what factors affect the change in the DVA of exports. Recent studies have found that the DVA of China's exports is associated with the substitution of domestic intermediate inputs for imported materials. However, few studies examine the effects of labor and capital income on the change in the DVA of exports. This chapter uses structural decomposition analysis (SDA) to break down the change in the DVA of China's exports into nine determinants. We find that the increase in the DVA of China's exports is associated with the substitution of labor income for capital income and the growth in labor productivity and wage per person. In addition, the SDA result shows that the changes in the DVA of Japanese and US exports are associated with the substitution of imported materials for domestic intermediate inputs.

Chapter 4 addresses the question of how the change in firm-level productivity affects the export performance of Chinese firms. Bernard, Redding and Schott (2011) introduce the multi-product firm model to show that high-productivity firms are more likely to enter the exporting market, supply a larger number of products to each market, and serve a wider range of destination countries. Is the export performance of Chinese firms consistent with this theoretical prediction? We apply the framework of the multi-product firm model to examine the relationship between firm-level productivity and the performance of Chinese exporters. The total export growth is decomposed into extensive and intensive margins. Specifically, the extensive margin of exports includes the number of exported products and export destination countries, while the intensive margin of exports accounts for the average firm-level exports per product-country. In addition, Chinese exporters choose different trade regimes to participate in international trade. However, few studies apply the multi-product firm model to compare the export performance among firms adopting different trade regimes. This chapter divides the Chinese exporters into three categories: firms only engaging in ordinary trade, firms only engaging in processing trade, and firms engaging in both ordinary and processing trade. Using Chinese firm-level production and trade data during the period 2000–2006, we confirm that firms with higher productivity export more products, serve a wider range of destination countries, and have larger average firm-level exports per product-country. We also find that the change in firm-level productivity has various effects on the extensive and intensive margins of exporters engaging in different trade regimes.

Chapter 5 focuses on the question of how imported inputs in production affect the skill structure of labor demand. Previous studies usually measure direct imports to capture the extent to which the production of a particular country relies on imported content. However, as the intermediate inputs cross national borders several times within the increasingly complex GVCs, such an indicator becomes less reliable in reflecting how value-added is exchanged between countries. This chapter uses international input–output tables to capture the cross-country and inter-sector production linkages in GVCs. The labor demand is measured by the cost share of domestic labor that is embedded directly and indirectly into final goods. We also estimate the cost shares of domestic high-skilled, medium-skilled, and low-skilled labor, respectively. The foreign value-added (FV) share is an indicator of the reliance of production on imported inputs. In addition, many studies are concerned with how the skill structure of labor demand in advanced countries is affected by direct imports from developing countries. Using input–output tables, we divide the FV share according to different sourcing origins, which include the FV share originating from advanced and developing countries, respectively. The division of the FV share is to measure how labor demand is affected by imported inputs that are sourced from advanced and from developing countries. The estimation results confirm that an increase in the FV share reduces the cost shares of domestic labor of all skill levels. We also find that the FV originating from advanced and developing countries exerts different effects on the demand for domestic labor. Finally, in comparison with the FV share, this chapter also estimates traditional indicators that only capture the direct imports of intermediate goods for production.

In the final chapter, we conclude the thesis and outline some policy implications.

Chapter 2 An Overview of Measuring the GVCs

2.1 Introduction

Recent decades have witnessed the development of global value chains (GVCs), in which the production process of final goods is broken down and scattered across various countries; the proliferation of GVCs is regarded as an important driving force to boost economic growth in East Asia. Multinational firms have constructed international production and distribution networks in this region, the most common example of which is the electrical machinery industry. Several studies have documented that the total export and import shares of electrical machinery products in each East Asian country has substantially increased. China has become an important production hub for electrical machinery products because the country is rapidly integrated into GVCs. However, the products made in China rely heavily on imported intermediate inputs, particularly from other Asian countries. Measuring the participation of China in GVCs has become a critical empirical issue that requires a new framework to quantify the linkages in GVCs between China and other countries. Various approaches have been applied to illustrate the development of GVCs; most of these methods use customs data and case studies, while input–output tables and detailed firm-level data have recently been proposed to quantify the participation of GVCs. This chapter focuses on the drivers and empirical measures of GVCs. Section 2.2 provides an overview of the development of GVCs. Section 2.3 explains the main drivers behind the dramatic expansion of GVCs in recent decades. Section 2.4 surveys different methodologies used in the literature to map and measure GVCs. Traditional methodological approaches include case studies and international trade statistics on parts and components. In addition, this chapter provides a brief overview of how input–output tables and firm-level data were used to investigate GVCs during recent decades. The final section concludes.

2.2 The Rise of Global Value Chains

GVCs have significantly changed the international trade and production landscape. A value chain can be referred to as the “full range of activities that firms and workers do to bring a product from its conception to its end use and beyond” (Gereffi and Fernandez-Stark 2011). Generally, a value chain typically includes different kinds of activities, such as design, production, marketing, distribution, and after-sales services. These activities can be conducted within the same firm or divided among different firms. In recent decades, they increasingly spread over several countries, which explains why a value chain is viewed as "global."

International production networks across multiple countries are not a new phenomenon. The 18th century Industrial Revolution was dependent on triangular trade. Workers were shipped from Africa to the Americas to work on cotton plantations. They supplied raw cotton to British factories which produced textiles for the global market. Nevertheless, international trade in the 19th century could largely be represented by the trade of final products, such as Ricardo's example of British cloth for Portuguese wine. Examples also documented that middle-income British citizens could afford bread baked with the American wheat while sipping tea brewed from Chinese leaves and sweetened with Jamaican sugar. Everything is set on a tablecloth made of Indian cotton (Baldwin 2016). Baldwin (2011) labelled this phenomenon the "globalization's first unbundling," which means that factories were unbundled from consumers. This first unbundling was fueled by the reduction of transportation costs due to steam power development and subsequent advances in transportation technology. Communication costs, however, remained high during this period.

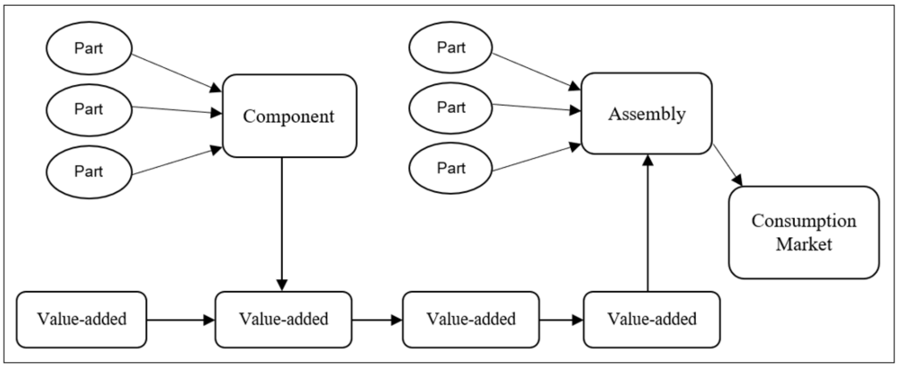
Rapid progress in information and communications technology (ICT) substantially reduces the cost of organizing complex activities over distances. The "globalization's second unbundling" has become prevalent since the 1980s (Baldwin 2011**)**. Production stages that previously performed in geographic proximity can now be located in different places without a significant loss of efficiency or timeliness. Production process is split and offshored to developing countries. To ensure that the offshored stages mesh seamlessly with those remaining onshore, multinational firms in advanced countries send some production processes abroad. As a result, the second unbundling is sometimes called the "global value chain revolution" (Baldwin 2011). In addition, working methods and product designs have changed in response to this spatial separation, thereby making production more modular. Recently, the scale of the second unbundling has not only been concentrated in the manufacturing sectors, but it has also spread to the service sectors.

Many GVCs have developed regionally, rather than globally, because there are still costs for the production offshoring (Baldwin and Venables 2010). The costs and unpredictable delays involved in intercontinental shipment and the activities of technicians and managers still matter. Early examples of large-scale offshoring can be traced back to the mid-1980s and was conducted over short distances. Multinational firms in the US put forward the Maquiladora

Program and created "twin plants," one in the US and one in Mexico; this program boomed in the 1980s, with employment growth of 20 percent annually from 1982–1989 (Feenstra and Hanson 1995). Moreover, GVCs started to spread in East Asia at about the same time. In Europe, GVCs were first promoted due to the European Union (EU) accession of Spain and Portugal in 1986 (Baldwin and Venables 2010).

Figure 2.1 illustrates a simplified GVC, which consists of intermediate-goods producers, final-goods assemblers, and consumers. Each cell represents a production stage at which value is added to a good, and each arrow is a physical movement of parts, components, or the good itself. These movements occur within a country or between firms in different countries. In the upstream of the GVC, the intermediate-good producer needs to source parts and components from other intermediate good producers; value is added to each production process. Finally, intermediate goods reach the factory for final assembly, which requires intermediate inputs from the intermediate-good producer. Thus, the product manufactured by final assembly contains the value-added sourced from both intermediate-goods producers and the final assembly itself.

Figure 2.1 The illustration of a simplified GVC



Source: Author's drawing, based on Baldwin and Venables (2013).

In reality, the structure of GVCs becomes increasingly complex because production processes are usually located in various countries. For example, iPhone assembly requires the collection of parts and components from hundreds of suppliers located in different countries. The label on the back of the iPhone body reads, "Designed by Apple in California, Assembled in China." The expression "assembled" is key, and it can be argued that iPhone production is possible due to worldwide cooperation of many firms from various countries. Apple's global management is given as a typical example for GVC organization. The importance of which country is responsible for producing and exporting products has declined. It is more important to examine which country accounts for more added-value embedded in the products.

2.3 Main Drivers of GVCs

There are several factors that contribute to the rise of GVCs. The production fragmentation is not new. Even though there were GVCs before the 1980s, technological improvement allowed production fragmentation to expand on a global scale. First, technological improvement has largely reduced trade costs since the 1990s thanks to the ICT revolution, which paved the way for the prevalence of global manufacturing. Trade costs refer to the total costs in each production stage, from the plant where the good is produced to the plant where the final product is assembled. For the trade of goods, trade costs contain land transport and port costs, freight and insurance costs, tariffs and duties, and costs related to non-tariff measures. Moreover, mark-ups by importers, wholesalers, and retailers are included in trade costs. For the trade of services, trade costs often refer to communication costs and non-tariff barriers. In addition, producers incur communication and coordination costs when spatially dispersed production sites need to be managed in a consistent way. Dramatic progress in ICT technology has lowered coordination and communication costs; in particular, development of the Internet, workflow software, and digital, mobile, personal, and virtual communication technologies have largely promoted the pervasiveness of production fragmentation. Furthermore, the availability of efficient and affordable logistics, transportation, and communication services supports the development of GVCs (Backer and Miroudot 2013).

Another important driver behind decreased trade costs is trade and investment liberalization (Amador and Cabral 2016). Reduced tariffs and multilateral agreements boost international trade. For example, tariff rates are declining globally due to the efforts of the WTO. Since the 1990s, tariff rates have substantially declined in low-income and middle-income countries; a reduction in tariff rates facilitates international dispersion of production processes. Moreover, the trade of intermediate goods and services has been promoted by international accords, such as the WTO Information Technology Agreement on computers, semiconductors, and a host of information technology (IT) products.

The demand side of the world economy has dramatically changed over the last decades (Backer and Miroudot 2013). Prominent economic growth in emerging economies, particularly in emerging Asian economies, has increased overall world demand and boosted international trade. Asia has played not just a role as the world’s factory. There are new consumers who can afford a broader range of products. As a result, trade in final goods and services has risen substantially.

Finally, many emerging countries have established export processing zones that aim to facilitate trade and foreign investment with the use of special administrative policies. These processing zones play an important role in the expansion of GVCs. In Asia, an early export processing zone was set up in Kandla, India in 1965, which was established as an export processing zone for the assembly of semiconductors. Export processing zones spread rapidly in many developing countries that regard them to be an integral part of their export-led growth strategies: In 2006, 3,500 export processing zones were operating in 130 countries, providing jobs for about 66 million people (WTO and IDE-JETRO 2011). Furthermore, the Chinese government implemented an export-oriented strategy in the 1980s. In order to attract foreign direct investment (FDI), China established special economic zones and export processing zones in some coastal provinces. In addition to Asia, export processing zones have become essential in many Latin American and African countries, which have launched policies to open their markets to foreign capital through export processing zones.

2.4 Measuring the Participation of GVCs

A country's participation in GVCs is measured through three kinds of widely used datasets: customs statistics at the product-level, input–output tables, and firm-level data. This section will first document the development of the electrical machinery industry in East Asia during the period 1993–2013. The sample countries or regions in East Asia refer to areas that include China, Hong Kong, Taiwan, Japan, South Korea, and five countries of the Association of Southeast Asian Nations (ASEAN): Singapore, Malaysia, Thailand, Indonesia, and Philippines. Export and import data are obtained from the United Nations Commodity Trade Statistics Database (UN Comtrade). In East Asia, China has become the largest manufacturing center for electrical machinery products. In order to assess the state of China's participation in GVCs, disaggregated trade data are used to identify the product groups of parts and components at the Harmonized System (HS) 4-digit and 6-digit levels. In addition, several case studies will then be used to illustrate the development of electronics firms in China and role of domestic firms in multinational firms' GVCs. Finally, a brief explanation of how input–output tables and firm-level data are used in recent studies will be provided.

2.4.1 Electrical Machine Industry in East Asia

Since the 1980s, a noteworthy development of intra-regional trade has been observed in East Asia. Because of the yen's appreciation against the US dollar, Japan's direct investment to Asian countries increased dramatically. At the same time, advanced Asian economies such as South Korea and Taiwan sought to improve their manufacturing technology and enhance the capacity of their technology-intensive industries. China and the ASEAN, which intended to catch up with Asian middle-income countries, shifted their policies from import substitution industrialization to export-oriented industrialization. From the mid-1980s in Malaysia and Thailand and from the early 1990s in Philippines, Indonesia, and China, they began to apply new strategies to attract FDI from the US, Japan, and other advanced countries. They started to accept as many foreign firms as possible and establish industrial clusters. In order to partially eliminate the negative effects of import-substituting industry protection, China and some ASEAN countries introduced a duty-drawback system, that is, the system of refunds of duties and indirect taxes on imported intermediate inputs that are produced for exports. Besides, FDI facilitation policies are crucial to attract multinational firms. In particular, the aggressive policy of inviting foreign small and medium enterprises (SMEs) effectively works in the formation of industrial clusters. In addition, public resources in these countries are focused on the development of economic infrastructure, including roads, ports, electricity and water supply, telecommunications, and industrial estate services. At the same time, these countries also improved the services of FDI hosting agencies (Ando and Kimura 2005). As a result, a number of multinational firms relocated their production sites to these countries because of the trade and investment liberalization in these countries. With the formation of international production and distribution networks in the manufacturing industry, trade in intermediate goods among East Asian countries became increasingly important. In particular, increased production of intermediate and final goods in the general machinery, electrical equipment, and transportation equipment sectors attracted attention.

The trade of electrical machinery products plays a role as a major driving force for economic development in the East Asian region. This subsection examines the exports and imports of electrical machinery products in ten East Asian economies (see Tables 2.1 and 2.2). The export and import values of the US and of the entire world are also included in the tables for comparison. For ease of exposition, the results for every four years during the period 1993–2013 are presented. The parenthetical figures are the shares of electrical machinery products in total exports of each economy and the compound annual growth rates of exports for each economy are reported in the final column.

Table 2.1 shows the exports of electrical machinery products during the period 1993–2013. It is apparent that the exports of electrical machinery products in these economies experienced rapid growth in the sample period. Notably, China's exports of electrical machinery products rose from $11 billion in 1993 to $815 billion in 2013. Annual growth rates of exports in China (23.9%), Hong Kong (11.5%), South Korea (10.4%), Thailand (9.5%), and Indonesia (10.3%) were higher than the world average growth rate (8.2%). Alternately, the annual growth rates of exports in Japan (0.4%), the USA (4.1%), Philippines (5%), Taiwan (5.3%), Singapore (6.9%), Malaysia (6.8%) were relatively low. Moreover, the share of electrical machinery products in total exports of most economies in the sample, except for Indonesia, was higher than the world average (15.1%). The electrical machinery products of East Asian countries play a more important role in total exports than other regions in 2013.

Table 2.1 The exports of electrical machinery products

	1993	1997	2001	2005	2009	2013	Growth rate
China	11 (12.2)	33 (18.0)	75 (28.2)	297 (39.0)	463 (38.5)	815 (36.9)	23.9
Japan	111 (30.8)	129 (30.7)	117 (29.0)	151 (25.4)	118 (20.4)	122 (17.0)	0.4
Hong Kong	31 (23.0)	53 (28.0)	69 (36.3)	142 (48.6)	171 (52.0)	273 (50.9)	11.5
Taiwan	46 (40.6)	49 (40.9)	59 (48.3)	88 (46.8)	90 (46.3)	130 (45.4)	5.3
South Korea	24 (29.3)	42 (31.2)	54 (35.7)	110 (38.8)	124 (34.1)	175 (31.3)	10.4
Singapore	37 (50.1)	74 (59.4)	72 (59.3)	119 (51.9)	106 (39.2)	142 (34.7)	6.9
Malaysia	21 (43.6)	41 (52.2)	51 (57.7)	72 (50.7)	65 (41.5)	77 (33.6)	6.8
Thailand	9 (23.6)	19 (32.9)	23 (34.8)	36 (32.4)	41 (27.0)	53 (23.4)	9.5
Indonesia	2 (4.4)	4 (7.3)	8 (14.3)	10 (12.0)	10 (8.5)	11 (6.2)	10.3
Philippines	10 (55.0)	15 (61.3)	23 (70.0)	28 (67.9)	24 (61.9)	25 (46.5)	5.0
USA	96 (20.7)	166 (24.2)	177 (24.2)	182 (20.1)	165 (15.6)	217 (13.8)	4.1
World	508 (17.9)	986 (19.3)	1180 (19.9)	1876 (18.8)	2010 (16.8)	2477 (15.1)	8.2

Source: UN Comtrade database.
Notes: The HS codes of electrical machinery products include 85, 8415, 8418, 8450, 8471, 8473, and 9013. The value of exports is expressed in US$ billion. The shares of electrical machinery products' exports in total exports are in the parentheses. The rightmost column shows the compound annual growth rate (%) of exports from 1993 to 2013.

Table 2.2 presents the imports of electrical machinery products during the period 1993–

2013. From the table, steady upward trends of electrical machinery product's imports can be observed in these economies. China's imports of electrical machinery products rose from $15 billion in 1993 to $544 billion in 2013. The annual growth rates of imports in China (19.7%), Hong Kong (11.2%), South Korea (9.4%), and Indonesia (9.7%) were higher than the world average growth rate (8.8%). By contrast, the annual growth rates of imports in Philippines (2.7%), Taiwan (4.7%), Singapore (6.2%), the USA (6.5%), Malaysia (6.9%), Thailand (8.1%), and Japan (8.8%) were relatively low. These results reveal that these economies imported a large proportion of electrical machinery products. In 2013, the share of electrical machinery products in total imports of most economies in the sample, except for Japan and Indonesia, were higher than the world average (15.9%). Due to the dramatic economic growth of China and the countries in the ASEAN region, domestic market demands in these developing countries will continue to rise. Thus, the exports and imports of electrical machinery products will continue to expand.

Table 2.2 The imports of electrical products

	1993	1997	2001	2005	2009	2013	Growth rate
China	15 (14.3)	27 (18.8)	70 (28.8)	241 (36.6)	319 (31.7)	544 (27.9)	19.7
Japan	23 (9.5)	56 (16.4)	69 (19.8)	94 (18.2)	85 (15.4)	123 (14.8)	8.8
Hong Kong	34 (24.4)	64 (29.9)	76 (37.5)	143 (47.5)	178 (50.4)	289 (46.4)	11.2
Taiwan	108 (26.0)	114 (25.8)	107 (34.4)	182 (27.9)	174 (25.2)	269 (22.1)	4.7
South Korea	14 (16.2)	28 (19.6)	35 (24.8)	57 (21.9)	61 (18.8)	83 (16.0)	9.4
Singapore	32 (38.0)	59 (44.5)	54 (46.5)	89 (44.7)	78 (31.8)	109 (29.1)	6.2
Malaysia	16 (34.6)	31 (39.9)	35 (48.0)	52 (45.9)	46 (37.1)	59 (28.8)	6.9
Thailand	10 (20.7)	17 (27.0)	19 (30.0)	29 (24.8)	31 (23.5)	45 (18.0)	8.1
Indonesia	3 (12.3)	5 (11.9)	2 (5.5)	4 (7.1)	14 (14.0)	22 (11.9)	9.7
Philippines	11 (34.1)	15 (38.8)	17 (48.3)	25 (49.8)	17 (37.1)	18 (27.5)	2.7
USA	120 (19.9)	197 (21.9)	237 (20.1)	316 (18.3)	302 (18.9)	420 (18.1)	6.5
World	492 (17.1)	986 (18.7)	1245 (20.3)	1992 (19.4)	2146 (17.6)	2645 (15.9)	8.8

Source: UN Comtrade database.
Notes: The HS codes of electrical machinery products include 85, 8415, 8418, 8450, 8471, 8473, and 9013. The value of imports is expressed in US$ billion. The shares of electrical machinery products' imports in total imports are in the parentheses. The rightmost column shows the compound annual growth rate (%) of imports from 1993 to 2013.

This subsection also examines the development of electrical machinery industry in East Asia using a method that is typically applied in empirical studies of intra-industry trade. The surge of intra-regional trade can be attributed to the ongoing geographical dispersion of production processes. Labor-intensive assembly activities are sent to relatively low-income countries, while high-income countries specialize in the capital- and technology-intensive activities. In recent years, firms have also begun to relocate high-value production processes abroad, further resulting in the increase in the intermediate goods trade within the region, whereas countries outside the region remain the major destination for final goods exports.

To illustrate the importance of intermediate goods in trade of the East Asia region, Table 2.3 details the shares of electrical machinery intermediate goods in intra-region trade. The increased presence of electrical machinery products in intra-regional trade reflects the prevalence of vertical specialization in the East Asia region. The upper panel shows intra-region exports of electrical machinery products. The share of intra-region exports of electrical machinery products increased from 32.9 percent in 1993 to 44.1 percent in 2013. Moreover, the intra-region exports of electrical machinery intermediate goods substantially increased from 52 percent in 1993 to 70.8 percent in 2013. The lower panel shows intra-region imports of electrical machinery products. The intra-region imports of electrical machinery products increased from 37.9 percent in 1993 to 53.7 percent in 2013. Meanwhile, intra-region imports of electrical machinery intermediate goods increased from 69.2 percent in 1993 to 83.7 percent in 2013. These results indicate that the proportion of intra-region trade of electrical machinery products has dramatically increased since the late 1990s. In particular, more than 50 percent of electrical machinery intermediate goods transactions were conducted within the East Asian region, which implies an increased reliance on imported inputs in the production of East Asian economies due to the rise of GVCs. Furthermore, the share of regional import is higher than that of exports, which implies that East Asian countries are more likely to source intermediate inputs within the region.

Table 2.3 Intra-regional trade of electrical machinery products in East Asia (%)

		1993	1997	2001	2005	2009	2013
Export	Electrical machinery	32.9	42.8	46.2	51.3	52.4	44.1
	Parts and Components in electrical machinery	52.0	58.2	63.3	70.5	71.3	70.8
Import	Electrical machinery	37.9	47.4	55.2	66.0	69.6	53.7
	Parts and Components in electrical machinery	69.2	65.9	71.5	82.5	85.0	83.7

Source: UN Comtrade database.
Notes: The upper panel shows the intra-regional exports shares of total electrical machinery products and electrical machinery parts and components. The lower panel shows the intra-regional imports shares of total electrical machinery products and electrical machinery parts and components.

To summarize, the above results show that electrical machinery products play an important role in the trade structure of most East Asian economies. In particular, electrical machinery products accounted for approximately 50 percent of Hong Kong, Taiwan, and Philippines exports, and this proportion was significantly higher than the world average. Additionally, we observe that a considerable share of electrical machinery product transactions occurred within the East Asian region. This finding confirms that East Asia has expanded and strengthened both intra-regional exports and imports of machinery parts and components to a significant degree. Importantly, the involvement of intra-regional trade is more pronounced for intermediate goods in the electrical machinery industry, which implies an increased interdependence in the East Asian region.

This phenomenon is attributed to these three characteristics of electrical machinery products. There is a vast variety of electrical machinery products in terms of manufacturing technology, quality, and design; the production process can be separated in different locations; and the transportation costs for electrical and electronic machinery intermediate goods are relatively low.

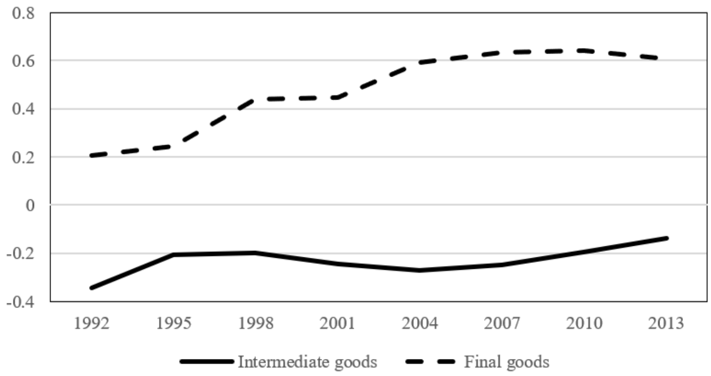
2.4.2 Parts and Components in China's Electronics Industry

The above result reveals that China has become the largest exporter and importer of electrical machinery products in East Asia since the late 2000s. China has been playing an important role in the trade of electrical machinery products. This subsection briefly examines the performance of the electrical machinery industry in China. GVCs in the East Asian region have deepened the interdependence between China and other East Asian countries. Previous studies highlight that Chinese firms mainly specialize in final goods assembly using a large proportion of imported intermediate goods. In this sense, China is a good example to illustrate how GVCs affect international trade participation. Because electrical machinery products are prone to production fragmentation, trade of intermediate goods in this industry has markedly increased during the last decades. Final and intermediate goods will be distinguished according to the definition put forth by Ando and Kimura (2005), which identifies parts and components in electrical machinery products on the basis of the HS classification.

To assess the trade of China's electrical machinery products, we use the trade specialization index (TSI). The TSI is defined as the ratio of the net flow of goods (i.e., exports minus imports) to the total flow of goods (i.e., exports plus imports). Specifically, the TSI of product i in country n is defined as $TSI_{ni} = (X_{ni} - M_{ni})/(X_{ni} + M_{ni})$, where X_{ni} and M_{ni} denote exports and imports, respectively. The TSI ranges from –1 to 1. A country tends to specialize in exporting a product and be more competitive in the world market if the TSI approaches 1. To the contrary, a country tends to specialize in importing a product if the TSI approaches –1.

Figure 2.2 shows the TSI of intermediate and final goods of China's electrical machinery products during the period 1992–2013. The TSI of final goods was greater than that of intermediate goods throughout the sample period. This result implies that China is relatively competitive in the production of final goods for electrical machinery products. The TSI of final goods rose from 0.2 in 1992 to 0.6 in 2013. This result indicates an upward trend in China's competitiveness related to the final goods for the electrical machinery industry. On the other hand, the TSI of intermediate goods was less than zero throughout the sample period. This result suggests that China was less competitive when producing electrical machinery intermediate goods. It can therefore be concluded that China's electrical machinery industry is more likely to specialize in importing intermediate goods for production. Moreover, the TSI of intermediate goods rose from –0.3 in 1992 to –0.1 in 2013. The increase in the TSI of intermediate goods was not as large as that of final goods. This result implies that the competitiveness of final good producers rose more substantially than intermediate good producers during the sample period.

Figure 2.2 TSI of electrical machinery product exports of China



Source: UN Comtrade database.

In summary, the above results provide a snapshot of China's performance in international trade based on gross trade flow statistics. China has achieved significant economic development in the early stages of reform and opening-up as a product-processing and assembly base, while relying on labor-intensive industries. In particular, China plays a prominent role in the GVCs of electrical machinery products, considering that the country has gained great competitiveness and comparative advantages in the global market.

Early studies relied on disaggregated trade data to measure the trade of parts and components. Ng and Yeats (1999) and Ando and Kimura (2005) recognized parts and components in the electrical machinery industry by searching for the keywords "part" or "component" in the descriptive labels within the HS classification. However, these studies have two shortcomings. First, some intermediate goods and services are not classified as a "part" or a "component." Second, when seeking to examine the effect of international trade on the labor market, customs statistics do not provide information on who (i.e., which firm or industry) used the intermediate input for production when one wants.

2.4.3 Case Studies of Electronics Firms in China

Recent decades have seen a boom in offshoring on a global scale as many multinational firms have shifted their production sites to East Asia, especially to China. Since the 1980s, China's indigenous enterprises have actively participated in GVCs and played an important role in international production networks. The "Made in China" label is usually found on low-end products, such as textiles, apparel, and furniture. Since the 1990s, however, China has rapidly moved up the ladder of GVCs by exporting more sophisticated products. Amiti and

Freund (2008) document an increased exported share of electronics and machinery products and a declined share of agricultural and apparel products. Even though some studies have observed dramatic changes in China's export composition, the country still heavily relies on imported parts and components to assemble final goods for global markets. The reliance on foreign intermediate goods and technology limits the sustainable growth of China's electronics industry.

The following subsection will examine how China's electronics companies strengthen their capacities and competitiveness over time through case studies. Two stylized facts will be presented: the increasing presence of indigenous firms in global production networks, and the decreasing dependence of the high-technology industry on imported intermediate inputs.

2.4.3.1 Switch Industry

Switch equipment is a critical component used in telecommunication equipment. During the period 1949–1978, the technology level of China's telecommunication manufacturing lagged far behind that of advanced countries. This historical background led to weak IT infrastructure in the country. The domestic telecommunication provider had to purchase out-of-date technologies and products from local suppliers, which could result in low quality of telecommunication service.

With implementation of the opening-up policy in the late 1970s, China began to embrace globalization and encourage a joint venture (JV) negotiation that targeted FDI and technology transfer. Direct imports of up-to-date switching and transmission equipment was pivotal in the early 1980s (Tan 2002). The Chinese government has allowed FDI to establish JVs that suited the interests of both multinational firms and the government since the 1980s. On the one hand, many multinational firms were attracted by the potential of China's domestic market. On the other hand, the Chinese government desired to foster domestic technological capability and catch up with advanced countries through technology transfer.

The first large JV in China's telecommunication manufacturing sector, Shanghai Bell Telephone Equipment Manufacturing Corporation (Shanghai Bell), was established in 1984 in the form of a JV agreement with France-based Alcatel. The company developed rapidly and had about 25 percent of the central office switch market in 1990 (Harwit 2007).[1] After limitations on inward FDI were alleviated in 1990, more multinational firms were allowed to

[1] Central office switch is used in telecommunications system to direct voice or data communications from one source to another (Harwit 2007).

establish JVs in China. As a consequence, China's switch market avoided over-reliance on direct imports, and since the early 1990s, JVs have dominated the market instead (Tan 2002).

The incentive of the Chinese FDI-attracting policy is to boost the technological capability of indigenous switch suppliers so they can compete with foreign companies in both domestic and overseas markets. This initiative was launched on the premise that imports of up-to-date switch equipment and the alleviation of JVs in China can foster technology diffusion across the country. Thus, FDI has a positive effect on domestic firm's growth by providing technology, capital financing, management skills, and access to the global market. In 1992, indigenous suppliers started supplying central office switches to rural areas, accounting for roughly 1.1 percent of the market (Zhang and Igel 2001). Due to the improved quality of products, indigenous suppliers were able to compete with JVs in both rural and urban markets in the mid-1990s. At that time, the four leading domestic manufacturers were DaTang, Great Dragon, Huawei, and ZTE, all of which were wholly Chinese-own companies. The six leading switch manufacturers of China in the 1990s are shown in Table 2.4. Two firm were JVs with foreign partners, and four were wholly Chinese-owned companies. In 1997, these six firms produced more than 20 million line SPC switches and approximately 80 percent of China's total output.[2] Shanghai Bell, which was a JV, became the largest switch manufacturer in China, with 4,561 million renminbi (RMB) sales in 1997, while wholly Chinese-owned firms such as Great Dragon and Huawei also grew significantly and accounted for considerable market shares (Zhang and Igel 2001).

The largest wholly Chinese-owned switch manufacturer was Great Dragon, which was a state-owned enterprise headquartered in Beijing, China. The company had registered capital of RMB 12.1 billion and a staff of roughly 50,000, with 6,000 technical and engineering personnel. The company's business covered switches, transmissions, network management, and data telecommunications. In 1991, Great Dragon launched its flagship product, the digital SPC HJD-04, which was the first office switching equipment made in China. Sales of SPC lines increased from 50 million units in 1992 to 17 billion units in 1998 (Lin, Liang and Wan 2001).

[2] Stored program control (SPC) is a telecommunications technology used for telephone exchanges controlled by a computer program stored in the memory of the switching system. SPC is introduced to production in the 1960s.

Table 2.4 Statistics of major SPC switch producers in China

Names	Ownership	Year registered	1997 sales (RMB million)
Shanghai Bell	Joint venture	1984	4,561
Beijing International Switching System Co. Ltd (BISC)	Joint venture	1988	1,988
Great Dragon Telecommunications Co. Ltd (Great Dragon)	Chinese firms	1994	5,000
Huawei Technologies Co. Ltd (Huawei)	Chinese firms	1988	4,189
Zhongxing Telecom Co. Ltd (ZTE)	Chinese firms	1993	1,997
Datang Telephone Ltd (DaTang)	Chinese firms	1993	520

Source: Zhang and Igel (2001).

China's switch market is a typical example of the ways in which the role of domestic suppliers evolves over time. The supply of switches follows a three-stage transition (Tan 2002). As shown in Table 2.5, China's switch market largely depended on direct imports until the early 1980s. However, FDI-attracting policy caused the emergence and development of JVs in the late 1980s and early 1990s. In 1992, JVs accounted for 36 percent in the switch market, while direct imports still made up as much as 54 percent. Until the early 1990s, Chinese suppliers and JVs accounted for approximately half of the market share, while the share of direct imports declined sharply. In 2000, the imports of the switch fell to zero percent. The example of SPC switch suppliers in China illustrates a process that has allowed domestic suppliers, including both JVs and wholly Chinese-owned suppliers, to increase their presence in the local market.

Table 2.5 SPC switch annual market shares by firm ownership (%)

	1982	1987	1992	1997	2000
Direct imports	100	89	54	5	0
Joint venture	0	11	36	63	57
Wholly Chinese-owned suppliers	0	0	10	32	43

Source: Tan (2002).

2.4.3.2 Semiconductor industry

Semiconductors are viewed as extremely important components of household electronics appliances. The production of semiconductors involves a major building block of high-technology machines. In 2015, China produced and exported more than half of smartphones and tablet computers worldwide (URL 1). Foreign companies profited the most, however, because they provided key and high-cost components, such as modems, application processors, image sensors, power amplifiers, transceivers, and displays. In particular, the semiconductor is the most important component that captures a large proportion of value-added in many electronics products.

China has become the largest and fastest growing market of electronics products in the world. China's semiconductor consumption grew by 6 percent in 2015 when reaching a new record of 59 percent of the global market. The size of China's semiconductor market rose from $14.4 billion in 2000 to $164.4 billion in 2012 (URL 2). However, as the world's largest exporter of electronics products, China remains heavily dependent on the imports of semiconductors and other new technologies, primarily from Japan, Korea, the US, and European countries. For example, about 43 percent of the parts and components for handsets and networking equipment of China's second largest telecom company, ZTE, are supplied by US companies, including Avnet, Qualcomm, Intel, and Nvidia (Ernst 2016). This is consistent with the fact that there was no Chinese firm within the top 30 suppliers in China's semiconductor market in 2012 (URL 2).

To reduce the trade deficit in semiconductors, Chinese government has launched new policies to upgrade the domestic semiconductor industry. The "National Semiconductor Industry Development Guidelines" and the "Made in China 2025" plan were published by China's State Council in 2014 and 2015, respectively. Both policies aim to strengthen the innovation and manufacturing capabilities in China's integrated circuit (IC) design industry and its domestic IC fabrication, primarily through foundry services. For the "National Semiconductor Industry Development Guidelines", a $19 billion national industry investment fund has been set up to help local companies build up advanced manufacturing processes, and also to support local IC firms to form mergers or make acquisitions internationally. As for the "Made in China 2025" plan, Chinese government seeks to improve the self-reliance rate for ICs in the country to 40 percent in 2020, and raise the rate further to 70 percent in 2025 (Ernst 2016). Both policies will play an important role in promoting the development of China's semiconductor industry.

Table 2.6 compares the revenue and consumption of China's semiconductor industry. The contribution of domestic suppliers to semiconductor production in China ranged from 27 to 41 percent during the period 2000–2015. Domestic suppliers seem to be approaching the goal set by the “Made in China 2025” plan. When it comes to the IC industry (Table 2.7), the level of self-reliance is even lower, as the share of domestic suppliers rose from 19 percent in 2000 to 33 percent in 2015. These results imply that although China’s semiconductor and integrated circuit industries have dramatically developed, they still rely on imported intermediate inputs to a considerable extent.

Table 2.6 Revenue and consumption of China’s semiconductor industry (US$ billion)

	Revenue	Consumption	Self-reliance
2000	5.0	14.4	35%
2003	8.3	30.7	27%
2006	21.7	71.0	31%
2009	29.2	101.2	29%
2012	56.3	164.4	34%
2015	89.3	215.6	41%

Source: China’s impact on the semiconductor industry: 2016 update (URL2).

Table 2.7 Production and consumption of China’s integrated circuit (US$ billion)

	Production	Consumption	Self-reliance
2000	2.2	11.4	19%
2003	4.2	25.0	17%
2006	12.6	59.5	21%
2009	16.2	83.1	19%
2012	34.3	135.6	25%
2015	57.5	175.5	33%

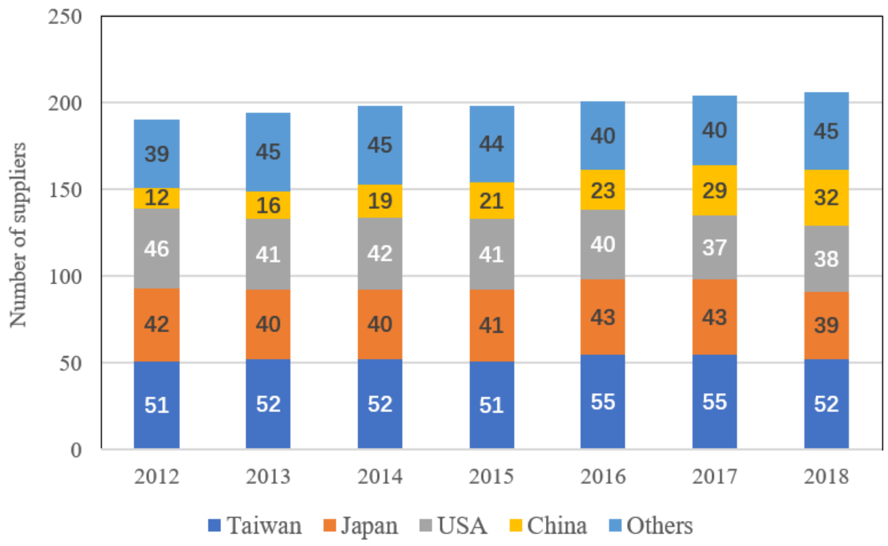
Source: China’s impact on the semiconductor industry: 2016 update (URL2).

2.4.3.3 Rising Presence of Chinese Firms in the Case of Apple

Apple is a high-technology company, and its products are produced via global production networks. The production process of Apple’s products heavily relies on contract manufacturers in different countries, while Apple itself mainly focuses on product design and the development of software for its operating systems. Apple moved its production processes overseas in the early 2000s and most of the supply chains are now located in China. According to Xing and Detert (2010), the production of the iPhone 3G was conducted in nine countries, which included China, South Korea, Japan, Germany, and the US. The key suppliers of iPhone 3G parts and components include Toshiba, Samsung, Infineon, Broadcom, Numunyx, Murata, Dialog Semiconductor, and Cirrius Logic. All iPhone parts and components produced by these companies are shipped to factories in China and assembled into final product there, then exported to the world's market. In 2009, the competitiveness of domestic suppliers in China was so weak that few Chinese firms were intermediate input suppliers of the iPhone. Chinese firms were mostly involved in the assembly of final products, heavily relying on imported materials from other countries. Chinese workers are simply responsible for assembling parts and components, which contribute a mere $6.50, roughly 3.6 percent of the total manufacturing costs, for each iPhone 3G. The bulk of the benefits are attributed to firms in the US, Japan, and South Korea that specialize in product design, software development, and supplying intermediate inputs.

The role of Chinese firms in Apple's supply chain has evolved during recent years. This is consistent with the tendency of an increasing number of multinational firms in the ICT industry to offshore their production sites to developing countries in order to exploit low production costs and the potential local market. In the 759 subsidiaries of Apple's suppliers in 2015, about 44 percent of them were located in China (Grimes and Sun 2016). Moreover, both core and non-core component suppliers tend to locate their production processes in China. Grimes and Sun (2016) show that 47 percent of subsidiaries supplied core components for the products, while roughly 38 percent of subsidiaries supplied non-core components. Even though the presence of Chinese companies is modest, this suggests that their competitiveness and technology are improved. To examine how China moves up in its production networks, it is necessary to assess the number of Chinese firms involved in Apple's supply networks and the range of tasks performed by Chinese firms. Figure 2.3 shows the number of Apple's suppliers during the period 2012–2018 (URL 3). There were only 12 Chinese firms on Apple's supplier list in 2012. However, the number of Chinese suppliers rose to 32 in 2018. This fact implies an increased presence of Chinese suppliers in Apple's supply chain. This figure also shows that Taiwan-based suppliers play a prominent role in Apple's supply chains. There were 51 Taiwan-based suppliers in 2012. Even though the number of Taiwan-based suppliers fell from 55 in 2017 to 52 in 2018, they still accounted for the largest share in Apple's supplier list. In addition, the number of US-based and Japan-based suppliers declined from 2012 to 2018.

Figure 2.3 Number of Apple's suppliers by countries or regions



Source: Author's drawing, based on URL3.

In summary, Apple's supply chain is a useful example to illustrate how Chinese firms evolve in the GVCs and the range of roles for which they are responsible. The rising presence of Chinese suppliers implies that, instead of only specializing in assembly activities, Chinese firms are able to produce increasingly sophisticated parts and components for the Apple's high-technology devices. An increased number of Chinese suppliers have participated in Apple's supply chain and fill the position in a wider range of production processes. These results also imply a remarkable upgrading of Chinese firms within Apple's supply chain.

Chinese parts and components suppliers have achieved significant developments by integrating into Apple's supply chains. Table 2.8 shows the revenue of six Chinese firms in Apple's supplier list during the period 2012–2016. The products provided by these companies include computer interconnection products, microphone components, batteries, and lens products. Most companies experienced a substantial increase in revenues during the sample period. Detailed information of some companies is presented below.

AAC Technologies is a promising China-based companies that produce complex miniature microphones for the iPhone. The company joined Apple's supply chains in 2011, when iPhone 5 upgraded its microphone system by adding a device to support high-definition video recording. AAC Technologies was founded in 1993 and is based in Shenzhen, China; the company manufactures miniaturized acoustic components for smartphones, tablets, and computers (URL 4). In 2016, the revenue of AAC Technologies reached $2,355 million. AAC

Technologies was ranked the third largest supplier of MEMS microphones in 2015, which is widely used in tablets and smartphones (URL 5).[3] Another prominent Chinese company that is moving up the Apple supply chains is GoerTek, a microphone manufacturing company based in China's Shandong Province. GoerTek, which has been on Apple's supplier list since 2013, fabricates speakers and earphones for the iPad and iPhone. The company also provides microphone components to Samsung. In 2016, the revenue of GoerTek reached $2,875 million. GoerTek's main competitor with respect to its manufacturing capabilities, including designing its own machines for automating its assembly line and faster turn-round time on production, is Knowles, a US-based company (URL 6). GoerTek was ranked the second-largest supplier of microphones in the 2015 global market (URL 5).

Table 2.8 Revenue of major Chinese firms in Apple's supplier list (US$ million)

	2012	2013	2014	2015	2016	Growth rate (%)
Luxshare	469	685	1,089	1,513	2,053	338
Desay	478	658	957	1,255	1,306	173
GoerTeK	1,084	1,501	1,896	2,041	2,875	165
AAC Tech	1,004	1,328	1,453	1,882	2,355	135
BYD	8,504	9,843	10,857	14,569	17,870	110
Lens Tech	1,667	1,989	2,162	2,569	2,263	36

Source: The Wall Street Journal (URL 7).
Note: All values are in millions of US dollar except the growth rate of revenue from 2012 to 2016.

In addition, Chinese battery maker Shenzhen Desay Battery Technology (hereafter Desay) has taken considerable market shares from Taiwanese companies such as Simplo Technology and Dynapack. Desay was founded in 1983 and primarily engaged in the manufacturing and sales of batteries. After more than thirty years of development, Desay has grown into a large battery management system and battery pack supplier with annual sales revenue that exceeded $1.3 billion in 2016. Desay first became an Apple supplier in 2004 and was responsible for 50 percent of Apple's battery order, which accounted for approximately 70 percent of the company's total revenues. Desay is also a supplier for Samsung and Sony, which collectively accounts for 20 percent of total sales. Moreover, Desay has provided batteries for Xiaomi, a Chinese smartphone brand, since 2011. The rise of domestic smartphone brands is expected to provide the next growth momentum for Desay.

[3] The MEMS (Micro Electrical-Mechanical System) microphone is also called a microphone chip or silicon microphone and is a component in smartphones.

Reviewing the development of domestic electronics firms suggests that China has become a center for manufacturing electronics products. China's national interest lies in both the growth of domestic enterprises and the integration of the global economy. Embracing GVCs compensates for the technology deficiency of local firms. By absorbing and digesting imported technology, indigenous firms are expected to improve their technological capability and competitiveness. The case study of switch products demonstrates that China has gained the ability to lessen dependence on direct imports and localize some production processes. However, China's domestic production activities still rely on imported inputs or final assembly of high-end products. The semiconductor exemplifies the low competitiveness in China's domestic production.

Apple has moved most of its production processes to China, and an increasing number of Chinese companies, including assemblers and components suppliers, are increasingly joining Apple's GVCs. However, Chinese suppliers are less competitive when producing some high-technology components, such as displays, IC manufacturing, and optical modules. In order to catch up with advanced countries, China needs to promote the development of indigenous firms. It is particularly important to improve competitiveness in the domestic high-technology industry.

The above anecdotal evidence, however, cannot provide a comprehensive picture of the way China participates in GVCs. Although the production of switch equipment and semiconductors illustrates the remarkable development of Chinese manufacturers, it inadequately represents the entire economy. It is also difficult to determine the exact role of every supplier in Apple's production networks because the transaction details among suppliers are commercially sensitive and Apple is typically reluctant to disclose such information. Thus, more systematic evidence and analysis are required to quantify the phenomenon of GVCs. Researchers recently attempted to measure the value-added contents that are embedded in production and exports. Input–output tables, for example, serve as a tool to analyze the linkage between industries and to track down the inputs from all the upstream industries required by a certain industry to produce its outputs. The next subsection will provide an explanation about tracing the value-added contents in trade.

2.4.4 Trade in Value-Added

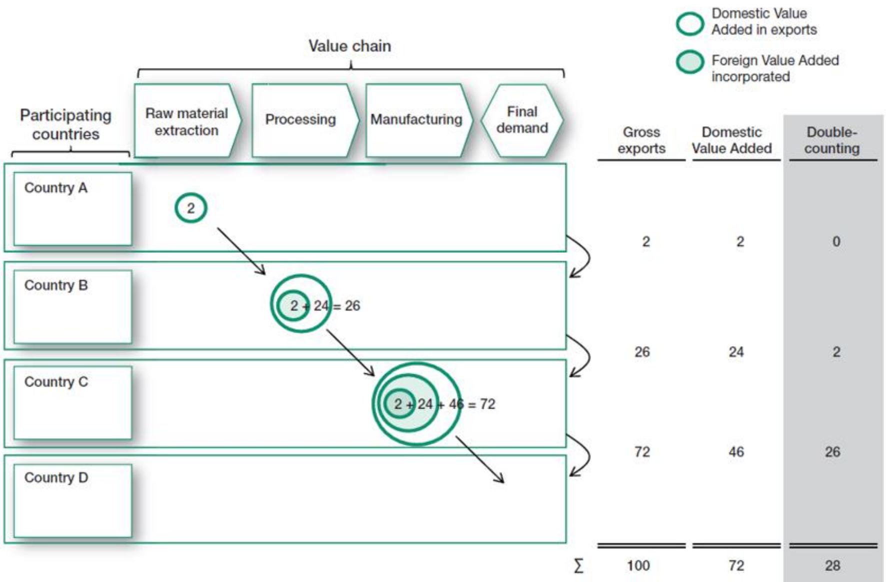
With the expansion of GVCs, many studies have documented that traditional trade statistics tend to get a misleading perspective of how a country participates in GVCs. This reflects the fact that traditional trade statistics are measured in terms of gross trade flows, and the value of products crossing national borders several times for further processing is counted multiple times. Some case studies have illustrated the concept of value-added trade using Apple's GVCs, such as Linden, Kraemer and Dedrick (2009) for the iPod, Xing and Detert (2010) for the iPhone, and Kraemer, Linden and Dedrick (2011) for the iPad. These electrical appliances were finally assembled and exported by firms located in China, so they are counted as an export value of China. However, these export flows do not reflect how China participates in Apple's GVCs. Some studies have documented that Chinese value-added represents only a small proportion of the value of these electrical appliances because production in China relies heavily on intermediate inputs imported from other countries. For example, Dedrick, Kraemer and Linden (2010) show that of the $144 factory-gate price of an iPod, Chinese workers contributed less than 10 percent of the total value, while the bulk of the components (approximately $100) were imported from Japan, the US, and South Korea.

Measuring value-added in trade yields a different description of the way how a particular country participates in GVCs. A bilateral trade balance in gross trade terms can be different from a bilateral balance in value-added terms, because a country's gross exports tend to contain a considerable proportion of imported contents. Compared with gross trade balances, value-added balances remove the portion of trade flows that is double-counted in official trade statistics. Koopman et al. (2010) find that China's trade surpluses with the US and Western EU countries estimated in value-added terms were, respectively, 41 percent and 49 percent less than those estimated in gross value terms. Conversely, Japan's trade surpluses with the US and Western EU countries were, respectively, 40 percent and 31 percent larger than those estimated in gross value terms. This result reflects that the final products exported to the US and EU markets contain a significant portion of value-added created by Japanese-based firms.

To depict a comprehensive picture of how a country participates in GVCs, empirical studies need to decompose the value of final outputs or exports into domestic and foreign value-added contents. The domestic value-added of exports denotes the proportion of exports created by the exporting country and represents the export's contribution to the GDP. Alternately, the foreign value-added of exports measures the share of intermediate inputs produced in foreign countries and represents the export's contribution to a foreign country's GDP. The sum of foreign and domestic value-added is equal to gross exports.

Figure 2.4 demonstrates how the value-added is created by each production stage in a simplified GVC which consists of four countries. Country A, which is assumed to lie in the upstream of the GVC, provides $2 worth of raw materials for Country B; in this stage, the exports and domestic value-added of Country A are both $2. In the next stage, Country B adds $24 to the product using the raw materials imported from Country A; the exports of Country B are $26, while the domestic and foreign value-added of exports are $24 and $2, respectively. In the third stage, Country C adds $46 to the product using the intermediate inputs imported from Country B and exports the final product to Country D; the exports of Country C are $72, while the domestic value-added of exports is $46.

Figure 2.4 An illustration of trade in value-added



Source: UNCTAD (2013)

It is insufficient to rely on case studies to capture the landscape of all the GVCs because they can only cover a small portion of producers. With the goal of tracing value-added contents in trade flows across countries, a body of work would need to combine information from customs statistics with national input–output tables to construct global input–output tables, which allow for devising alternative measures to document the extent to which various countries and sectors take part in GVCs.

2.4.5 Input–Output Tables

Most of the initial evidence on GVCs and production fragmentation focuses on measuring imported inputs embedded in gross outputs, total inputs, and exports. Tracing the intermediate goods in production requires a detailed production classification by which the features of various production processes can be properly identified and tracked. Because such data are not available for all products, however, time-series and inter-country analyses are difficult to implement.

Better methods are therefore needed to measure international trade contributions to a country's value-added, income, and employment. Many scholars have turned their interests to the input–output table, which is a dataset that links production processes within and across countries. There have recently been important improvements in measuring GVCs. The national input–output table, which only provides transaction information within a country, has been extended to incorporate bilateral trade flows by using disaggregated trade data to link existing national input–output tables across countries. The constructed international input–output tables provide information on all bilateral transactions of intermediate and final goods and enable us to trace the value-added content along the GVCs to each producer.

The use of input–output tables in empirical studies is intended to address two problems stemming from traditional trade statistics. First, the "double counting" issue has attracted considerable academic attention as GVCs have become increasingly complex. The traditional trade statistics record goods several times in a certain gross trade flow because of back-and-forth shipments that take place in a cross-national production process (Koopman, Wang and Wei 2014; Borin and Mancini 2019).

Second, traditional trade statistics cannot fully reflect the origins and destinations of value-added in production. Customs statistics, which serve as the traditional data source for recording international trade flows, provide information about where the transacted goods are produced, but include no details as to how the transacted goods are produced; in other words, customs statistics do not reflect information about all of the sectors or countries that contributed value to the transacted goods. Moreover, customs statistics record where the goods flow to, but not how they will be used, such as whether they will be consumed in the importing country, or whether they will be re-exported after the importing country adds value to them.

Estimating value-added contents in trade requires international input–output tables with information on the bilateral shipment of intermediate and final goods to allocate the value-added along the GVCs to each producer. It is worth noting that producers participate in GVCs in two broad ways (Antràs 2019). On the one hand, a country's exports encompass foreign value-added that was previously sourced abroad; this type of GVC participation is often called "backward GVC participation." On the other hand, a country's exports are not fully absorbed in the importing country, and are instead embodied in the importing country's exports to a third country; this type of GVC participation is often referred to as "forward GVC participation."

There are bodies of works that have combined customs trade statistics with national input–output tables to construct global input–output table databases to trace value-added contents in trade flows across countries. The most widely used international input–output table databases include the World Input–Output Database (WIOD), the OECD Inter-Country Input–Output (ICIO) Tables database, and the Eora Global Supply Chain Database.

The WIOD was constructed within the official WIOD Project, which was funded by the European Commission. This database contains harmonized supply-and-use tables and international trade data in goods and services, and these two sets of data have been combined into a set of international input–output tables. The WIOD released in 2016 covered 56 industries in 28 EU countries and 15 other major countries in the world during the period 2000–2014. Together with environmental and socio-economic indicators, these industry-level data provide information that can be used to examine various policy objectives (Timmer et al. 2016).

The joint OECD-WTO project constructed the OECD ICIO tables. The 2018 edition of the database included 64 economies and included OECD, EU28 countries, most East and Southeast Asian economies, and a selection of South American countries. The industry list includes 36 sectors and covers the period 2005–2015 (Yamano and Webb 2018).

The Eora Global Supply Chain Database consists of a multi-region input–output table (MRIO) model that provides a time series of input–output tables with matching environmental and social satellite accounts. In addition to balanced global MRIO tables that cover inter-sectoral transfers among 15,909 sectors across 190 countries during the period 1990–2015, this database also provides a set of environmental indicators, such as GHG emissions, labor inputs, air pollution, energy use, water requirements, land occupation, and primary inputs to agriculture (including 172 crops) from FAOSTAT, and Human Appropriation of Net Primary Productivity (URL 8).

An input–output analysis is based on the framework developed by Leontief (1936), which is often referred to as the Leontief model (or input–output model). The term "inter-industry analysis" is also used, because one of the most important purposes of the input–output framework is to measure the interdependence of industries within an economy. The structure of the input–output model has been incorporated into the national accounting systems of many countries and can be used to calculate important measures, such as national GDP. A primary use of input–output analysis is to measure the economic impact of events, as well as that of public investments or programs; it is also used to identify linkages between industries.

Leontief's basic framework has been widely applied in such areas as economics, energy, and environmental analysis. As an extension of national input–output tables, international input–output tables have rapidly developed in recent years, thereby allowing for analysis of inter-country linkages.

Table 2.9 presents an outline of an international input–output table from the WIOD, which provides detailed information on all transactions between industries and final consumption across countries in the global economy (Timmer et al. 2015). The columns in the international input–output table illustrates how industries and countries source intermediate inputs from other industries or countries in the production process. When expressed as ratios to gross output, the cells in a column are the shares of intermediate inputs in total production costs; these cost share vectors represent production technology. Products can be used as intermediate inputs by other industries, or as final consumption for households, governments, or firms (i.e., stocks and gross fixed-capital formation). Furthermore, each row in the international input–output illustrates how the outputs of an industry or country are distributed across user categories. The gross outputs of each industry, which are given in the last element of each column, are equal to the total uses of the outputs from that industry, which are given in the last element of each row. In addition, the imports of an industry or country are broken down according to the country and industry of origin in an international input–output table. These pieces of information provide a powerful tool to analyze global production networks.[4]

Table 2.9 An example of input-output table

			Use by country-industries							**Final use by countries**			**Total use**
			Country 1			…	Country M			Country 1	…	Country M	
			Industry 1	…	Industry N	…	Industry 1	…	Industry N		…		
Supply from country-industries	Country 1	Industry 1											
		…											
		Industry N											
	……												
	Country M	Industry 1											
		…											
		Industry N											
Value added by labour and capital													
Gross output													

Source: Timmer et al. (2015).

[4] Miller and Blair (2009) provide a comprehensive overview the input–output analysis.

2.4.6 Micro-Level Data

Empirical studies that utilize customs trade statistics and input–output tables focus on the analysis at the country or industry level. In the real world, however, firms directly participate in international trade. As such, interest in firm-level international strategies has increased in international trade research. This intellectual trend is promoted by the increased availability of longitudinal plant- and firm-level databases, which allow researchers to reveal a series of new facts that challenge existing economic models. The seminal work of Melitz (2003) focused on exporting decisions of heterogeneous firms within an industry. Recent studies have examined how a firm sources intermediate inputs (Antràs, Fort and Tintelnot 2017), how imports are connected with exports at the firm level (Bernard et al. 2009), and how multinational firms organize their production networks (Harrison and McMillan 2011).

An advantage of firm-level data is that they allow researchers to examine trade flows between firms and their foreign partners. In addition, firm-level data provide detailed information related to firm heterogeneity that is neglected when aggregated industry-level data are used (Johnson 2017). Lu et al. (2018) use China's disaggregated customs data and firm-level production data during the period 2000–2006, and they found that China's GVC participation is associated with firm-related factors, such as productivity, firm size, R&D expenditures, firm age, market concentration, processing trade, state-owned enterprises, and foreign-invested firms. Kee and Tang (2016) explore the effects of FDI and input tariffs on domestic value-added ratios based on Chinese firm-level data. Furthermore, firm-level data from the World Bank's Enterprise Surveys cover 111 countries and 38,966 firms. This database allows researchers to investigate how firms in a wide range of countries participated in GVCs (Urata and Baek 2020).

Firm-level data can also be applied to measure offshoring, input sourcing, vertical specialization in trade, and the GVC activities of multinational firms. However, firm-level data also have limitations in some respects. For example, firm-level data do not contain the full set of firm-level shipments.

2.5 Conclusion

GVCs have profoundly changed the landscape of world production, thereby affecting international trade, investment, labor market, and the way policymakers interpret trade policies. The production fragmentation has become prevalent on a global scale. As interdependence between countries has deepened, many empirical studies have turned to new tools to investigate the GVC participation of various countries. This chapter provided an overview of the development of GVCs over the past few decades and the factors which have facilitated the expansion of GVCs all over the world. Furthermore, measuring the participation of a country within GVCs has become an important issue among researchers. Particular attention has been given to the imported intermediate contents in production. Based on the traditional analysis method, customs data and case studies are used. Recently, many studies have begun to trace the value-added in international trade. By using constructed international input–output tables, it is possible to unveil cross-industry and cross-country linkages within GVCs in a more comprehensive way. Research in this thesis relies heavily on the method which have recently been explored.

Chapter 3 Why has Domestic Value-Added in China's Exports Increased? [5]

3.1 Introduction

During recent decades, two important phenomena have occurred so that the landscape of international trade dramatically changed. First, production processes have been sliced into many stages, and the resulting production fragmentation is carried out in different locations. Thus, the production of a final good requires the participation of firms in many countries that specialize in different segments of the vertical production chain. International trade is then increasingly dominated by intermediate goods and services. The amplification of intermediate inputs trade has been boosted by the reductions of tariff and non-tariff barriers within the framework of bilateral and multilateral trade agreements.

Second, China has increasingly participated in global value chains (GVCs) and has been recognized as an important manufacturing center and exporter of final goods. Since the early 1990s, China has integrated into the global economy at an extraordinary pace. China's exports of goods and services increased from $49 billion in 1990 to $2,656 billion in 2018. The country's imports of goods and services increased from $38 billion in 1990 to $2,549 billion in 2018. Meanwhile, the contribution of total exports to the gross domestic product (GDP) rose from 24 to 38 percent in the same period.[6] The country has become the largest exporter of manufacturing goods since 2009, and "Made in China" has become one of the most common labels in shopping malls all over the world. In addition, the surge in trade value has been accompanied by the upgrading of China's export structure. Products exported by China include not only labor-intensive products such as apparel, shoes, and furniture, but also technology-intensive products such as computers, mobile phones, and digital cameras (Rodrik 2006; Schott 2008). The share of medium-tech and high-tech products in China's total exports rose from 28 percent in 1990 to 61 percent in 2018.[7] Some empirical studies have found that China's exports include capital-intensive, skill-intensive, and high-technology products, in which advanced countries specialize. Rodrik (2006) shows that China is an outlier with the overall sophistication of its exports: the export bundle of China is similar to that of higher-income countries. Moreover, Schott (2008) finds that China's export bundle has gradually come to

[5] Chapter 3 is based on the previously published article of Zhu (2019).
[6] World Development Indicators.
[7] World Development Indicators.

resemble that of advanced economies.

However, pervasive GVCs and production fragmentation pose new challenges to the study of international trade. Traditional trade statistics are based on the assumption that all production activities take place at home and use domestic inputs only. However, as international specialization expands and the use of imported inputs increases, this assumption becomes invalid. Some case studies show that traditional trade statistics based on flows of exports and imports cannot reflect the actual circumstance of how GVCs and production fragmentation determine the cross-country transactions of intermediate goods and final goods. In a case study of the iPhone, Xing and Detert (2010) show how the iPhone 3G is exclusively assembled in China from parts and components which are mostly sourced abroad. Assembling and testing activities by Chinese firms contributed only 3.6 percent to the $2 billion of iPhone exports to the US in 2009. In contrast, firms in Japan, South Korea, Germany, and the US capture the bulk of profits by manufacturing high-value components, such as hard-disk drives, displays, and memories. Other case studies focusing on tablets, mobile phones, and laptops find a similar pattern of participation: advanced countries specialize in capital-intensive and technology-intensive activities, capturing most of the benefits, whereas developing countries specialize in low-skilled activities that add little value (Linden, Kraemer and Dedrick 2009; Dedrick, Kraemer and Linden 2010). These examples illustrate that the contribution of a country specializing in the production of final goods in GVCs is overestimated if we use a method based on traditional trade statistics. Gross exports based on traditional trade statistics attribute all the value of exported products to the assembly country or exporting country within GVCs. However, it fails to reveal the direct and indirect inter-industrial linkages in GVCs. For example, a product shipped from one country to another may encompass a third country's intermediate goods. Using traditional trade statistics may lead to a double-counting problem, and in particular may cause misleading bilateral trade balances (Meng et al. 2017).

While case studies provide an intuitive understanding of how a country participates in GVCs, they are mainly conducted for high-end electronics products at a singular point in time. Consequently, they cannot depict a comprehensive picture of production networks and inter-industry linkages in the whole economy. Thanks to the development of international input–output tables, however, important progress has been made in measuring GVCs. The fundamental information in an input–output table contains inter-industry transactions within a given country, which describes the distribution of a producer's output throughout the economy and the composition of inputs required by a particular sector to produce its output (Miller and

Blair 2009). Moreover, the development of international input–output tables enhances the understanding of linkages across countries by including more information on how exports are distributed abroad and how imports are sourced from foreign countries.

Researchers seek to measure value-added contents (the payment to labor and capital inputs) in exports based on input–output tables in order to overcome the shortcomings of traditional trade statistics. A widely used method for measuring the extent of a country's participation in GVCs is to estimate the domestic value-added (DVA) of exports on the basis of input–output tables. It captures the contribution of all upstream domestic sectors to value-added in a specific country-sector's exports. In the automobile sector, for example, the DVA includes value-added content created by the domestic automobile sector itself as well as value-added in intermediate inputs from all other upstream domestic sectors, such as plastic products, electrical and optical equipment, and machinery equipment. Moreover, because the DVA of exports accounts for a part of GDP, it can accurately reflect the gains which a country benefits from international trade.[8]

This chapter focuses on two research questions. The first is whether existing evidence based on traditional trade statistics accurately describes the state of China's exports. Koopman, Wang and Wei (2008) propose a framework to calculate the DVA of China's exports, and by their estimation, the DVA share in China's manufacturing exports was about 50 percent before its WTO entry, and increased to about 60 percent in 2007. There are also significant variations across industries. On the one hand, industries that produce sophisticated goods, such as electronic devices, have a relatively low domestic content (less than 30 percent). On the other hand, industries that specialize in the production of less sophisticated goods such as apparel have relatively high DVA shares. Their analysis is only available for specific benchmark years, however, and cannot examine long-term trends. Moreover, due to data availability, their estimation is limited to China. To depict a comprehensive picture of China's participation in the GVCs, it is also necessary to compare the domestic content of China's exports with those of other countries.

The second question asks what factors affect the change in DVA of exports over time. Over the past two decades, production fragmentation has enabled firms to depend less on domestically produced intermediate inputs for production, and some studies have found that domestic content in exports has declined in many countries. Johnson and Noguera (2012), for example, use the Global Trade Analysis Project (GTAP) input–output tables to show that the

[8] In Koopman, Wang and Wei (2014), the DVA of exports is also referred to as GDP in exports.

domestic content of exports fell for most countries in their sample period of 1970–2009. China, however, is an intriguing exception. Using firm-level data, Kee and Tang (2016) find that the ratio of DVA to manufacturing exports in China increased from 2000 to 2006.

How does China go against this worldwide downward trend of domestic contents in exports, despite its deep involvement in GVCs? There are several possible answers to this question. The rise in domestic content could be affected by the changing composition of China's exports, implying that the country has shifted its comparative advantage toward industries with high domestic content. For example, if the export share of low technology manufacturing products increases, the domestic content of China's total exports may increase because the domestic content of low technology manufacturing products is usually higher. Another possible reason could be the substitution of domestic intermediate inputs for imported materials. As intermediate input sectors become more competitive, the production in China may rely more on domestically produced intermediate inputs. As a consequence, the domestic content in exports will rise. In addition, the change in labor and capital income could affect the value-added embedded in production. For example, the rise in labor wages could cause labor income to increase. As a result, value-added embedded in production could also increase provided that the capital income is unchanged. Understanding the determinants of changing the domestic content of China's exports may offer instructive policy insights into the economic growth of China and other developing countries.

This chapter contributes to the literature in two ways. First, it is difficult to examine annual changes in the DVA of China's exports based only on the results available for specific benchmark years. This can be overcome through the development of the World Input–output Database (WIOD), which provides an annual time-series of world input–output tables for recent studies of DVA (Timmer et al. 2015). Following Koopman, Wang and Wei (2014), this chapter calculates the DVA of China's exports from 2000 to 2014 on the basis of the WIOD. The result reveals that the DVA share (the ratio of DVA to exports) of China's total exports fell during the period 2000–2007 but rose thereafter. We also estimate the DVA of exports across six composite industries and find that the DVA share of high technology manufacturing exports of China is lower than in other industries, despite high technology manufacturing accounting for the largest share of total Chinese exports.

The second significant contribution is to use an extended structural decomposition analysis (SDA) to examine the pattern of change in the DVA of exports. The SDA provides an effective approach to decompose the total amount of change into specific components so that the contributions of each component can be quantified. This chapter presents a modified structural decomposition of DVA growth by applying the SDA to the framework of Koopman, Wang and Wei (2014). The change in the DVA of exports is broken down into nine determinants: (1) capital coefficients (capital-output ratio), (2) labor productivity, (3) wage per person, (4) the ratio of labor income to capital income, (5) the substitution between domestic intermediate inputs and imported materials, (6) the substitution of intermediate inputs among each sector, (7) total export effect, (8) export structure effect, and (9) export destination effect.

Previous studies have documented that the substitution between domestic intermediate inputs and imported materials, total export effect, and export structure effect tend to affect changes in DVA. However, these studies only consider the aggregate effect of value-added coefficients and fail to explicitly explain the contribution of specific value-added content to changes in DVA of exports. To fill this gap, this chapter refines the SDA to quantify the effects of capital coefficients, labor productivity, wage per person, and the ratio of labor income to capital income on changes in DVA of exports.

Labor income and capital income are two important components in the value-added. The neoclassical theory provides a starting point for explaining the change in factor income shares: a fall in labor income share is associated with a decline in the relative price of investment goods, such as computer equipment, encouraging firms to replace labor with machines. This theory highlights the roles of capital-labor substitutability and capital-output ratio in determining labor income shares. Lawrence (2015) explains the change in factor income share based on the neoclassical theory. The study emphasizes that elasticity of substitution is a key parameter that captures whether capital and labor are gross complements or substitutes. Bai and Qian (2010) document that the labor share of China was on the decline during the period 1995–2007. In addition, labor productivity could affect labor income share when labor augmenting technical change is taken into consideration. Enhanced labor productivity is equivalent to a rise in the supply of "effective labor," which could increase the effective labor-capital ratio and reduce labor income share in value-added. Wage per worker is also a determinant of the change in DVA of China. Cui, Meng and Lu (2018) find that labor wages in China rose by about 16 percent annually during the period 2008-2015, which played a direct role in increasing labor income. The most important results of the SDA show that the increase in labor income relative to capital income plays a pronounced role in raising the DVA of China's exports. Moreover, the substantial rise in labor productivity and wage per person exerts a positive effect on the growth in DVA of China's exports. Finally, this chapter also reveals that the change in export structure has a negative impact on the DVA of China's exports during the period 2000–2005. In the subsequent period, however, the export structure effect on DVA of exports becomes invisible.

This chapter's third contribution is to compare the DVA of China's exports with that of Japanese and US exports. For comparison, the same method is applied to compute the DVA of Japanese and US exports. A notable result is that the DVA share of China's export of high technology manufacturing was much lower than that of the US and Japan in the early 2000s. The gap, however, was shrinking over time. It implies that the high technology manufacturing industry of China becomes more competitive. In addition, the result shows that the rise in the DVA of China's exports is associated with other determinants such as the substitution of labor income for capital income and the increase in labor productivity and wage per person. Conversely, the rise in the DVA of US exports can be attributed to the substitution of capital income for labor income and capital coefficients. Moreover, China is increasingly dependent on domestically produced intermediate inputs after the mid-2000s, suggesting the increasing presence of domestic suppliers in China's exports. Conversely, Japan and the US appear to have increased their reliance on imported intermediate inputs for production.

This chapter proceeds as follows. Section 3.2 presents related literature in response to the two research questions. Section 3.3 outlines the procedure by which this chapter measures the DVA of exports and how the SDA approach is applied to decompose the changes in DVA. Section 3.4 explains the data source and presents empirical results for the DVA of exports. The final section summarizes the conclusions.

3.2 Literature Review

This chapter is related to two strains of previous literature in response to the two research questions above. The first question to answer is whether the existing evidence based on traditional statistics describes the real state of China's exports. Case studies focusing on a specific sector or product are inadequate to examine the performance of the entire economy. Most researchers tended to use macro-level data to map and measure GVCs. Early studies initiated with the work of Ng and Yeats (1999) compare the trade statistics of parts and components with final products. Based on disaggregated trade statistics on parts and components, Athukorala (2005) examines the international product fragmentation and its implications for trade patterns in East Asia. Kimura, Takahashi and Hayakawa (2007) investigate the patterns of international trade in machinery parts and components in East Asia and Europe and conclude that production fragmentation has become prevalent in the production networks in East Asia. A shortcoming of this type of analysis is that it highly depends on the production classifications of trade statistics. Consequently, it probably leads to the low accuracy of the measure. In addition, the increased intermediate goods in international trade that frequently cross national borders pose a measurement challenge. Traditional trade statistics record the value of intermediate goods multiple times. As a result, countries specializing in the assembly of final goods often account for most of the value of exports, while the role of countries that supply intermediate inputs in the upstream sectors tends to be underestimated.

To depict a precise landscape of country's participation in GVCs, researchers need to use input–output tables to measure the domestic and foreign contents embedded in exports. The development of international input–output database provides a rich description of how a country or sector sources intermediate inputs for its production and distributes its products all over the world. Hummels, Ishii and Yi (2001) propose an indicator to measure the share of imported content in exports, which is called vertical specialization (VS). This measure of VS captures situations where the production is carried out in at least two countries and goods cross national borders multiple times. Compared with previous studies, the VS can capture the imported intermediate inputs that are used in multinational production directly and indirectly. Using national input–output tables for ten OECD countries during the period 1970–1990, Hummels, Ishii and Yi (2001) document that the VS account for 21 percent of these countries' exports. Dean, Fung and Wang (2007) and Daudin, Rifflart and Schweisguth (2011) apply the approach using the VS to confirm the fact that the degree of production fragmentation substantially increases in many countries. Their work, however, is turned out to be incomplete, which cannot capture the imported value-added in back-and-forth trade. Recent works attempt to keep track of the value-added embedded in complicated production chains. Johnson and Noguera (2012) measure the ratio of value-added to gross exports, which is called value-added export (VAX), based on synthesized international input–output tables. The VAX tracks the amount of domestic value-added content in final demand that is absorbed abroad. An alternative approach by Wang, Wei and Zhu (2013) and Koopman, Wang and Wei (2014) decomposes a country's gross exports into value-added components regardless of where the exports are ultimately absorbed. Specifically, gross exports are decomposed into domestic value-added of exports, foreign value-added of exports, and additional pure double-counting terms. Their studies quantify the value-added contents in exports while accounting for back-and-forth trade of intermediate goods and avoiding double counting items. However, the above studies measure vertical specialization and value-added content based on their own databases, typically combining international trade statistics with a collection of input–output tables from the Global Trade Analysis Project (GTAP) project. And their analyses are only available for specific benchmark years and are not available for the examination of long-term trends. The difficulty can be overcome with the development of the World Input–output Database in 2016, which provides annual time-series of world input–output tables. The database is widely used to measure the value-added contents in exports (Timmer et al., 2015).[9]

The second question is what factors affect the change in DVA of exports. Despite the significant change in value-added content of China's exports, little attention has been devoted to the driving forces behind it. This, however, is crucial for researchers and policymakers to understand how to maintain the sustainable growth of DVA of exports in the long term. This chapter not only measures the DVA of exports but also quantifies factors that affect DVA of China's exports. Is the growth of DVA caused by the increase in domestic intermediate inputs? Do the changes in capital and labor compensation influence DVA? Does the change in export structure affect China's DVA? Investigating the relationship between these factors and DVA of exports provides policy implications for the economic development of China.

To isolate the driving forces underlying the change in DVA of exports, this chapter uses the structural decomposition analysis (SDA), which is an effective approach to break down the total amount of change into specific components so that the contributions of each component can be determined and quantified. Miller and Blair (2009) demonstrate the fundamental concepts of SDA within an input–output framework. Some studies have applied the SDA approach to decompose the change in value-added content (Meng, Yamano and Webb 2011; Pei, Oosterhaven and Dietzenbacher 2012; Nagengast and Stehrer 2016; Duan et al. 2018). Generally, SDA decomposes the change in value-added content into three broad components: changes in direct value-added (capital and labor compensation), intermediate inputs, and final demand (or exports). For example, Nagengast and Stehrer (2016) decompose the change in value-added content during the period 2008–2009 financial crisis. They show that the changes in international production sharing, which is represented by the change in intermediate inputs sourcing, account for a large proportion of the great trade collapse. Additionally, Duan et al. (2018) apply the SDA approach to analyze the decline in international production sharing in China's exports. Their results reveal that the downward trend is primarily caused by the substitution of imported intermediate goods for domestically produced intermediate materials.

[9] Amador and Cabral (2016) and Johnson (2017) provide detailed discussions on the measurement of GVCs.

Recently, an extension of the SDA approach is also used to quantify factors that affect the change in DVA of exports. Yang, L and Yang, C (2017) use the SDA to examine driving forces that affect the changes in the DVA of China's ordinary exports and processing exports, respectively. According to their study, the increased ordinary exports largely contribute to the rise in the DVA of China's exports. Using firm-level data, Kee and Tang (2016) confirm that rising domestic content in China's exports is associated with the substitution of cheaper domestic intermediate inputs for imported materials. Most of the previous studies focus on the effects of intermediate inputs and exports on the growth of DVA. However, the contribution of value-added to DVA remains unclear.

The direct value-added includes payments to primary inputs, such as capital and labor income. Previous studies focus on the aggregate effect of value-added on the DVA. Few, however, measures the influence of capital and labor income on DVA. Timmer et al. (2014) decompose the DVA into capital and labor that are directly and indirectly required for the production of final manufacturing goods based on WIOD. Their result shows a shift towards value being added by capital and high-skilled labor, and away from less-skilled labor in GVCs on a global scale. Further, they find that capital share in value-added is rising for many developing countries (including China), implying that developing countries increasingly specialized in capital-intensive production activities. Dietzenbacher, Lahr and Los (2004) use the SDA to dissect the decline of labor income share in the US value-added. This chapter distinguishes from previous literature by further decomposing the direct value-added term into four components: capital coefficients (the ratio of capital income to output), labor productivity (the ratio of value-added to the number of labor), wage level per person (the ratio of labor income to the number of labor), and the ratio of labor income to capital income. Overall, this chapter decomposes DVA of China's exports into 9 components: (1) capital coefficients, (2) labor productivity, (3) wage per person, (4) the ratio of labor income to capital income, (5) the substitution between domestic intermediate inputs and imported materials, (6) the substitution of intermediate inputs among each sector, (7) total exports effect, (8) export structure effect, and (9) export destination effect.

3.3 Methodology

In this section, we explain the estimation of DVA of exports following Koopman, Wang and Wei (2014). Furthermore, we provide details about how to decompose the change in DVA of exports into several determinants using the SDA approach.

3.3.1 Measuring the DVA of Exports

This subsection illustrates how to calculate the DVA of exports on the basis of input–output tables in WIOD, in which a set of national input–output tables that are connected with each other by bilateral international trade flows. To calculate the DVA of China's exports, a time-series national input–output tables of China are needed. In addition, the WIOD provides detailed data on trade flows by origins and destinations.

In the input–output table of N industries, let $\mathbf{Z}$ be an $N \times N$ matrix representing the transaction values of intermediate inputs among sectors within a country. Let $\mathbf{Y}$ be an $N \times G$ final demand matrix, which denotes the transactions of final goods. Summing up the matrix $\mathbf{Y}$ along rows yields the total final outputs of a given sector, which can be expressed as $\mathbf{y} = \mathbf{Y}\boldsymbol{\mu}$, and $\boldsymbol{\mu}$ is a conformable vector of ones (the dimension of which differs depending on the context). Let $\mathbf{x}$ be an $N \times 1$ gross output vector. The domestic input coefficient matrix $\mathbf{A^d}$ gives the production requirements per unit of output, and is defined as $\mathbf{A^d} = \mathbf{Z}\hat{\mathbf{x}}^{-1}$, in which $\hat{\mathbf{x}}$ denotes a diagonal matrix with gross output vector $\mathbf{x}$ on its main diagonal.[10] The gross output consists of intermediate goods and final goods; that is, $\mathbf{x} = \mathbf{A^d}\,\mathbf{x} + \mathbf{y}$. This equation can be rearranged as $\mathbf{x} = (\mathbf{I} - \mathbf{A^d})^{-1}\,\mathbf{y} = \mathbf{L^d}\,\mathbf{y}$, where $\mathbf{I}$ is the identity matrix, and $\mathbf{L^d}$ is a domestic Leontief inverse matrix, which represents the gross output values that are generated in all stages of the production process of one unit of final demand.

The Leontief inverse matrix can be expressed as a geometric series. Multiplying by the final demand vector, the zero-order term $\mathbf{y}$ is the direct output absorbed as final goods, the first-order term $[\mathbf{I} + \mathbf{A^d}]\,\mathbf{y}$ is the direct output absorbed plus the intermediates used to produce that output, the second-order term $[\mathbf{I} + \mathbf{A^d} + (\mathbf{A^d})^2]\,\mathbf{y}$ includes the additional intermediates used to produce the first round of intermediates ($\mathbf{A^d}\mathbf{y}$), and the sequence continues as such. Therefore, $(\mathbf{I} - \mathbf{A^d})^{-1}\,\mathbf{y}$ is the vector of output used both directly and indirectly to produce final goods.

Gross output requirement can be translated into the effect on value-added by using value-added coefficients. Thus, the DVA of an individual country's exports based on input–output model is calculated as follows:[11]

$$\mathbf{DVA} = \mathbf{v}(\mathbf{I} - \mathbf{A^d})^{-1}\hat{\mathbf{e}} = \mathbf{v}\mathbf{L^d}\hat{\mathbf{e}}, \tag{3.1}$$

[10] Throughout this thesis, matrices are indicated by bold capital symbols and vectors by bold lowercases. The notation "hat" over a vector denotes a diagonal matrix with the elements of the vector along the main diagonal and zeros in off-diagonal elements.

[11] The derivation of equation (3.1) follows Koopman, Wang and Wei (2014).

where, $\mathbf{v}$ is a *1×N* vector of value-added coefficients, which can be calculated as $\mathbf{v} = \mathbf{p}\hat{\mathbf{x}}^{-\mathbf{1}}$,with $\mathbf{p}$ be a *1×N* vector of direct value-added. In other words, value-added coefficients reflect the share of direct value-added in total outputs. Let $\mathbf{e}$ denote the gross export vector, including both the final good exports and intermediate good exports of a country. The product of the Leontief inverse matrix $\mathbf{L^d}$ and the value-added coefficient vector $\mathbf{v}$ gives the DVA that is needed to produce one additional unit of product (or the DVA share in one unit of product). Finally, multiplying $\mathbf{vL^d}$ by gross exports $\hat{\mathbf{e}}$ yields the DVA embedded in a country's exports.

3.3.2 Structural Decomposition Analysis (SDA)

The DVA in exports is decomposed into nine determinants by employing an extended SDA approach: capital coefficients (the ratio of capital income to output), labor productivity (the ratio of value-added to labor inputs), wage per person (the ratio labor income to labor inputs), the substitution between labor income and capital income (the ratio of labor income to capital income), the substitution between domestically produced inputs and imported inputs, the substitution of intermediate inputs among each sector, total exports effect, export structure effect (i.e., how the exports of each destination are distributed across sectors), and export destination effect (i.e., how total exports are distributed across export destination countries).

First, the change in intermediate inputs is decomposed into the effect of the substitution between domestically produced inputs and imported inputs, the substitution of intermediate inputs among each sector. $\mathbf{A^d}$ and $\mathbf{A^m}$ are domestic input coefficient matrix (i.e., the amount of domestically produced intermediate inputs required per unit of output) and imported input coefficient matrix (i.e., the amount of imported intermediate inputs required per unit of output). $\mathbf{A^{TOT}} = \mathbf{A^d} + \mathbf{A^m}$ indicates the total input coefficient. In order to quantify the substitution between domestic intermediate inputs and imported materials, one can use a matrix of $\mathbf{T^d}$ to capture the share of domestically produced intermediate inputs,

$$\mathbf{A^d} = \mathbf{T^d} \otimes \mathbf{A^{TOT}}, \tag{3.2}$$

where the Hadamard product $\otimes$ denotes cell-by-cell multiplication, with $\mathrm{a_{ij}^d} = \mathrm{t_{ij}^d} \times \mathrm{a_{ij}^{TOT}}$. For example, a 2×2 matrix $\mathbf{T^d}$ can be expressed as follows:

$$\begin{bmatrix} t_{11}^{d} & t_{12}^{d} \\ t_{21}^{d} & t_{22}^{d} \end{bmatrix} = \begin{bmatrix} \frac{a_{11}^{d}}{a_{11}^{TOT}} & \frac{a_{12}^{d}}{a_{12}^{TOT}} \\ \frac{a_{21}^{d}}{a_{21}^{TOT}} & \frac{a_{22}^{d}}{a_{22}^{TOT}} \end{bmatrix}.$$

The change of $\mathbf{T^d}$ reflects the substitution between domestically produced intermediate inputs and imported materials. For example, an increase in each element of matrix $\mathbf{T^d}$ means more domestic intermediate inputs are used for the production. Then equation (3.1) can be rewritten as follows:

$$\mathbf{DVA} = \mathbf{v}(\mathbf{I} - \mathbf{A^d})^{-1}\,\hat{\mathbf{e}} = \mathbf{v}(\mathbf{I} - \mathbf{T^d} \otimes \mathbf{A^{TOT}})^{-1}\,\hat{\mathbf{e}}. \tag{3.3}$$

Note that the change of value-added coefficients ($\mathbf{v}$), domestic input coefficients ($\mathbf{A^d}$), and imported input coefficients ($\mathbf{A^m}$) are not fully independent, as $\mathbf{v} + \boldsymbol{\mu}\mathbf{A^{TOT}} = \boldsymbol{\mu}$ (Diezenbacher and Los 2000). To solve this dependent problem, this chapter uses normalized total intermediate input coefficients, $\widetilde{\mathbf{A}} = \mathbf{A^{TOT}}(\mathbf{I} - \hat{\mathbf{v}})^{-\mathbf{1}}$. The matrix provides the mix of intermediate inputs in each sector. The change of $\widetilde{\mathbf{A}}$ reflects the inter-sector substitution between intermediate inputs. Then equation (3.3) is rewritten as follows:

$$\mathbf{DVA} = \mathbf{v}\left[\mathbf{I} - \mathbf{T^d} \otimes \widetilde{\mathbf{A}}(\mathbf{I} - \hat{\mathbf{v}})\right]^{-\mathbf{1}}\,\hat{\mathbf{e}}. \tag{3.4}$$

Furthermore, the value-added coefficients ($\mathbf{v}$) is equal to the product of four components including the capital coefficient ($\mathbf{k}$), labor productivity ($\boldsymbol{\pi}$), the ratio of inputs to wage compensation ($\boldsymbol{\theta}$), and the ratio of labor compensation to capital compensation ($\boldsymbol{\varphi}$). Let $\mathbf{r}$ and $\mathbf{c}$ denote the vector of labor income and capital income, respectively. The capital coefficient is expressed by $\mathbf{k} = \mathbf{c}\hat{\mathbf{x}}^{-1}$. Let $\boldsymbol{l}$ denote the number of labor inputs. The labor productivity is expressed by $\boldsymbol{\pi} = \mathbf{p}\hat{\boldsymbol{l}}^{-1}$. The level of wage per person is expressed by the reciprocal of $\boldsymbol{\theta} = \boldsymbol{l}\hat{\mathbf{r}}^{-1}$, and the ratio of labor income to capital income is expressed by $\boldsymbol{\varphi} = \mathbf{r}\hat{\mathbf{c}}^{-1}$. Thus, the value-added coefficient is calculated as $\mathbf{v} = \mathbf{k}\hat{\boldsymbol{\pi}}\hat{\boldsymbol{\theta}}\hat{\boldsymbol{\varphi}}$. Therefore, equation (3.4) can be rearranged as follows:

$$\mathbf{DVA} = \left(\mathbf{k}\hat{\boldsymbol{\pi}}\hat{\boldsymbol{\theta}}\hat{\boldsymbol{\varphi}}\right)\left[\mathbf{I} - \mathbf{T^d} \otimes \widetilde{\mathbf{A}}(\mathbf{I} - \hat{\mathbf{v}})\right]^{-1}\hat{\mathbf{e}}. \tag{3.5}$$

Finally, the exports matrix can be decomposed into three components: (1) the total export effect (scalar *G*), which expresses the total value of exports; (2) the export structure effect (matrix **M**), which captures how exports to an particular country are distributed across sectors; and (3) the exports destination effect (vector **d**), which captures how total exports are distributed across export destination countries. Thus, the exports vector can be expressed as $\mathbf{e} = \mathrm{G}\mathbf{Md}$, and equation (3.5) is rewritten as follows:

$$\mathbf{DVA} = \left(\mathbf{k}\hat{\boldsymbol{\pi}}\hat{\boldsymbol{\theta}}\hat{\boldsymbol{\varphi}}\right)\left[\mathbf{I} - \mathbf{T^d} \otimes \widetilde{\mathbf{A}}(\mathbf{I} - \hat{\mathbf{v}})\right]^{-1}\widehat{\mathrm{G}\mathbf{Md}}. \tag{3.6}$$

Equation (3.6) is the basic formula of the SDA that is developed by this chapter to decompose the change in the DVA of exports. Specifically, the annual percentage change in the DVA of exports over time is conducted in an additive decomposition framework.

In order to decompose the change of DVA in exports into nine determinants over the periods 2000–2005, 2005–2010, and 2010–2014, respectively, this chapter uses the average of the two so-called polar decompositions. The principle can be illustrated in the case with three determinants. Suppose $U = QTP$, in which $Q\,, T\, and\,\, P$ can change independently from each other. Subscripts 0 and 1 stand for two different years.

$$\Delta U = Q_1T_1P_1 - Q_0T_0P_0, \tag{3.7}$$

$$= (Q_1T_1P_1 - Q_0T_1P_1) + (Q_0T_1P_1 - Q_0T_0P_1) + (Q_0T_0P_1 - Q_0T_0P_0), \quad \text{(one polar)} \tag{3.8}$$

$$= (Q_1T_0P_0 - Q_0T_0P_0) + (Q_1T_1P_0 - Q_1T_0P_0) + (Q_1T_1P_1 - Q_1T_1P_0), \quad \text{(counter polar)} \tag{3.9}$$

$$\begin{aligned} &= \frac{1}{2}\Delta Q(T_1P_1 + T_0P_0) + \frac{1}{2}(Q_1T_1 + Q_0T_0)\Delta P + \\ &\quad + \tfrac{1}{2}[(Q_0T_1P_1 - Q_0T_0P_1) + (Q_1T_1P_0 - Q_1T_0P_0)]. \end{aligned} \quad \text{(the average)} \tag{3.10}$$

Equations (3.8) and (3.9) are the polar decompositions using different weights. The notation Δ denotes the difference between two periods. Taking the average of the two polar decompositions yields equation (3.10). The first term of equation (3.10) measures the change of *U* due to the change of Q when *T* and *P* are constant; the second term measure the change of *U* due to the change of *P* assuming Q and *T* are constant; the third term captures the change of *U* due to the change of *T* when Q and *P* are constant. Thus, the actual decomposition of equation (3.6) can be derived in the same way as equation (3.7). From equation (3.6), the DVA can be expressed as a function with 9 variables, that is, $f\left(k, \pi, \theta, \varphi, T^d, \widetilde{\mathrm{A}}, G, M, d\right)$. Thus, the first polar decomposition is as follows:

$$
\begin{aligned}
&\mathrm{DVA}_1 - \mathrm{DVA}_0 \\
&= f\left(k_1,\pi_1,\theta_1,\varphi_1,T_1^d,\tilde{A}_1,G_1,M_1,d_1\right) - f\left(k_0,\pi_0,\theta_0,\varphi_0,T_0^d,\tilde{A}_0,G_0,M_0,d_0\right), \\
&= f\left(k_1,\pi_1,\theta_1,\varphi_1,T_1^d,\tilde{A}_1,G_1,M_1,d_1\right) - f\left(k_0,\pi_1,\theta_1,\varphi_1,T_1^d,\tilde{A}_1,G_1,M_1,d_1\right) \\
&+ f\left(k_0,\pi_1,\theta_1,\varphi_1,T_1^d,\tilde{A}_1,G_1,M_1,d_1\right) - f\left(k_0,\pi_0,\theta_1,\varphi_1,T_1^d,\tilde{A}_1,G_1,M_1,d_1\right) \\
&\qquad\qquad\qquad\qquad\vdots \\
&+ f\left(k_0,\pi_0,\theta_0,\varphi_0,T_0^d,\tilde{A}_0,G_0,M_0,d_1\right) - f\left(k_0,\pi_0,\theta_0,\varphi_0,T_0^d,\tilde{A}_0,G_0,M_0,d_0\right).
\end{aligned}
$$

As the mirror image of the first polar decomposition above, the other polar decomposition is expressed as follows:

$$
\begin{aligned}
&DVA_1 - DVA_0 \\
&= f\left(k_1,\pi_1,\theta_1,\varphi_1,T_1^d,\tilde{A}_1,G_1,M_1,d_1\right) - f\left(k_0,\pi_0,\theta_0,\varphi_0,T_0^d,\tilde{A}_0,G_0,M_0,d_0\right), \\
&= f\left(k_1,\pi_0,\theta_0,\varphi_0,T_0^d,\tilde{A}_0,G_0,M_0,d_0\right) - f\left(k_0,\pi_0,\theta_0,\varphi_0,T_0^d,\tilde{A}_0,G_0,M_0,d_0\right) \\
&+ f\left(k_1,\pi_1,\theta_0,\varphi_0,T_0^d,\tilde{A}_0,G_0,M_0,d_0\right) - f\left(k_1,\pi_0,\theta_0,\varphi_0,T_0^d,\tilde{A}_0,G_0,M_0,d_0\right) \\
&\qquad\qquad\qquad\qquad\vdots \\
&+ f\left(k_1,\pi_1,\theta_1,\varphi_1,T_1^d,\tilde{A}_1,G_1,M_1,d_1\right) - f\left(k_1,\pi_1,\theta_1,\varphi_1,T_1^d,\tilde{A}_1,G_1,M_1,d_0\right).
\end{aligned}
$$

Then, calculating the average effect of the corresponding terms yields the final decomposition. For example, the effect of capital coefficient E(k) can be calculated as follows:

$$
\begin{aligned}
\mathrm{E(k)} = \tfrac{1}{2}\big[&f\left(k_1,\pi_1,\theta_1,\varphi_1,T_1^d,\widetilde{A}_1,G_1,M_1,d_1\right) - f\left(k_0,\pi_1,\theta_1,\varphi_1,T_1^d,\widetilde{A}_1,G_1,M_1,d_1\right) \\
&+ f\left(k_1,\pi_0,\theta_0,\varphi_0,T_0^d,\widetilde{A}_0,G_0,M_0,d_0\right) - f\left(k_0,\pi_0,\theta_0,\varphi_0,T_0^d,\widetilde{A}_0,G_0,M_0,d_0\right)\big].
\end{aligned}
\tag{3.11}
$$

Then, we can calculate $\mathrm{E}(\pi)\sim\mathrm{E}(d)$ in the same manner.

3.4 Data and Empirical Results

This section will first explain the data sources that are used to estimate the DVA of exports. Then we present the estimation results for the DVA of exports at the industry and country levels. Finally, we decompose the change in DVA of exports into several components using the SDA approach.

3.4.1 Data Sources

This chapter measures the DVA of exports by using international input–output tables and supplementary data from the WIOD, which is constructed by connecting a set of national input–output tables. The WIOD released in 2016 provides time-series of international input–output tables, covering 43 countries and 56 sectors for the period 2000–2014 (Timmer et al. 2016). The variables used in equation (3.1) rely on the data from international input–output tables, such as the flows of intermediate inputs ($\mathbf{Z}$), the flows of final products ($\mathbf{y}$), outputs ($\mathbf{x}$), and value-added ($\mathbf{p}$).

In addition to input–output tables, a unique characteristic of the WIOD is the availability of the quantity and prices of factor inputs, including data on labor input (number of workers), labor income, and capital income. These data are provided in the so-called socio-economic accounts and can be used in conjunction with international input–output tables as similar industry classifications are used. These data are crucial for our analysis, including labor income ($\mathbf{r}$), capital income ($\mathbf{c}$), and the number of workers ($\boldsymbol{l}$). A table of summary statistics for the data of China, Japan, and US is provided in the Appendix A.

By applying the concepts and measurement described above, this section presents the estimation results of the DVA of exports across 56 industries during the period 2000–2014. For ease of exposition, the 56 industries are grouped into six composite industries: agriculture, mining and utility, low technology manufacturing, medium technology manufacturing, high technology manufacturing, and service.[12]

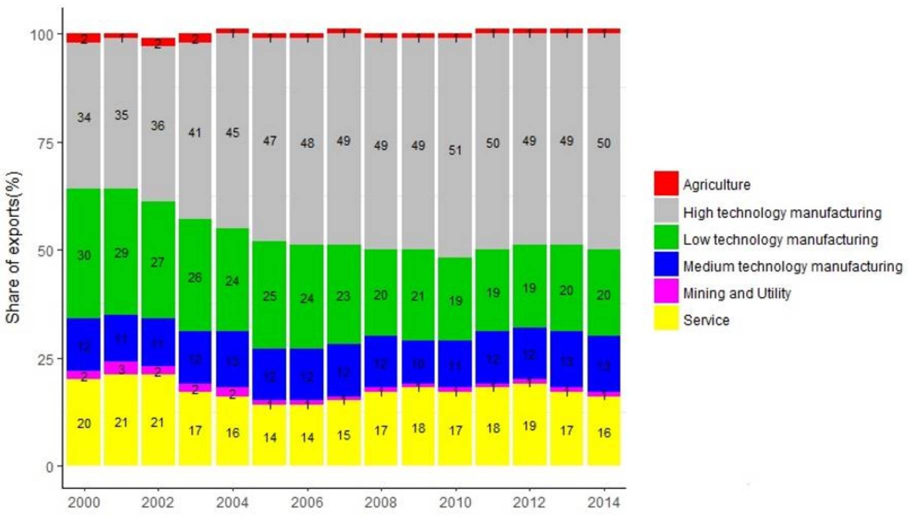
3.4.2 Results for the DVA of Exports

In response to the first research question, this subsection discusses China's gross exports and the DVA of China's exports during the period 2000–2014 using WIOD. For comparison, the DVA embedded in US and Japanese exports is also calculated. Figure 3.1 shows the composition of China's total exports by six composite industries and reveals the increased importance of high-end manufacturing goods in China's total exports. The manufacturing industry accounted for the largest share of total exports, which ranged from 74 to 84 percent from 2000 to 2014, while the total export share of services ranged from 14 to 21 percent. Due to heterogeneity across sectors, manufacturing sectors are divided into three groups: high technology manufacturing exports (e.g., computer, chemical products), medium technology

[12] The definition of the six composite industries is inspired by Nagengast and Stehrer (2016).

manufacturing exports (e.g., basic metal fabrication), and low technology manufacturing exports (e.g., textile, leather, and furniture products). The remaining two industries, agriculture and mining and utility, collectively accounted for less than 5 percent. The share of high technology manufacturing in total exports increased from 34 percent in 2000 to 50 percent in 2014; the share of medium technology exports rose slightly, from 12 percent in 2000 to 1 3 percent in 2014; and the share of low technology manufacturing exports declined from 30 percent in 2000 to 20 percent in 2014. These results are consistent with previous studies (Rodrik 2006; Schott 2008), which document that China's exports of sophisticated goods have risen dramatically. China's exports now include not only low technology products such as apparel and electrical toys, but also a large number of high technology exports such as cell phones, computers, and other electronic products. The prima facie evidence shows that the export structure of China's exports has changed dramatically, but it fails to take into consideration the imported content that are embedded in its exports. To assess the extent to which China has moved up the GVC ladder, this chapter traces value-added contents directly and indirectly embedded in exports by employing international input–output tables.

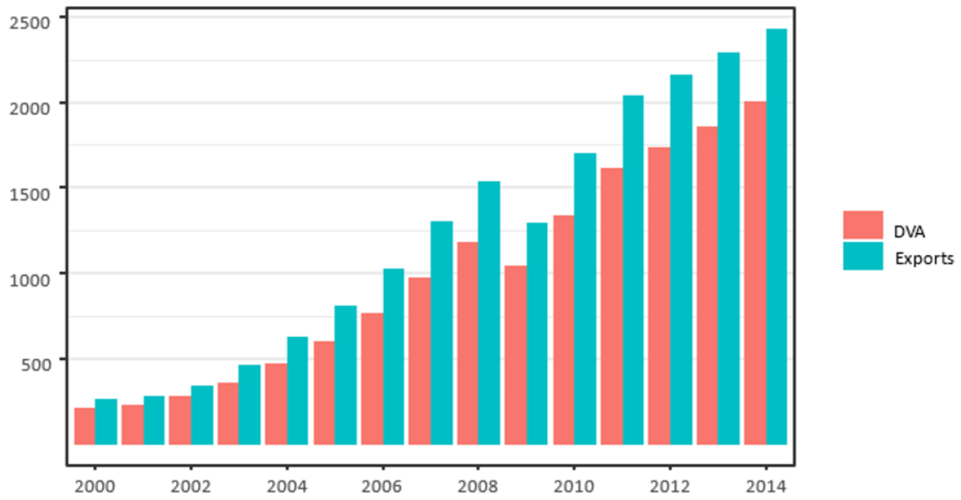
Figure 3.1 The composition of China's exports



Source: Calculated by the author based on World Input–Output Database (WIOD).

Figure 3.2 illustrates the DVA of China's exports and the value of total exports. The DVA of exports is calculated on the basis of equation (3.1). The DVA of China's exports showed an overall upward trend over the sample period, except for a short-run decline due to the 2008 global financial crisis. In 2000, the DVA of China's exports was roughly $215 billion, accounting for 82 percent of total exports. In 2014, the DVA of China increased to $2003 billion, accounting for 83 percent of total exports. The result confirms that there is a gap between DVA and gross exports. The value of DVA is smaller than exports mainly because of the existence of foreign value-added in exports, which represent imported intermediate inputs for production. This suggests that traditional trade statistics are likely to overestimate a country's exports and cannot accurately reflect China's gains from international trade.

Figure 3.2 DVA of China's exports (billion US$)



Source: Calculated by the author based on World Input–Output Database (WIOD).

Figure 3.3 illustrates the ratio of DVA to total exports, namely, the DVA share, at the country and industry levels. First, the result shows that the DVA share of China's total exports ranged from 73 to 83 percent during the period 2000–2014. The DVA share experienced a substantial decline from 83 percent in 2001 to 73 percent in 2004. After a leveling-off period, the DVA share began to rebound, increasing from 74 percent in 2007 to 82 percent in 2014. It is worthwhile to note that the downward trend of China's DVA during the period 2001–2004 responds to the WTO entry in 2001. Enhanced trade liberalization allows Chinese firms to use more imported content for production, resulting in the reduction of DVA share after the WTO accession.

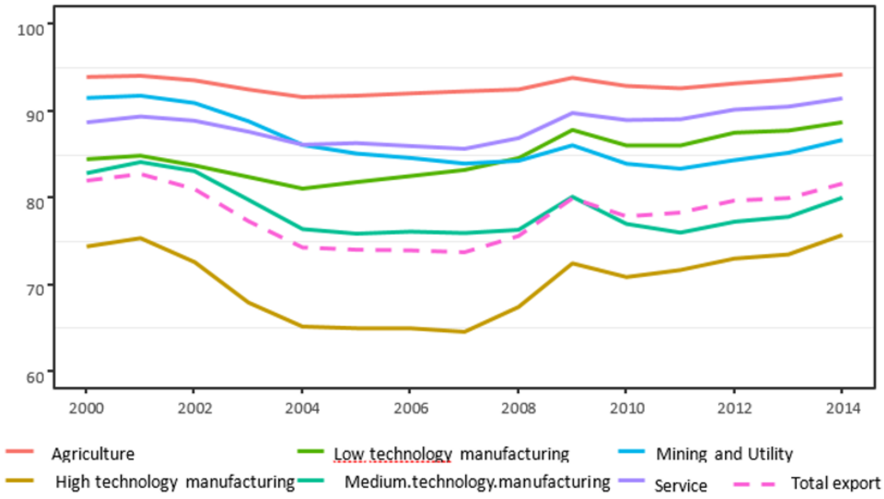
Furthermore, we calculate the average DVA shares of the six composite industries to examine the heterogeneity across industries. Figure 3.3 shows that agriculture, on average, had the highest level of DVA share among the six composite industries, followed by the service and mining and utility industries. The changes in DVA share of agriculture and service exhibit two phases from 2000 to 2014, with a moderate downward trend during the period 2000–2004 and an upward trend in the subsequent period. The DVA share of the mining and utility industry declined substantially, from 92 percent in 2001 to 84 percent in 2010. It rebounded thereafter and rose to 87 percent in 2014.

The manufacturing industry has lower DVA shares. However, significant heterogeneity is confirmed across the three manufacturing industries. High technology manufacturing had the lowest DVA share among all the industries, although it accounted for the largest share in China's total exports during the sample period. In contrast, low technology manufacturing had the highest DVA share of the three manufacturing industries. The figure reveals a common trend that the DVA shares of the three manufacturing industries declined during the period 2001–2004. However, the magnitudes of declines are different across the three manufacturing industries. High technology manufacturing fell substantially by roughly 9 percentage points, while medium and low technology manufacturing fell by 6 and 3 percentage points, respectively. The patterns of changes in the subsequent period were slightly different among the three manufacturing industries. For low technology manufacturing, the DVA share trended upward from 82 percent in 2004 to 89 percent in 2014, while the DVA shares of high and medium technology manufacturing leveled off for years and took an upward trend thereafter. Focusing on restoration period, the DVA share of high technology manufacturing went up from 66 percent in 2007 to 77 percent in 2014, while the DVA share of medium technology manufacturing rose from 77 percent in 2007 to 81 percent in 2014.

The above results imply that China's WTO entry in 2001 had a relatively large impact on the high technology manufacturing, medium technology manufacturing, and mining and utility industries and had relatively a small impact on the DVA share of agriculture, service, and low-technology manufacturing industry. Johnson (2014) offers two explanations for this result. First, many producers in the manufacturing industry have to source intermediate inputs from agriculture, non-manufacturing (raw materials), and service industries. As a result, the value-added will accrue to agriculture, non-manufacturing, and service industries, which often lie upstream of GVCs. Second, the manufacturing industry is characterized by a higher degree of vertical specialization than other industries, which decreases the DVA share in manufacturing exports.

In summary, evidence shows that the DVA of China's exports has risen steadily during the period 2000–2014. However, the share of DVA in China's exports varies over time. Entry into the WTO played a key role in decreasing the DVA share of China's exports in the early 2000s. It is likely that trade liberalization encourages Chinese firms to rely more on imported inputs for production. In particular, the DVA shares of the high technology manufacturing industry fell dramatically during the period 2001–2004. Even though the DVA share of China's high technology manufacturing exports began to rise after 2007, it was still lower than other industries throughout the sample period. This result is consistent with case studies showing that China's indigenous producers are heavily relying on direct imports of some key parts and components for production. In contrast, the DVA share of low technology manufacturing is higher, which implies a low reliance on foreign intermediate inputs in production activities.

Figure 3.3 DVA shares in China's exports by industries (%)

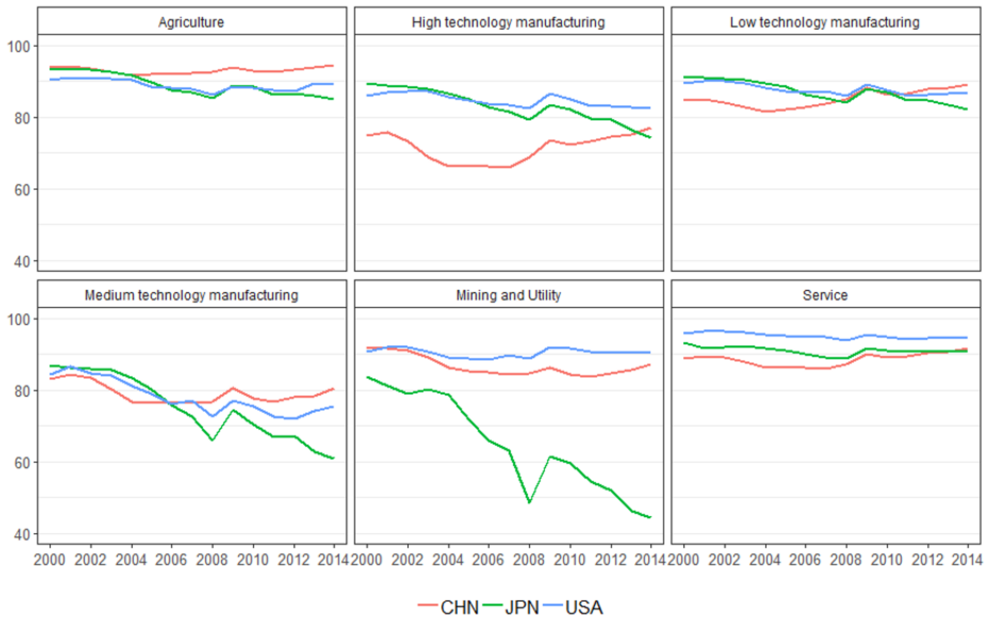


Source: Calculated by the author based on World Input–Output Database (WIOD).

Furthermore, Figure 3.4 compares the DVA shares of the six composite industries of China, Japan, and the US during the period 2000–2014. A common result is that the DVA shares in the manufacturing exports of Japan and the US fell during the sample period, indicating a rising dependency of export goods on the imported intermediate inputs. For the US, the DVA share of high technology manufacturing fell by 4 percentage points from 86 percent in 2000 to 82 percent in 2014; the DVA share of medium technology manufacturing dropped by 8 percentage points from 84 percent in 2000 to 76 percent in 2014; and the DVA share of low technology manufacturing decreased by 3 percentage points from 90 percent in 2000 to 87 percent in 2014. The DVA shares of Japan's manufacturing exports declined more substantially during the period 2000–2014. For the three manufacturing industries of Japan, the DVA share of high technology manufacturing fell by 15 percentage points from 89 percent in 2000 to 74 percent in 2014; the DVA share of medium technology manufacturing fell by 26 percentage points from 87 percent in 2000 to 61 percent in 2014; the DVA share of low technology manufacturing fell by 9 percentage points from 91 percent in 2000 to 82 percent in 2014. The result also reveals that the DVA shares of agriculture, service, and mining and utility were relatively stable during the period 2000–2014.

However, China's DVA share exhibited an upward trend after the mid-2000s, defying the downward trends of Japan and the US. The DVA shares of China's low and medium technology manufacturing exports exceeded those of Japan and the US after the mid-2000s, which suggests that China had enhanced their competitiveness in those areas. The DVA share of Chinese high technology manufacturing exports is much lower than that of Japanese and the US high technology manufacturing exports. However, the gap has continued to shrink since the mid-2000s, which reflects the development of China's high technology manufacturing industry.

Figure 3.4 DVA shares of China, Japan, and the USA (%)



Source: Calculated by the author based on World Input–Output Database (WIOD).

3.4.3 Decomposing the Change in the DVA of China's Exports

In response to the second research question, this subsection shows what specific determinants affect the change in the DVA of China's exports. Before estimating the results for the decomposition of DVA of China's exports, it is necessary to see the changes in value-added term consisting of four components: capital coefficients (the ratio of capital income to output), labor productivity (the ratio of value-added to labor inputs), the ratio of labor inputs to labor income, and the ratio of labor income to capital income. Table 3.1 shows the changes in these four components over the periods 2000–2005, 2005–2010, and 2010–2014. Capital coefficients declined by roughly 10.7, 12.1, and 10.2 percent over the three periods, respectively. This result implies that the production for exports requires less capital input per unit of output. Moreover, labor productivity increased significantly by 79.3 and 79.8 percent during the first two periods, respectively. In the third period, it fell by 23 percent. The ratio of labor inputs to labor income exhibited a downward trend, which implied that the wage per person was on the rise. In particular, the largest increase in wage per person was observed during 2005–2010. Finally, the ratio of labor income to capital income decreased by 8.2 percent from 2000 to 2005, whereas it increased by 40.1 percent during 2005–2010 and 22.9 percent during 2010–2014. This result suggests that a substitution of labor income for capital income occurred after the mid-2000s.

Table 3.1 changes in four determinants related to the value-added term

	2000-2005	2005-2010	2010-2014
Capital coefficients (k)	-10.7	-12.1	-10.2
Labor productivity (π)	79.3	79.7	23.0
The ratio of labor inputs to labor income (θ)	-38.0	-52.2	-29.7
The ratio of labor income to capital income (φ)	-8.2	40.1	22.9

Source: Calculated by the author based on World Input–Output Database (WIOD).

Table 3.2 presents the results of the decomposition of the DVA of China's exports over time by applying the SDA approach. The first three columns show the results during the periods 2000–2005, 2005–2010, and 2010–2014, while the fourth and fifth columns report the results for the periods 2000–2008 and 2008–2014, which compare the changing pattern before and after the 2008 global financial crisis. The final column shows the overall changes during the period 2000–2014. By using an extended SDA approach, the change in the DVA of China's exports is broken down into nine determinants: capital coefficients (k), labor productivity (π), the ratio of labor inputs to labor income (θ), the ratio of labor income to capital income (φ), domestic inputs coefficients (T^d), the substitution between intermediate inputs ($\widetilde{A}$), total exports effect (G), export structure effect (M) and export destination effect (d). We interpret the results as manner such that the DVA of exports will change due to a particular determinant under the condition that the other determinants stay constant. The upper panel gives the annual percentage change of each determinant, while the lower panel reports the contribution of each determinant to the total change in DVA. For example, when other factors did not change, the

DVA fell by 1 percent annually during the period 2000–2005 due to the change in capital coefficients. Meanwhile, the change in capital coefficient accounted for roughly 2.8 percent of the change in the DVA of China's total exports in absolute value over the same period.

As shown on the bottom of the first three columns in Table 3.2, the DVA of China's exports rose by approximately $383 billion, $725 billion, and $659 billion during the periods 2000–2005, 2005–2010, and 2010–2014, respectively. And the annual growth rates of DVA were roughly 35.6, 24.3, and 12.4 percent during the periods 2000–2005, 2005–2010, and 2010–2014, respectively. The fourth and fifth columns illustrate the changes in DVA of China's exports during the periods 2000-2008 and 2008–2014. The DVA increased by $951 billion before the 2008 financial crisis, while it rose by $816 billion in the subsequent years. Comparing the annual growth rates, the increase in the DVA of China's exports speeded up after 2008, with 55.1 percent during the period 2000–2008 and 63.1 percent during the period 2008–2014.

How do the changes in value-added terms affect DVA growth? The DVA of China's exports decreased by 2.9 percent annually due to capital coefficients during the period 2000–2014. The DVA of China's exports annually decreased by approximately 1 percent during the periods 2000–2005, 2005–2010, and 2010–2014 due to the capital coefficients. Its contribution increased throughout the three periods in absolute value, with -2.8 percent during the period 2000–2005 and -8.8 percent during the period 2010–2014. The role of capital coefficients was distinct in the periods 2000–2008 and 2008–2014. The DVA annually fell by roughly 1.6 percent prior to 2008 and by 6.9 percent after 2008. Meanwhile, the contribution of capital coefficients was -3 percent before 2008 and -11 percent in the following period. These results imply that the capital income did not contribute to the growth of the DVA of China's exports during the sample period, as the capital needed per unit of output was on the decline.

The DVA of China's exports increased by about 9.4 percent annually due to the effect of labor productivity during the period 2000–2014. As shown in the first three columns, the DVA annually increased by 4.3 and 4.8 percent due to labor productivity during the periods 2000–2005 and 2005–2010, respectively. However, the magnitude of annual increase became much smaller during the period 2005–2014, at roughly 1.7 percent. In addition, its contribution increased during the first two periods, with 12 percent during the period 2000–2005 and 19.7 percent during the period 2005–2010, finally falling to 13.5 percent during the period 2010–2014. Comparing between the fourth and fifth columns, the annual increase in DVA was larger during the period 2008–2014 than during the period 2000–2008. Moreover, the contribution of labor productivity to DVA growth increased during the period 2008–2014.

The effects of the ratio of labor inputs to labor income were negative throughout the sample period. As stated in the previous section, the reciprocal of this term is interpreted as the wage per person. The negative sign for this term indicates an increase in the wage per person. This result is consistent with the prevalent observation that labor costs in China have increased in recent years. Inspection of the first three columns suggests that the increase in the wage per person was associated with the growth of DVA during the periods 2000–2005, 2005–2010, and 2010–2014. In particular, the magnitude of growth in DVA due to the rise in wage per person was large during the period 2005–2010. Comparing the changes during the periods 2000–2008 and 2008–2014, the rise in DVA is more pronounced in the latter period than the former. The prominent role of wage per person in raising the DVA of China's exports shows that the ongoing rise in labor costs is an important explanation of the DVA growth of China's exports.

The ratio of labor income to capital income made an overall positive contribution to the growth of the DVA of China's exports during the period 2000–2014, which implied that the substitution of labor income for capital income was an important determinant of China's DVA growth. During the period 2000–2005, the DVA annually decreased by about 0.2 percent due to the ratio of labor income to capital income. This decline in DVA was associated with the fact that capital income grew faster than labor income during this period, and the substitution of capital income for labor income in this period dominated the change in DVA. However, the ratio of labor income to capital income annually raised the DVA by 2.1 and 1.3 percent during the periods 2005–2010 and 2010–2014. The result implies that the substitution of labor income for capital income dominated the increase in DVA in the last two periods. However, there was a stark difference in comparing the periods 2000–2008 and 2008–2014. The ratio of labor income to capital income annually raised the DVA by 0.6 percent before 2008, while it annually increased the DVA by 10.1 percent in the subsequent period. The lower panel also shows that the contribution of the ratio of labor income to capital income increased in absolute value, with -0.7 percent during the period 2000–2005 and 10.6 percent during the period 2010–2014.

Table 3.2 Decomposing the change in the DVA of China's total exports

	2000-2005	2005-2010	2010-2014	2000-2008	2008-2014	2000-2014
Annual percentage change (%)						
Capital coefficients (k)	-1.0	-1.3	-1.1	-1.6	-6.9	-2.9
Labor productivity (π)	4.3	4.8	1.7	8.6	11.5	9.4
The ratio of labor inputs to labor income (θ)	-4.1	-5.8	-2.2	-8.8	-16.2	-10.8
The ratio of labor income to capital income (φ)	-0.2	2.1	1.3	0.6	10.1	3.1
Domestic inputs coefficients (T^d)	-0.9	1.5	1.3	-0.5	9.0	2.2
Normalized input coefficients ($\tilde{A}$)	-0.9	0.2	0.4	-0.8	1.5	-0.5
Total exports effect (G)	39.8	22.7	11.0	58.9	53.8	58.9
Export structure effect (M)	-1.2	0.0	0.0	-1.2	0.0	-0.9
Export destination effect (d)	-0.1	0.1	0.0	0.0	0.2	0.1
Total	35.6	24.3	12.4	55.1	63.1	59.0
Contribution of each factor (%)						
Capital coefficients (k)	-2.8	-5.3	-8.8	-3.0	-11.0	-4.9
Labor productivity (π)	12.0	19.7	13.5	15.6	18.2	16.0
The ratio of labor inputs to labor income (θ)	-11.5	-23.9	-18.0	-16.0	-25.7	-18.4
The ratio of labor income to capital income (φ)	-0.7	8.7	10.6	1.1	16.1	5.3
Domestic inputs coefficients (T^d)	-2.6	6.1	10.8	-0.9	14.2	3.7
Normalized input coefficients ($\tilde{A}$)	-2.5	0.7	3.0	-1.4	2.4	-0.9
Total exports effect (G)	111.8	93.5	88.2	106.8	85.4	100.6
Export structure effect (M)	-3.5	0.2	0.3	-2.2	0.0	-1.6
Export destination effect (d)	-0.2	0.3	0.3	0.0	0.4	0.2
Total (%)	100.0	100.0	100.0	100.0	100.0	100.0
Total change in value (billion US$)	383	725	659	951	816	1766

Source: Calculated by the author based on World Input-Output Database (WIOD).
Notes: Negative contribution indicates the decline in DVA due to a specific factor. The results in upper panel are expressed as unweighted average annual percentage change in each period.

The change in domestic input coefficients reflects the substitution between domestically produced intermediate inputs and imported intermediate inputs. The DVA of China's exports increased annually by 3.7 percent during the period 2000–2014 due to domestic input coefficients. This result implies that China's DVA growth was associated with the substitution of domestically produced intermediate inputs for imported intermediate inputs. There are variations in different periods. The DVA decreased annually by 2.6 percent due to domestic input coefficients during the period 2000–2005. This result implies the substitution of imported intermediate inputs for domestic inputs. The domestic input coefficients caused the DVA to rise annually by 1.5 and 1.3 percent during the periods 2005–2010 and 2010–2014. Moreover, the fourth and fifth columns show that the DVA decreased annually by 0.5 percent during the period 2000–2008 and rose annually by 9 percent during the period 2008–2014 due to the domestic input coefficients.

One possible explanation for using imported intermediate inputs over domestic inputs during the period 2000–2005 is that China's WTO entry in 2001 encouraged more Chinese firms to import intermediate inputs for production. On the other hand, the result of the substitution of domestically produced intermediate inputs for imported intermediate inputs is consistent with the study of Kee and Tang (2016). They find that this substitution is caused by trade and foreign direct investment (FDI) liberalization from the mid-2000s. They also show that declined input tariffs and increased FDI have led to a greater variety of domestically produced materials available at lower prices. The results in this chapter also reveal that the reliance on imported intermediate inputs decreased significantly after the 2008 financial crisis.

Normalized inputs coefficients reflect the substitution between intermediate inputs sectors, which include both the domestic and imported intermediate inputs. During the period 2000–2014, the impact of the change in normalized inputs coefficients was relatively small. The DVA of China's exports annually decreased by 0.9 percent due to normalized inputs coefficients during the period 2000–2005. In the two subsequent periods, the DVA annually increased by 0.2 and 0.4 percent due to normalized inputs coefficients, respectively. The contribution of normalized inputs coefficients was relatively large during the periods 2000–2005 and 2010–2014. The results also show that normalized inputs coefficients annually declined the DVA by 0.8 percent before 2008, while it raised the DVA annually by roughly 1.5 percent after 2008. It implies that the exports of China increasingly rely on intermediate input sectors which create more DVA after the 2008 global financial crisis.

The total exports effect is a dominant factor to affect the growth of DVA. However, the annual percentage change in DVA due to total exports shows a downward trend, with 39.8 percent during the period 2000–2005, 22.7 percent during 2005–2010, and 11 percent during the period 2010–2014. The fourth and fifth columns show that the annual percentage change in DVA due to total exports declined from 58.9 percent during the period 2000-2008 to 53.8 percent during the period 2008–2014. These results suggest that the growth of China's DVA was mainly fueled by the expansion of total exports in the sample period. However, as the rate of increase in China's total exports slows down after the mid-2000s, the rise in DVA tends to lose its impetus.

The export structure effect measures the change in DVA of China's exports due to the change in the export structure effect, that is, a given sector's share of exports to an individual destination country. During the period 2000–2005, the DVA decreased by about 1.2 percent annually due to the change in the export structure. The export structure effect contributed to about 3.5 percent of the total change in the DVA of China's exports in the same period. The change in the export structure effect became trivial in the last two periods, accounting for about 0.2 and 0.3 percent of the total change in the DVA of China's exports during the periods 2005–2010 and 2010–2014, respectively.

The export destination effect measures how the DVA of exports changes due to the change in the share of an individual export destination in China's total exports. The results show that the contribution of the export destination effect was 0.2 percent during the period 2000–2014. The DVA of China's exports rose annually by roughly 0.1 percent due to the export destination effect in the same period. The change in the DVA of exports due to the export destination effect was tiny during the sample period. This result implies that the export destination effect is a minor factor to affect the change in the DVA of China's exports.

In summary, decomposing the DVA of China's exports yields several notable findings. First, the increased wages per person and labor productivity in recent years had positive effects on the growth of China's DVA. Second, capital coefficients lowered China's DVA during the sample period, as the capital requirement per unit of output has declined during recent years. Third, the substitution of labor income for capital income played a significant role in the growth of China's DVA during the periods 2005–2010 and 2010–2014. This finding is consistent with the fact that Chinese labor costs have increased substantially. In particular, China's minimum wage policy reform in 2004 effectively raised the wages of Chinese labor. Moreover, as an increased number of Chinese workers receive higher education, it puts forward to the rise in labor productivity and wages of Chinese workers. Fourth, the domestic input coefficients had a positive effect on the DVA after 2005. This result implies a substitution of domestic inputs for imported inputs for production and exports. Fifth, the total exports effect plays a dominant role in the DVA growth of China's exports during the sample period. However, the change in DVA due to the total exports effect showed a downward trend. Finally, the change in DVA due to the export structure effect was substantial during the period 2000–2005 and became much less pronounced during the periods 2005–2010 and 2010–2014.

Table 3.3 shows the annual percentage changes in the DVA of exports across the six composite industries (agriculture, mining and utility, service, high technology manufacturing, medium technology manufacturing, and low technology manufacturing) due to the nine determinants. For example, the first column in the upper panel presents the change in DVA of agricultural exports during the period 2000–2005 due to changes in the nine determinants. The interpretation of the results is focused on high technology manufacturing, medium technology manufacturing, and low technology manufacturing because they account for relatively large shares in China's exports

High technology manufacturing plays an important role in China's exports. The fourth column of Table 3.3 shows several notable findings for the DVA of high technology manufacturing exports. First, the DVA of high technology manufacturing exports achieved the highest annual rate of increase among the six composite industries during the period 2000–2005, rising by roughly 53.6 percent in this period. The magnitude of this annual increase, however, showed a downward trend in the next two periods, falling from 30 percent during the period 2005–2010 to 12 percent during the period 2010–2014. Second, the expansion of total exports served as the most important driving force for the growth of the DVA of high technology manufacturing exports throughout the sample period. The annual increase rate of DVA due to the total exports, however, decelerated during the periods 2005–2010 and 2010–2014. Third, another influential factor is the export structure effect. The export structure raised the DVA of high technology manufacturing exports annually by 12.4 and 4 percent during the periods 2000–2005 and 2005–2010, respectively. However, it decreased the DVA slightly by 0.6 percent in the last period. Notably, while the DVA of high technology manufacturing exports rose due to the export structure effect during the period 2000–2005, the DVA of other industries declined during this period. This result is associated with a substantial increase in the export share of some high technology manufacturing sectors in total exports. However, the export structure effect on high technology manufacturing was trivial in the last two periods.

Fourth, domestic input coefficients caused the DVA of high technology manufacturing exports to fall by 1.6 percent annually during the period 2000–2005, a greater decline than for other composite industries in the same period. For example, the DVA of low technology manufacturing exports dropped by 0.3 percent annually in the same period. This implies that the substitution of imported intermediate inputs for domestically produced intermediate inputs played a more substantial role in high technology manufacturing in the early 2000s. Domestic input coefficients had a positive effect on the DVA of high technology manufacturing during the periods 2005–2010 and 2010–2014. The magnitude of the increase was larger than for other composite industries. This result suggests a more significant substitution of domestic inputs for imported materials in high technology manufacturing because of trade and FDI liberalization in the late 2000s.

Finally, the results show that labor productivity raised the DVA of high technology manufacturing by roughly 6.4 and 5.6 percent annually during the periods 2000–2005 and 2005–2010, respectively. The magnitude of increase in high technology manufacturing was larger than in low and medium technology manufacturing over the same period. Meanwhile, capital coefficients played a pronounced role in decreasing the DVA of high technology manufacturing exports. The ratio of labor income to capital income exerted a positive effect on DVA growth during the last two periods. This result suggests that the relative importance of labor income increased after 2005.

Table 3.3 Decomposing the change in DVA of China's exports by composite industries

	Agriculture	Mining and Utility	Service	High tech manufacturing	Medium tech manufacturing	Low tech manufacturing
2000–2005						
Capital coefficients (k)	-1.3	-0.9	-0.2	-2.0	-0.4	-0.8
Labor productivity (π)	2.7	4.3	2.5	6.4	5.5	3.0
The ratio of labor inputs to labor income (θ)	-3.0	-4.0	-2.4	-6.2	-4.9	-2.8
The ratio of labor income to capital income (φ)	1.5	-0.4	-0.2	-0.3	-1.0	0.0
Domestic inputs coefficients (T^d)	-0.5	-0.6	-0.4	-1.6	-1.9	-0.3
Normalized input coefficients ($\tilde{A}$)	-0.2	-0.2	-0.1	-2.3	-0.8	-0.1
Total exports effect (G)	34.0	31.9	35.3	46.6	39.8	37.2
Export structure effect (M)	-12.6	-14.7	-10.1	12.4	-0.3	-7.3
Export destination effect (d)	-0.9	-0.9	-1.5	0.7	0.3	0.1
Total	19.7	14.5	22.9	53.6	36.3	28.9
2005–2010						
Capital coefficients (k)	-2.5	-0.5	-1.2	-1.5	-0.8	-1.3
Labor productivity (π)	3.5	3.0	5.7	5.6	4.7	3.2
The ratio of labor inputs to labor income (θ)	-3.9	-3.4	-6.8	-7.2	-5.0	-3.7
The ratio of labor income to capital income (φ)	2.9	0.7	2.3	2.8	0.9	1.6
Domestic inputs coefficients (T^d)	0.3	0.2	0.6	2.3	0.6	1.3
Normalized input coefficients ($\tilde{A}$)	0.0	-0.1	0.4	0.0	0.0	0.3
Total exports effect (G)	19.0	16.2	25.0	24.2	21.4	20.2
Export structure effect (M)	-10.7	-15.9	4.2	4.0	-2.1	-6.0
Export destination effect (d)	1.4	-0.1	3.2	-0.3	-0.3	-1.2
Total	10.1	0.0	33.3	30.0	19.4	14.4
2010–2014						
Capital coefficients (k)	-1.4	-0.6	-0.8	-1.3	-1.2	-1.0
Labor productivity (π)	2.2	1.5	1.3	1.7	1.7	2.0
The ratio of labor inputs to labor income (θ)	-2.3	-1.9	-1.8	-2.4	-2.2	-2.4
The ratio of labor income to capital income (φ)	1.5	0.9	1.2	1.6	1.0	1.1
Domestic inputs coefficients (T^d)	0.4	0.9	0.5	1.9	1.5	0.9
Normalized input coefficients ($\tilde{A}$)	0.1	0.3	0.2	0.4	0.4	0.3
Total exports effect (G)	9.5	11.0	10.6	10.9	11.8	11.1
Export structure effect (M)	-8.1	0.4	-3.2	-0.6	5.1	2.3
Export destination effect (d)	0.7	0.4	1.5	-0.2	0.2	-0.9
Total	2.5	12.9	9.6	12.0	18.4	13.5

Source: Calculated by the author based on World Input–Output Database (WIOD).
Note: The results are expressed as unweighted average annual percentage change in each period.

Table 3.3 also shows that during the period 2000–2005, the annual growth rates of the DVA of medium technology and low technology manufacturing exports were 36.3 and 28.9 percent, respectively. In the period 2005–2010, the annual increase rates of the two industries fell to 19.4 and 14.4 percent, respectively. During the period 2010–2014, the annual increase rates of the two industries fell further to 18.4 and 13.5 percent. A closer inspection of the nine determinants reveals that the increase in total exports was the most important driving force of the growth of DVA of medium and low technology manufacturing exports, although its influence diminished over time. In contrast to high technology manufacturing, the export structure effect reduced the DVA of medium technology and low technology manufacturing exports during the first two periods. In particular, the DVA of low technology manufacturing exports fell annually by 7.3 and 6 percent during the periods 2000–2005 and 2005–2010, which was a consequence of the export shares of medium and low technology manufacturing sectors in total exports declining after 2000. During the last period, however, the export structure effect raised the DVA of medium and low technology manufacturing exports annually by 5.1 and 2.3 percent, respectively. Furthermore, domestic input coefficients decreased the DVA of low technology manufacturing by a much smaller magnitude than high and medium technology manufacturing during the period 2000–2005. This implies that domestic suppliers of low-technology manufacturing were less affected by entry into the WTO. Similar to the results for high technology manufacturing, capital coefficients had a negative effect on the growth of DVA of medium and low technology manufacturing exports, while labor productivity and wage per person exerted positive effects. Consistent with the overall results, the ratio of labor income to capital income reduced the DVA of medium technology and low technology manufacturing exports during the period 2000–2005. And the ratio of labor income to capital income increased DVA in the subsequent two periods, though not to the same magnitude as high-technology manufacturing.

The DVA of service exports increased annually by 22.9 and 33.3 percent during the periods 2000–2005 and 2005–2010, with the annual increase rate of the DVA of service exports being the highest among the six composite industries in the second period, although its increase rate fell to 9.6 percent during the period 2010–2014. The contribution of labor productivity and wage per person to the growth of DVA in service exports was pronounced prior to 2010, however, it decreased during the period 2010–2014. Moreover, the negative effect of capital coefficients continued throughout the sample period. It was also observed that the DVA of service exports decreased due to the ratio of labor income to capital income during the period 2000–2005, but this reversed in the following two periods. This result implies that the increased labor income relative to capital income predominated the growth in the DVA of service exports. The effect of domestic input coefficients on the DVA of service exports was small and negative during the period 2000–2005. This result means that entry into the WTO had a limited impact on service sectors. In the subsequent periods, domestic input coefficients had a small but positive effect on the growth of the DVA of service exports.

With respect to the changes in the DVA of agriculture and mining and utility industries, several noticeable findings are obtained. First, the annual increase rates of the DVA of agriculture and mining and utility exports were smaller than those of service and manufacturing industries. The change in export structure had a significantly negative impact on the DVA of agriculture and mining and utility exports during the first two period. Second, the ratio of labor income to capital income had a positive effect on the DVA of agricultural product exports throughout the sample period. This finding suggests that the substitution of labor income for capital income dominated the DVA growth in agricultural product exports. Third, the export structure effect declined the DVA of agriculture and mining and utility exports significantly. This result was related to declined export shares of agriculture and mining and utility industry in total exports.

The results in this subsection show that the three manufacturing industries had relatively high annual growth rates of DVA of exports during the periods 2000–2005 and 2010–2014, while service outpaced the three manufacturing industries during the period 2005–2010. China’s entry into the WTO in 2001 impacted the DVA of the six composite industries differently. For example, the substitution of imported intermediate goods for domestic materials had a larger impact on the high and medium technology manufacturing industries during the period 2000–2005 and exerted a smaller effect on low technology manufacturing and the service sector. Another significant finding is that the export structure effect had a positive effect on the DVA of high technology manufacturing exports during the periods 2000–2005 and 2005–2010 but had negative effects on the agriculture, mining and utility, medium technology, and low technology manufacturing industries in the same periods. This result implies that the DVA growth of high technology manufacturing exports is associated with an increased export share of high technology manufacturing products in China’s total exports.

3.4.4 Decomposing the Change in the DVA of Japanese and US Exports

The changes in the DVA of Japanese and US exports are also decomposed into nine components by applying the SDA approach. Table 3.4 presents the results in the case that the change in DVA of Japan’s exports is decomposed during the periods 2000–2005, 2005–2010, and 2010–2014. The DVA of Japan’s total exports increased annually by 4.3 and 4.4 percent during the first two periods, respectively, whereas it decreased annually by 3.1 percent during the last period. Several features are notable in the DVA of Japan’s exports. First, the total exports effect is the most prominent factor for the DVA growth of Japan’s exports during the first two periods. However, the DVA of Japan’s exports decreased annually by 0.6 percent due to the total export effect during the last period.

Second, the DVA of mining and utility exports rose annually by 25.2 percent due to the export structure effect during the period 2000–2005. This result suggests that the export structure effect made a significant contribution to the growth of DVA of mining and utility exports in this period. Third, the DVA of Japan’s exports in most industries declined due to capital coefficients during 2000–2005 and 2005–2010 (except for service and high technology manufacturing industry). The change in capital coefficients had a positive effect on the DVA of service, medium technology manufacturing, and mining and utility exports during the period 2010–2014. Fourth, the change in the ratio of labor income to capital income had a negative effect on the DVA of Japan’s exports during the periods 2000–2005 and 2010–2014 but had a positive effect on it during the period 2005–2010. Notably, the ratio of labor income to capital income had a pronounced impact on medium technology manufacturing industry, as DVA decreased by more than 10 percent during the period 2010–2014. Fifth, the changes in labor productivity and wage per person (that is, the decrease in the ratio of labor inputs to labor income) had positive impacts on the DVA growth of most industries during the periods 2000–2005 and 2010–2014. However, the labor productivity and wage per person exerted a negative effect on the DVA of Japan’s exports in most industries during the period 2005–2010. The largest decline in the DVA of Japan’s exports in this period was in medium technology manufacturing industry. Compared with China, the magnitudes of the change in the DVA of Japan’s exports due to labor productivity and wage per person were relatively small. Finally, the DVA of Japan’s exports of all industries declined due to domestic input coefficients during the period 2010–2014. It fell by 1.2 percent annually during this period. This result implies an increased reliance on imported inputs for production activities. The decline in domestic input coefficients was pronounced in the mining and utility industry, high and medium technology manufacturing industries during the last period.

Table 3.4 Decomposing the changes in the DVA of Japan's exports

	Agriculture	Mining and Utility	Service	High tech manufacturing	Medium tech manufacturing	Low tech manufacturing	All industries
2000-2005							
Capital coefficients (k)	-0.2	-2.1	0.9	0.0	-0.3	-2.1	0.1
Labor productivity (π)	0.3	0.2	0.8	0.4	0.9	0.9	0.5
The ratio of labor inputs to labor income (θ)	-0.1	-0.3	0.1	-0.2	-0.3	0.2	-0.1
The ratio of labor income to capital income (φ)	-0.1	0.3	-1.9	-0.3	-0.8	0.8	-0.6
Domestic inputs coefficients (T^d)	-0.3	-1.3	-0.2	-0.7	-0.7	-0.4	-0.6
Normalized input coefficients ($\tilde{A}$)	-0.4	-1.8	-0.3	-0.2	-0.6	-0.1	-0.3
Total exports effect (G)	4.7	7.7	5.5	5.2	5.9	5.1	5.3
Export structure effect (M)	-6.4	25.2	1.0	-0.8	3.1	-3.8	0.0
Export destination effect (d)	1.5	-4.9	0.1	-0.4	1.6	1.5	0.0
Total	-1.0	22.9	6.1	3.0	8.9	2.1	4.3
2005-2010							
Capital coefficients (k)	-0.1	-1.3	-0.4	-0.8	-3.0	-0.6	-1.0
Labor productivity (π)	-0.1	0.0	-0.4	-0.5	-1.9	-0.2	-0.7
The ratio of labor inputs to labor income (θ)	0.2	0.1	0.2	0.2	0.4	0.0	0.2
The ratio of labor income to capital income (φ)	-0.2	-0.2	0.5	0.8	2.8	0.6	1.0
Domestic inputs coefficients (T^d)	0.0	-0.3	0.0	-0.1	-0.3	-0.1	-0.1
Normalized input coefficients ($\tilde{A}$)	-0.1	-1.1	0.0	-0.3	-0.7	-0.2	-0.3
Total exports effect (G)	5.1	5.0	5.8	5.1	5.8	5.3	5.4
Export structure effect (M)	-2.1	-0.5	0.9	-1.2	3.8	-1.1	0.0
Export destination effect (d)	-0.4	-1.3	2.0	-0.9	0.7	-0.1	0.0
Total	2.3	0.4	8.5	2.4	7.6	3.6	4.4
2010-2014							
Capital coefficients (k)	-0.7	1.0	0.2	-1.3	7.9	-0.3	0.6
Labor productivity (π)	0.1	1.3	0.2	0.0	0.9	-0.2	0.2
The ratio of labor inputs to labor income (θ)	-0.8	-1.3	0.0	-0.7	1.9	0.0	-0.1
The ratio of labor income to capital income (φ)	1.4	-0.6	-0.5	1.8	-10.5	0.3	-0.8
Domestic inputs coefficients (T^d)	-0.7	-2.2	0.0	-1.4	-1.3	-0.7	-1.2
Normalized input coefficients ($\tilde{A}$)	-0.3	-4.9	-0.2	-0.7	-2.0	-0.5	-0.9
Total exports effect (G)	-0.6	-0.6	-0.5	-0.5	-0.5	-0.5	-0.6
Export structure effect (M)	6.9	7.7	-4.1	0.9	1.7	1.5	-0.3
Export destination effect (d)	-0.4	-0.4	-1.3	0.5	0.0	0.1	0.0
Total	4.9	0.1	-6.1	-1.5	-2.1	-0.3	-3.1

Source: World Input–Output Database (WIOD).
Note: The results are expressed as unweighted average annual percentage change in each period.

Table 3.5 shows the results in the case that the change in DVA of US exports is decomposed during the periods 2000–2005, 2005–2010, and 2010–2014. The DVA of US total exports rose constantly throughout the sample period, and its annual growth rates ranged between 3.6 and 8.1 percent over the three periods. The most significant annual increase in the DVA of US exports was observed in the industry of mining and utility during the periods 2000–2005 and 2005–2010, while the DVA of medium technology manufacturing exports exhibited the highest annual growth rate during the period 2010–2014. An inspection of the nine determinants for the DVA of US exports reveals some noticeable features. First, the total export effect was the dominant factor of the increase in DVA of US exports, which was similar to the result for China. In addition, it is worthwhile to note that the industry of mining and utility experienced a dramatic growth of DVA due to the export structure effect over the first two periods. Second, labor productivity made a sizable contribution to the growth of DVA of US total exports. Specifically, the DVA rose by 1 percent due to the labor productivity during the first two periods, respectively. And it rose by 0.4 percent due to the labor productivity in the last period.

Third, the ratio of labor inputs to labor income had negative signs throughout the sample period, which means that the rise in the wage per person has a positive effect on the growth in DVA of US exports. Fourth, the capital coefficients had positive effects on the DVA of US exports during the periods 2000–2005 and 2005–2010, which implied that more capital inputs were needed for one unit of output. However, the capital coefficients exerted a negative effect on the DVA of US total exports during the period 2010–2014, reducing the DVA of US exports annually by 0.2 percent. Fifth, the ratio of labor income to capital income decreased the DVA of US exports, which suggested a substitution of capital income for labor income in the first two periods. In the last period, however, the ratio of labor income to capital income increased the DVA of US exports, which implied a modest substitution of labor income for capital income in the last period. Finally, domestic input coefficients had slightly negative impacts on the DVA of most industries, which implied an increased dependence on imported intermediate inputs in the production even though the magnitude of increase was modest. Particularly, these large declines in DVA due to domestic input coefficients were found in manufacturing industries. This result can be explained by the fact that more US manufacturing production activities has been offshored.

Table 3.5 Decomposing the changes in the DVA of US exports

	Agriculture	Mining and Utility	Service	High tech manufacturing	Medium tech manufacturing	Low tech manufacturing	All industries
2000-2005							
Capital coefficients (k)	0.4	1.0	0.5	0.7	0.7	-0.2	0.6
Labor productivity (π)	1.3	2.5	0.7	1.2	2.0	0.8	1.0
The ratio of labor inputs to labor income (θ)	-0.9	-1.2	-0.6	-0.8	-1.0	-0.7	-0.7
The ratio of labor income to capital income (φ)	-0.6	-1.9	-0.5	-1.0	-1.7	-0.1	-0.8
Domestic inputs coefficients (T^d)	-0.2	-0.4	-0.2	-0.4	-0.7	-0.3	-0.3
Normalized input coefficients ($\tilde{A}$)	-0.4	-0.6	-0.1	0.0	-0.3	-0.1	-0.1
Total exports effect (G)	3.9	5.0	4.1	3.6	3.9	3.6	3.8
Export structure effect (M)	1.8	14.5	2.3	-2.5	2.3	-0.9	0.0
Export destination effect (d)	-0.9	-0.3	0.6	-0.2	-0.3	-0.5	0.0
Total	4.3	18.7	6.8	0.6	5.0	1.6	3.6
2005-2010							
Capital coefficients (k)	0.6	0.7	0.3	1.0	-0.4	0.8	0.6
Labor productivity (π)	1.4	1.5	0.7	1.4	0.8	1.0	1.0
The ratio of labor inputs to labor income (θ)	-0.8	-1.7	-0.5	-0.8	-1.3	-0.6	-0.7
The ratio of labor income to capital income (φ)	-1.0	0.4	-0.4	-1.2	0.3	-0.9	-0.7
Domestic inputs coefficients (T^d)	-0.3	-0.1	-0.1	-0.2	0.1	-0.3	-0.2
Normalized input coefficients ($\tilde{A}$)	0.0	0.1	0.0	0.0	0.0	0.0	-0.0
Total exports effect (G)	9.5	10.2	8.3	7.6	9.0	7.9	8.1
Export structure effect (M)	7.1	12.1	0.2	-2.9	6.8	-0.3	-0.1
Export destination effect (d)	1.0	-0.8	0.9	-0.3	-1.3	-1.1	0.1
Total	17.5	22.5	9.4	4.6	14.1	6.5	8.1
2010-2014							
Capital coefficients (k)	0.2	-0.4	-0.1	-0.2	-0.2	-0.5	-0.2
Labor productivity (π)	0.8	0.3	0.3	0.5	0.8	0.4	0.4
The ratio of labor inputs to labor income (θ)	-0.4	-0.5	-0.4	-0.5	-0.7	-0.4	-0.5
The ratio of labor income to capital income (φ)	-0.5	0.2	0.1	0.0	-0.2	0.3	0.1
Domestic inputs coefficients (T^d)	0.0	0.0	0.0	-0.4	0.3	-0.1	-0.1
Normalized input coefficients ($\tilde{A}$)	0.1	-0.1	0.0	0.0	0.2	0.0	-0.0
Total exports effect (G)	4.6	4.8	4.8	4.6	5.3	4.8	4.8
Export structure effect (M)	-1.7	0.5	-0.2	-1.2	4.0	0.6	-0.1
Export destination effect (d)	-0.2	0.0	0.0	0.1	0.0	-0.3	-0.0
Total	2.9	4.9	4.5	2.9	9.7	4.7	4.4

Source: World Input–Output Database (WIOD).
Note: The results are expressed as unweighted average annual percentage change in each period.

The DVA of Chinese, Japanese, and US exports shows different patterns of change. A comparison between China and Japan implies some interesting findings. First, the DVA of China's exports increased constantly throughout the sample period. On the other hand, the DVA of Japan's exports increased during the periods 2000–2005 and 2005–2010 but decreased during the period 2010–2014. Second, by decomposing the change in the DVA of exports, we find that the increase in the DVA of China's exports was largely attributed to the total export effect, which was also the dominant factor in the growth of the DVA of Japan's exports during the periods 2000–2005 and 2005–2010. However, the total export effect led to a decline in the DVA of Japan's exports during the period 2010–2014. The reduction in Japan's total exports could be attributed to The Great East Japan Earthquake in 2011. This natural disaster generated damage to domestic supply chains, leading to declines in production and exports. Third, capital coefficients had a negative effect on the DVA of China's exports throughout the sample period. The DVA of China's exports also increased due to the substitution of labor income for capital income after 2005. This result implies that labor income has become more important than capital income in explaining the DVA growth of China's exports. In the case of Japan, the effects of capital coefficients and the substitution of labor income for capital income were ambiguous, as the results varied over different periods. For example, capital coefficients had a negative effect on the DVA growth of Japan's exports during the period 2005–2010 but had a positive effect on it during the period 2010–2014. Fourth, the increase in labor productivity and wage per person contributed largely to the DVA growth of China's exports. However, the effects of labor productivity and wage per person on the DVA growth of Japan's exports were ambiguous during the sample period. For example, labor productivity had a positive impact on the DVA growth of Japan's exports during the period 2000–2005 but had a negative effect on it during the period 2005–2010. Steinberg and Nakane (2011) show that the labor productivity of Japan declined substantially due to the 2008 global financial crisis. They explain that Japanese firms preserved employment even though the outputs declined during the global recession, which resulted in the reduction of output per employee or labor productivity. Finally, the substitution of domestic intermediate inputs for imported materials had a positive effect on the DVA of China's exports after 2005. This result suggests that the exports of China are relying less on imported intermediate inputs. On the other hand, the DVA of Japan's exports declined due to the substitution of imported intermediate inputs for domestic inputs. This result implies that the exports of Japan are increasingly dependent on intermediate inputs supplied by foreign producers.

A comparison between China and the US also yields some interesting results. First, the DVA of both China's and US exports increased steadily throughout the sample period. However, the magnitude of the increase in the DVA of China's exports was much larger than that of the US. Second, the increase in the DVA of both China's and US exports was due largely to the total export effect. Third, during the first two periods, capital coefficients were associated with an increase in the DVA of US exports and a decrease in the DVA of China's exports. Capital coefficients had a negative effect on the DVA of both China and US exports during the last period. Fourth, the growth of DVA of China's and US exports was associated with a greater increase in capital income relative to labor income during the first period and a greater increase in labor income relative to capital income during the last periods. However, the results for the two countries are different in the second period. Fifth, labor productivity and wage per person had positive effects on the DVA growth of both Chinese and US exports. Finally, US exports are increasingly reliant on intermediate inputs supplied by foreign producers. This result is different from China.

3.5 Conclusion

Using input–output tables from the WIOD, this chapter calculates the DVA of China's exports at the country and composite industry levels during the period 2000–2014. The DVA of China's exports shows an overall upward trend. Moreover, the DVA share is used as a proxy to measure the gap between the DVA and gross exports. Notably, the DVA share of China's high technology manufacturing exports is lower than that of other industries, which implies that China's high technology manufacturing relies heavily on imported intermediate inputs. For comparison, this chapter also calculates the DVA of Japan's and US exports during the period 2000–2014. The DVA share of China's high technology manufacturing exports is lower than that of Japan and the US.

This chapter also examines the factors that affect the change in the DVA of China's exports. Using a modified SDA approach, the increase in the DVA of China's exports is decomposed into nine determinants. The main contribution of this chapter is to explore how capital coefficients, labor productivity, wage per person, and the substitution of labor income for capital income affect the change in the DVA of exports. The results show that the total export effect is the dominant factor that affects the change in the DVA of China's exports. The rise in the DVA of China's exports is also associated with the substitution of labor income for capital income together with increasing labor productivity and wages per person. Capital coefficients have a negative effect on the growth of the DVA of China's exports. We confirm that the substitution of domestic intermediate inputs for imported materials contributes to the increase in the DVA of China's exports after the mid-2000s. This result implies a decreasing reliance of China on imported intermediate inputs. This chapter also quantifies the factors that affect the change in the DVA of Japan's and US exports. Compared with China, the substitution of capital income for labor income and the increase in capital coefficients have larger effects on the DVA growth of Japan's and US exports. Moreover, the production of Japan and the US is associated with an increasing reliance on imported intermediate inputs.

This chapter provides empirical evidence to explore the patterns of change of the DVA of exports, but a theoretical model is still required to examine the relationship between the DVA of exports and determinants, including capital coefficients, labor productivity, wage per person, and the substitution of labor income for capital income. In addition, the empirical analysis described so far is implemented at the industry and country levels. Many studies have noted that export performance is largely associated with firm-specific factors such as trade regimes, revenue, or employment. A limitation of the examination using input–output tables is that it cannot account for firm heterogeneity. Thus, the next chapter considers firm heterogeneity in examining the export performance of Chinese firms.

Chapter 4 Export Performance of Multi-Product Firms: Evidence from Chinese Firm-level Data

4.1 Introduction

In the field of international trade, one of the issues that researchers have deep interest is the extent to which international trade is increasingly dominated by a few firms. The top one percent of firms account for approximately 90 percent of the value of US trade, even though they account for only approximately 15 percent of employment. One reason that such a concentration in international trade occurs is that larger exporters not only export a larger number of products to a particular destination country than smaller exporters but also export more products to more destinations (Bernard et al. 2012). Bernard et al. (2007) show that on the one hand, roughly 40 percent of exporting firms in the US export a single product to a single destination. These firms account for less than one percent of US export value. On the other hand, 12 percent of the US firms that export more than five products to more than five destinations account for more than 90 percent of the US export value.

A large volume of empirical studies has examined firms participating in international trade and revealed significant heterogeneity across firms. Specifically, exporters are superior to non-exporters in terms of productivity, output, wages, skill-intensity, and capital-intensity. However, these studies typically assume that each firm produces a single product. With the prevalence of the multi-product and multi-destination exporters, recent studies have begun to develop theoretical models to explain how heterogeneous firms choose the scope of their products and export destinations and why some firms export one product while others export multiple products. The multi-product firm model of Bernard, Redding and Schott **(**2011) predicted that high-productivity firms are more likely to enter the exporting market, supply a larger number of products to each market, and serve a wider range of destination markets. Medium-productivity firms only serve the domestic market, while low-productivity firms exit.

This chapter applies the framework of the multi-product firm model to examine the performance of Chinese exporters. An important implication of the multi-product firm model sheds light on the mechanisms through which heterogeneous firms optimally select the range of product varieties and destination countries to serve. This model is also useful for investigating how production process and export structures are affected by firm-level productivity. The research on multi-product firms allows for a more detailed decomposition of exports than earlier researches which used aggregate trade flows across firms. The recent availability of transaction-based datasets provides detailed information about the variety of products that a particular firm exports, and the range of destination countries to which a firm's exports are shipped. These data allow researchers to explore both the extensive and intensive margins of exports. The extensive margin of exports reflects the scope of exported products and export destination countries, while the intensive margin of exports includes the average firm-level exports of a firm per product per destination country. Since trade has become an essential part of most countries' development strategies, the study of a firm's performance through its extensive and intensive margins of exports provides significant suggestions for the economic growth of many developing countries.

This chapter will focus on the question of how the change in productivity affects the export performance of Chinese firms. Following the empirical strategy of Bernard, Van Beveren and Vandenbussche (2014), we decompose China's total exports into extensive and intensive margins. Specifically, extensive margins of exports include the number of exported products and export destinations. On the other hand, the intensive margin is measured by the average firm-level exports per product-country and the exports of the firm's largest product. The study of Bernard, Redding and Schott (2011) argues that the extensive margin of exports is positively associated with firm-level productivity, while the intensive margin of exports has an indeterminate relationship with firm-level productivity. Using Chinese firm-level data, this chapter aims to provide empirical evidence to confirm this theoretical prediction. In addition, Chinese firms participate in international trade through various types of trade regimes, such as ordinary and processing exports. To complement the existing literature, this chapter also examines the effect of firm-level productivity on the extensive and intensive margins of firms in various types of trade regimes.

There are several reasons that China is an interesting example for this type of analysis. First, its WTO entry in 2001 accelerated trade liberalization in the country, which further encouraged China to embrace global value chains (GVCs). Imbruno (2016) documents a substantial reduction of import tariff after the WTO entry, with the average tariff at the product level down from 16.3 percent in 2000 to 9.5 percent in 2006. Trade liberalization has a profound effect on firm performance such as exports, imports, productivity, and markups (Brandt, Van Biesebroeck and Zhang 2012; Brandt et al. 2017). Second, engaging in processing exports leads firms to incur lower fixed costs and receive favoring industrial and trade policies such as special tariff treatments. Some studies have demonstrated that Chinese firms engaging in processing exports are very different from those engaging in non-processing exports in terms of firm size, productivity, profitability, wages, capital intensity, and skill-intensity (Fernandes and Tang 2015; Dai, Maitra and Yu 2016). Processing exporters also respond differently to trade liberalization according to the extent to which they are involved in ordinary and processing exports (Yu 2015; Brandt and Morrow 2017). Thus, it is necessary to account for this different performance of firms engaging in ordinary and processing exports.

This chapter uses a Chinese firm-level dataset during the period 2000–2006, which includes the firm's balance sheet information, such as intermediate inputs, outputs, capital stock, and employment, and disaggregated trade data, such as the value and quantity of the shipment, product varieties, export destinations, and trade regimes (e.g., ordinary and processing trade). Using this dataset, we estimate firm-level total factor productivity (TFP) to reflect the productivity of firms. One of the significant features of Chinese customs data is that it separates trade data into ordinary exports and processing exports. Exporting firms in China are divided into those only involved in ordinary exports (referred to as ordinary exporters), those only involved in processing exports (referred to as processing exporters), and those involved in both ordinary and processing exports (referred to as mixed exporters). Thus, this chapter will examine the export performance of Chinese firms involved in different trade regimes.

Under the above settings, we find several major results. First, Chinese firms with high productivity, more employees, and longer histories tend to have larger total exports. Furthermore, the total export value is decomposed into extensive and intensive margins. The productivity of Chinese firms is positively associated with the number of products and destination countries, the average firm-level exports per product-country, and the export value of the firm's largest product. These results are generally consistent with the predictions in Bernard, Redding and Schott (2011). Second, as noted above, the exporters are divided into three groups: ordinary exporters, processing exporters, and mixed exporters. The estimation result shows that ordinary exporters with higher productivity tend to have a wider range of products and destination countries, larger average firm-level exports per country-product, and larger exports of their largest (top-exporting) products. Third, processing exporters with higher productivity tend to export more products and serve a wider range of destination countries, have larger average firm-level exports per country-product, and concentrate on the top-exporting product. However, the relationship between productivity and the average firm-level exports per product-country is unclear. Fourth, high-productivity mixed exporters have more products, larger average firm-level exports per product-country, and larger exports of their top-exporting products. Moreover, mixed exporters with higher productivity have a larger share of processing exports in their total exports.

The rest of this chapter is organized as follows. Section 4.2 reviews the previous literature related to this chapter. Section 4.3 documents some preliminary evidence to compare the ordinary and processing exports in China. Section 4.4 demonstrates the empirical strategies adopted in this chapter. Section 4.5 gives a description of the data sources. Section 4.6 presents the estimation results. The final section concludes.

4.2 Literature Review

This chapter is related to several strands of literature. International trade research has changed dramatically as its focus has shifted from the levels of industries and countries to the levels of firms and products. As a wide range of micro-level data becomes available, empirical research has come to show that exporters and importers account for only a small proportion of producers across many countries. From such empirical studies, it becomes clear that exporters and importers are more productive, larger, more skill-intensive, and pay higher wages than firms only serving the domestic market. This fact suggests a self-selection effect: exporters are more productive, not because the entry into the global market makes them improve, but because only firms which are by nature productive can overcome obstacles to enter the export market. Recent international trade models have made remarkable improvements in explaining patterns of trade and productivity increases by incorporating heterogeneous characteristics of firms. The seminal work of Melitz (2003) modeling heterogeneous firms leads to noticeable progress of recent international trade research. The key feature of this model is that lower-productivity firms are mainly concerned with covering their fixed costs (or exit the market), while higher-productivity firms decide whether to cover the domestic market only or engage in serving both domestic and foreign markets. Recent studies in international trade theory have devoted to generalizing or extending this basic model, such as the interaction between comparative advantage and heterogeneous firms (Bernard et al. 2007) and variable markups and market size (Melitz and Ottaviano 2008). [13]

The empirical analysis in this chapter is based on the predictions of recent theoretical models of multi-product firms. Extending Melitz (2003) single-product model, Bernard, Redding and Schott (2011) develop a general equilibrium model, in which firms export multiple products

[13] Melitz and Redding (2014) provide a comprehensive overview of the theoretical literature on heterogeneous firms and trade.

and serve multiple destination countries. Firms' abilities to produce a particular product depend on the attributes of both the firm and product. Based on these attributes, firms choose whether to serve specific export destinations or which products to supply to those export destinations. Each firm observes an initial productivity level after incurring a sunk cost. Moreover, firms incur fixed costs in production to export each product to a particular destination country. High-productivity firms generate larger profits to cover the fixed cost of production. Thus, productive firms export a larger number of products to each destination country. Bernard, Redding and Schott (2011) argue that higher productivity is associated with a larger share of products exported by the firm to a given country, and a larger number of countries to which a given product is exported by the firm. High-productivity firms tend to increase the exports of a given product to a given country but have an ambiguous effect on average firm-level exports per product per destination country.

The model in Eckel and Neary (2010) indicates that multi-product firms adjust their product mix in response to the circumstance in international market by keeping those for which they have "core competence" and dropping those produced less efficiently. In the model of Mayer, Melitz and Ottaviano (2014), firms are assumed to face a product ladder in which productivity and quality decline discretely for each additional variety produced. They predict that firm sales tend to concentrate on higher-productivity or higher-quality products in more competitive markets.

On the empirical side, Bernard et al. (2007) provide comprehensive evidence on firms' heterogeneity and the multi-product firms in international trade. Using Hungarian firm-level data, Görg, Kneller and Muraközy (2012) find that firms with higher productivity are less likely to drop their products from the export mix. Bernard, Van Beveren and Vandenbussche (2014) examine multi-product exporters in Belgium, showing that more productive firms export more products to more countries and have higher average firm-level product-country export flows. The extensive and intensive margins of exports are equally important in total firm exports. Using Chinese customs data, Manova and Yu (2017) find that Chinese firms concentrate on their core product varieties by shifting towards high-quality products on the intensive margin and by dropping low-quality goods on the extensive margin. Regis (2018) finds that higher productivity exerts a positive effect on both extensive and intensive margins of exports for a wide range of developing countries.[14] To complement the existing literature, this chapter uses

[14] Other empirical studies include Iacovone and Javorcik (2008) for Mexico, Arkolakis and Muendler (2010) for Brazil, and Mayer, Melitz and Ottaviano (2014) for France.

China’s firm-level production data and customs statistics to examine the relationship between trade margins and productivity.

Furthermore, a large volume of works have investigated the characteristics of China’s exports by different trade regimes (Fernandes and Tang 2015; Yu 2015; Dai, Maitra and Yu 2016; Manova and Yu 2016; Brandt et al. 2017). Most of these studies use China’s firm-level production database and product-level trade data during the period 2000–2006, which divide the trade into different regimes. Fernandes and Tang (2015) document that in comparison with firms involved in processing exports, firms involved in ordinary exports are smaller in size but more diversified in products and destinations within the same industry. Dai, Maitra and Yu (2016) find that processing exporters are less productive than non-processing exporters and non-exporters. Meanwhile, processing exporters have lower profitability, lower wages, lower research and development (R&D) expenditures, and lower skill-intensity. The impact of trade liberalization on firm-level productivity is also an important topic in empirical trade research. A common result in the existing literature shows that tariff reduction tends to have a positive effect on a firm’s productivity (Amiti and Konings 2007; Goldberg et al. 2010; Topalova and Khandelwal 2011). Using China’s firm-level data, Yu (2015) examines how tariff reduction affects the productivity of Chinese firms, which are further divided into two firm groups according to trade regimes: processing firms and non-processing firms. Both types of firms have positive impacts on their productivity from tariff reduction. However, the positive impact of tariff reduction on non-processing firms is larger than that on processing firms.

Different from the previous studies which focus on pure ordinary and processing exporting firms, this chapter documents the important role of mixed exporters that engage in both ordinary and processing exports. The Chinese exporters will be divided into three groups: ordinary exporters, processing exporters, and mixed exporters. Comparing the three firm groups yields novel empirical evidence relevant to the firm heterogeneity of Chinese exporting firms. The results provide new insights into how participation in GVCs affects the performance of Chinese firms.

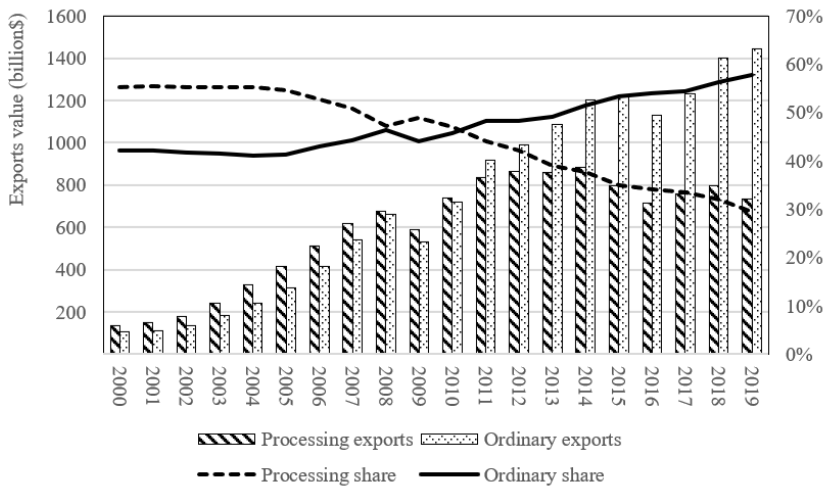
4.3 Preliminary Results for Ordinary and Processing Trade

For the past decades, China has used a set of policy tools to promote export activities. Since the mid-1980s, the formation of processing trade has enhanced the relationship between local firms and overseas companies seeking to offshore production process to China. Processing trade firms exempt from duties of imported inputs as long as they are used for further processing, assembly, and ultimately re-exporting on behalf of foreign buyers. As an important means of trade liberalization, the Chinese government encourages firms to import raw materials and intermediate inputs, and re-export final goods after local processing or assembly.

Two broad trade regimes are classified by Chinese customs authorities: ordinary trade and processing trade. Processing trade is officially defined as "business activities in which the operating enterprise imports all or part of the raw materials, spare parts, components, and packaging materials, and re-exports finished products after processing or assembling these materials or parts" (Manova and Yu 2016). A firm conducting processing trade can claim import-duty exemption only if, at the time of importing, it shows the agreement with a foreign buyer to whom it will export the processed goods. Thus, Chinese firms are allowed to participate in international trade via ordinary and processing trade. The differences between the two trade regimes generate trade-offs between ex-ante costs and ex-post profits: more profitable export modes are associated with higher up-front expenditures. Thus, firms with limited access to resources, such as capital, technology, or marketing, are forced into less profitable trade regimes (Manova and Yu 2016). In addition, firms engaging in processing exports typically receive orders from foreign buyers for further processing, which is associated with lower fixed costs. Since the production of processing firms is more subject to the orders of foreign clients, they are likely to face less uncertainty. This would encourage processing firms to have larger initial export sales and serve more destination markets (Fernandes and Tang 2015).

Figure 4.1 shows the comparison between China's processing and ordinary exports during the period 2000–2019. The change in ordinary exports shows an overall upward trend during the sample period, rising from $105 billion in 2000 to $1444 billion in 2019. On the other hand, processing exports rose from $138 billion in 2000 to $884 billion in 2014. Afterward, it turned to a downward trend during the period 2014–2019, with $735 billion in 2019. This figure also shows that the share of processing exports in China's total exports was larger than that of ordinary exports during the period 2000–2010, which implied that processing exports contributed more to China's exports growth during the period. However, this tendency reversed from 2011 as the share of ordinary exports surpassed that of processing exports. Overall, the share of processing exports in China's total exports declined from 55 percent in 2000 to 29 percent in 2019. On the contrary, the share of ordinary exports in China's total exports increased from 42 percent in 2000 to 58 percent in 2019. The strong presence of ordinary exports in total exports over the recent two decades reflects that the importance of ordinary exports has been growing relative to processing exports.

Figure 4.1 China's processing exports versus ordinary exports



Sources: Chinese Customs trade data (2000–2019), author's own calculation.

4.4 Measures and Empirical Strategies

The multi-product firm model predicts the relationship between the underlying firm productivity and the margins of trade. The number of export destinations served and products exported is expected to rise in response to higher firm productivity, while the average firm-level exports to a particular destination or average exports per product-destination may or may not rise due to the confounding effects of increasing exports within product-country and the arrival of new marginal products and countries. This section examines the effect of Chinese firm's productivity on the export performance. For this purpose, we provide explanations about the measurement of TFP, the decomposition of total exports, and the regression framework.

4.4.1 Measurement of TFP

This chapter uses the Olley and Pakes (1996) approach to construct measures of Chinese firm-level TFP. Traditionally, the TFP is measured as the deviation between observed output and the estimated output. In the traditional sense, the TFP is considered as the "residual" productivity level after deducting the contribution of input factors, and accounts for the contribution of non-production inputs such as technological progress and institutional improvement. However, the estimation by the ordinary least squares (OLS) approach suffers from two problems: simultaneity bias and selection bias. Olley and Pakes (1996) provide a semiparametric approach to address the two biases. Several studies such as Levinsohn and Petrin (2003) and De Loecker (2011) have modified the approach of Olley and Pakes (1996) to calculate the firm-level TFP. Recent studies such as Yu (2015) and Brandt et al. (2017) also tailor the method to estimate the TFP of Chinese firms.[15] The TFP is usually estimated based on macro-level data, such as total outputs, total fixed assets, and employment at the industry-level. In recent years, the emergence of statistical data at the firm-level has made it possible to estimate TFP at the micro-level.

To estimate the TFP, the Cobb-Douglas production function is the most commonly used. Specifically, the production function is expressed as follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + u_{it}, \tag{4.1}$$

where y_{it} denotes the output of firm i in time period t. Let k_{it}, l_{it}, and m_{it} refer to the logarithm of capital stock, labor input, and intermediate input, respectively. The error term u_{it} captures the TFP. Traditional estimation of TFP is based on equation (4.1). When the above OLS estimation is applied to the firm-level TFP estimation, measurement problems are inevitable. The most troublesome issue is the correlation between unobservable productivity shocks and input levels, namely, simultaneous bias. In the actual production process, profit-maximizing firms tend to expand their outputs in response to productivity improvement, which requires more intermediate inputs. On the other hand, negative productivity shock leads firms to reduce their outputs and the use of intermediate inputs. In this case, if the error term represents the TFP, then the error term and the regression term are correlated, which will cause the OLS estimation to be biased.

Another problem that is easily generated in the course of estimating the production function is the selection bias. It is mainly caused by the correlation between productivity and the probability that firms exit the market. Generally, because large-scale firms often have higher expectations for future earnings and will not easily exit the current market, firms with large capital stock at a given level of productivity are more likely to stay in the market than those with smaller capital stock at the same level of productivity. This leads to a negative correlation between the firm's decision on capital input and productivity conditional on its survival. Thus, the estimated coefficient for the capital stock is prone to underestimation bias.

This chapter estimates Chinese firm-level TFP during the period 2000–2006 following the

[15] Van Beveren (2012) provides a comprehensive review of the TFP estimation at the firm level.

approach of Olley and Pakes (1996). As mentioned above, to addresses the problems of simultaneous bias and selection bias, the study of Olley and Pakes (1996) develops a semiparametric method to control for these biases by using investment to proxy for an unobserved time-varying productivity shock, and the selection problems are addressed by using survival probabilities. The detailed explanation about the approach of Olley and Pakes (1996) is provided in Appendix B.

4.4.2 Extensive and Intensive Margins of Exports

This chapter follows the empirical strategy in Bernard, Van Beveren and Vandenbussche (2014), which examines the relationship between the margins of exports and firm-level productivity. A firm's total exports E_i can be decomposed into the number of destination countries served C_i, the number of distinct products exported S_i, a measure of coverage or density that corresponds to the share of the firms exported products sent to the average destination D_i, and the average firm-level exports per product-country $\bar{E}_i$.

$$E_i = C_i S_i D_i \bar{E}_i, \tag{4.2}$$

where $D_i = O_i/(C_i S_i)$ and $\bar{E}_i = E_i/O_i$. And O_i refers to the number of firm-level export transactions at the product-country level. The measure of density D_i considers how many product-country combinations are being actively served by the exporter. For example, if the firm exports 10 unique products and exports to 10 destination countries, then the total possible number of product-country combinations is 100. In the case that the firm exports 3 products to each destination country, then the actual number of product-country combinations is 30. The density of export activity for this firm will be 0.3. A high density implies that the firm is more likely to distribute each of its products to each of its export destination countries. On the other hand, a low density implies that the firm exports a small number of products to each of its destination countries.

4.4.3 Empirical Specification

To investigate the effects of firm-level productivity on the extensive and intensive margins of exports, the baseline estimation of this chapter will use the following empirical framework:

$$ln\, E_{it} = \lambda\, ln\, TFP_{it} + \gamma_1 Cont_{it} + \gamma_2 Dummy_i + \delta_i + \delta_{th} + \varepsilon_{it}, \qquad (4.3)$$

where E_i refers to the firm-level export value or means its four components of the decomposition given by equation (4.2), which includes the number of destination countries C_i, the number of distinct products S_i, a measure of density D_i, and the average firm-level exports of a firm per product-country $\bar{E}_i$, and an alternative measure of intensive margin. The coefficient for TFP is of main interest, which is predicted to be positively correlated with the aggregate exports. Many studies point to self-selection effect that more productive firms are more likely to enter export markets. Thus, a positive coefficient λ implies that firms with high productivity tend to have a larger export value. Several recent studies based on multi-product firm model also investigate the effects of productivity on export performance through the extensive and intensive margins. In equation (4.3), the extensive margin of exports is measured by $C_i, S_i,$ and D_i. The coefficient λ is expected to be positive when the dependent variable is C_i or S_i, while the coefficient λ is negative when the dependent variable is D_i. Moreover, the intensive margin is measured by $\bar{E}_i$, and its coefficient is predicted to be ambiguous in the model. The export value of the firm's largest product is an alternative measure of intensive margin. As firms tend to drop its unsuccessful products and focus on its more successful products, its coefficient is expected to be positive. In addition, control variables ($Cont_{it}$) including the number of employees, fixed capital stock, and the firm age are used in the specification. Dummy variables indicate whether the firm is state-owned, foreign-invested, or private firms. δ_i and δ_{th} are firm and year-sector fixed effects, respectively.

4.5 Data Sources

This section will provide an explanation for the data sources used in the analysis of this chapter. First, merging the firm-level production and customs databases of China enables us to examine an index of new dimensions of international trade, such as the concentration of exports, the product scope, and destination countries that firms export. Second, the results show the distribution of different types of firms in the sample data. Finally, the section illustrates the prevalence of multi-product and multi-destination firms.

4.5.1 Data Sources

This chapter uses two micro-datasets to evaluate the export performance of Chinese firms: (1) the Chinese Annual Survey of Industrial Firms (CASIF) from the National Bureau of Statistics of China (NBS) and (2) the Chinese Customs Trade Statistics (CCTS). The CASIF dataset is an annual survey covering main types of manufacturing firms in China, such as state-owned enterprises, foreign-invested enterprises, and other types of enterprises, with annual sales over RMB 5 million (around $770,000). The firms in the sample account for about 95 percent of China's manufacturing outputs. The database includes about 100 variables providing basic characteristics of manufacturing firms such as firm identification number, company name, contact telephone number, postal code, specific address, industry, ownership structure, affiliation, opening year, and the number of employees. In addition, financial information is also included, such as total production output, the use of intermediate materials, fixed capital assets, total wages, and value-added. Following Yu (2015), this chapter eliminates misreporting observations to clean the data. First, the duplicates and abnormal values are dropped from the sample, and the observations with missing critical values such as profits, inputs, employment, and fixed assets are then removed. Second, the small-scale firms with less than eight employees are removed to rule out extreme values. Third, from the sample, we drop the firms that violate the "Generally Accepted Accounting Principles (GAAP), such as the case that liquid assets are greater than total assets, total fixed assets are greater than total assets, the net value of fixed assets is greater than total assets, the firm's identification number is missing, and an invalid established time exists (for example, the opening month is later than December or earlier than January).

In addition, the transaction-level trade data are obtained from CCTS database, provided by China's General Administration of Customs. It covers Chinese exports and imports at the Harmonized System (HS) 8-digit level during the period 2000–2006. Detailed information of each transacted product is recorded, including import and export values, quantities, products, source or destination countries, contact information of the firm (such as company name, telephone, post code, and contact person), and firm ownership (such as state-owned, domestic private, foreign-invested, and joint ventures). An important advantage of the CCTS database is that its trade regimes are classified into 18 categories (such as ordinary trade, processing with assembly, processing with imported materials, outward processing, and equipment imported for processing trade). This chapter primarily focuses on ordinary exports and (inward) processing exports which contain the trade categories of processing with assembly and processing with imported materials. On the one hand, processing exporters are required by law to sell all of their outputs abroad instead of obtaining permission to import intermediate inputs free of duties. On the other hand, ordinary exporters can sell their outputs in both domestic and foreign markets without duty-free exemption. Moreover, this chapter notices the fact that a large number of firms are involved in both ordinary and processing trade. This type of firm is referred to as mixed exporters in this chapter. Under the setting, we investigate the differences among three types of firms: (1) ordinary exporters that only engage in ordinary exports, (2) processing exporters that only engage in processing exports, and (3) mixed exporters that engage in both ordinary and processing exports.

Finally, a dataset merging the CASIF database with the CCTS database is used to calculate the firm-level TFP. The merging of the two databases faces technical difficulties. Although the two databases both have the same firm identification number, the coding systems of the two databases are completely different. Thus, it is difficult to merge the two databases using firm identification ID. The procedures of Feenstra et al. (2014) provide an appropriate way to match a large number of firms in the two databases. Firms with the same name, telephone number (the last seven digits), and postcode across time are regarded as the same firm. The two databases cannot be completely matched for a few reasons. First, in the CASIF database, firms that export through intermediary agents are recorded as exporters, but their exports will be reported by using the intermediary agents' name in the CCTS data. Second, the CASIF database contains a large number of non-trade firms, which are not observed in the CCTS database. Third, only manufacturing firms with annual sales over RMB 5 million are recorded in the CASIF, while the CCTS database reports all the trading transactions, including those conducted by small firms and firms in non-manufacturing sectors (Upward et al. 2013). To eliminate noise, the intermediary agents are dropped from the sample. The study of Ahn et al. (2011) identifies intermediary agent firms on the basis of Chinese characters that have the English-equivalent meaning of "importer", "exporter", and/or "trading" in the firm's name. [16] Table 4.1 shows a description of the matched firms. The number of matched firms, on average, accounted for around 16 percent of the CASIF samples and 30 percent of the CCTS sample during the period 2000–2006. The outputs of the matched firms, on average, account for about 34 percent of the outputs of the total firms in the CASIF.

[16] Specifically, all Chinese characters that mean "trading," "importer," and "exporter" are identified. In pinyin (Romanized Chinese), these phrases are "jin4chu1kou3," "jing1mao4," "mao4yi4," "ke1mao4," and "wai4jing1".

Table 4.1 Data description of the matched firms

Year	Observations	Firms	% in CASIF	% in CCTS	% in total output
2000	2,720,305	20,769	12.8	25.9	30.0
2001	3,298,532	23,943	14.2	27.4	33.4
2002	3,613,564	27,300	15.0	28.1	34.4
2003	4,284,967	31,462	16.0	27.8	34.2
2004	6,044,321	47,603	17.1	35.3	34.8
2005	6,243,947	47,477	17.5	33.9	33.6
2006	6,975,769	57,233	19.0	29.0	35.0

Notes: Columns 2 and 3 give the number of observations and firms that can be matched between the CASIF database and CCTS database. Columns 4 and 5 are the shares of matched firms in the sample of CASIF CCTS databases. The last column provides the share of matched firms' output in the total output of CASIF.

4.5.2 Different Features Across Trade Regimes

This subsection surveys the distribution for four types of Chinese firms during the period 2000–2006. Exporters refer to the firms that can be matched in the two databases, while non-exporters are the firms that appear in the CASIF database but cannot be matched in CCTS database. Table 4.2 shows that non-exporters account for the largest share throughout the sample period, which ranges from 89.27 percent in 2000 to 83.37 percent in 2006. On the other hand, the number of exporting firms accounts for less than 20 percent of total firms. Further inspection of the trade regimes reveals that the share of ordinary exporters in total firms rose most substantially from 4.11 percent in 2000 to 10.06 percent in 2006. Conversely, the share of processing exporters shows a mild downward trend, decreasing from 2.46 percent in 2000 to 1.89 percent in 2006. In addition, mixed exporters are an important presence in the sample, with the shares ranging between 4.14 and 4.74 percent.

Table 4.2 Share of four types of firms (%)

	2000	2001	2002	2003	2004	2005	2006
Ordinary exporters	4.11	5.16	6.03	7.28	8.23	8.91	10.06
Processing exporters	2.46	2.27	2.13	2.00	2.21	2.06	1.89
Mixed exporters	4.14	4.45	4.64	4.60	4.56	4.74	4.64
Non-exporters	89.27	88.09	87.18	86.09	84.98	84.26	83.37

Note: Ordinary exporters refer to firms that only engage in ordinary exports. Processing exporters refer to firms that only engage in processing exports. Mixed exporters are firms that engage in both ordinary and processing exports. Non-exporters refer to firms that do not have export value.

Table 4.3 divides the shares of the export value into the three types of exporting firms during the period 2000–2006. Mixed exporters that engage in both ordinary and processing exports accounted for the largest export share throughout the sample period. In particular, the export share of mixed exporters reached 60.13 percent in 2002, which was much higher than ordinary and processing exporters. Moreover, processing exporters had larger shares than ordinary exporters during the period 2000–2005. However, the share of ordinary exporters exceeded that of processing exporters in 2006. These results based on the merged database reflect an increasingly important presence of mixed exporters in terms of both export value and the number of firms.

Table 4.3 Share of export value across three types of exporting firms (%)

	2000	2001	2002	2003	2004	2005	2006
Ordinary exporters	10.01	12.06	13.64	16.17	19.51	18.72	22.11
Processing exporters	29.95	27.55	25.68	25.45	23.47	23.32	22.03
Mixed exporters	59.63	60.05	60.13	58.21	56.84	57.72	55.74
Total value (billion$)	77.02	97.52	110.50	145.57	232.27	280.81	338.83

Note: Ordinary exporters refer to firms that only engage in ordinary exports. Processing exporters refer to firms that only engage in processing exports. Mixed exporters are firms that engage in both ordinary and processing exports.

4.5.3 Different Features of Multi-Product and Multi-Destination Exporters

This subsection reports the summary statistics on the extensive margins of exports during the period 2000–2006. Table 4.4 shows the mean value of the firm's characteristics, which include the share of firms for each group, firm age, the logarithm of TFP, output, the number of employees, fixed capital stock, and total exports. The 11 groups of firms are defined and ranked by the number of export products. Throughout the sample period, the number of non-exporters, on average, accounts for 73.92 percent of the total firms. We also confirm that firm productivity, output, number of employees, and fixed capital stock of non-exporters are all lower than those of exporters. About 5.01 percent of the total firms export a single product, on average, and about 21.07 percent of the total firms export more than one product. Moreover, firms that export more than one product have high levels of output, employment, and total exports. The non-exporters are older than exporting firms. This table also shows that the firms exporting more than 12 products have the highest TFP level, while firms exporting 4 products have the lowest TFP level among the exporting firms.

Table 4.4 Firms' characteristics by the number of export products

Number of products	Share of firms (%)	ln(TFP)	ln(output)	ln(employee)	ln(capital)	ln(export)	Age
0	73.92	0.81	9.82	4.65	8.40		11.14
1	5.01	0.82	10.42	5.10	9.21	12.24	9.90
2	4.22	0.85	10.50	5.18	9.25	13.17	9.82
3	3.37	0.86	10.54	5.26	9.26	13.61	9.87
4	2.64	0.81	10.60	5.33	9.29	13.90	9.92
5	2.12	0.84	10.64	5.39	9.30	14.10	9.82
6	1.72	0.85	10.69	5.43	9.32	14.27	9.97
7	1.37	0.81	10.71	5.47	9.32	14.42	9.95
8	1.13	0.81	10.72	5.48	9.32	14.48	9.81
9～12	2.26	0.94	10.78	5.53	9.33	14.69	9.73
Above 12	2.24	1.02	11.04	5.80	9.51	15.27	10.09

Note: The ten groups of exporters are sorted by the number of export products. The value is calculated by taking simple mean during the period 2000–2006.

Table 4.5 shows a set of firm's characteristics across 11 groups of firms, which are defined and sorted by the number of export destinations. This table's items are the same as the ones in Table 4.4. The table shows that about 4.93 percent of the total firms serve only one destination, on average, and about 21.15 percent of the total firms serve more than one destination. Exporters that serve more than one destination have higher levels of output, employment, and total exports. Firms serving more than 12 destinations, on average, have the highest TFP level, while firms serving 7 destinations, on average, have the lowest TFP level among the exporting firms. In addition, the ages of exporting firms tend to increase in the number of export destinations.

Table 4.5 Firms' characteristics by the number of export destinations

Number of destinations	Share of firms (%)	ln(TFP)	ln(output)	ln(employee)	ln(capital)	ln(export)	Age
0	73.92	0.81	9.82	4.65	8.40		11.14
1	4.93	0.87	10.25	5.04	9.03	12.28	9.31
2	4.73	0.88	10.36	5.16	9.11	13.06	9.51
3	2.75	0.89	10.44	5.22	9.17	13.37	9.71
4	2.18	0.83	10.52	5.27	9.23	13.60	9.83
5	1.80	0.85	10.58	5.30	9.27	13.82	9.92
6	1.51	0.87	10.63	5.36	9.30	13.98	9.92
7	1.26	0.82	10.70	5.41	9.34	14.14	10.14
8	1.09	0.86	10.69	5.39	9.33	14.18	10.07
9～12	2.53	0.88	10.81	5.48	9.42	14.48	10.19
Above 12	3.29	0.94	11.23	5.82	9.74	15.26	10.65

Note: The ten groups of exporters are sorted by the number of export destinations. The value is calculated by taking simple mean during the period 2000–2006.

4.6 Empirical Results

This section uses a regression framework based on equation (4.3) to quantify the effect of firm productivity on the extensive and intensive margins of China's exports during the period 2000–2006. Furthermore, we divide the Chinese exporting firms into ordinary, processing, and mixed exporters and examine the relationship between firm-level productivity and export margins of these three types of exporters, respectively.

Table 4.6 presents the results based on the full sample data. In column (1), we regress the firm's total exports (in log) on the changes in firm-level TFP, the number of employees, fixed capital stock, firm age, and ownerships (state-owned, foreign-invested, and private firms). As expected, the coefficient on TFP is positive and significant. A one percent increase in TFP is associated with a 0.089 percent increase in firm-level total exports. This result confirms that Chinese firms with higher productivity have larger total exports. In addition, the coefficients on control variables are also positive and significant. The firm-level total exports increase by 0.479 and 0.156 percent associated with a one percent increase in the number of employees and fixed capital stock, respectively. This result implies that firms with bigger sizes and fixed capita stock have larger total exports. The coefficient on firm age is positive and significant, which suggests that firms with longer histories tend to have larger total exports. Dummy variables are also included in the specification to quantify export performance of foreign-invested, state-owned, and private firms, respectively. The coefficient on the dummy variable of state-owned firms is negative and significant, which implies that the exports of state-owned firms are smaller than those of foreign-invested firms. The coefficient on the dummy variable of private firms is not statistically significant.

Column (2) shows the results in the case that the number of products (in log) is the dependent variable. The coefficient on TFP is positive and significant. A one percent increase in TFP is associated with a 0.024 percent increase in the number of products. This result is consistent with the prediction that more productive firms tend to export a wider range of products. In addition, the coefficients on the number of employees and fixed capital stock are also positive and significant. It shows that a one percent increase in the number of employees and fixed capital stock is associated with a 0.142 and 0.041 percent increase in the number of exporting products, respectively. This result implies that firms with larger sizes and more abundant capital are more likely to export a wider range of products. Moreover, the coefficient on firm age is positive and significant, which suggests that older firms have a larger number of exported products. The coefficient on the dummy variable of private firms is negative and significant.

This implies that private firms tend to export a smaller number of products than foreign-invested firms. However, the coefficient on the dummy variable of state-owned firms is not statistically significant.

In column (3), the dependent variable is the number of export destinations (in log). The estimation result shows that the coefficient on TFP is positive and significant. A one percent increase in TFP is associated with a 0.026 percent increase in the number of export destinations. This result confirms the theoretical prediction that more productive firms tend to serve a wider range of export destination countries. The coefficients on the number of employees and fixed capital stock are also positive and significant. The number of export destinations rises by 0.175 and 0.035 percent due to a one percent increase in the number of employees and fixed capital stock, respectively. In addition, the coefficient on firm age is positively associated with the number of export destinations. These results suggest that firms with larger size, fixed capital stock, and longer histories serve more export destination countries. However, the coefficients on the two dummy variables are not statistically significant. It is unclear whether foreign-invested firms serve a wider range of export destinations than state-owned and private firms.

Column (4) shows the results in the case that the dependent variable is the measure of density (in log). The estimation result shows that the coefficient on TFP is negative and significant. A one percent increase in TFP is associated with a 0.019 percent decrease in the measure of density. The negative correlation between the density measure and firm productivity implies that more productive firms export a larger number of products and destination countries but do not ship every product to every destination country. The coefficients on the number of employees, fixed capital stock, and firm age are negative and significant. These results suggest that firms with more employees, fixed capital stock, and longer histories tend to have lower density. In addition, the coefficients on the two dummy variables are not statistically significant.

The last two columns give the results for intensive margins of exports. Column (5) presents the results in the case that the dependent variable is the average firm-level exports of per product-country (in log). The coefficient on TFP is positive and significant. A one percent increase in TFP is associated with a 0.058 percent increase in the average firm-level exports per product-country. This result implies that TFP has a positive effect on the average firm-level exports per product-country. In addition, the coefficients on the number of employees, fixed capital stock, and firm age are positive and significant. This result suggests that firms with more employees, fixed capital stock, and longer histories have higher average firm-level exports per product-country. The coefficient on the dummy variable of state-owned firms is negative and significant at the 10 percent level, implying that state-owned firms tend to have lower average firm-level exports of per product-country than foreign-invested firms. The coefficient on the dummy variable of private firms is negative but not statistically significant.

Furthermore, the export value of the firm's largest or top-exporting product (in logs) serves as an alternative measure of the intensive margin of exports. As shown in column (6), the coefficient on TFP is positive and significant. A one percent increase in TFP is associated with a 0.091 percent increase in the exports of the firm's top-exporting product. The coefficients on the number of employees, fixed capital stock, and firm age are positive and significant. This result suggests that firms with more employees, fixed capital stock, and longer histories have larger exports of the firm's top-exporting product. Moreover, the coefficient on the dummy variable of state-owned firms is negative and significant at the 10 percent level. Compared with foreign-invested firms, state-owned firms have smaller exports of their top-exporting product. The coefficient on the dummy variable of private firms is negative but not statistically significant.

The above results show the positive effects of firm-level productivity on the number of products and export destinations and a negative effect of firm-level productivity on the density of product-country coverage by the firm. These empirical results are generally consistent with the theoretical prediction of Bernard, Redding and Schott (2011). The theoretical prediction for the intensive margin of exports is ambiguous. On the one hand, firms with higher productivity tend to have larger exports of a given product to a given country. On the other hand, higher productivity enables firms to export a wider range of products and destinations. The net change in average exports depends on the two effects. The empirical result in this subsection shows that firm productivity is positively correlated with the average firm-level exports per product-country. This finding implies that high-productivity firms are more likely to increase the exports of their existing products than to expand the scope of products and export destinations. The previous study also demonstrates that more productive firms tend to focus on their core products and drop their unsuccessful products. The above result confirms that there is a positive correlation between firm-level productivity and the exports of the firm's top-exporting product.

Moreover, the results show that Chinese firms with more employees, larger fixed capital stock, and longer histories tend to export more products and export destinations, larger average exports, and larger exports of their top-exporting product. Furthermore, this analysis also compares the export performance of firms by different types of ownership. State-owned firms have smaller total exports, average firm-level exports per product-country, and exports of top-exporting product than foreign-invested firms. Meanwhile, the number of exported products of private firms is lower than that of foreign-invested firms.

Table 4.6 Firm productivity and export margins in full sample, 2000–2006

	(1) ln(exports)	(2) ln(products)	(3) ln(destinations)	(4) ln(density)	(5) ln(average exports)	(6) ln(top product)
ln(TFP)	0.089***	0.024***	0.026***	-0.019***	0.058***	0.091***
	(0.014)	(0.007)	(0.007)	(0.005)	(0.011)	(0.014)
ln(employment)	0.479***	0.142***	0.175***	-0.079***	0.242***	0.459***
	(0.008)	(0.004)	(0.004)	(0.003)	(0.006)	(0.008)
ln(capital)	0.156***	0.041***	0.035***	-0.018***	0.098***	0.146***
	(0.006)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)
Age	0.125***	0.039***	0.080***	-0.035***	0.041***	0.116***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Private(dummy)	-0.041	-0.036**	-0.007	0.015	-0.012	-0.023
	(0.032)	(0.016)	(0.016)	(0.012)	(0.025)	(0.031)
State (dummy)	-0.091***	-0.026	-0.022	0.004	-0.047*	-0.082**
	(0.032)	(0.016)	(0.016)	(0.012)	(0.025)	(0.032)
Observations	194,212	194,212	194,212	194,212	194,212	194,212
R^2	0.107	0.043	0.103	0.042	0.037	0.098

Notes: All results are included in sector and year dummies based on fixed effects, using data during 2000-2006. The dependent variable used is reported at the top of each column. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

As noted earlier in this chapter, Chinese exporters engaging in different trade regimes tend to have different performance in international trade. Thus, the regression analysis will be conducted for ordinary, processing, and mixed exporters, respectively.

Table 4.7 reports the regression results for ordinary exporters that only engage in ordinary exports. The result in column (1) shows that the coefficient on TFP is positive and significant. A one percent increase in TFP is associated with a 0.111 percent increase in firm exports. This result implies that TFP has a positive effect on the increase in the total exports of ordinary exporters. The coefficients on control variables are also statistically significant. The number of a firm’s employees, fixed capital stock, and firm age are positively associated with the total exports of ordinary exporters.

In columns (2)–(4), the extensive margins of exports are dependent variables. Similar results are found in the positive correlation between TFP and the number of products and export destination. A one percent increase in TFP is associated with a 0.021 and 0.038 percent increase in the number of products and export destinations, respectively. This result suggests that ordinary exporters with higher productivity tend to export more products and serve more destination countries, which is consistent with the prediction in the previous study. The correlation between TFP and density is negative and significant. This implies that ordinary firms with higher productivity export more products and reach more destinations but do not ship every product to every destination country. For the control variables, the number of employees, fixed capital stock, and firm age have positive correlations with the number of products and export destinations, while having negative correlations with the density of product-country coverage by the firm.

In the case that the intensive margins of exports are dependent variables, the coefficients on TFP in columns (5)–(6) are both positive and significant. A one percent increase in TFP is associated with a 0.07 and 0.108 percent increase in the average exports and the exports of top-exporting product, respectively. This result suggests that ordinary exporters with higher productivity tend to have larger average firm-level exports per product-country and larger export value of their top-exporting products. Moreover, the number of employees, fixed capital stock, and firm age are also positively correlated with the two intensive margins of exports. However, the coefficients on dummy variables are not statistically significant.

Table 4.7 Firm productivity and export margins for ordinary exporters, 2000–2006

	(1) ln(exports)	(2) ln(products)	(3) ln(destinations)	(4) ln(density)	(5) ln(average exports)	(6) ln(top product)
ln(TFP)	0.111***	0.021**	0.038***	-0.016**	0.070***	0.108***
	(0.022)	(0.010)	(0.010)	(0.007)	(0.017)	(0.021)
ln(employment)	0.454***	0.122***	0.178***	-0.075***	0.230***	0.442***
	(0.013)	(0.006)	(0.006)	(0.004)	(0.010)	(0.013)
ln(capital)	0.114***	0.045***	0.062***	-0.033***	0.040***	0.108***
	(0.009)	(0.004)	(0.004)	(0.003)	(0.007)	(0.009)
Age	0.210***	0.047***	0.101***	-0.037***	0.100***	0.203***
	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)	(0.004)
Private(dummy)	0.008	-0.051**	-0.018	0.022	0.055	0.036
	(0.047)	(0.023)	(0.023)	(0.016)	(0.036)	(0.047)
State (dummy)	0.022	-0.024	-0.013	0.001	0.059	0.042
	(0.048)	(0.023)	(0.023)	(0.016)	(0.037)	(0.048)
Observations	105,164	105,164	105,164	105,164	105,164	105,164
R^2	0.124	0.037	0.119	0.043	0.056	0.119

Notes: All results are included in sector and year dummies based on fixed effects, using data during 2000-2006. The dependent variable used is reported at the top of each column. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 4.8 reports the regression results for processing exporters that only engage in processing exports. The result in column (1) shows that the coefficient on the TFP is positive and significant. A one percent increase in TFP is associated with a 0.089 percent increase in processing exports. This result means that processing exports rise with the firm-level TFP. In addition, the number of firm’s employees and fixed capital stock are positively associated with processing exports. The coefficient on firm age is not statistically significant.

From the results in columns (2)–(4), we find that TFP is positively correlated with the extensive margins of exports. A one percent increase in TFP is associated with a 0.026 and 0.05 percent increase in the number of products and export destinations, respectively. This result implies that processing exporters with higher productivity tend to export a wider range of products and serve more destination countries. In addition, the relationship between the TFP and the density is negative and significant. These results for processing exporters are similar to those for ordinary exporters. For the control variables, processing exporters with more employees and larger fixed capital stock have a larger number of products and export destinations. Firm age has a positive effect on the number of export destinations, while the correlation between firm age and the number of products is not statistically significant.

Moreover, control variables are negatively correlated with density.

In column (6), the coefficient on TFP is positive and significant. A one percent increase in TFP is associated with a 0.089 percent increase in the exports of top-exporting product. This result means that processing exporters with higher productivity have large exports of their top-exporting products. In column (5), the relationship between TFP and the average firm-level exports per product-country is not statistically significant. Moreover, fixed capital stock and the number of employees are positively correlated with the two intensive margins of exports. Firm age is negatively associated with the intensive margin, which implies that older firms tend to have lower average firm-level exports per product-country. The coefficient on private firms in column (5) is negative and significant at the 10 percent level. This result implies that the average firm-level exports of private processing firms are lower than those of foreign-invested processing firms.

Table 4.8 Firm productivity and export margins for processing exporters, 2000–2006

	(1) ln(exports)	(2) ln(products)	(3) ln(destinations)	(4) ln(density)	(5) ln(average exports)	(6) ln(top product)
ln(TFP)	0.089***	0.026***	0.050***	-0.016**	0.030	0.089***
	(0.023)	(0.010)	(0.013)	(0.007)	(0.021)	(0.023)
ln(employment)	0.597***	0.112***	0.140***	-0.049***	0.394***	0.583***
	(0.020)	(0.009)	(0.011)	(0.006)	(0.018)	(0.020)
ln(capital)	0.142***	0.040***	0.053***	-0.025***	0.074***	0.130***
	(0.016)	(0.007)	(0.009)	(0.005)	(0.014)	(0.016)
Age	0.003	0.002	0.040***	-0.012***	-0.027***	0.003
	(0.005)	(0.002)	(0.003)	(0.001)	(0.005)	(0.005)
Private(dummy)	-0.063	0.025	0.047	0.027	-0.162*	-0.126
	(0.101)	(0.043)	(0.055)	(0.029)	(0.091)	(0.100)
State (dummy)	-0.007	0.046	-0.041	0.021	-0.033	-0.014
	(0.096)	(0.041)	(0.052)	(0.028)	(0.087)	(0.095)
Observations	27,235	27,235	27,235	27,235	27,235	27,235
R^2	0.081	0.028	0.057	0.027	0.042	0.076

Notes: All results are included in sector and year dummies based on fixed effects, using data during 2000-2006. The dependent variable used is reported at the top of each column. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 4.9 reports the regression results for mixed exporters that engage in both ordinary and processing exports. In column (1), the coefficient for TFP is positive and significant. A one percent increase in TFP is associated with a 0.085 percent increase in exports. This result implies that TFP has a positive effect on the increase in the exports of mixed firms. The coefficients on control variables are also statistically significant. The number of firm's employees, fixed capital stock, and firm age are positively associated with the total exports of mixed exporters. In addition, the exports of state-owned mixed exporters are lower than those of foreign-invested mixed firms. However, the coefficient on private firms is not statistically significant.

Columns (2)–(4) present the results in the case that the extensive margins of exports are dependent variables. A one percent increase in TFP is associated with a 0.033 percent increase in the number of products and 0.026 percent decrease in density. The result implies that high-productivity mixed exporters have a larger number of products. However, the coefficient on the number of export destinations is not statistically significant. These results are different from those of ordinary and processing exporters. Looking at the control variables, firms with more employees, larger fixed capital stock, and longer histories have more products and export destinations. The control variables are negatively correlated with density.

Columns (5)–(6) show the results for the intensive margins of exports. The coefficients on TFP are positive and significant. A one percent increase in TFP is associated with 0.065 and 0.098 percent increase in the average exports and the exports of top-exporting product, respectively. This result suggests that mixed exporters with higher productivity tend to have larger average firm-level exports per product-country and larger exports of their top-exporting product. Moreover, the number of employees, fixed capital stock, and firm age are positively correlated with the two intensive margins of exports. The coefficients on the dummy variable of state-owned firms are negative and significant. This result suggests that state-owned firms have lower levels of intensive margins than foreign-invested firms.

As mixed exporters are involved in both ordinary and processing exports, firms with different productivity may choose the extent of being involved in processing exports. Thus, we also examine the relationship between mixed exporter's TFP and processing intensity, which is measured by the share of processing exports in total exports. A higher processing intensity implies a high degree of engagement in processing exports by a mixed exporter. In column (7), the coefficient on TFP is positive and significant. The processing intensity increases by 0.047 percent due to a one percent increase in TFP. This result implies that mixed exporters with higher productivity have a larger share of processing exports in their total exports. The coefficient on the number of employees is positive and significant. Firms with more employees have larger processing intensity. We also observe that older firms tend to have lower processing intensity.

Table 4.9 Firm productivity and export margins for mixed exporters, 2000–2006

	(1) ln(exports)	(2) ln(products)	(3) ln(destinations)	(4) ln(density)	(5) ln(average exports)	(6) ln(top product)	(7) ln(processing intensity)
ln(TFP)	0.085***	0.033***	0.013	-0.026***	0.065***	0.098***	0.047**
	(0.015)	(0.011)	(0.010)	(0.009)	(0.013)	(0.016)	(0.019)
ln(employment)	0.407***	0.128***	0.133***	-0.081***	0.227***	0.400***	0.046***
	(0.009)	(0.007)	(0.006)	(0.006)	(0.008)	(0.009)	(0.011)
ln(capital)	0.121***	0.039***	0.053***	-0.030***	0.058***	0.113***	0.012
	(0.007)	(0.005)	(0.005)	(0.004)	(0.006)	(0.008)	(0.009)
Age	0.075***	0.037***	0.066***	-0.035***	0.007***	0.061***	-0.065***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)
Private(dummy)	0.004	0.018	0.006	-0.013	-0.007	0.003	0.015
	(0.038)	(0.029)	(0.026)	(0.024)	(0.034)	(0.041)	(0.049)
State (dummy)	-0.094**	0.004	-0.022	-0.009	-0.068*	-0.118***	-0.037
	(0.039)	(0.029)	(0.027)	(0.025)	(0.035)	(0.042)	(0.050)
Observations	61,813	61,813	61,813	61,813	61,813	61,813	61,813
R^2	0.179	0.058	0.124	0.052	0.057	0.137	0.019

Notes: All results are included in sector and year dummies based on fixed effects, using data during 2000-2006. The dependent variable used is reported at the top of each column. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

In summary, the above results confirm the positive relationship between TFP and the firm's total exports, which is consistent with the theoretical prediction. For firms only engaging in ordinary exports, productivity exerts a positive effect on the total exports through the number of products and export destinations and the average firm-level exports per product-country. For firms only engaging in processing exports, productivity exerts a positive effect on the total exports through the number of products and export destinations. For firms engaging in both ordinary and processing exports, productivity exerts a positive effect on the total exports via the number of products and average firm-level exports per product-country. The result also shows that the export value of a firm's top-exporting product tends to increase in productivity across the three types of exporters. In addition, the result indicates that mixed exporters with higher productivity tend to have a larger share of processing exports.

4.7 Conclusion

This chapter documents the export performance of Chinese firms during the period 2000–2006 using firm-level production and customs data. Recent empirical studies have highlighted the importance of multi-product and multi-destination firms in international trade. Extending the single-product heterogeneous firm model, Bernard, Redding and Schott (2011) develop a model for heterogeneous firms involved in more than one product and export destination. This study provides theoretical prediction on the relationship between firm-level productivity and aggregate exports and the relationship between firm productivity and the firm's decision to select the range of products to export and destinations to serve. Following the empirical work of Bernard, Van Beveren and Vandenbussche (2014), this chapter examines the effects of productivity on China's exports, which are decomposed into extensive and intensive margins at the firm-level. The extensive margin of exports is measured by the number of products and export destinations, while the intensive margin of exports is measured by the average firm-level exports per product-country and the exports of the firm's top-exporting product.

The estimation results provide evidence to confirm the theoretical predictions about the importance of multi-product exporters and their abilities to export many products to many destinations. This chapter finds that the productivity of Chinese firms is positively correlated with the value of firm's total exports. For the extensive margins, firms with higher productivity tend to serve more products and destination countries. Moreover, the intensive margins of average firm-level exports per product-country and the exports of the firm's top-exporting product are positively associated with productivity.

This chapter also considers the heterogeneity of Chinese firms. They participate in international trade via different trade regimes. Chinese exporting firms are divided into three groups: firms that engage only in ordinary exports, firms that engage only in processing exports, and firms that engage in both ordinary and processing exports. Higher-productivity ordinary exporters tend to have a larger number of products and export destination countries and have larger average firm-level exports per product-country and the exports of the firm's top-exporting products. The results for processing exporters are slightly different. Processing exporters with higher productivity tend to serve more products and export destination countries, while the relationship between productivity and average firm-level exports per product-country is not statistically significant. In addition, more productive processing exporters have large exports of their top-exporting products. Mixed exporters with higher productivity have a larger number of products, average firm-level exports per product-country, and exports of the top-exporting product. Moreover, the result indicates that more productive mixed exporters are associated with a larger share of processing exports in their total exports.

This study has some limitations. First, we examine only how firm-level productivity affects the extensive and intensive margins of exports. However, export performance is also affected by other factors such as trade costs, imports, skill-, and capital-intensities. For example, Bernard, Redding and Schott (2011) predict that tariff reduction may cause firms to drop their least-successful products and concentrate on their core products. In particular, the WTO entry in 2001 accelerated trade liberalization in China. Both the changes in productivity and trade costs are crucial factors in explaining the export performance of Chinese firms. In addition, the measurement of firm-level productivity is problematic for firms that can choose multiple products. This problem can be handled if data on intermediate inputs, outputs, and prices are available at the firm-product level (Bernard, Redding and Schott 2011). However, the data used in this chapter do not include information on intermediate inputs at the firm-product level. To obtain a more precise measure of the productivity of multi-product firms, alternative methods should be considered in future studies.

Chapter 5 The Skill Structure of Labor Demand and Global Value Chains [17]

5.1 Introduction

With the development of global value chains (GVCs), two notable consequences have been documented: the increased use of international outsourcing and rising demand for high-skilled labor relative to that for low-skilled labor. Over the last three decades, the GVCs have changed the pattern of international trade and production. The fragmentation of production is prevalent across the world as a result of the decreasing transportation costs. Consequently, an increased proportion of imported intermediate inputs are embedded in production (Johnson and Noguera 2012). This production fragmentation can also be called "international outsourcing," "offshoring," or "vertical specialization." [18]

The establishment of GVCs not only affects the structure of international trade but also has significant impacts on the labor market. Less-skilled labor-intensive production tends to be transferred to developing countries, whereas, technology-intensive production is retained in advanced countries. The evidence for the 1990s and 2000s indicates that an increased number of production activities are sent abroad, and these activities range from low-skilled to high-skilled jobs. Despite a concurrent rise in the supply of high-skilled labor, the relative wages of high-skilled labor compared with that of less-skilled labor have not fallen. Rather, the income share of highly skilled workers has increased dramatically since the early 1980s in many OECD economies (Goos, Manning and Salomons 2009). Timmer et al. (2014) find significant upward trend in the value added that is created by high-skilled labor in both advanced and developing countries. Meanwhile, they observe a significant downward trend in the value added that is created by low-skilled labor. A large body of literature explores the debate on why the relative demand for high-skilled labor has risen over time. The consensus points to two sources behind this ongoing change in the skill structure of the labor market: international trade and skill-biased technical change (SBTC). Although many empirical works have confirmed the hypothesis regarding the effect of SBTC on the changes in labor demands, the effect of trade structure on labor demand remains unclear. Thus, making investigation into the effect of international trade on the labor market is still important.

[17] Chapter 5 is based on the previously published article of Zhu (2020).

[18] Many studies examining the imported inputs in production refer to this situation as "offshoring" probably because they mainly focus on advanced countries. Because this chapter covers both advanced and developing countries, we use "imported intermediate inputs," "imported inputs," and "international sourcing" interchangeably.

In many studies, the examination of the relationship between labor demand and international trade has limitations. With the development of GVCs, the production process is split into separate activities and performed in different places with little variation in quality. For example, the GVCs of the manufacturing sector include not only production activities in the manufacturing sector itself but also the activities in other sectors such as agriculture, business, transport, and financial services that provide intermediate inputs at any stage of the production process. These indirect linkages between sectors are sizable and can be explicitly accounted for using an input–output model across sectors (Timmer et al. 2014). When measuring the cost share of labor inputs in production, previous studies have only captured the direct contribution of labor inputs in the manufacturing sector while being blind to the indirect contribution from other sectors.

Given the fact that GVCs have become increasingly complex, measures based on traditional trade statistics cannot reliably capture the linkages between suppliers and users in GVCs. Many previous studies follow the method in Feenstra and Hanson (1999) to calculate the share of imported intermediate inputs in total outputs on the basis of national input–output tables. An increase in this share indicates an increased reliance on international fragmentation or imported intermediate inputs under the assumption that the total value of imports is created in foreign countries. However, as GVCs have become increasingly complex with more than two production stages, the imports may include the value that the importing country added itself in previous production stages. For example, when China imports semiconductors from Korea for the production of cell phones, they could contain value-added content originating from China itself. In a more complicated case, the semiconductors imported from Korea could also contain value-added content originating from third-party countries such as the US, Japan, and Malaysia. Therefore, an indicator using the share of direct imports is likely to overestimate or underestimate the reliance on imported inputs because it fails to account for the value-added indirectly embedded in production activities within GVCs.

The main objective of this chapter is to address the question of how imported intermediate inputs in production affect the skill structure of labor demand, which is measured as the cost shares of labor inputs in final outputs. Timmer et al. (2014) introduce a framework to break down the total value of a final good into the value-added content created by domestic and foreign factors in GVCs. This approach can be further extended to decompose domestic labor income into different skill levels. This chapter estimates the cost shares of domestic high-skilled, medium-skilled, and low-skilled labor in the final output.[19] We measure the cost share of domestic labor inputs to reflect the demand for domestic labor. These cost shares of domestic labor cannot be directly derived from primary data, and this chapter will use an input–output model to map final goods to the value added by different labor inputs in each sector-country pair. This estimating framework identifies how value-added content is sourced from a particular sector or country.

Furthermore, the reliance on imported inputs for production is measured by the share of foreign value-added (hereafter referred to as FV) in final outputs, which is viewed as a "second-generation" statistic for measuring offshoring in Feenstra (2017). For each final good, its GVC is defined as the set of all activities that are required in its production. Tracing the location of these activities based on the input–output model can identify the domestic and foreign contents directly and indirectly embedded in production. In the case of producing cell phones, the manufacturing process ends at a firm in China. However, the production activities of the intermediate inputs that are delivered to the firm also create value-added content, partly within China and partly abroad because some of these parts and components are imported. Many upstream industries, such as product design and semiconductor production, are also involved both inside and outside China. Using international input–output tables, we can decompose the value of the cell phones into value-added ones created in China and abroad.

This chapter also addresses the question of how labor demand is affected by imported intermediate inputs originating from advanced and developing countries. One of the advantages of using international input–output tables is that they can provide information on the origin and destination of FV in production. For example, we can estimate the FV in China's electronics sector originating from an origin of country, such as Japan or the US. Aggregating the country-level origins of FV yields the FV sourced from advanced and developing countries, respectively. In addition, FV captures all the imported content that is directly and indirectly embedded in production. The FV originating from Japan in China's electronics sector, for example, contains not only value-added directly imported from Japan to China, but also value-added created in Japan, and then imported by China through third-party countries. As the GVCs become increasingly complex, it is common to see that the value-added travels across national borders multiple times before reaching the production site for its final output. Compared with the traditional measure, which is based on observable trade flows, using the input–output model

[19] In this chapter, the cost share of a specific domestic factor will mean the domestic cost share of the factor in the total outputs. For example, the cost share of domestic high-skilled labor means the cost share of domestic high-skilled labor in the total outputs.

is an effective tool for capturing direct and indirect linkages between countries within GVCs.

To apply the model to the data, this chapter demonstrates how to measure the factor contents of the domestic and offshore stages of production based on the World Input–output Database (WIOD). This chapter also documents the changes in the factor cost shares and factor prices for 35 sectors across 40 economies during the period from 1995 to 2009. In addition, the WIOD also provides raw industry-level data in connection with input–output tables, including total value-added, labor income by skill levels, working hours by skill levels, and capital stock. However, the shortcoming of the WIOD is that it covers only a small number of developing countries. To measure the FV shares originating from both advanced and developing countries, this chapter uses the Inter-country input–output (ICIO) tables from the OECD database, which cover a wider range of developing countries.

From the preliminary results on the cost shares at the sector and country levels, we confirm an increased share of domestic high-skilled labor and a declining share of domestic low-skilled labor for most sectors from 1995 to 2009, leaving an unclear trend in medium-skilled labor. The result implies that domestic high-skilled labor is more likely to benefit from the change of trade structure in the sample period and most sectors are experiencing an upgrade of skill structure. Conversely, the demand for domestic low-skilled labor may decline due to participation in GVCs.

To quantify the relationship between the skill structure of labor demand and imported intermediate inputs econometrically, this chapter uses a standard approach for analyzing labor demand based on the estimation of a translog cost function. In the regression framework, dependent variables include the cost shares of domestic labor inputs by skill levels in final outputs. Independent variables, on the other hand, include hourly wages, capital stocks, outputs, and two indicators for the imported contents in production: the FV share in final outputs and the direct import share of intermediate inputs in final outputs. The variable of main interest is the FV share in the final outputs, which reflects the proportion of imported contents required directly and indirectly by one unit of the final output. Our estimation is based on year-by-year and long-term (12 years) differences. The baseline result shows that FV share has a negative and significant effect on the cost shares of domestic labor, irrespective of skill level when the change in wages of domestic labor, fixed capital stocks, and outputs are controlled. Particularly, the FV share exerts a larger impact on medium-skilled labor. These results are consistent with the previous literature, which has documented significant job losses of medium-skilled workers due to international trade (Autor, Levy and Murnane 2003). Similarly, the direct import share of intermediate inputs in the final outputs also has a negative and significant effect on the cost shares of domestic labor.

Furthermore, the origin of the FV share is decomposed based on sourcing countries. Specifically, the FV share of an individual sector can originate from advanced or developing countries. The FV sourced from different country categories is likely to have different effects on the cost shares of the domestic labor demand. Furthermore, the destination countries of FV are split into advanced and developing countries. Decomposing the origin and destination of FV, for example, allows us to examine how offshoring to developing countries affects the labor demand in advanced countries.[20] The result implies that the proportion of FV originating from advanced countries is larger than that originating from developing countries. This result holds true for both advanced and developing countries.

Through the regression, we confirm that the FV share sourced from developing countries accounts for a larger proportion of the decreases in the cost shares of domestic high-skilled and medium-skilled labor in advanced countries in the case of year-by-year differences. However, the negative correlation between the FV share sourced from developing countries and the cost shares of domestic high-skilled and medium-skilled labor in advanced countries becomes insignificant in the case of long-term differences. The negative effect of FV share sourced from developing countries on the cost share of domestic low-skilled labor in advanced countries is significant in the cases of both year-by-year and long-term differences. Moreover, the FV share sourced from advanced countries contributes more to the decreases in the cost share of domestic medium-skilled labor in developing countries. A notable result is that the FV share originating from advanced countries is positively associated with the cost share of domestic low-skilled labor in developing countries in the case of long-term differences. Furthermore, the indicators of FV share and the share of directly imported intermediate goods and services in production are used in the specification. The result shows that the two indicators have slightly different magnitudes of influence on changes in the domestic labor demand.

The rest of this chapter is organized as follows. Section 5.2 reviews the previous literature on the relationship between labor demand and trade structure. In Section 5.3, we explain how to use input–output model to estimate the cost shares of domestic labor inputs by skill levels and the indicators of imported inputs in production activities. A simple econometric model is also presented, which provides the basic environment for analyzing the relationship between

[20] Following the nomenclature used in the input–output analysis, the “sourcing country” or “country of origin” is the country from which intermediate inputs are imported, while the “destination country” is the country where the imported inputs are used.

the cost shares of labor factors and the related variables. In addition, an explanation about the data sources is given. Section 5.4 reports the empirical results derived from the estimation framework in the preceding section. Some crucial findings concerning the trends in labor cost shares and foreign value-added shares are presented. Moreover, from the regression framework, we show the results on the effect of imported inputs on the cost shares of domestic labor by skill levels. The final section gives the conclusions.

5.2 Literature Review

This chapter is related to several streams of literature that construct theoretical and empirical frameworks to examine the effects of trade structure on the labor market. The seminal work of Stolper and Samuelson (1941) presents that the demand for skilled labor increases relative to unskilled labor in countries specializing in skill-intensive goods. This effect is reversed in countries specializing in less skill-intensive goods. Afterward, the studies of how trade structure affects labor demand have traditionally been based on their work. However, Feenstra and Hanson (1995, 1997) propose a model in which a continuum of imported intermediate goods within each industry are sourced from the low-cost country. The model predicts that offshoring would be associated with an increase in the relative demand for high-skilled labor in both the countries conducting the offshoring and receiving these transferred production processes. This suggests that both the relative wages and relative demand for high-skilled workers would rise in both the countries during the 1980s. This prediction partly contradicts Stolper and Samuelson. In addition, some studies, such as Lawrence et al. (1993) and Davis and Mishra (2007), have shown that the prediction of Stolper and Samuelson cannot be empirically proved.

There has been an increase in the relative wages of high-skilled workers in US manufacturing since the 1990s. However, the relative employment of high-skilled labor has declined. This finding responds to the observation that high-skilled labor in service tasks can also be offshored as more routine service jobs are sent overseas. Grossman and Rossi-Hansberg (2008) provide an explanation for the case that both low-skilled and high-skilled production activities are exposed to offshoring, which results in local job losses. They identify three channels through which the rising imported intermediate inputs affect the income of low-skilled and high-skilled workers. First, as the costs of offshoring decline, multinational firms are more likely to reallocate low-skilled tasks abroad. The offshoring acts like a low-skilled labor-saving innovation, leading to a reduction in production costs. Profits rise in the sectors that intensively use low-skilled tasks. This could cause the outputs of these sectors to increase. As a consequence, the demand for low-skilled labor and the relative wages of low-skilled workers will rise. This channel is termed the productivity effect, in which low-skilled labor benefits from offshoring because labor productivity is improved. The second channel is called the relative price effect. Advances in the technology for offshoring lead to larger cost savings in labor-intensive industries than in skill-intensive industries. Therefore, the relative price of labor-intensive goods that require more low-skilled workers tends to decline. Following the Stolper-Samuelson theorem, the wages of low-skilled workers will decline. The relative price effect exerts downward pressure on the relative wages of low-skilled labor. The third channel is the labor-supply effect, in which offshoring does not work to the advantage of low-skilled workers. The intuition behind this effect is that technological advancement expands the range of offshoring tasks, freeing up the fraction of domestic low-skilled workers that initially engage in these tasks. These workers must be reallocated to other occupations, resulting in a fall in the relative wages of low-skilled labor. Summing up the three effects, the change in the relative wage of low-skilled labor is unclear in the three channels, while domestic high-skilled labor benefits from offshoring. Domestic low-skilled labor tends to gain or lose depending on the relative effect of productivity, the relative price effects, and the share of labor-intensive goods.

On the empirical side, Feenstra and Hanson (1995) quantify the factors that affect the relative wages of high-skilled labor against low-skilled labor in the US during the 1980s. They show that rising imports account for about 31 percent of the increase in the relative wages of high-skilled workers in the US. In addition, Feenstra and Hanson (1997) find that the increase in US foreign investment in Mexico was associated with about half of the rise in high-skilled labor's share of the total wage bill in Mexico during the period 1975–1988. Feenstra and Hanson (1999) find that the increase in offshoring positively affected the demand for US skilled workers during the period 1979–1990.

Notably, Feenstra and Hanson (1999) introduce an indicator to measure the reliance of production on imported contents or offshoring using national input–output tables. They calculate the cost share of imported intermediate inputs based on the "proportionality" assumption, whereby an input used in an industry has the same ratio of imports to domestically sourced value as does the whole economy (Feenstra 2017). Feenstra and Hanson (1999) also distinguish between a broad definition of offshoring which includes all imported inputs from upstream sectors and a narrow definition of offshoring, one that only includes imported inputs within the same industry. The former definition reflects the offshoring that takes place across industries, while the latter is thought to be closer to the offshoring that occurs within the same industry. This straightforward method based on national input–output tables has been widely applied in other studies to measure the effect of offshoring on the labor market, including by Hijzen, Görg and Hine (2005) for the UK, Hsieh and Woo (2005) for China, and Mion and Zhu (2013) for Belgium. In addition, Foster-McGregor, Stehrer and de Vries (2013) provide worldwide evidence about the trends in offshoring and the labor market over a large set of countries based on a sample of 40 countries. They confirm that offshoring puts downward pressure on the wages of high-skilled, medium-skilled, and low-skilled labor.

However, the approach of Feenstra and Hanson (1999) has limitations as international trade becomes more complex. It implicitly supposes that there is no domestic content embedded in the imported intermediate goods and there is no foreign content embedded in domestically produced intermediate goods. This assumption becomes implausible because it neglects the fact that the production of intermediate goods needs multi-stage production processes that are located both at home and abroad. In particular, this measure could generate misleading results when the transactions of intermediate goods cross borders more than one time. To overcome this shortcoming, recent studies have been directed at capturing the linkages in GVCs based on the international input–output table. Hummels, Ishii and Yi (2001) measure the use of imported intermediate inputs in exports, which is referred to as vertical specialization. Johnson and Noguera (2012) relax the assumption that a country's exports of final goods and intermediate goods are entirely absorbed abroad. Studies such as Koopman, Wang and Wei (2014) and Los, Timmer and de Vries (2015) decompose total exports into domestic and foreign value-added content along the backward linkage in GVCs. Here, the backward linkage is referred to as the use of foreign inputs in production that are exported, in other words, importing intermediate inputs in order to export. For example, Bangladesh may import textile fabric produced in Pakistan which is then used to make clothing exported by Bangladesh (Hollweg 2019). The backward linkage is usually estimated at the sector-country level (foreign value-added of exports) and in terms of intensity (the share of foreign value-added in total exports). These new approaches capture the imported contents from all of the upstream sectors that are directly and indirectly required for production.

Moreover, the use of international input–output tables allows us to estimate the geographical origin and destination of imported intermediate inputs. So far, most studies have focused on the labor market of advanced countries, which are suffering from job losses as parts of the production process have been transferred to developing countries. In the public debate, the increasing imports from developing countries have been viewed as a primary culprit behind the domestic job losses in many advanced countries. Autor, Dorn and Hanson (2013) find that the increase in US imports from China can explain about 25 percent of the decline in US manufacturing employment. In addition, other studies show that similar but less pronounced trends can be observed in some European countries. This chapter is also related to several studies, which quantify the effects of offshoring according to sourcing countries. In other words, they distinguish the destination of offshoring between high-income and low-income countries. Despite conventional worries, Falk and Wolfmayr (2005) show that increased intermediate imports from developing countries account for a relatively small proportion of reduction in manufacturing employment: only 0.25 percentage points per year in their sample of seven EU countries during the period 1995–2000. Additionally, Falk and Wolfmayr (2008) find that the negative effect of imported intermediate materials from low-income countries on the demand for labor tends to be relatively small. The negative effect is more substantial for imported intermediate inputs from China and East Asian countries. Using US plant-level data, Bernard, Jensen and Schott (2006) find that a firm's survival and employment growth are relatively low in industries exposed to imports from developing country imports. Based on a sample of 40 countries, Wolszczak-Derlacz and Parteka (2018) reveal that offshoring to developing countries is associated with a decline in the wages of domestic medium-skilled and low-skilled workers.

However, these examinations using direct import data have been improved since considering the direct and indirect linkages within GVCs. Wang et al. (2018) find that direct imports decline employment in the US. An indirect upstream channel further increases these job losses. The negative effect arises because suppliers in the upstream sectors are hurt by import competition if their buyers' demands for their products shrink. However, the negative effect could be offset by the job creation from the downstream channel. In other words, industries in the downstream might benefit from import competition because they can reduce their production costs by shifting from local suppliers to lower-price foreign suppliers. As a result, the outputs and employment of industries in the downstream sector increase. Considering the direct and indirect linkages within GVCs has attracted great attention in the literature, which particularly focuses on the indirect effect of job creation through backward linkages (Acemoglu et al. 2016; Feenstra and Sasahara 2018). Even though the magnitude of the indirect effect varies depending on different measurements of offshoring, some studies find that the overall effect of the imports from China on US employment is much smaller than that estimated by Autor, Dorn and Hanson (2013), who did not take into consideration the perspectives of GVCs.

5.3 Methodology and Data Sources

5.3.1 Empirical Specification

This subsection describes the empirical strategy in order to examine how a change in imported contents in production affects the skill structure of labor demand. When analyzing the relative demand for labor, a translog function is widely used as in Berman, Bound and Griliches (1994), Feenstra and Hanson (2001). The explanation of this subsection follows Foster-McGregor, Stehrer and de Vries (2013), which illustrate the estimation of a translog cost function. We consider a gross output production function as follows:

$$X = f(L, M, H, K), \tag{5.1}$$

where X is gross output, L is low-skilled labor, M is medium-skilled labor, H is high-skilled labor, and K is the capital stock. We assume the production function is increasing and concave in (L, M, H, K). As in Berman et al. (1994), capital is assumed to be quasi-fixed, meaning that both output and capital can be treated as fixed in the short run. When the levels of capital and output are fixed but labor of different skill levels are flexible, the short-run cost function is defined as follows:

$$C(w_l, w_m, w_h, K, X, z) = \min_{L,M,H} w_l L + w_m M + w_h H, \tag{5.2}$$

subject to equation (5.1), where $w_l, w_m,$ and w_h are the factor prices of low-skilled, medium-skilled, and high-skilled labor, and z refers to technological change. We assume that equation (5.2) can be approximated by a second order flexible functional form such as the translog function. This function is written in a general form as follows:

$$\ln C = \alpha_0 + \sum_{\tau=1}^{\mathrm{T}} \alpha_\tau \ln w_\tau + \sum_{\kappa=1}^{\mathrm{K}} \beta_k \ln r_\kappa + \gamma_z z$$

$$+\frac{1}{2}\sum_{\tau=1}^{\mathrm{T}}\sum_{\sigma=1}^{\mathrm{T}}\alpha_{\tau\sigma}\ln w_{\tau}\ln w_{\sigma}+\frac{1}{2}\sum_{k=1}^{\mathrm{K}}\sum_{\rho=1}^{\mathrm{K}}\beta_{\kappa\rho}\ln r_{\kappa}\ln r_{\rho}+\frac{1}{2}\gamma_{zz}\,z^{2}$$

$$+\frac{1}{2}\sum_{\tau=1}^{\mathrm{T}}\sum_{\kappa=1}^{\mathrm{K}}\varphi_{\tau\kappa}\ln w_{\tau}\ln r_{\kappa}+\sum_{\tau=1}^{\mathrm{T}}\varphi_{z\tau}\,z\ln w_{\tau}+\sum_{\kappa=1}^{\mathrm{K}}\varphi_{z\kappa}\,z\ln r_{\kappa}\,, \tag{5.3}$$

where w_τ denotes the prices of various labor factors (that is, the hourly wages of domestic high-skilled, medium-skilled, and low-skilled labor in this chapter), and r_κ denotes outputs and fixed inputs (that is, gross output and fixed capital stock in this chapter). The variable z refers to any structural variables that will shift the production function and therefore affect costs. It is assumed that the translog cost function is twice differentiable, linearly homogenous, and concave in factor prices. Taking the first derivative of the translog cost function with respect to factor prices (w_τ) yields $\partial lnC/\partial lnw_\tau = (\partial C/\partial w_\tau)(w_\tau/C) = w_\tau D_\tau/C = S_\tau$, where the demand for labor inputs τ can be obtained by $D_\tau = \partial C/\partial w_\tau$ according to Shephard's lemma. Thus, partially differentiating equation (5.3) gives the cost shares of the labor inputs as follows:

$$S_{\tau}=\ \alpha_{\tau}+\frac{1}{2}\sum_{\sigma=1}^{T}\alpha_{\tau\sigma}\ln w_{\sigma}\ +\frac{1}{2}\sum_{\kappa=1}^{K}\varphi_{\tau\kappa}\ln r_{\kappa}+\varphi_{z\tau}\,z,\qquad(\tau=1,\cdots,\mathrm{T}) \tag{5.4}$$

Equation (5.4) will be used to analyze the cost share of labor factor of a given sector, which depends on wages of all types of labor factors (w), capital stock (K), output (X), and other structural variables (z). Let S_τ denote the cost share of domestic high-skilled, medium-skilled, and low-skilled labor in final outputs, where $\tau \in \{h, m, l\}$. A popular method is to take difference between two years in order to eliminate sector-specific time-invariant effects. The equations for the cost shares of different workers are expressed as follows:

$$\begin{aligned}\Delta S_{\tau}=\ &\alpha_{0}+\ \alpha_{\tau h}\,\Delta\ln w_{h}+\ \alpha_{\tau m}\,\Delta\ln w_{m}+\ \alpha_{\tau l}\,\Delta\ln w_{l}+\beta_{\tau}\Delta\ln K+\delta_{\tau}\Delta\ln X\\&+\varphi_{z\tau}\Delta z+\ \varepsilon_{\tau}\,.\end{aligned} \tag{5.5}$$

In the context of this chapter, the variable z in equation (5.5) will include indicators that measure imported contents in production. Thus, $\varphi_{z\tau}$ is expected to be negative, implying a negative correlation between the cost share of domestic labor and imported contents in production. A full set of year and sector dummies is included to control the trends in cost shares of labor although these results will not be reported.

Alternatively, equation (5.5) is estimated using a 12-year difference between 1995 and 2007 instead of year-by-year differences. Long difference can mitigate the problem of small size of variation in regressors when taking year-by-year differences, and to account for lags in the adjustment of labor demand to shocks. Moreover, estimates based on long differences are less sensitive to bias due to measurement error than either fixed effects or first differences (Griliches and Hausman 1986). Country and sector dummies are added in the specification to capture the country-specific sector-specific features. The reason that the data up to 2007 is used is that there are a large number of missing data in the sample of 2009. Moreover, results in 2009 tend to be affected by the 2008 global financial crisis. Thus, the long difference between 1995 and 2007 will be used. In addition, since the error terms in the three labor demand equations are likely to correlate with each other, efficiency can be improved by running the equations jointly as seemingly unrelated regressions (SUR).

5.3.2 Using Input–Output Model

The above subsection illustrates the empirical specification. Equation (5.5) is derived from a translog cost function to examine the relationship between domestic labor demand and the imported contents in production. This subsection demonstrates how to measure variables such as cost shares of domestic labor, wages, and imported contents in production based on an input–output model.

In an international input–output table, it is expanded to track intermediate and final goods linkages across countries and sectors. Assume an economy with g countries and n sectors in each country. A country set is defined by $\mathrm{G} \equiv \{1 \cdots g\}$, and a sector set is defined by $\mathrm{N} \equiv \{1 \cdots n\}$. The economic structure can be expressed by the following international input–output model. Let $\mathbf{Z}$ be a $gn \times gn$ matrix representing the transaction values of intermediate inputs, $\mathbf{y}$ be an $gn \times 1$ final demand vector, $\mathbf{x}$ be a $1 \times gn$ gross output vector, and $\mathbf{p}$ be a $1 \times gn$ vector of direct value-added. The vector $\mathbf{p}$ here is defined as direct value-added, which is derived directly from primary data. And it is distinct from the value-added content, which is measured by an input–output model. The input coefficient matrix is defined as $\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1}$, giving the production requirements per unit of output, in which $\hat{\mathbf{x}}$ denotes a diagonal matrix with gross output vector $\mathbf{x}$ on its main diagonal. Gross output consists of intermediate goods and final goods, that is,

$\mathbf{x} = \mathbf{Ax} + \mathbf{y}$. This equation can be rearranged as follows:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-\mathbf{1}}\, \mathbf{y} = \mathbf{Ly}, \tag{5.6}$$

where **I** is a *gn*×*gn* identity matrix. And **L** denotes a *gn*×*gn* global Leontief inverse matrix, giving the amount of gross outputs required by one unit increase in final demand. The global Leontief inverse matrix can be expressed in the matrix form as follows:

$$\mathbf{L} = \begin{bmatrix} L_{11}^{11} & L_{12}^{11} & \cdots & L_{1n}^{11} & L_{11}^{12} & \cdots & L_{1n}^{12} & L_{11}^{13} & \cdots & L_{1n}^{1g} \\ L_{21}^{11} & L_{22}^{11} & \cdots & L_{2n}^{11} & & & & & & \vdots \\ \vdots & \vdots & \ddots & \vdots & & & & & & \vdots \\ L_{n1}^{11} & L_{n2}^{11} & \cdots & L_{nn}^{11} & & & & & & \vdots \\ L_{11}^{21} & & & & L_{11}^{22} & & & & & \vdots \\ \vdots & & & & & \ddots & & & & \vdots \\ L_{n1}^{21} & & & & & & L_{nn}^{22} & & & \vdots \\ L_{11}^{31} & & & & & & & L_{11}^{33} & & \vdots \\ \vdots & & & & & & & & \ddots & \vdots \\ L_{n1}^{g1} & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & L_{nn}^{gg} \end{bmatrix}.$$

Thus, **x** in equation (5.6) is the vector of gross outputs used both directly and indirectly to produce final goods of a specific sector. Next, the gross outputs can be transferred into factor demand. Value-added coefficients are defined as the ratio of direct value-added to outputs, $\mathbf{v} = \mathbf{p}\hat{\mathbf{x}}^{-\mathbf{1}}$. Pre-multiplying the *gn*×*gn* diagonal matrix of direct value-added coefficients $\hat{\mathbf{v}}$ into equation (5.6) yields the following equation:

$$\mathbf{Q} = \hat{\mathbf{v}}(\mathbf{I} - \mathbf{A})^{-1}\, \hat{\mathbf{y}} = \hat{\mathbf{v}}\mathbf{L}\hat{\mathbf{y}}. \tag{5.7}$$

In matrix form, **Q** can also be expressed as

$$\mathbf{Q}=\begin{bmatrix} v_1^1 & 0 & \cdots & 0 \\ 0 & v_2^1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & v_n^g \end{bmatrix}\begin{bmatrix} L_{11}^{11} & L_{12}^{11} & \cdots & L_{1n}^{1g} \\ L_{21}^{11} & L_{22}^{11} & \cdots & L_{2n}^{1g} \\ \vdots & \vdots & \ddots & \vdots \\ L_{n1}^{g1} & L_{n2}^{g1} & \cdots & L_{nn}^{gg} \end{bmatrix}\begin{bmatrix} y_1^1 & 0 & \cdots & 0 \\ 0 & y_2^1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & y_n^g \end{bmatrix}$$

$$=\begin{bmatrix} v_1^1 L_{11}^{11} y_1^1 & v_1^1 L_{12}^{11} y_2^1 & \cdots & v_1^1 L_{1n}^{1g} y_n^g \\ v_2^1 L_{21}^{11} y_1^1 & v_2^1 L_{22}^{11} y_2^1 & \cdots & v_2^1 L_{2n}^{1g} y_n^g \\ \vdots & \vdots & \ddots & \vdots \\ v_n^g L_{n1}^{g1} y_1^1 & v_n^g L_{n2}^{g1} y_2^1 & \cdots & v_n^g L_{nn}^{gg} y_n^g \end{bmatrix}=\begin{bmatrix} q_{11}^{11} & q_{12}^{11} & \cdots & q_{1n}^{1g} \\ q_{21}^{11} & q_{22}^{11} & \cdots & q_{2n}^{1g} \\ \vdots & \vdots & \ddots & \vdots \\ q_{n1}^{g1} & q_{n2}^{g1} & \cdots & q_{nn}^{gg} \end{bmatrix}.$$

Each element in the matrix **Q** represents the value-added directly and indirectly used in the production of final goods and services on a country-sector basis. For example, the element q_{ij}^{sr} of matrix **Q** denotes the total value-added of sector *i* in country *s* (directly and indirectly) embedded in final goods produced by sector *j* of country *r*, where $s, r \in G$, and $i, j \in N$. On the one hand, looking at the matrix **Q** along a column captures the contribution of value-added from all upstream countries-sectors that are embedded in final goods and services of a particular country-sector. Summing up the elements in the column *j* equals the value of final good outputs of sector *j* in country *r*. On the other hand, looking at the matrix **Q** along a row captures the distribution of value-added of a sector that is absorbed by final goods production in all downstream sectors. Adding up the elements in row *i* yields total value-added created by production factors employed in sector *i* of country *s*. In other words, it equals gross domestic product (GDP) of sector *i* in country *s*.

In summary, the elements along a column of matrix **Q** measure the contribution of all upstream countries-sectors to a particular country-sector's final good outputs. In other words, it captures the backward linkages across upstream countries-sectors from a user's perspective. Tracing the elements along a column allows us to decompose a country-sector's final good outputs according to where the inputs are originated from. Whereas, the elements along a row of matrix **Q** show how the GDP of a country-sector is used by the sector itself and all its downstream countries-sectors. It keeps track of forward linkages across all downstream countries-sectors from a supplier's perspective. The forward linkages allow us to break down a sector's GDP according to where it is used.

Furthermore, the value-added embedded in final goods can be decomposed into value-added by capital and labor used in its GVCs. Labor income is decomposed by educational levels: high-skilled, medium-skilled, and low-skilled labor. In other words, value-added coefficient is expressed by the combination of four factors: $\mathbf{v} = \boldsymbol{\theta_h} + \boldsymbol{\theta_m} + \boldsymbol{\theta_l} + \boldsymbol{\theta_k}$ **,** where $\boldsymbol{\theta_h}$ denotes the ratio of high-skilled labor income to output; $\boldsymbol{\theta_m}$ is the ratio of medium-skilled labor income to output; $\boldsymbol{\theta_l}$ is the ratio of low-skilled labor income to output; $\boldsymbol{\theta_k}$ is the ratio of capital income to output. Thus, replacing **v** in equation (5.7) with the above four factors yields the value-added matrix contributed by different factors, respectively,

$$\mathbf{Q}_{\psi} = \widehat{\boldsymbol{\theta}}_{\psi}(\mathbf{I}-\mathbf{A})^{-1}\,\hat{\mathbf{y}} = \widehat{\boldsymbol{\theta}}_{\psi}\mathbf{L}\hat{\mathbf{y}}, \tag{5.8}$$

where $\boldsymbol{\theta_{\psi}}$ denotes a set of vectors of factor coefficients, where $\psi \in \{h, m, l, k\}$**.** They represent the payment of factor ψ of one unit of gross output for each of the country–sector. Thus, $\mathbf{Q}_{\psi}$ in equation (5.8) gives the value-added matrices contributed by high-skilled, medium-skilled, low–skill labor and capital, required by final products of a sector, respectively. The element $\mathrm{q}_{ij\,\psi}^{sr}$ in $\mathbf{Q}_{\psi}$ denotes the payment to factor ψ of sector *i* in country *s* embedded in the final products of sector *j* in country *r*. This chapter will focus backward linkages to trace where a country-sector sources intermediate inputs for production. Summing the elements along columns yields the value-added created by factor ψ. Let y_j^r denote the final outputs of sector *j* in country *r*. Then, the proportion of factor ψ in overall costs of sector *j* in country *r* is expressed as follows:

$$TS_{j\psi}^{r} = \left(\sum_{s\in G}\sum_{i\in N} q_{ij\,\psi}^{sr}\right)\Big/ y_j^r. \tag{5.9}$$

In addition, the main interest of this chapter is to identify the cost share of domestic factors which accounts for the overall value-added embedded in the production of a specific domestic sector. It provides a more precise measure of demand for domestic factors. The definition of the cost share of domestic labor inputs based on an input–output model is similar to Reijnders, Timmer and Ye (2016). The cost share of domestic factor ψ in the overall cost of sector *j* in country *r* is given as follows:

$$S_{j\psi}^{r} = \left(\sum_{i\in N} \mathrm{q}_{ij\,\psi}^{rr}\right)\Big/ y_j^r\ . \tag{5.10}$$

Furthermore, quantities of factor ψ needed in the production of sector *j* in country *r* can be measured in the same fashion. For example, let the element of $\boldsymbol{\theta}_{\boldsymbol{\psi}}$ be the working hours of labor required by one unit of output in a country-sector. Then, matrix $\mathbf{Q}_{\boldsymbol{\psi}}$ in equation (5.8) gives the working hours matrix contributed by high-skilled, medium-skilled, and low-skill labor, required by final products of a sector, respectively. By equations (5.9) and (5.10), $TS_{j\psi}^{r}$ and $S_{j\psi}^{r}$ refer to the working hours of total factor ψ and domestic factor ψ embedded in the final products of sector *j* in country *r*, respectively. The hourly wage is defined as the ratio of labor income to working hours.

Next, FV share in final outputs captures the imported value-added that is embedded in the final good output (Los, Timmer and de Vries 2015). The FV share of sector *j* in country *r* is given as follows:

$$\mathrm{FVS}_j^r = \left(\sum_{s \in G, s \neq r} \sum_{i \in N} \mathrm{q}_{ij}^{sr} \right) \Big/ y_j^r. \tag{5.11}$$

This decomposition technique allows us to break down the FV according to its sourcing country or sector based on backward linkage. Summing up the imported value-added from advanced countries yields the FV which is originated from advanced countries. Thus, the FVS_j^r can be decomposed into two components: the FV imported from advanced countries, and the FV imported from developing countries.[21, 22]

This chapter also calculates the share of direct imported intermediate goods in production proposed by the Feenstra and Hanson (1999). They distinguish between a narrow measure of outsourcing (IIMN) and a broad measure of outsourcing (IIMB). The IIMN refers to the share of imported intermediate goods of a sector from the same sector in foreign countries. Let z_{ij}^{sr} denotes the direct shipment of intermediate inputs form the sector *i* in country *s* to the sector *j* in country *r*. Then IIMN share of sector *j* in country *r* is given as follows:

$$IIMN_j^r = \left(\sum_{s \in G, s \neq r} z_{jj}^{sr} \right) \Big/ y_j^r. \tag{5.12}$$

[21] Throughout this chapter, the terms "FVS" and "FV share" are used interchangeably to mean the foreign value-added share in final output.
[22] The FVS sourced from advanced countries can be calculated when $s \in \mathrm{G_{adv}}$, where $\mathrm{G_{adv}}$ is the set of advance countries. The FVS sourced from developing countries can be calculated when $s \in \mathrm{G_{dev}}$, where $\mathrm{G_{dev}}$ is the set of developing countries. IIMN and IIMB can be decomposed according to sourcing origins in the same fashion.

In equation (5.12), the denominator is the final outputs of sector *j* in country *r*, while the numerator is the imported intermediate goods of sector *j* sourcing from the same sector abroad. Furthermore, the $IIMN_j^r$ can be decomposed into two components: the intermediate goods directly imported from advanced and developing countries.

On the other hand, the IIMB denotes the proportion of imported inputs from all upstream sectors of foreign countries:

$$IIMB_j^r = \left(\sum_{s \in G, s \neq r} \sum_{i \in N} z_{ij}^{sr} \right) \Big/ y_j^r. \tag{5.13}$$

The denominator in equation (5.13) is the final output of sector *j* in country *r*, while the numerator is the imported intermediate goods of sector *j* in country *r* sourcing from all sectors abroad. Similar to the $IIMN_j^r$, the $IIMB_j^r$ can also be decomposed into two components: the intermediate goods directly imported from advanced and developing countries.

5.3.3 Data Sources

The data used in this chapter is derived from two sources: World Input–Output Database (WIOD) and the OECD Inter-Country Input–Output (ICIO) Tables. The cost shares of labor inputs in final output can be calculated from the data in WIOD. International input–output tables and supplementary data come from the WIOD, which is constructed by connecting a set of national accounts statistics with supply and use tables. The WIOD provides time-series of international input–output tables from 1995 to 2011. The input–output tables cover information on the supply and use of intermediate goods of 35 sectors, together with data on final good outputs, value-added, and gross output. The sector-level data are classified at the two-digit International Standard Industrial Classification (ISIC) revision 3 level or group (including three aggregate industries: 2 primary industries, 14 manufacturing industries, and 19 services industries). The WIOD also provides national data across 40 economies (including 29 advanced economies, 11 developing economies), which account for 85 percent of world GDP in 2008. (Timmer et al., 2015).

In addition, the analysis in this chapter relies on the data on quantities and value of labor and capital used in production. This collection of information is available in the so-called

Socio-economic account in WIOD, which can be used in conjunction with international input–output tables where similar industry classifications are used. An important feature of Socio–economic account is that it provides data on income and working hours of labor by the level of educational attainment. Three types of workers are classified according to the International Standard Classification of Education (ISCED): low-skilled (ISCED categories 1 and 2), medium-skilled (ISCED categories 3 and 4), and high-skilled (ISCED categories 5 and 6). Low-skilled roughly corresponds to less than secondary schooling; medium-skilled is equivalent to secondary schooling and above, including professional qualifications, but below college degree; high-skilled includes those with a college degree and above. Capital income is defined as a residual term, that is, gross value added minus labor income.

The limitation of the WIOD is that it covers merely a small number of developing countries. It is not sufficient to use WIOD only to decompose FV according to sourcing origins. To overcome this shortcoming, the data sources also include the OECD ICIO Tables, which cover 34 sectors of 63 economies (including 36 advanced economies and 27 developing economies).[23] Most sectors in OECD ICIO Tables can be used in conjunction with the Socio-economic account in WIOD. The crosswalk of sectors between the WIOD and ICIO Tables is provided in the Appendix C. The use of the OECD ICIO Tables is helpful to distinguish the FV sources from advanced countries and developing countries.

5.4 Empirical Results

This section shows the estimation results for the changes in the cost shares of domestic labor inputs by skill levels. We also calculate the foreign value-added share, an indicator that measures the reliance of production activities on imported intermediate inputs. Finally, a regression analysis is conducted to examine the effect of imported content on the cost shares of domestic labor inputs by skill levels.

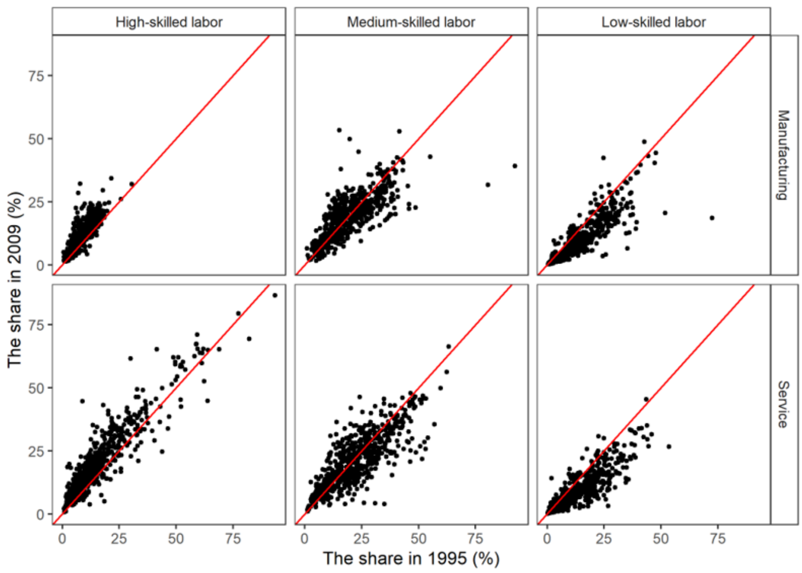
5.4.1 Labor Cost Shares by Skill Levels

This subsection presents how the cost shares at the sector and country levels change between 1995 and 2009. Figure 5.1 illustrates the changes in the cost share of domestic labor based on equation (5.10). Each dot represents the cost share of domestic labor in the final output of an

[23] In addition to 63 economies, there is an RoW region, four splitting tables of China, and three splitting tables of Mexico in the OECD ICIO Tables.

individual sector in a country. The cost share in 1995 is put on the horizontal axis, and 2009 is placed on the vertical axis, along with a 45-degree line. A sector experiences an increase in the cost share of domestic labor if the dot lies above the 45-degree line and a decrease if the dot lies below the 45-degree line. The upper panels are manufacturing sectors, while the lower panels are service sectors. For high-skilled labor, roughly 76 percent of manufacturing sectors and 72 percent of service sectors lie above the 45-degree line. This result implies that in most sectors, the change in the cost share of domestic high-skilled labor was on an upward trend during the period 1995–2009. Conversely, for low-skilled labor, about 19 percent of manufacturing sectors and 21 percent of service sectors lie above the 45-degree line, implying a pervasive decline in the cost share of domestic low-skilled workers. In particular, manufacturing sectors suffered more than service sectors. The changing pattern of medium-skilled labor is ambiguous, with roughly 54 percent of both manufacturing and service sectors above the 45-degree line. This result suggests that half of the selected sectors experience a decline in the cost share of domestic medium-skilled labor, while the other half experienced an increase during the same period.

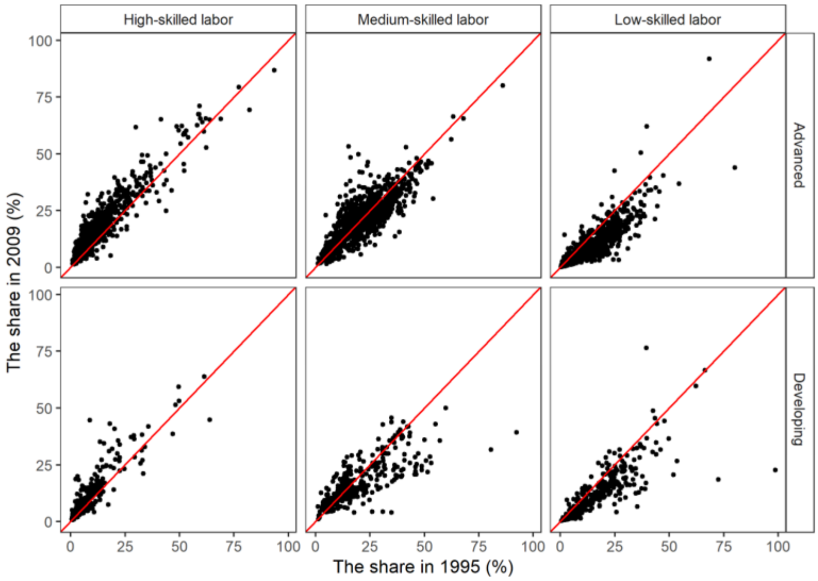
Figure 5.1 Changes in the cost shares of labor by skill-industry



Note: Each dot in the figure represents a sector's cost share of domestic labor in the final output. The cost share in 1995 is put on the horizontal axis, and 2009 on the vertical axis, together with a 45-degree line.

Figure 5.2 shows the changes in the cost share of domestic labor by skill levels in advanced and developing countries. The upper panels show the results in advanced countries, while the lower panels do in developing countries. For the high-skilled labor, roughly 89 percent of the advanced countries and 83 percent of the developing countries lie above the 45-degree line. This result implies that the cost share of domestic high-skilled labor in most sectors was on an upward trend during the period 1995–2009. For low-skilled labor, about 14 percent of advanced countries and 13 percent of developing countries lie above the 45-degree line. This result suggests a pervasive decline in the cost share of domestic low-skilled workers in both advanced and developing countries. However, the pattern of change in medium-skilled labor is ambiguous, with roughly 47 percent of sectors in both advanced and developing countries above the 45-degree line.

Figure 5.2 Changes in the cost shares of labor by skill-country group



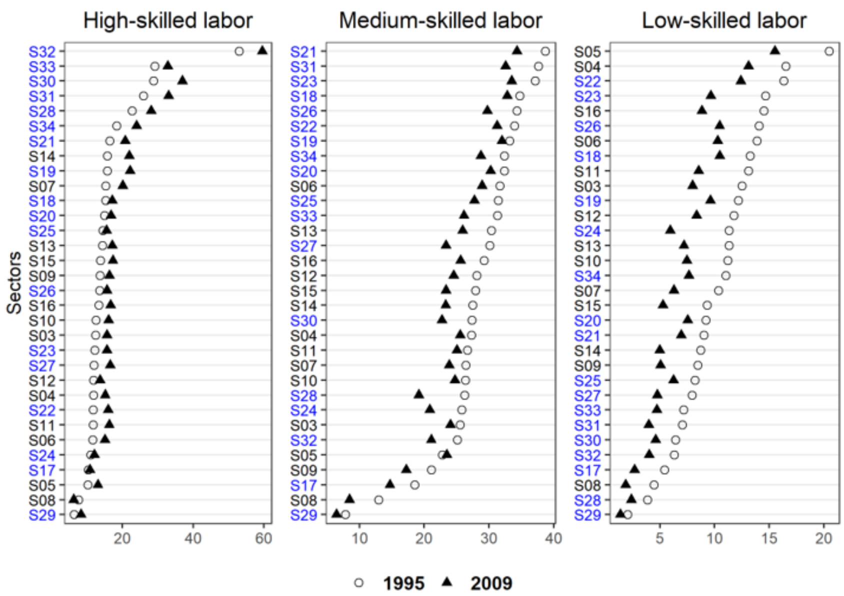
Note: Each dot in the figure represents a sector's cost share of domestic labor in the final output. The cost share in 1995 is put on the horizontal axis, and 2009 on the vertical axis, together with a 45-degree line.

Although Figures 5.1 and 5.2 show the overall trends in each skill group, they do not provide information on the labor costs in a specific sector. This chapter also estimates the average cost shares of 32 sectors in 1995 and 2009, which are weighted by each sector's final good outputs. Figure 5.3 shows the cost shares of domestic high-skilled, medium-skilled, and low-skilled labor at the sectoral level in advanced countries. The results show that the service sectors tend to have larger cost shares of domestic high-skilled and medium-skilled labor, while having smaller cost shares of low-skilled labor. For the manufacturing sectors, the cost share of domestic high-skilled labor in the "electrical and optical equipment" sector is relatively large.

The cost shares of domestic low-skilled labor in the “textiles and textile products” and “leather and footwear” sectors are relatively small. The cost shares of high-skilled labor in most sectors rose during the period 1995–2009, except for the “coke, refined petroleum, and nuclear fuel” sector. Conversely, the cost shares of medium-skilled and low-skilled labor experienced downward trends for all sectors in the sample period.

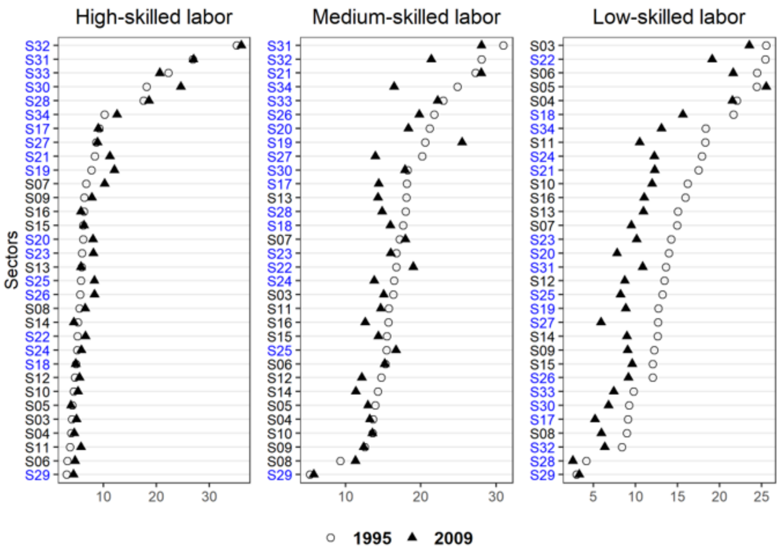
Figure 5.4 shows the cost shares of domestic high-skilled, medium-skilled, and low-skilled labor at the sectoral level in developing countries in 1995 and 2009. The results show that more service sectors have larger cost shares of domestic high-skilled and medium-skilled labor and have smaller cost shares of low-skilled labor. For the manufacturing sectors, the cost share of domestic high-skilled labor in the “pulp, paper, printing, and publishing” sector is relatively large. The cost share of domestic low-skilled labor in the “food, beverages, and tobacco” sector is relatively large. Similar to the advanced countries, the results show that the cost shares of domestic high-skilled labor in most sectors of developing countries increased from 1995 to 2009. Conversely, the change in domestic low-skilled labor of developing countries experienced downward trends for most sectors from 1995 to 2009, except for two sectors: the “leather and footwear” and “real estate activities” sectors. The cost share of domestic medium-skilled labor in developing countries also experienced a downward trend for most sectors, except for three service sectors.

Figure 5.3 The cost shares of domestic labor at the sectoral level for advanced countries



Notes: The horizontal axis is the cost share of labor. The vertical axis is sectors, which are sorted in descending order of the cost share in 1995. Manufacturing sectors are in black, while service sectors are in blue.

Figure 5.4 The cost shares of domestic labor at sectoral level for developing countries



Notes: The horizontal axis is the cost share of labor. The vertical axis is sectors, which are sorted in descending order of the cost share in 1995. Manufacturing sectors are in black, while service sectors are in blue.

Figures 5.5 and 5.6 plot the cost shares of domestic labor in the manufacturing and service sectors, respectively, in 1995 and in 2009 at the country level. The country-level calculation uses the final good outputs as weights in the same manner as the sector-level calculation. The 40 countries are divided into two groups: 29 advanced economies and 11 developing economies.[24]

As shown in Figure 5.5, the cost shares of domestic high-skilled workers showed upward trends during the period 1995–2009, except for Mexico, which experienced a significant decrease. Countries such as the UK, Luxembourg, and Ireland had large magnitude increase in this period. Conversely, the cost shares of domestic low-skilled workers in most countries showed downward trends during the same period, except for Turkey, Estonia, and Denmark. However, the trends for the cost shares of domestic medium-skilled workers are unclear. Countries with smaller cost shares of domestic medium-skilled labor tend to exhibit slight upward trends, while countries with larger cost shares of domestic medium-skilled labor exhibit downward trends. In particular, Poland and Hungary show substantial decreases, whereas Italy and Cyprus show dramatic increases. Countries with larger cost shares of domestic high-skilled workers are concentrated in advanced countries, such as Korea, the USA, Germany, and Japan. On the other side of the spectrum, developing countries such as China, Turkey, and Bulgaria

[24] The 11 developing countries are classified according to the International Monetary Fund's World Economic Outlook Database, including Bulgaria, Brazil, China, Hungary, Indonesia, India, Mexico, Poland, Romania, Russia, and Turkey.

have smaller shares of domestic high-skilled workers. As for domestic medium-skilled and low-skilled workers, the distribution across advanced and developing countries is ambiguous.

Figure 5.6 shows the cost shares of domestic labor in the service sectors. The cost shares of domestic high-skilled workers showed upward trends during the period 1995–2009, except for Mexico, which experienced a significant decrease. Countries such as the UK, Indonesia, and Ireland had large magnitude of increase in this period. Conversely, the cost shares of domestic low-skilled workers showed downward trends during the same period. However, the shares of countries such as Turkey and Estonia increase. The trend for the cost shares of domestic medium-skilled workers is ambiguous. Countries with larger cost shares of domestic medium-skilled labor exhibit downward trends, while countries with smaller cost shares of domestic medium-skilled labor exhibit slight upward trends. In particular, Poland and Hungary showed substantial decreases, whereas Italy and Greece showed dramatic increases in the sample period. Similar to the results in manufacturing sectors, countries with larger cost shares of domestic high-skilled workers in service sectors are concentrated in advanced countries, such as Korea, Cyprus, and Estonia. On the other side of the spectrum, developing countries such as China, Indonesia, and Turkey have smaller shares of domestic high-skilled workers in service sectors. As for domestic medium-skilled and low-skilled workers, the distribution across advanced and developing countries is mixed. Overall, the patterns of change in service sectors across the three skill types of labor have similar features with those in manufacturing sectors.

Figure 5.5 The cost shares of domestic labor in manufacturing at the country level

Notes: The horizontal axis is the cost share of labor. The vertical axis is countries, which are sorted in descending order of the cost share in 1995. Advanced countries are in black, while developing countries are in blue.

Figure 5.6 The cost shares of domestic labor in services at the country level

Notes: The horizontal axis is the cost share of labor. The vertical axis is countries, which are sorted in descending order of the cost share in 1995. Advanced countries are in black, while developing countries are in blue.

In summary, the empirical results in this subsection show that the cost share of domestic high-skilled labor in most sectors increased during the period 1995–2009, while the cost share of domestic low-skilled labor in most sectors decreased in the same period. However, the change in the cost share of domestic medium-skilled labor is ambiguous. The results also show that service sectors tend to have larger cost shares of domestic high-skilled and medium-skilled labor, while having a smaller cost share of domestic low-skilled labor. Compared with the country-level results, we find that more advanced countries have larger cost shares of domestic high-skilled labor, while more developing countries have small shares. The distribution of the cost shares of domestic medium-skilled and low-skilled workers across advanced and developing countries is ambiguous. In addition, the declining cost shares of domestic medium-skilled labor tends to concentrate in the countries with larger cost shares of domestic medium-skilled labor, while countries with smaller cost shares of medium-skilled labor have in increase in the cost shares of domestic medium-skilled labor.

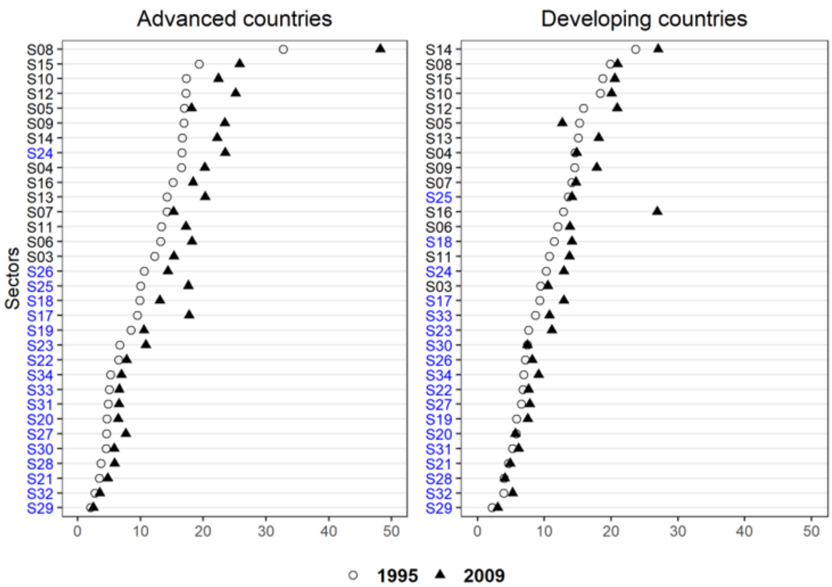
5.4.2 Foreign Value-Added Share

This subsection presents the results for the FV share in production, which is derived from equation (5.11). Figure 5.7 shows the average FV shares of 32 sectors in 1995 and in 2009. The results for advanced countries are illustrated in the left panel, while the results for developing countries are illustrated in the right panel. It is clear that most manufacturing sectors lie above service sectors, which implies that manufacturing sectors tend to have higher FV shares. In particular, sectors in advanced countries, such as “coke, refined petroleum, and nuclear fuel” and “transport equipment,” have higher FV shares. On the other hand, sectors in developing countries, such as “electronic and optical equipment” and “coke, refined petroleum, and nuclear fuel,” have higher FV shares. This result is consistent with the fact that production fragmentation is more prevalent in manufacturing sectors, so the production processes of manufacturing tend to be located in multiple locations around the world, relying on imported intermediate inputs for production. Moreover, the increase in the FV share is larger in advanced countries than in developing countries. This result corresponds to the fact that many multinational firms in advanced countries tend to offshore their production processes. As a result, an increased amount of imported intermediate inputs are needed for domestic production.

Figure 5.8 shows the average FV shares at the country-level in manufacturing and service sectors. The result for manufacturing sectors is illustrated in the left panel, while the result for service sectors is in the right panel. For manufacturing sectors, higher FV shares are more likely to be concentrated in advanced countries, such as Ireland, Slovak Republic, and Czech Republic. For service sectors, the FV share of Luxembourg is higher and increases substantially.

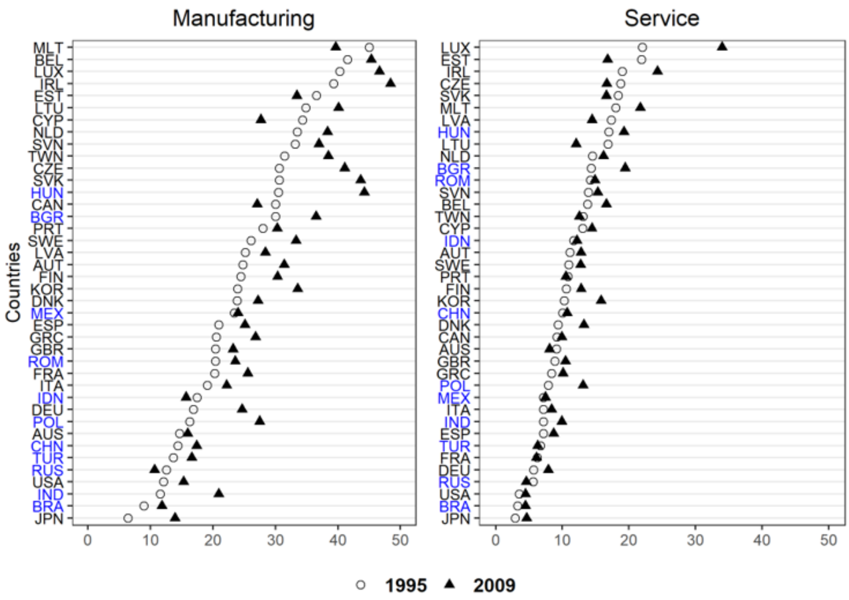
The territories of these countries are relatively small, so they are more likely to depend on imported intermediate contents in production. In addition, EU countries such as Luxembourg, Belgium, and Spain tend to have higher FV shares because of the high level of trade liberalization within the region. As a result, these countries also exhibit dramatic increases in FV share. Conversely, some advanced economies such as Japan and the USA have lower levels of FV shares. This result suggests that these countries tend to rely more on domestically produced inputs in production. Moreover, Brazil and Russia show lower FV shares because they rely on the exports of primary goods.

Figure 5.7 FV shares at the sectoral level



Notes: The horizontal axis is the cost share of labor. The vertical axis is countries, which are sorted in descending order of the cost share in 1995. Advanced countries are in black, while developing countries are in blue.

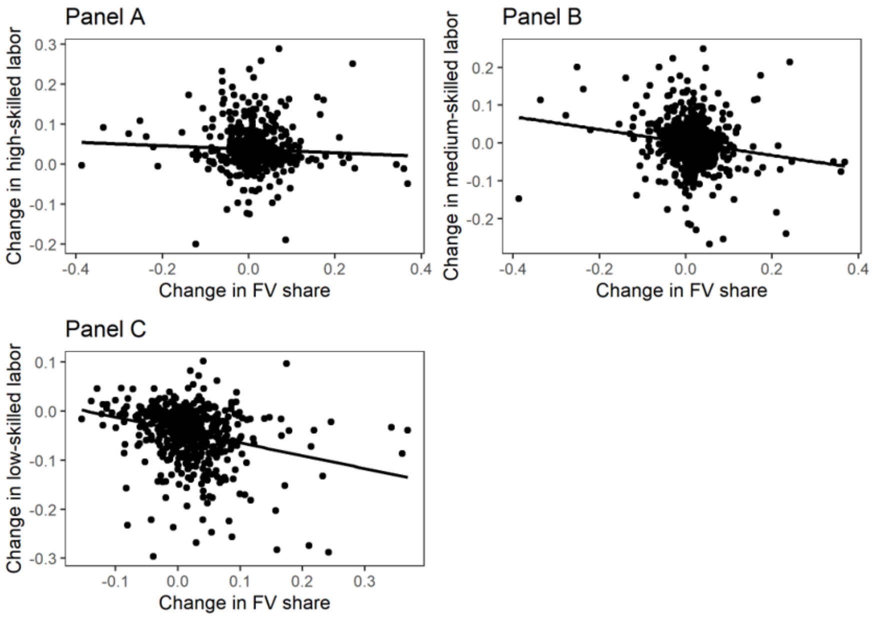
Figure 5.8 FV shares at the country level



Notes: The horizontal axis is the cost share of labor. The vertical axis is countries, which are sorted in descending order of the cost share in 1995. Advanced countries are in black, while developing countries are in blue.

A primary interest of this chapter lies in the correlation between the FV share and the cost share of domestic labor inputs. Figure 5.9 consists of three panels, which plot the changes in the cost shares of domestic high-skilled, medium-skilled, and low-skilled labor, against the changes in FV shares from 1995 to 2009. Each dot corresponds to a certain sector-country pair in the sample, which covers 32 sectors in 40 countries. These three panels provide a glimpse of the correlation between the FV share and the cost shares of different types of labor. In Panel A, the cost share of domestic high-skilled labor shows a slight downward trend as the FV share rises. However, the cost shares of domestic medium-skilled and low-skilled labor fall significantly as the FV share increases. These results imply that the impact of imported inputs on the demand for domestic high-skilled labor is relatively small. On the other hand, domestic medium-skilled and low-skilled labor are more likely to be threatened when they are exposed to imported inputs.

Figure 5.9 The relative changes in FV share and cost share of different labor inputs



Notes: The x-axes in the three panels are changes in FV share from 1995 to 2009. The y-axes in panel A, panel B and panel C are changes in the cost shares of high-skilled, medium-skilled, and low-skilled labor from 1995 to 2009, respectively. A linear regression line is added in each panel to reflect the correlation between change in the FV share and change in the cost share of labor inputs.

This subsection shows that compared with the service sectors, the manufacturing sectors in advanced and developing countries have larger FV shares. Finally, the negative correlation between imported inputs and the demand for medium-skilled and low-skilled labor is more noticeable than domestic high-skilled labor. To examine this relation more rigorously, we proceed to an econometrics analysis in the next subsection.

5.4.3 Baseline Regression Results

The regression analysis in this subsection draws on the data from WIOD. Two primary sectors of “agriculture, hunting, forestry and fishing” and “mining and quarrying” are excluded because the main interests of this chapter focus on the manufacturing and service sectors. Furthermore, we drop five service sectors containing a large number of missing data from the sample. Because the variable of the capital stock has many missing and negative values in 2008 and 2009, we remove the data for these two years. Thus, the regression is based on an unbalanced panel dataset during the period 1995–2007. Independent variables include the wages of three types of labor (w), output (X), capital stock (K), foreign value-added (FV) share, the narrow measure of outsourcing (IIMN), and a broad measure of outsourcing (IIMB). Table 5.1 shows the statistics summary of the variables in the regression analysis, which are reported in terms of average log change during the period 1995–2007. First, the average changes in the cost shares of domestic labor inputs range from -0.003 to 0.002. The cost share of domestic high-skilled labor increases, on average. On the other hand, the cost shares of domestic medium-skilled and low-skilled labor decrease. Second, the average change in wages, which is the ratio of domestic labor income to the working hours of domestic labor, is also reported. The result shows that the wages of all three types of labor exhibit upward trends. Third, the working hours of domestic labor decline. Particularly, the decrease in low-skilled labor is larger than that in high-skilled and medium-skilled labor. Fourth, the changes in the three indicators of imported intermediate inputs (FV share, IIMB, and IIMN) show slight upward trends, which implies that the increased reliance of production on offshoring or foreign intermediate inputs. Finally, the outputs and capital stock increased during the sample period.

Table 5.1 Statistics summary of variables

	Mean	Standard deviation	Minimum	Maximum
Shares of domestic labor				
ΔS_h	0.002	0.011	–0.146	0.126
ΔS_m	–0.001	0.017	–0.332	0.189
ΔS_l	–0.003	0.016	–0.468	0.216
Hourly wages of domestic labor				
$\Delta \ln (w_h)$	0.076	0.167	–1.587	2.525
$\Delta \ln (w_m)$	0.076	0.165	–1.605	2.497
$\Delta \ln (w_l)$	0.078	0.179	–1.622	2.487
Working hours of domestic labor				
$\Delta \ln (\Gamma_h)$	–0.053	0.186	–2.825	1.749
$\Delta \ln (\Gamma_m)$	–0.077	0.170	–2.752	1.693
$\Delta \ln (\Gamma_l)$	–0.112	0.172	–2.580	1.635
Indicators of imported content				
ΔFV share	0.002	0.025	–0.609	0.484
ΔIIMN	0.000	0.014	–0.286	0.248
ΔIIMB	0.002	0.026	–0.659	0.625
Output and capital stock				
Δln (X)	0.065	0.163	–2.398	2.803
Δln (K)	0.086	0.378	–5.792	4.539

Notes: The notation Δ denotes the difference between two periods. Subscripts *h, m,* and *l* denote high-skilled, medium-skilled, and low-skilled labor, respectively.

Tables 5.2–5.4 show the baseline results for the regression framework based on equation (5.5). The dependent variables are the domestic labor demand for the three types of labor inputs, which are each measured by the respective cost shares of domestic high-skilled, medium-skilled, and low-skilled labor in final outputs. Furthermore, the regression framework uses three indicators for the imported inputs in production, including the FV share, IIMN, and IIMB. Th control variables include the hourly wages of domestic labor inputs, the outputs, and the capital stock of a sector.[25] In the first three columns, the results are estimated by taking year-by-year differences over the period 1995–2007. One of the potential problems in first differencing panel data is that it reduces the variation in the explanatory variables, probably resulting in estimation bias. To address this shortcoming, the regression is also implemented using a longer time difference between 1995 and 2007. These results are reported in the last three columns.

The results suggest that the effects of wages on the cost shares of domestic labor inputs are ambiguous. The own-wage coefficients are positive and significant, while the cross-wage coefficients are negative. For example, Table 5.2 shows that the cost share of domestic high-skilled labor is positively affected by the change in the wages of domestic high-skilled labor, while it is negatively affected by the changes in the wages of domestic medium-skilled and low-skilled labor. Tables 5.3 and 5.4 also show that the same results can be observed in medium-skilled and low-skilled labor. Because the primary interest of this chapter is the effects of imported inputs on the cost share of domestic labor, the explanation about the coefficient on wages will be omitted hereafter.

Table 5.2 shows the results in the case that the cost share of domestic high-skilled labor is the dependent variable. The coefficients on FV share, IIMB, and IIMN are negative and significant across different specifications. This result suggests that imported inputs in production have an adverse effect on the demand for domestic high-skilled labor. It should be noted that there are variations across the coefficients on FV share, IIMB, and IIMN. The IIMB and IIMN, which measure the direct imports of intermediate goods, have larger impacts on labor demand than the FV share. In addition, when using long-term differences, the coefficients on the three indicators are still negative and significant. Similarly, the coefficients on IIMB and IIMN are larger than those on the FV share. The output and capital stock have significant and negative effects on the cost share of domestic high-skilled labor.

[25] The hourly wage of a sector is measured by the ratio of domestic labor income to the working hours of domestic labor. The results for domestic labor income and working hours of domestic labor are calculated based on the input–output model. Data on capital stock and output are directly obtained from the WIOD.

Table 5.2 The impact of imported inputs on the cost share of domestic high-skilled labor

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ln(w_h)$	0.056***	0.056***	0.056***	0.063***	0.061***	0.062***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.010)	(0.010)
$\Delta\ln(w_m)$	-0.029***	-0.029***	-0.029***	-0.003	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.014)	(0.014)	(0.014)
$\Delta\ln(w_l)$	-0.019***	-0.019***	-0.019***	-0.015	-0.015	-0.015
	(0.001)	(0.001)	(0.001)	(0.010)	(0.010)	(0.010)
Δln (X)	-0.010***	-0.010***	-0.009***	-0.015***	-0.016***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Δln (K)	-0.002***	-0.002***	-0.002***	0.002	0.002	0.002
	(0.0003)	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.001)
Δ FV share	-0.067***			-0.096***		
	(0.004)			(0.016)		
ΔIIMN		-0.081***			-0.102***	
		(0.006)			(0.021)	
ΔIIMB			-0.074***			-0.102***
			(0.004)			(0.015)
Constant	0.003***	0.003***	0.002***			
	(0.001)	(0.001)	(0.001)			
Observations	12,865	12,865	12,865	1,071	1,071	1,071
R^2	0.187	0.192	0.183	0.169	0.159	0.177

Notes: The first three columns are estimated by taking year-by-year differences and using pooled OLS over the period 1995–2007. And sector, country, and time year dummies are added in the specification. The last three columns use a long-period difference between 1995 and 2007 based on SUR, including sector and country dummies in the specification. Dependent variable is the cost share of domestic high-skilled labor. Independent variables include the wages of three types of labor (w), output (X), capital stock (K), foreign value-added (FV) share, IIMN, and IIMB. Standard errors are reported in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 5.3 presents the results in the case that the cost share of domestic medium-skilled labor is the dependent variable. The results, which are similar to those in Table 5.2, show that imported inputs have negative effects on the cost shares of domestic medium-skilled labor. In particular, the magnitude of these negative impacts on medium-skilled labor is much larger than those on high-skilled labor. This finding is consistent with Foster-McGregor, Stehrer and de Vries (2013), who show that domestic medium-skilled workers suffer the most from international sourcing. Moreover, the coefficients on IIMB and IIMN are larger than those on the FV share in absolute value. This result may suggest that direct imports of intermediate goods have larger impacts on the domestic labor demand than the FV share. Moreover, in the case of using long-term differences, the coefficients on the three indicators are still negative and significant. Similarly, the coefficients on IIMB and IIMN are larger than that on the FV share. The output and capital stock have significant and negative effects on the cost share of domestic medium-skilled labor.

Table 5.3 The impact of imported inputs on the cost share of domestic medium-skilled labor

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ln(w_h)$	-0.035***	-0.035***	-0.035***	-0.053***	-0.056***	-0.055***
	(0.003)	(0.003)	(0.003)	(0.014)	(0.014)	(0.013)
$\Delta\ln(w_m)$	0.076***	0.076***	0.076***	0.110***	0.112***	0.110***
	(0.003)	(0.003)	(0.003)	(0.019)	(0.019)	(0.019)
$\Delta\ln(w_l)$	-0.018***	-0.018***	-0.019***	0.016	0.015	0.016
	(0.002)	(0.001)	(0.002)	(0.014)	(0.014)	(0.014)
Δln (X)	-0.017***	-0.014***	-0.017***	-0.029***	-0.029***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Δln (K)	-0.004***	-0.004***	-0.004***	0.007***	0.007***	0.007***
	(0.0004)	(0.0004)	(0.0004)	(0.002)	(0.002)	(0.002)
Δ FV share	-0.176***			-0.182***		
	(0.007)			(0.022)		
ΔIIMN		-0.203***			-0.217***	
		(0.009)			(0.029)	
ΔIIMB			-0.195***			-0.206***
			(0.006)			(0.020)
Constant	0.002***	0.002***	0.002**			
	(0.001)	(0.001)	(0.001)			
Observations	12,865	12,865	12,865	1,071	1,071	1,071
R^2	0.173	0.158	0.188	0.257	0.248	0.280

Notes: The first three columns are estimated by taking year-by-year differences and using pooled OLS over the period 1995–2007. And sector, country, and time year dummies are added in the specification. The last three columns use a long-period difference between 1995 and 2007 based on SUR, including sector and country dummies in the specification. Dependent variable is the cost share of domestic medium-skilled labor. Independent variables include the wages of three types of labor (w), output (X), capital stock (K), foreign value-added (FV) share, IIMN, and IIMB. Standard errors are reported in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 5.4 shows the results in the case that the cost share of domestic low-skilled labor is the dependent variable. We confirm a strongly negative correlation between the cost share of domestic low-skilled labor and imported inputs. In the first three columns, we find that the FV share has a larger impact on the cost share of domestic low-skilled labor than the direct imports of intermediate goods do. Conversely, the results in the last three columns show that the direct imports of intermediate goods have larger impacts on the cost share of domestic low-skilled labor than the FV share does. Thus, the magnitudes of the impacts of the FV share and the direct imports of intermediate goods are ambiguous. The output and capital stock have significant and negative effects on the cost share of domestic low-skilled labor.

Table 5.4 The impact of imported inputs on the cost share of domestic low-skilled labor

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ln(w_h)$	-0.013***	-0.013***	-0.013***	-0.0003	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.012)	(0.013)	(0.012)
$\Delta\ln(w_m)$	-0.026***	-0.026***	-0.026***	-0.002	-0.001	-0.002
	(0.003)	(0.003)	(0.003)	(0.018)	(0.018)	(0.018)
$\Delta\ln(w_l)$	0.059***	0.058***	0.059***	0.058***	0.058***	0.058***
	(0.001)	(0.001)	(0.001)	(0.013)	(0.013)	(0.013)
Δln (X)	-0.007***	-0.006***	-0.007***	-0.015***	-0.016***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Δln (K)	-0.004***	-0.004***	-0.004***	0.002	0.002	0.002
	(0.0004)	(0.0004)	(0.0004)	(0.002)	(0.002)	(0.002)
Δ FV share	-0.131***			-0.096***		
	(0.006)			(0.020)		
ΔIIMN		-0.086***			-0.105***	
		(0.009)			(0.027)	
ΔIIMB			-0.120***			-0.109***
			(0.006)			(0.019)
Constant	-0.007***	-0.007***	-0.007***			
	(0.001)	(0.001)	(0.001)			
Observations	12,865	12,865	12,865	1,071	1,071	1,071
R^2	0.258	0.238	0.256	0.130	0.124	0.139

Notes: The first three columns are estimated by taking year-by-year differences and using pooled OLS over the period 1995–2007. And sector, country, and time year dummies are added in the specification. The last three columns use a long-period difference between 1995 and 2007 based on SUR, including sector and country dummies in the specification. Dependent variable is the cost share of domestic low-skilled labor. Independent variables include the wages of three types of labor (w), output (X), capital stock (K), foreign value-added (FV) share, IIMN, and IIMB. Standard errors are reported in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

In summary, this subsection has examined the relationship between imported intermediate inputs and the cost shares of domestic labor of different skill levels. We confirm that the imported inputs in production have a significant negative impact on domestic labor demand, irrespective of skill levels. In other words, the cost shares of high-skilled, medium-skilled, and low-skilled labor in production tend to decline due to imported inputs. In particular, the reduction in the demand for domestic medium-skilled labor is the most substantial. In addition, the direct imports of intermediate goods tend to exaggerate the role of international sourcing by declining the cost shares of domestic high-skilled and medium-skilled labor. It is natural to speculate that the domestic labor demand of a sector would be impacted more by the direct imports of intermediate inputs from the same sector. The measures of IIMB and IIMN are based on the assumption that no domestic content is embedded in imported intermediate goods. This assumption is weak because it does not consider the fact that the production of intermediate goods also requires multi-stage production processes that are located at home and abroad. Thus, the role of the direct imports of intermediate inputs could be exaggerated if there is a proportion of domestic content indirectly embedded in the imported intermediate goods. The domestic content embedded in imported intermediate inputs may be associated with an increasing demand for domestic labor. Thus, the effects of the FV share and direct imports of intermediate inputs are likely to be different. Moreover, the magnitudes of the impacts of the FV share and direct imports of intermediate goods are ambiguous in low-skilled labor. A possible explanation for this is that the domestic content embedded in imported intermediate goods and services requires more high-skilled and medium-skilled labor, and only a small proportion of low-skilled labor. Thus, the effect of domestic content embedded in imported intermediate inputs could be much smaller than that of direct imports.

5.4.4 Results According to Different Sourcing Origins

This subsection examines the effects of imported inputs on the cost shares of domestic labor inputs by taking into consideration different sourcing countries. In the preceding subsections, the FV is calculated regardless of origins, that is, tracing the overall FV from all the upstream countries and sectors. However, the FV originating from different countries tends to exert different effects on the labor demand. On the one hand, offshoring or foreign outsourcing to developing countries has been blamed for job and income losses in many advanced countries. Therefore, it is worthwhile to examine the effects of imported intermediate inputs on the labor demand by distinguishing among different sourcing origins.

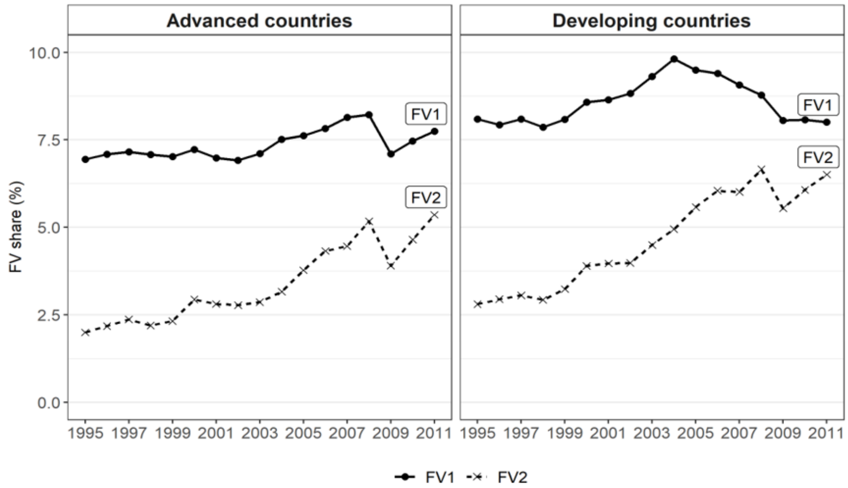
As noted earlier, because the WIOD only contains a small number of developing countries, it provides limited information about the imported content from developing countries. To overcome the difficulty, this subsection merges the WIOD with the OECD ICIO tables, which cover a collection of data across 64 countries. In particular, 34 advanced and 30 developing countries are included in the ICIO database, which covers a wider range of countries than the WIOD. Data on quantities and value of labor and capital inputs are derived from the WIOD, while the input–output tables are derived from the ICIO database. This merged dataset can identify the imported contents from different sourcing origins more precisely.

Figure 5.10 plots the average FV share in the final output, which is divided into two destination country groups: advanced countries (left panel) and developing countries (right panel). The average FV share of each group is measured by using the final outputs of each sector as weights. For each destination country group, the FV is split according to sourcing origins. In each panel, the origin of the FV is divided into advanced countries (FV1) and developing countries (FV2). Specifically, FV1 represents the FV share originating from advanced countries, while FV2 represents the FV share originating from developing countries.

In both advanced and developing countries, FV1 is higher than FV2. In the left panel, the FV1 of advanced countries ranges from 6.9 to 8.2 percent, while the FV2 of advanced countries ranges from 2 to 5.4 percent during the period 1995–2011. In the right panel, the FV1 of developing countries ranges from 7.9 to 9.8 percent, while the FV2 of developing countries ranges from 2.8 to 6.7 percent during the same period. Even though the importance of developing countries in the GVCs has risen dramatically during recent decades, advanced countries still have comparative advantages over developing countries in many high value-added sectors. The production of both advanced and developing countries relies more on the FV imported from advanced countries.

Furthermore, the gap between FV1 and FV2 has decreased over time, especially for developing countries. In the left panel, the FV1 of advanced countries showed an overall upward trend from 1995 to 2011, rising by roughly 0.8 percentage points from 6.9 percent in 1995 to 7.7 percent in 2011. Similarly, the FV2 of advanced countries also increased during the same period, rising by 3.4 percentage points from 2 percent in 1995 to 5.4 percent in 2011. In the right panel, the change in FV1 of developing countries exhibits two phases. The FV1 rose during the period 1995–2004, reaching a peak of 9.8 percent in 2004. However, the FV1 took on a downward trend during the period 2005–2011, falling from 9.5 percent in 2005 to 8 percent in 2011. On the other hand, the FV2 of developing countries increased by 3.7 percentage points from 2.8 percent in 1995 to 6.5 percent in 2011. Given that advanced countries are superior in producing high-value intermediate inputs, they tend to lie in the upstream position of GVCs, supplying intermediate inputs to other countries. Since the mid-2000s, the souring origins of developing countries shifted from advanced countries to developing countries. Notably, the role of developing countries in producing intermediate inputs for other countries in GVCs has increased. This result can be explained by the trend that a large number of multinational firms in advanced countries began to shift their labor-intensive manufacturing processes toward developing countries. It is not surprising that advanced countries' production increasingly depends on foreign content imported from developing countries. Some developing countries have gained the ability to provide a wide range of intermediate inputs for other countries, which has contributed to a phenomenal increase in the FV sourced from developing countries. This trend has become more marked since China joined the WTO in 2001 and began to supply more intermediate inputs in GVCs.

Figure 5.10 The changes in average FV shares



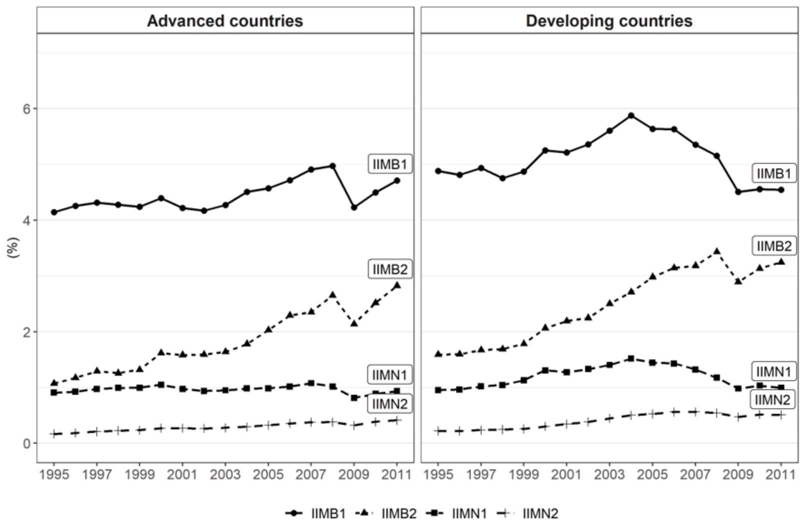
Notes: The left diagram plots the result of FV share when the destination country is the group of advanced countries, while the right diagram plots the result when the destination country is the group of developing countries. FV1 and FV2 denote the shares of foreign value–added sourced from advanced and developing countries, respectively.

Alternatively, the imported contents in production are measured by the share of directly imported intermediate goods and services in final outputs following Feenstra and Hanson (1999), including the broad measure of foreign outsourcing (IIMB) and the narrow measure of foreign outsourcing (IIMN). Figure 5.11 shows the changes in IIMB and IIMN during the period 1995–2011, by different destination country groups: advanced countries (left panel) and developing countries (right panel). The average IIMB and IIMN of each group are measured by using the final outputs of each sector as weights. For each destination country group, the IIMB and IIMN are divided according to sourcing origins. For the broad measure of foreign outsourcing, IIMB1 and IIMB2 refer to the share of directly imported intermediate inputs from advanced and developing countries, respectively. Similarly, for the narrow measure of foreign outsourcing, IIMN1 and IIMN2 refer to the share of directly imported intermediate inputs from advanced and developing countries, respectively.

Similar to the results of FV share, both advanced and developing countries tended to import a larger share of direct intermediate inputs from advanced countries during the period 1995–2011. In the left panel, the IIMB1 of advanced countries ranges from 4.1 to 5 percent, while the IIMB2 of advanced countries ranges from 1.1 to 2.8 percent. In the right panel, the IIMB1 of developing countries ranges from 4.5 to 5.9 percent, while the IIMB2 of developing countries ranges from 1.6 to 3.4 percent.

The changes in IIMB and IIMN during the period 1995–2011 are comparable to those in FV shares. In the left panel, the IIMB1 of advanced countries showed an overall upward trend from 1995 to 2011, rising by roughly 0.6 percentage points from 4.1 percent in 1995 to 4.7 percent in 2011. And the IIMB2 of advanced countries increased by roughly 1.7 percentage points from 1.1 percent in 1995 to 2.8 percent in 2011. Furthermore, the changes in IIMN1 and IIMN2 of advanced countries were stable in the sample period, showing slight upward trends. In the right panel, IIMB1 of developing countries rose by roughly one percentage point from 1995 to 2004, while it fell by 1.4 percentage points during the period 2004–2011. On the other hand, IIMB2 of developing countries showed an overall upward trend, increasing by approximately 1.6 percentage points. Furthermore, IIMN1 and IIMN2 of developing countries leveled off around 1.2 and 0.4 percent, respectively, during the sample period.

Figure 5.11 The changes in average IIMB and IIMN



Notes: The left diagram plots the result of IIMB and IIMN when the destination country is the group of advanced countries, while the right diagram plot the result when the destination country is the group of developing countries. IIMN1 and IIMN2 denote the shares of direct intermediate goods imported from advanced and developing countries, respectively, based on the narrow measure outsourcing. IIMB 1 and IIMB2 denote the shares of direct intermediate goods imported from advanced and developing countries, respectively, based on the broad measure of outsourcing.

This subsection shows the changes in the three indicators of FV share, IIMB, and IIMN, which are decomposed by different destination country groups and sourcing origins. By examining the indicators of FV share, IIMB, and IIMN, we confirm that the production in both advanced and developing countries tends to rely more on foreign content from advanced countries. In particular, the foreign content in the outputs of developing countries is larger than those of advanced countries. In addition, the above results reveal that the proportion of imported content that originate from developing countries has increased substantially. Notably, developing countries tend to shift their sourcing origins from advanced countries to developing countries. Finally, the increase in IIMB is larger than IIMN, which means that the development of international sourcing across different industries is more remarkable than international sourcing within the same industry. The next subsection will show how different sourcing origins affect the demand for domestic labor.

5.4.5 Regression Results by Different Sourcing Origins

This subsection examines the effect of imported inputs on the skilled structure of labor demand by taking into consideration the origins of imported inputs. Tables 5.5–5.7 present the results for when the dependent variables are the cost shares of domestic high-skilled, medium-skilled, and low-skilled labor. Furthermore, the dependent variables are divided into two groups: the labor cost shares of advanced and developing countries. The odd-numbered columns contain the results for when the dependent variables are the cost shares of labor factors of advanced countries, and the even-numbered columns contain the results for when the dependent variables are the cost shares of the labor factors of developing countries.

On the side of independent variables, the origin of FV share is decomposed into two components: the FV sourced from advanced countries (FV1) and the FV sourced from developing countries (FV2). In addition, the measures of the directly imported intermediate inputs in production are added in the specification. Because the measure for foreign outsourcing across different industries is more prevalent and similar to the estimation of FV shares, only the IIMB are included in the specification. The origin of the directly imported intermediate goods is divided into two components: the proportion sourced from advanced countries (IIMB1) and the proportion sourced from developing countries (IIMB2). In addition, both the OLS estimation, which is based on year-by-year differences, and the SUR estimation, which is based on long-term (12 years) differences during the period 1995–2007, are presented in the table.

Column (1) in Table 5.5 shows that the FV1 and FV2 have significant negative effects on the cost share of domestic high-skilled labor in advanced countries. For advanced countries, a percentage point increase in the FV1 and FV2 is associated with 0.016 and 0.038 percentage point declines, respectively, in the cost share of domestic high-skilled labor. These results suggest that the FV originating from developing countries accounted for a larger proportion of the declining domestic high-skilled labor in advanced countries over the sample period.

Furthermore, column (2) presents the results for when the dependent variable is the cost share of domestic high-skilled labor in developing countries, and the coefficients on both FV1 and FV2 are not statistically significant. The results, which are based on long-term differences between 1995 and 2007, in columns (3) and (4) indicate that the coefficients on both FV1 and FV2 are not statistically significant.

The results in column (5) show that IIMB1 and IIMB2 exert negative and significant effects on the cost share of high-skilled labor in advanced countries. Specifically, a percentage point increase in the IIMB1 and IIMB2 is associated with 0.017 and 0.03 percentage point declines, respectively, in the cost share of domestic high-skilled labor in advanced countries. This result implies that direct imports from developing countries account for a larger proportion of the declining domestic high-skilled labor in advanced countries. In column (6), IIMB1 and IIMB2 are negatively correlated with the cost share of domestic high-skilled labor in developing countries at the 10 percent significance level. A percentage point increase in the IIMB1 and IIMB2 is associated with 0.023 and 0.022 percentage point declines, respectively, in the cost share of domestic high-skilled labor in developing countries. Next, the results in columns (7) and (8) show SUR estimations for the long-term differences. Column (7) reveals that IIMB1 has a negative and significant effect on the cost share of high-skilled labor in advanced countries at the 10 percent significance level, and the cost share of domestic high-skilled labor in advanced countries decreases by 0.052 percentage points due to the change in IIMB1. On the other hand, the coefficient on IIMB2 is not statistically significant. In column (8), IIMB1 has a negative and significant effect on the cost share of domestic high-skilled labor in developing countries at the 10 percent significance level, and the cost share of domestic high-skilled labor in developing countries decreases by 0.118 percentage points due to the change in IIMB1. However, the coefficient on IIMB2 is not statistically significant.

Overall, the above results reveal that both FV1 and FV2 have significant negative effects on the cost share of domestic high-skilled labor in advanced countries based on the OLS estimation. In addition, we find that the coefficient on FV2 is larger than that on FV1, which implies that the imported intermediate inputs from developing countries account more for the falling demand for domestic high-skilled labor in advanced countries. The effects of FV1 and FV2 on domestic high-skilled labor in developing countries is not clear. However, using the indicator of IIMB, we find that the cost share of domestic high-skilled labor in developing countries is negatively impacted by the direct imports of intermediate inputs from both advanced and developing countries.

Table 5.5 The impact of imported inputs on the cost share of domestic high-skilled labor by sourcing origins

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔFV1	-0.016**	-0.015	-0.036	-0.067				
	(0.006)	(0.011)	(0.026)	(0.054)				
ΔFV2	-0.038***	-0.018	-0.033	0.083				
	(0.007)	(0.012)	(0.044)	(0.081)				
ΔIIMB1					-0.017***	-0.023*	-0.052*	-0.118*
					(0.006)	(0.013)	(0.027)	(0.063)
ΔIIMB2					-0.030***	-0.022*	-0.048	0.027
					(0.007)	(0.013)	(0.044)	(0.084)
Constant	0.002	-0.003*	0.028	-0.057	0.002	-0.003**	0.029**	-0.042
	(0.001)	(0.002)	(0.012)	(0.056)	(0.001)	(0.002)	(0.012)	(0.054)
Sample	Advanced countries	Developing countries	Advanced countries	Developing countries	Advanced countries	Developing countries	Advanced countries	Developing countries
	year-by-year	year-by-year	Long difference	Long difference	year-by-year	year-by-year	Long difference	Long difference
	OLS	OLS	SUR	SUR	OLS	OLS	SUR	SUR
Observations	8,421	3,234	697	267	8,421	3,234	697	267
R^2	0.191	0.291	0.406	0.517	0.190	0.291	0.409	0.520

Notes: Dependent variable is the cost share of domestic high-skilled labor. Pooled OLS specification includes sector, country, and time year dummies for the period of 1995–2007. And a long-period difference based on SUR includes sector and country dummies. The coefficients for wages, outputs, and capital stock are omitted. Standard errors are reported in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 5.6 presents the results for when the dependent variable is the cost share of domestic medium-skilled labor in final outputs. Column (1) shows that FV1 and FV2 are negatively associated with the cost share of domestic medium-skilled labor in advanced countries during the sample period. Specifically, a percentage point increase in the FV1 and FV2 leads to 0.024 and 0.033 percentage point declines, respectively, in the cost share of domestic medium-skilled labor in advanced countries. The results also imply that the FV originating from developing countries tends to have a larger impact on the demand for domestic medium-skilled labor in advanced countries. Column (2) reports the change in the cost share of domestic medium-skilled labor in developing countries due to FV1 and FV2. Similarly, the coefficients on FV1 and FV2 are negative and significant as a percentage point increase in the FV1 and FV2 is associated with 0.036 and 0.033 percentage point declines, respectively, in the cost share of domestic medium-skilled labor in developing countries. The coefficient on FV1 is slightly larger than that on FV2 in absolute value. Columns (3) and (4) present the SUR estimation based on long-term differences. However, the coefficients on FV1 and FV2 are not statistically significant.

The last four columns show the results for when the independent variables include IIMB1 and IIMB2. In column (5), a percentage point increase in IIMB1 and IIMB2 is associated with 0.027 and 0.033 percentage point declines, respectively, in the cost share of domestic medium-skilled labor in advanced countries. The coefficient on IIMB2 is larger than that on IIMB1 in absolute value in advanced countries, which implies that the cost share of domestic medium-skilled labor in advanced countries declines due largely to the imported inputs originating from developing countries. Column (6) reveals that IIMB1 and IIMB2 have negative and significant effects on the cost shares of domestic medium-skilled labor in developing countries. In other words, a percentage point increase in the IIMB1 and IIMB2 is associated with 0.053 and 0.029 percentage point declines, respectively, in the cost share of domestic medium-skilled labor in developing countries. The coefficient on IIMB1 is larger than that on IIMB2 in absolute value in developing countries, which suggests that the cost share of domestic medium-skilled labor in developing countries declines due largely to imported inputs originating from advanced countries. Columns (7) and (8) present the SUR estimation based on the long-term differences between 1995 and 2007. There is a negative and significant correlation between IIMB2 and the cost share of domestic medium-skilled labor in advanced countries. A percentage point increase in the IIMB2 is associated with a 0.062 percentage point decline in the cost share of domestic medium-skilled labor in advanced countries.

To summarize, the above results reveal that FV1 and FV2 exert significant negative effects on the cost share of domestic medium-skilled labor. In addition, we find that imported inputs from developing countries accounts for a larger proportion of the declined domestic medium-skilled labor demand in advanced countries, whereas the imported inputs from advanced countries contribute to a larger proportion of the decreased demand for domestic medium-skilled labor in developing countries. The results hold true when we use the indicators of FV share and IIMB in the regression framework. The result using the SUR estimation based on long-term differences shows that the IIMB originating from developing countries is negatively associated with the cost share of domestic medium-skilled labor in advanced countries.

Table 5.6 The impact of imported inputs on the cost share of domestic medium-skilled labor by sourcing origins

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔFV1	-0.024***	-0.036***	-0.037	0.088				
	(0.007)	(0.013)	(0.028)	(0.076)				
ΔFV2	-0.033***	-0.033***	-0.040	-0.011				
	(0.008)	(0.013)	(0.048)	(0.115)				
ΔIIMB1					-0.027***	-0.053***	-0.044	0.020
					(0.006)	(0.017)	(0.029)	(0.090)
ΔIIMB2					-0.033***	-0.029*	-0.062***	-0.116
					(0.008)	(0.017)	(0.048)	(0.119)
Constant	0.001	-0.002	0.001	-0.339***	0.001	-0.002	0.002	-0.328***
	(0.001)	(0.002)	(0.013)	(0.079)	(0.001)	(0.002)	(0.013)	(0.077)
Sample	Advanced countries	Developing countries	Advanced countries	Developing countries	Advanced countries	Developing countries	Advanced countries	Developing countries
	year-by-year	year-by-year	Long difference	Long difference	year-by-year	year-by-year	Long difference	Long difference
	OLS	OLS	SUR	SUR	OLS	OLS	SUR	SUR
Observations	8,421	3,234	697	267	8,421	3,234	697	267
R^2	0.258	0.238	0.558	0.665	0.258	0.238	0.559	0.664

Notes: Dependent variable is the cost share of domestic medium-skilled labor. Pooled OLS specification includes sector, country, and time year dummies for the period of 1995–2007. And a long-period difference based on SUR includes sector and country dummies. The coefficients for wages, outputs, and capital stock are omitted. Standard errors are reported in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 5.7 presents the results when the dependent variable is the cost share of domestic low-skilled labor in the final outputs. Column (1) shows that both FV1 and FV2 reduce the cost share of domestic low-skilled labor in advanced countries, and the magnitudes of their decreases are almost identical. Specifically, in advanced countries, a percentage point increase in the FV1 and FV2 is associated with 0.02 and 0.018 percentage point declines, respectively, in the cost share of domestic low-skilled labor. Column (2) reports the change in the cost share of domestic low-skilled labor in developing countries due to FV1 and FV2. The results reveal that FV1 and FV2 negatively impact the cost share of domestic low-skilled labor in developing countries. A percentage point increase in the FV1 and FV2 is associated with 0.104 and 0.069 percentage point declines, respectively, in the cost share of domestic low-skilled labor for developing countries. In particular, the coefficient on FV1 is larger than that for FV2 in absolute value, which suggests that the demand for domestic low-skilled labor in developing countries decreases more substantially due to FV from advanced countries. Furthermore, the SUR estimation results in column (3) show that FV1 and FV2 are negatively associated with the cost share of domestic low-skilled labor in advanced countries. And a percentage point increase in the FV1 and FV2 causes 0.085 and 0.105 percentage point declines, respectively, in the cost share of domestic low-skilled labor in advanced countries. The coefficient on FV2 is larger than that on FV1 in absolute value, which implies that the demand for domestic low-skilled labor in advanced countries decreases more substantially due to FV from developing countries based on long-term differences. In column (4), the coefficient on FV2 is not statistically significant, which suggests that the correlation between the cost share of domestic low-skilled labor in developing countries and the FV2 is not clear for a long period. However, the cost share of domestic low-skilled labor in developing countries increases due to the change in FV1. This result suggests that the cost share of domestic low-skilled labor in developing countries tends to benefit from the FV originating from advanced countries. A possible interpretation of this result is that most firms in developing countries participate in GVCs by specializing in labor-intensive tasks, most of which disproportionately require low-skilled labor. Multinational firms in advanced countries tend to relocate labor-intensive production processes to developing countries that require imported inputs such as capital, technology, and intermediate goods from advanced countries. Thus, the outputs of labor-intensive industries in developing countries could rise, which further increases the demand for low-skilled labor.

The last four columns show the results when IIMB1 and IIMB2 are included in the specification. In columns (5) and (6), a percentage point increase in the IIMB1 and IIMB2 is associated with 0.016 and 0.014 percentage point declines, respectively, in the cost share of domestic low-skilled labor in advanced countries. Moreover, a percentage point increase in the IIMB1 and IIMB2 is associated with 0.147 and 0.072 percentage point declines, respectively, in the cost share of domestic low-skilled labor in developing countries. These results suggest that both the IIMB1 and IIMB2 have significant negative effects on the cost share of domestic low-skilled labor, which are basically consistent with the results in columns (1) and (2). In addition, the results based on the long-term differences in columns (7) and (8) are close to those in columns (3) and (4). In other words, the cost share of domestic low-skilled labor in advanced countries decreases by 0.081 and 0.083 percentage points due to a one percentage point rise in IIMB1 and IIMB2, respectively. And the cost share of domestic low-skilled labor in developing countries increases by 0.173 percentage points due to a one percentage point rise in IIMB1, confirming that the direct imports from advanced countries exert a positive impact on the cost share of domestic low-skilled labor in developing countries. A distinctive feature here is that all the coefficients on the constant terms are negative and statistically significant, which means that, on average, the cost share of domestic low-skilled labor falls during the sample period. Specifically, the magnitude of the decrease is more pronounced in developing countries.

The above results show that the cost share of domestic low-skilled labor is negatively impacted by FV1 and FV2. Based on year-by-year difference estimation, we find that domestic low-skilled labor demand in advanced countries declines almost equally due to imported inputs from advanced and developing countries. Imported inputs from advanced countries account for a larger proportion of the declining domestic low-skilled labor demand in developing countries. Additionally, based on long-term differences estimation, we find that imported inputs from advanced and developing countries are associated with the declining domestic low-skilled labor demand in advanced countries. The imported inputs sourced from advanced countries lead to the increased demand for domestic low-skilled labor in developing countries.

Table 5.7 The impact of imported inputs on the cost share of domestic low-skilled labor by sourcing origins

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔFV1	-0.020***	-0.104***	-0.085***	0.188***				
	(0.006)	(0.021)	(0.023)	(0.060)				
ΔFV2	-0.018***	-0.069***	-0.105***	-0.058				
	(0.007)	(0.022)	(0.039)	(0.091)				
ΔIIMB1					-0.016***	-0.147***	-0.081***	0.173**
					(0.006)	(0.024)	(0.024)	(0.072)
ΔIIMB2					-0.014**	-0.072***	-0.083**	-0.063
					(0.007)	(0.024)	(0.039)	(0.095)
Constant	-0.006***	-0.022***	-0.061***	-0.484***	-0.006***	-0.023***	-0.061***	-0.488***
	(0.001)	(0.003)	(0.011)	(0.063)	(0.001)	(0.003)	(0.011)	(0.061)
Sample	Advanced countries	Developing countries	Advanced countries	Developing countries	Advanced countries	Developing countries	Advanced countries	Developing countries
	year-by-year	year-by-year	Long difference	Long difference	year-by-year	year-by-year	Long difference	Long difference
	OLS	OLS	SUR	SUR	OLS	OLS	SUR	SUR
Observations	8,421	3,234	697	267	8,421	3,234	697	267
R^2	0.312	0.240	0.667	0.531	0.312	0.244	0.665	0.525

Notes: Dependent variable is the cost share of domestic low-skilled labor. Pooled OLS specification includes sector, country, and time year dummies for the period of 1995–2007. And a long-period difference based on SUR includes sector and country dummies. The coefficients for wages, outputs, and capital stock are omitted. Standard errors are reported in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

5.5 Conclusion

Focusing on sector-level studies, this chapter has examined the impacts of the expanding GVCs on the cost shares of domestic labor inputs and has refined the empirical strategy of previous studies. Using international input–output tables allows us to measure the changes in the cost share of domestic labor due to participating in GVCs. In addition, compared with gross trade statistics, the analysis based on the input–output model can capture the linkages directly and indirectly embedded in production. In this chapter, we measure the cost share of domestic labor in final outputs to reflect the demand for domestic labor. In addition, the reliance of production on imported inputs is measured by FV share, which captures the foreign content directly and indirectly embedded in the production of final outputs. The empirical framework is derived from a short-run translog cost function to quantify the effect of imported inputs on the labor market.

Using international input–output tables from the WIOD, several characteristics of the skill structure of labor demand and foreign intermediate inputs can be found. First, the cost share of domestic high-skilled labor in most sectors increased during the period 1995–2009, while the cost share of domestic low-skilled labor in most sectors decreased in the same period. The change in the cost share of domestic medium-skilled labor is ambiguous. Second, the results also show that compared with manufacturing sectors, service sectors tend to have larger cost shares of domestic high-skilled and medium-skilled labor while having a smaller cost share of low-skilled labor. Third, advanced countries are more likely to have a larger cost share of domestic high-skilled labor, while developing countries tend to have a small cost share of domestic high-skilled labor. Fourth, the declining cost share of domestic medium-skilled labor tends to be the countries with larger cost shares of domestic medium-skilled labor, while countries with small cost shares of medium-skilled labor tend to increase the cost shares of domestic medium-skilled labor. Finally, compared with service sectors, manufacturing sectors in advanced and developing countries have larger FV shares.

Our regression analysis yields several interesting findings. First, the FV share reduces the cost shares of domestic labor across all skill levels. In particular, the demand for domestic medium-skilled labor decreases most significantly due to imported inputs. Second, this chapter has examined how the skill structure of the labor demand in advanced countries responds to imported inputs originating from advanced and developing countries. The results indicate that the demand for domestic high-skilled and medium-skilled labor in advanced countries is negatively impacted by the FV share sourced from developing countries in the case of year-by-year difference estimation. The FV share sourced from developing countries is negatively associated with the demand for domestic low-skilled labor in advanced countries in the case of both year-by-year and long-term differences estimation. Third, the regression results also show how the skill structure of the labor demand in developing countries responds to imported inputs originating from advanced and developing countries. The FV share sourced from advanced countries contributes more to the decreases in demand for medium-skilled labor in developing countries. However, a notable result shows that the FV share originating from advanced countries increases the demand for low-skilled labor in developing countries when the estimation is based on long-term differences estimation.

Furthermore, when compared with the FV share, this study also uses a traditional indicator to measure the direct imported intermediate inputs. The results based on this traditional indicator are generally close to those based on the FV share. However, these two indicators have slightly different magnitudes of influence on the labor demand. A potential explanation is that traditional indicators fail to account for the indirect linkage within GVCs. As GVCs become increasingly sophisticated, we need a reliable indicator in empirical studies to measure the dependence of production activities on GVCs. The FV share directly and indirectly captures the imported contents embedded in products that usually cross the international borders several times. For this reason, the use of the FV share is preferred to capture how a sector or country relies on imported inputs for production.

The analysis of this chapter has some limitations. First, the cost shares of domestic labor by skill levels can be estimated mainly for advanced countries because only a small sample of developing countries are covered in the WIOD. As developing countries become increasingly important in the GVCs, it is natural to speculate that an upgraded skill structure will be observed in many developing countries, particularly in East Asia. Examining the effects of GVC participation on the skill structure of labor demand in this region would provide insights into the economic growth in developing countries. Second, further investigation of how indirect linkages between countries affect the skill structure of labor demand is needed. For example, Wang, Wei and Zhu (2013) decompose the exports into value-added terms. Following their method, we can estimate the value-added created by domestic labor but re-imported back to the home country as imported intermediate goods. Third, this chapter has only examined the effects of international trade on the labor market without considering technological changes. The use of new technology is an important factor that affects the skill structure of labor demand. The "routinization hypothesis" introduced by Auto, Levy and Murnane (2003) shows that new information technology capital complements workers who are engaged in abstract tasks, substitutes for workers performing routine tasks, and has little effect on workers performing manual and service tasks. A large body of research has sought to examine how technological changes affect labor demand by using the routinization hypothesis (Goos, Manning and Salomons 2014; Michaels, Natraj and Reenen 2014; Reijnders, Timmer and Ye 2016). The next step of this study would use proxies for technology improvements such as ICT capital and research and development expenditure to empirically test the routinization hypothesis.

In addition, the recent research tends to focus on worker-level and occupation-level data to consider heterogeneity in worker ability. The impacts of international sourcing may arise through changes in the skilled structure of labor demand within industry. To address this issue, studies using a matched worker-firm database could examine various characteristics of worker. The link between offshoring and skill structure plays an important role for policy recommendations and needs to be analyzed comprehensively both at macro- and micro-levels.

Chapter 6 Conclusion

6.1 Conclusion Remarks

The rise of global value chains (GVCs) has dramatically reshaped production patterns and international trade, which creates the scope to derive new insights into trade theories and policy implications relevant to globalization. This thesis focuses on the following four questions relevant to GVCs and Chinese economy. First, do traditional trade statistics reflect the real picture of China's participation in GVCs? Second, why does the domestic value-added (DVA) of China's exports change? Third, how does the change in productivity affects the export performance of Chinese firms? Fourth, how does participation in GVCs affect the skill structure of labor demand?

This study is based on a crucial implication that gross trade statistics are not reliable to reflect a country's participation in GVCs. As production fragmentation becomes prevalent across many countries, an increasing discrepancy occurs between gross trade and value-added trade. Recent studies turn to evaluate value-added terms in exports. For example, the exports of a product can be decomposed into value-added that is created domestically and abroad. To answer the first two research questions, Chapter 3 measures the DVA of China's exports during the period 2000–2014 using the World Input–Output Database. The results confirm that the gap between the DVA and gross exports varies across industries. In addition, we use a structural decomposition analysis (SDA) to examine nine determinants that affect the change in DVA of China's exports over time. Moreover, the SDA analysis of China is compared with those of Japan and the US to reveal different changing patterns of DVA in the exports of the three countries. From the above analysis, we find the following four notable facts. First, although the export share of high technology manufacturing goods has risen significantly, the change in export structure does not lead to the increase in the DVA of China's exports. Second, the substitution of domestically produced intermediate inputs for imported intermediate inputs raised the DVA of China's exports after the mid-2000s, while it decreased the DVA of Japanese and US exports in most time. Third, the rise in DVA of China's exports was accompanied by the substitution of labor income for capital income. However, the same result was absent in Japan and the US. Finally, the increases in labor productivity and wage per person contributed greatly to the growth in DVA of China's exports.

A growing volume of empirical studies have explored firms' participation in GVCs and identified heterogeneous characteristics across firms. This firm heterogeneity provides important evidence to show about its position occupied in GVCs. Chapter 4 examines the performance of China's manufacturing firms. The multi-product firm model of Bernard, Redding and Schott (2011) allows firms with different levels of productivity to endogenously choose the scope of products and export destinations. Following this model, this chapter empirically investigate the relationship between firm-level productivity and exports, which are decomposed into extensive and intensive margins. The extensive margin includes the number of products and export destinations. On the other hand, the intensive margin includes the average firm-level exports per product-country and the amount of the firm's top-exporting product. In addition, we explore various effects of firm-level productivity on exports in the case that Chinese firms engage in ordinary and processing exports. Using Chinese production and trade data during the period 2000–2006, we get the following results. First, as firms are more productive, they have larger total exports. For the extensive margins, the productivity of Chinese firms is positively associated with the number of export products and destination countries, the average exports per product-country, and the export value of firm's top-exporting product. These results are generally consistent with the predictions of Bernard, Redding and Schott (2011). Second, ordinary exporters with higher productivity tend to serve a wider range of destination countries and concentrate on the exports of their top-exporting products. Third, processing exporters with higher productivity tend to export more products and serve a wider range of destination countries, while the relationship between productivity and average exports per product-country is not statistically significant. Finally, mixed exporters whose top-exporting product is processing exports have larger total exports, average exports per product-country, and top-export product value while covering a smaller number of products.

The increasing prevalence of production fragmentation within GVCs has attracted substantial attention in the field of international trade. Production activities in GVCs increasingly rely on foreign content and international outsourcing, which boosts trade in intermediate goods. GVCs not only affect international trade but also have profound impacts on the labor market. In response to the fourth research question, in Chapter 5, we examine the impacts of the expanding GVCs on the demand for domestic high-skilled, medium-skilled, and low-skilled labor. Using international input–output tables, we trace the cost share of domestic labor inputs directly and indirectly embedded in domestic production activities. In addition, two indicators are employed to measure the extent to which production activity relies on imported inputs: the foreign value-added (FV) share and the direct import share of intermediate goods. Furthermore, the two indicators of imported inputs are broken down by different sourcing origins. In particular, this decomposition allows us to examine how the imported inputs from developing countries affect the labor demand in advanced countries. From the analysis in this chapter, we get the following findings. First, the results show that an increase in the FV share reduces the cost shares of all skill levels of domestic labor. Specifically, the increase in the FV share contributes more largely to the decrease in the demand for medium-skilled labor. Second, an increase in the FV share sourced from developing countries accounts for a larger proportion of declines in the demand for domestic high-skilled and medium-skilled labor in advanced countries in the case that the estimation is based on year-by-year differences. The FV share sourced from developing countries has a negative effect on the demand for domestic low-skilled labor in advanced countries in the cases of both year-by-year and long-term differences. Third, the FV share originating from advanced countries raises the demand for low-skilled labor in developing countries in the case that the estimation is based on long-term differences. Finally, the results based on the traditional indicator of direct imports are generally close to those based on the FV share. However, these two types of indicators tend to have different magnitudes of influence on labor demand.

6.2 Policy Implications

The analysis of GVCs provides crucial implications to international trade, industrial development, and labor markets. Traditional trade statistics tend to be increasingly unrepresentative to reflect the real status of a country's participation in GVCs for both advanced and developing countries. In particular, many developing countries often occupy the downstream position of GVCs, specializing in labor-intensive production activities. In some high-technology product exports, only a small proportion of DVA is likely to be attributed to developing countries. Even though the exports of the country can be very large in gross term, it cannot accurately reflect the country's position in GVCs. Measuring the value-added content in trade has presented a new perspective for traditional trade indicators, such as trade balance, comparative advantage, trade gains, and trade barriers. For example, if policymakers and researchers use the traditional trade statistics, their estimation results become less likely to depict an accurate picture of trade in value-added from now on. In making some trade policies, it will be important for policymakers to be well aware of a new view of value-added.

Quantifying the determinants that affect the DVA growth of China has important implications in policy analysis. As the DVA reflects a part of GDP, the measurement of DVA is utilized for investigating the relationship between trade policies and economic growth. Our empirical result in Chapter 3 shows a decreased effect of total exports on the DVA of China's exports. This implies that as the global demand falls, the DVA growth relies less on the expansion of exports. We also find that the improvement of labor productivity, the rise in labor wages, and the substitution of labor income for capital income are associated with DVA growth. These findings may suggest that China has focused more on enhancing the productivity of workers and increasing labor income to boost the growth of DVA. The examination of the DVA of China's exports provides evidence for policymakers in other developing countries to find better strategies to increase the DVA of exports.

Governments in many countries usually encourage firms to participate in international trade because the performance of exporters is superior to non-exporters so that exporters can act as an engine of economic growth. Processing trade provides opportunities for firms in developing countries to participate in international trade under special policies, such as import duty exemption. However, firms adopting processing trade face some disadvantages such as low productivity and limited access to the domestic market. The result in Chapter 4 shows that ordinary exporters with higher productivity have larger average firm-level exports per product-country. However, China's trade policy to facilitate processing exports is a type of protection policy with a limited period of validity. Policy reforms are needed to better guide the transformation and upgrading of processing trade. Then, an analysis of the current state which we provide in this chapter serves as a useful reference.

Chapter 5 reveals that imported inputs exert negative effects on the demand for domestic labor, in particular for medium-skilled labor. The rise of GVCs promotes countries to specialize in specific production activities according to comparative advantage. Even though countries benefit from participating in international trade, welfare improvement does not necessarily apply to all workers. Our empirical results reveal that the demand for high-skilled labor has increased in many countries, while the demand for low-skilled labor has declined. This finding suggests an upgrading of skill structure in production activities coexists with inequality in the labor market. In addition, our result shows that the increased foreign content embedded in production activities causes a worldwide decline in domestic labor demand. Thus, it is important to make policies that reduce the negative effect of GVC participation on the domestic labor market.

(49,166 words)

Appendix

A. Summary Statistics

Table A1 shows the summary statistics of percentage changes in the data for China, Japan, and the USA during the period 2000-2014. The data of capital income, labor income, and number of employments are directly derived from the socio-economic accounts in WIOD. And the value-added, output, and exports are derived from input-output tables in WIOD. The notation Δ denotes the difference between two years. Table A2 shows the description of composite industries.

Table A1 Summary statistics of main data

	Minimum	Maximum	Mean	Standard deviation
China				
ΔCapital income (C)	4.5	24.4	13.2	5.4
ΔLabor income (R)	8.9	24.1	15.2	5.2
ΔEmployment (l)	0.0	7.1	1.3	1.7
ΔValue-added (P)	8.6	22.9	14.2	4.5
ΔOutput (X)	7.7	24.3	15.3	6.0
ΔExport (E)	-16.0	36.9	18.1	14.6
Japan				
ΔCapital income (C)	-9.2	6.9	0.1	4.2
ΔLabor income (R)	-5.2	3.3	-0.7	2.1
ΔEmployment (l)	-1.6	0.4	-0.5	0.7
ΔValue-added (P)	-6.8	2.9	-0.4	2.3
ΔOutput (X)	-12.5	3.4	-0.1	3.9
ΔExport (E)	-25.7	30.5	4.3	14.3
USA				
ΔCapital income (C)	-0.2	8.7	4.6	2.4
ΔLabor income (R)	-3.4	5.9	3.3	2.4
ΔEmployment (l)	-4.4	2.0	0.3	1.7
ΔValue-added (P)	-2.0	6.7	3.8	2.2
ΔOutput (X)	-8.1	8.4	3.8	4.0
ΔExport (E)	-15.2	15.8	5.7	9.0

Source: Calculated by the author based on World Input-Output Database (WIOD).

Table A2 Description of composite industries

Agriculture:	Medium technology manufacturing:
crop and animal production, hunting and related service activities	coke and refined petroleum products
Forestry and logging	rubber and plastic products
Fishing and aquaculture	other non-metallic mineral products
	basic metals
Mining and utilities:	fabricated metal products
mining and quarrying, electricity	
gas and water supply	**High technology manufacturing:**
	chemicals and chemical products
Low technology manufacturing:	pharmaceutical products
food products, beverages and tobacco products	computer, electronic and optical products
textiles, wearing apparel and leather products	electrical equipment
wood and of products	machinery and equipment.
paper and paper products	motor vehicles, trailers and semi-trailers
Printing and reproduction of recorded media	other transport equipment
furniture; other manufacturing	

Source: World Input-Output Database (WIOD).
Notes: The 34 service sectors are omitted.

B. Measurement of TFP based on Olley and Pakes (1996)

Following the Olley and Pakes (1996) approach, the firm-level TFP is estimated. In this appendix, we explain the way of the estimation in brief. The explanation is based on Van Beveren (2012), which provides a comprehensive review of the TFP estimation by the firm-level data. The method consists of two steps. The error term u_{it} in equation (4.1) is decomposed into two components: the unobservable productivity ω_{it} and an error term η_{it}. Then, equation (4.1) can be rewritten as follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \eta_{it}. \quad \text{(B1)}$$

In equation (B1), the variable ω_{it} has impacts on firm's decision rules, while the error term (η_{it}) is uncorrelated with input choices. As ω_{it} cannot be observed directly by researchers, but it affects the use of inputs, the simultaneity problem occurs in the estimation of production function.

Investment can be derived from the capital rule as $I_{it} = K_{it+1} - (1-\delta)K_{it}$, where K_{it} denotes the capital stock and I_{it} denotes the investment. Notice that the capital stock is a state variable and it is only affected by current and past level of ω_{it}. Thus, the investment function can be expressed as $i_{it} = i_t(\omega_{it}, k_{it})$.

Suppose that investment is strictly increasing in productivity for given capital stock. Then, the investment function has an inverse function. Thus, we can treat the unobserved productivity as a function of observable investment and capital as follows:

$$\omega_{it} = h_t(i_{it}, k_{it}), \tag{B2}$$

where the inverse function is expressed as $h_t(\cdot) = i_t^{-1}(\cdot)$. Putting equation (B2) into (B1) yields

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + h_t(i_{it}, k_{it}) + \eta_{it}. \tag{B3}$$

Next, define the function $\phi(i_{it}, k_{it})$ as follows:

$$\phi(i_{it}, k_{it}) = \beta_0 + \beta_k k_{it} + h_t(i_{it}, k_{it}). \tag{B4}$$

Then, using function $\phi(i_{it}, k_{it})$, we can rewrite the equation (B3) as follows:

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \phi(i_{it}, k_{it}) + \eta_{it}. \tag{B5}$$

As a result, equation (B5) includes a non-parametric function $\phi(i_{it}, k_{it})$ for control. Estimating equation (B5) using OLS, we get consistent estimates of the coefficients of β_l and β_m. This is the first step.

The next step aims to estimate a consistent coefficient for capital. Productivity ω_{it} is assumed to follow a first-order Markov process. In other words, the productivity in the next period is conditional on productivity in the current period. In addition, productivity needs to be conditional on survival in our context. Then, we introduce a survival indicator variable χ_{it+1} which is used to show whether the firm stays in market at the period t+1. If the firm continues to operate in the next period, then $\chi_{it+1} = 1$, otherwise, $\chi_{it+1} = 0$. From the assumption that probability follows a first-order Markov process and is conditional on survival, we set the following condition,

$$\omega_{it+1} = E[\omega_{it+1} | \omega_{it}, \chi_{it+1} = 1] + \xi_{it+1}.$$

The first term $E[\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1]$ is the expected value of productivity in the period t+1 conditional on productivity and survival in the period t. And prediction error term ξ_{it+1} is the new component and is assumed to be uncorrelated with productivity and capital at the period t+1. From the equation (B4), we easily confirm the following relation,

$$
\begin{aligned}
&E[y_{it+1} - \beta_l l_{it+1} - \beta_m m_{it+1}|\omega_{it}, \chi_{it+1} = 1] \\
&= \beta_0 + \beta_k k_{it+1} + E[\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1].
\end{aligned}
$$

From the above, the following equation will be derived,

$$
y_{it+1} - \beta_l l_{it+1} - \beta_m m_{it+1} = \beta_k k_{it+1} + E(\omega_{it+1}|\omega_{it}, \chi_{it+1}) + \xi_{it+1} + \eta_{it+1}. \quad \text{(B6)}
$$

Notice that we already have estimates of ϕ_t. Thus, the following condition holds from the equation (B4).

$$
\omega_{it} = \phi_t - \beta_k k_{it}.
$$

In addition, notice that the variable χ_{it+1} is a survival indicator. Taking these two points into consideration, we can get the following equation through some technical discussion,

$$
g(P_{it}, \phi_t - \beta_k k_{it}) = E[\omega_{it+1}|\omega_{it}, \chi_{it+1}],
$$

where the notation P_{it} expresses the survival probability of the firm in the next period, that is, $P_{it} = Pr\{\chi_{it+1} = 1\}$. Olley and Pakes (1996) shows that the survival probability is a function of investment and capital. In addition, the survival probabilities can be estimated by running a probit model where the independent variables take the form of a high-order polynomial in investment and capital. Thus, we can get the following equation:

$$
y_{it+1} - \beta_l l_{it+1} - \beta_m m_{it+1} = \beta_k k_{it+1} + g(P_{it}, \phi_t - \beta_k k_{it}) + u_{it+1} + \eta_{it+1}.
$$

As in the first step of the estimation procedure, the function $g(P_{it}, \phi_t - \beta_k k_{it})$ is approximated using a higher-order polynomial expansion in $P_{it}\ and\ \ \phi_t - \beta_k k_{it}$. Finally, the result is derived from the following equation:

$$y_{it+1} - \beta_l l_{it+1} - \beta_m m_{it+1} = \beta_k k_{it+1} + g\left(\hat{P}_{it}, \hat{\phi}_t - \beta_k k_{it}\right) + u_{it+1} + \eta_{it+1}. \quad \text{(B7)}$$

The coefficient on capital can then be obtained by applying non-linear least squares on equation (B7). Then, the logarithm of TFP is calculated as follows:

$$\ln(\mathrm{TFP}_{it}) = y_{it} - \widehat{\beta_l} l_{it} - \widehat{\beta_m} m_{it} - \widehat{\beta_k} k_{it}.$$

Following Yu (2015), we include additional variable in investment function to capture the features of Chinese economy. The FM_{it} denotes a dummy variable to measure whether firm *i* imports in year t as firm's import decision may affect the firm-level investment. In addition, the WTO_{it} dummy is included (i.e., one for a year after 2001 and zero for before) in the investment function. Finally, SOE_{it} dummy is equal to one if the firm is state-owned firm and zero otherwise. Then, equation (B2) can be rewritten as $\omega_{it} = h_t(i_{it}, k_{it}, FM_{it}, WTO_{it}, SOE_{it})$. The estimation of production function based on Olley and Pakes (1996) uses the Stata package "prodest."

C. Description of Abbreviation

Table C1 Description of country

Label	Country	Label	Country
AUS	Australia	IRL	Ireland
AUT	Austria	ITA	Italy
BEL	Belgium	JPN	Japan
BGR	Bulgaria	KOR	Korea, Republic of
BRA	Brazil	LTU	Lithuania
CAN	Canada	LUX	Luxembourg
CHN	China	LVA	Latvia
CYP	Cyprus	MEX	Mexico
CZE	Czech Republic	MLT	Malta
DEU	Germany	NLD	Netherlands
DNK	Denmark	POL	Poland
ESP	Spain	PRT	Portugal
EST	Estonia	ROU	Romania
FIN	Finland	RUS	Russia
FRA	France	SVK	Slovak Republic
GBR	United Kingdom	SVN	Slovenia
GRC	Greece	SWE	Sweden
HUN	Hungary	TUR	Turkey
IDN	Indonesia	TWN	Taiwan
IND	India	USA	United States

Table C2 Description of country groups

	WIOD	ICIO
Developed economies	Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom, Greece, Ireland, Italy, Japan, Korea, Republic of Lithuania, Luxembourg, Latvia, Malta, Netherlands, Portugal, Slovak Republic, Slovenia, Sweden, Taiwan, United States	Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Germany, Hong Kong SAR, Estonia, Finland, France, United Kingdom, Greece, Iceland, Ireland, Israel, Italy, Japan, Korea, Republic of Lithuania, Luxembourg, Latvia, Malta, Netherlands, New Zealand, Norway, Portugal, Slovak Republic, Slovenia, Spain, Singapore, Sweden, Switzerland, Chinese Taipei, United States
Developing economies	Bulgaria, Brazil, China, Hungary, Indonesia, India, Mexico, Poland, Romania, Russia, Turkey	Argentina, Bulgaria, Brazil, Brunei Darussalam, China, Chile, Colombia, Costa Rica, Croatia, Cambodia, Hungary, Indonesia, India, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Romania, Russian Federation, Saudi Arabia, Thailand, Turkey, Tunisia, Viet Nam, South Africa

Notes: The classification is defined according to the International Monetary Fund's World Economic Outlook Database.

Table C3 Description of sectors

Sector	Description
S01	Agriculture, hunting, forestry and fishing
S02	Mining and quarrying
S03	Food, beverages and tobacco
S04	Textiles and textile products
S05	Leather, and footwear
S06	Wood and of wood and cork
S07	Pulp, paper, printing and publishing
S08	Coke, refined petroleum and nuclear fuel
S09	Chemicals and chemical
S10	Rubber and plastics
S11	Other non-metallic mineral
S12	Basic metals and fabricated metal
S13	Machinery, nec
S14	Electrical and optical equipment
S15	Transport equipment
S16	Manufacturing nec; recycling
S17	Electricity, gas and water supply
S18	Construction
S19	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
S20	Wholesale trade and commission trade, except of motor vehicles and motorcycles
S21	Retail trade, except of motor vehicles and motorcycles; repair of household goods
S22	Hotels and restaurants
S23	Other Inland transport
S24	Other Water transport
S25	Other Air transport
S26	Other Supporting and auxiliary transport activities; activities of travel agencies
S27	Post and telecommunications
S28	Financial intermediation
S29	Real estate activities
S30	Renting of m&eq and other business activities
S31	Public admin and defence; compulsory social security
S32	Education
S33	Health and social work
S34	Other community, social and personal services
S35	Private households with employed persons

Table C4 Crosswalk of industry description between WIOD and ICIO

WIOD	29 sectors	ICIO	Aggregate industry
Agriculture, hunting, forestry and fishing	Agriculture, hunting, forestry and fishing	Agriculture, hunting, forestry and fishing	Primary
Mining and quarrying	Mining and quarrying	Mining and quarrying	
Food products, beverages and tobacco	Food products, beverages and tobacco	Food products, beverages and tobacco	
Textiles and textile	Textiles and textile, Leather, leather and footwear	Textiles, textile products, leather and footwear	
Leather, leather and footwear			
Wood and products of wood and cork	Wood and products of wood and cork	Wood and products of wood and cork	
Pulp, paper, paper products, printing and publishing	Pulp, paper, paper products, printing and publishing	Pulp, paper, paper products, printing and publishing	
Coke, refined petroleum and nuclear fuel	Coke, refined petroleum and nuclear fuel	Coke, refined petroleum products and nuclear fuel	
Chemicals and chemical	Chemicals and chemical	Chemicals and chemical products	
Rubber and plastics	Rubber and plastics	Rubber and plastics products	Manufacturing
Other non-metallic mineral	Other non-metallic mineral	Other non-metallic mineral products	
		Basic metals	
Basic metals and fabricated metal products	Basic metals and fabricated metal products	Fabricated metal products	
Machinery,nec	Machinery,nec	Machinery and equipment, nec	
Electronic and optical equipment	Electronic and optical equipment	Computer, Electronic and optical equipment	
		Electrical machinery and apparatus, nec	
Transport equipment	Transport equipment	Motor vehicles, trailers and semi-trailers	
		Other transport equipment	
Manufacturing nec; recycling	Manufacturing nec; recycling	Manufacturing nec; recycling	
Electricity, gas and water supply	Electricity, gas and water supply	Electricity, gas and water supply	
Construction	Construction	Construction	
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	Wholesale and retail trade; repairs	Wholesale and retail trade; repairs	
Wholesale trade and commission trade, except of motor vehicles and motorcycles			
Retail trade, except of motor vehicles and motorcycles; repair of household goods			
Hotels and restaurants	Hotels and restaurants	Hotels and restaurants	
Other Inland transport	Transports activities	Transport and storage	
Other Water transport			
Other Air transport			
Other Supporting and auxiliary transport activities; activities of travel agencies			
Post and telecommunications	Post and telecommunications	Post and telecommunications	Service
Financial intermediation	Financial intermediation	Financial intermediation	
Real estate activities	Real estate activities	Real estate activities	
Renting of machinery and equipment and other business activities	Renting of machinery and equipment and other business activities	Renting of machinery and equipment	
		Computer and related activities	
		R&D and other business activities	
Public admin. and defence; compulsory social security	Public admin. and defence; compulsory social security	Public admin. and defence; compulsory social security	
Education	Education	Education	
Health and social work	Health and social work	Health and social work	
Other community, social and personal services	Other community, social and personal services	Other community, social and personal services	
Private households with employed persons	Private households with employed persons	Private households with employed persons	

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import Competition and the Great US Employment Sag of the 2000s. *Journal of Labor Economics*, 34 (S1), 141–98.

Ahn, J., Khandelwal, A. K., and Wei, S. J. (2011). The Role of Intermediaries in Facilitating Trade. *Journal of International Economics*, 84 (1), 73–85.

Amador, J., and Cabral, S. (2016). Global Value Chains: A Survey of Drivers and Measures. *Journal of Economic Surveys*, 30 (2), 278–301.

Amiti, M., and Freund, C. (2008). *The Anatomy of China's Export Growth*. The World Bank.

Amiti, M., and Konings, J. (2007). Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia. *American Economic Review*, 97 (5), 1611–38.

Ando, M., and Kimura, F. (2005). The Formation of International Production and Distribution Networks in East Asia. *International Trade in East Asia*, University of Chicago Press, 177–216.

Antràs, P. (2019). Conceptual Aspects of Global Value Chains. NBER Working Paper No. 26539.

Antràs, P., Fort, T. C., and Tintelnot, F. (2017). The Margins of Global Sourcing: Theory and Evidence from US Firms. *American Economic Review*, 107 (9), 2514–64.

Arkolakis, C., Demidova, S., Klenow, P. J., and Rodríguez-Clare, A. (2008). Endogenous Variety and the Gains from Trade. *American Economic Review*, 98 (2), 444–50.

Arkolakis, C., Ganapati, S., and Muendler, M. A. (2010). The Extensive Margin of Exporting Products: A Firm-level Analysis. NBER Working Paper No.16641.

Athukorala, P. (2005). Product Fragmentation and Trade Patterns in East Asia. *Asian Economic Papers*, 4 (3), 1–27.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103 (6), 2121–68.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, 118 (4), 1279–333.

Backer, K. D., and Miroudot, S. (2013). Mapping Global Value Chains. OECD Trade Policy Papers, 159.

Bai, C. E., and Qian, Z. (2010). The Factor Income Distribution in China: 1978–2007. *China*

Economic Review, 21 (4), 650–70.

Baldwin, R. (2011). Trade and Industrialisation after Globalisation's 2nd Unbundling: How Building and Joining a Supply Chain are Different and Why it Matters. NBER Working Paper No. 17716.

Baldwin, R. (2016). *The Great Convergence*. Harvard University Press.

Baldwin, R., & Venables, A. J. (2010). Relocating the Value Chain: Off-Shoring and Agglomeration in the Global Economy. CEPR Discussion Paper No. DP8163.

Baldwin, R., and Venables, A. J. (2013). Spiders and Snakes: Offshoring and Agglomeration in the Global Economy. *Journal of International Economics*, 90 (2), 245–54.

Bernard, A. B., Redding, S. J., and Schott, P. K. (2011). Multiproduct Firms and Trade Liberalization. *Quarterly Journal of Economics*, 126 (3), 1271–318.

Bernard, A. B., Jensen, J. B., Redding, S. J., and Schott, P. K. (2007). Firms in International Trade. *Journal of Economic Perspectives*, 21 (3), 105–30.

Bernard, A. B, Jensen, J. B., Redding, S. J., and Schott, P. K. (2009). The Margins of US Trade. *American Economic Review*, 99 (2), 487–93.

Bernard, A. B., Jensen, J. B., Redding, S. J., and Schott, P. K. (2012). The Empirics of Firm Heterogeneity and International Trade. Annual Review of Economics, 4 (1), 283–313.

Bernard, A. B., Jensen, J. B., and Schott, P. K. (2006). Survival of the Best Fit: Exposure to Low-Wage Countries and the (Uneven) Growth of U.S. Manufacturing Plants. *Journal of International Economics*, 68 (1), 219–37.

Bernard, A. B, Redding, S. J., and Schott, P. K. (2010). Multiple-Product Firms and Product Switching. *American Economic Review*, 100 (1), 70–97.

Bernard, A. B., Van Beveren, I., and Vandenbussche, H. (2014). Multi-Product Exporters and the Margins of Trade. *Japanese Economic Review*, 65 (2), 142–57.

Berman, E., Bound, J., and Griliches, Z. (1994). Changes in the Demand for Skilled Labor within U. S. Manufacturing: Evidence from the Annual Survey of Manufactures. *Quarterly Journal of Economics*, 109 (2), 367–97.

Borin, A., and Mancini, M. (2019). *Measuring What Matters in Global Value Chains and Value-Added Trade*. The World Bank.

Brandt, L., Biesebroeck, J. V., and Zhang, Y. (2012). Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing. *Journal of Development Economics*, 97 (2), 339–51.

Brandt, L., and Morrow, P. M. (2017). Tariffs and the Organization of Trade in China. *Journal* *of International Economics*, 104, 85–103.

Brandt, L., Van Biesebroeck, J., Wang, L., and Zhang, Y. (2017). WTO Accession and Performance of Chinese Manufacturing Firms. *American Economic Review*, 107 (9), 2784–820.

Cui, Y., Meng, J., and Lu, C. (2018). Recent developments in China's Labor Market: Labor Shortage, Rising Wages and their Implications. *Review of Development Economics*, 22 (3), 1217–38.

Dai, M., Maitra, M., and Yu, M. (2016). Unexceptional Exporter Performance in China? The Role of Processing Trade. *Journal of Development Economics*, 121, 177–89.

Daudin, G., Rifflart, C., and Schweisguth, D. (2011). Who Produces for whom in the World Economy? *Canadian Journal of Economics/Revue Canadienne d'économique*, 44 (4), 1403–37.

Davis, D. R., and Mishra, P. (2007). Stolper-Samuelson is Dead: And other Crimes of Both Theory and Data. *Globalization and poverty*, 87–108, University of Chicago Press.

De Loecker, J. (2011). Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity. *Econometrica*, 79 (5), 1407–51.

Dean, J., Fung, K. C., and Wang, Z. (2007). Measuring the Vertical Specialization in Chinese Trade. USITC Office of Economics Working Paper No. 2007-01-A.

Dedrick, J., Kraemer, K. L., and Linden, G. (2010). Who Profits from Innovation in Global Value Chains?: A Study of the iPod and Notebook PCs. *Industrial and Corporate Change*, 19 (1), 81–116.

Dietzenbacher, E., Lahr, M. L., and Los, B. (2004). The Decline in Labor Compensation's Share of GDP: A Structural Decomposition Analysis for the United States, 1982 to 1997. In E. Dietzenbacher and M. L. Lahr (Eds.), *Wassily Leontief and Input-Output Economics*, 188–212. Cambridge University Press.

Dietzenbacher, E., and Los, B. (2000). Structural Decomposition Analyses with Dependent Determinants. *Economic Systems Research*, 12 (4), 497–514.

Duan, Y., Dietzenbacher, E., Jiang, X., Chen, X., and Yang, C. (2018). Why has China's Vertical Specialization Declined? *Economic Systems Research*, 30 (2), 178–200.

Eckel, C., and Neary, J. P. (2010). Multi-Product Firms and Flexible Manufacturing in the Global Economy. *Review of Economic Studies*, 77 (1), 188–217.

Ernst, D. (2016). From Catching Up to Forging Ahead? China's New Role in the Semiconductor Industry. *Solid State Technology May*.

Falk, M., and Koebel, B. M. (2002). Outsourcing, Imports and Labour Demand. *Scandinavian Journal of Economics*, 104 (4), 567–86.

Falk, M., and Wolfmayr, Y. (2005). Employment Effects of Outsourcing to Low Wage Countries: Empirical Evidence for EU Countries. WIFO Working Papers No. 262.

Falk, M., and Wolfmayr, Y. (2008). Services and Materials Outsourcing to Low-Wage Countries and Employment: Empirical Evidence from EU Countries. *Structural Change and Economic Dynamics*, 19 (1), 38–52.

Feenstra, R. (2017). Statistics to Measure Offshoring and its Impact. NBER Working Paper No. 23067.

Feenstra, R. C., and Hanson, G. H. (1995). Foreign Investment, Outsourcing and Relative Wages. NBER Working Paper No. 5121.

Feenstra, R. C., and Hanson, G. H. (1997). Foreign Direct Investment and Relative Wages: Evidence from Mexico's Maquiladoras. *Journal of International Economics*, 42 (3), 371–93.

Feenstra, R. C., and Hanson, G. H. (1999). The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979–1990. *Quarterly Journal of Economics*, 114 (3), 907–40.

Feenstra, R., and Hanson, G. (2001). Global Production Sharing and Rising Inequality: A Survey of Trade and Wages. NBER Working Papers No. 8372.

Feenstra, R. C., Li, Z., and Yu, M. (2014). Exports and Credit Constraints under Incomplete Information: Theory and Evidence from China. *Review of Economics and Statistics*, 96 (4), 729–44.

Feenstra, R. C., and Sasahara, A. (2018). The 'China Shock,' Exports and U.S. Employment: A Global Input–Output Analysis. *Review of International Economics*, 26(5), 1053–83.

Fernandes, A. P., and Tang, H. (2015). Scale, Scope, and Trade Dynamics of Export Processing Plants. *Economics Letters*, 133, 68–72.

Foster-McGregor, N., Stehrer, R., and de Vries, G. J. (2013). Offshoring and the Skill Structure of Labour Demand. *Review of World Economics*, 149 (4), 631–62.

Gereffi, G., and Fernandez-Stark, K. (2011). Global Value Chain Analysis: A Primer. Center on Globalization, Governance and Competitiveness (Retrieved on January 1, 2020, http://www.cggc.duke.edu/pdfs/2011–05-31_GVC_analysis_a_primer.pdf).

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., and Topalova, P. (2010). Imported Intermediate Inputs and Domestic Product Growth: Evidence from India. *Quarterly Journal* *of Economics*, 125 (4), 1727–67.

Goos, M., Manning, A., and Salomons, A. (2009). Job Polarization in Europe. *American Economic Review*, 99 (2), 58–63.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review*, 104 (8), 2509–26.

Görg, H., Kneller, R., and Muraközy, B. (2012). What Makes a Successful Export? Evidence from Firm-Product-Level Data. *Canadian Journal of Economics/Revue Canadienne d'économique*, 45 (4), 1332–68.

Griliches, Z., and Hausman, J. A. (1986). Errors in Variables in Panel Data. *Journal of Econometrics*, 31 (1), 93–118.

Grimes, S., and Sun, Y. (2016). China's Evolving Role in Apple's Global Value Chain. *Area Development and Policy*, 1 (1), 94–112.

Grossman, G. M., and Rossi-Hansberg, E. (2008). Trading Tasks: A Simple Theory of Offshoring. *American Economic Review*, 98 (5), 1978–97.

Harrison, A., and McMillan, M. (2011). Offshoring Jobs? Multinationals and US Manufacturing Employment. *Review of Economics and Statistics*, 93 (3), 857–75.

Harwit, E. (2007). Building China's Telecommunications Network: Industrial Policy and the Role of Chinese State-Owned, Foreign and Private Domestic Enterprises. *China Quarterly*, 190, 311–32.

Hijzen, A., Görg, H., and Hine, R. C. (2005). International Outsourcing and the Skill Structure of Labour Demand in the United Kingdom. *Economic Journal*, 115 (506), 860–78.

Hollweg, C. H. (2019). Global Value Chains and Employment in Developing Economies. *Global Value Chain Development Report 2019*, 63.

Hsieh, C. T., and Woo, K. T. (2005). The Impact of Outsourcing to China on Hong Kong's Labor Market. *American Economic Review*, 95 (5), 1673–87.

Hummels, D., Ishii, J., and Yi, K. M. (2001). The Nature and Growth of Vertical Specialization in World Trade. *Journal of International Economics*, 22.

Hummels, D., Munch, J. R., and Xiang, C. (2018). Offshoring and Labor Markets. *Journal of Economic Literature*, 56 (3), 981–1028.

Iacovone, L., and Javorcik, B. S. (2008). Multi-Product Exporters: Diversification and Micro-Level Dynamics. The World Bank Policy Research Working Paper No. 4723.

Imbruno, M. (2016). China and WTO Liberalization: Imports, Tariffs and Non-Tariff Barriers. *China Economic Review*, 38, 222–37.

Johnson, R. C. (2014). Five Facts About Value-Added Exports and Implications for Macroeconomics and Trade Research. *Journal of Economic Perspectives*, 28 (2), 119–42.

Johnson, R. C. (2017). Measuring Global Value Chains. NBER Working Paper No. 24027.

Johnson, R. C., and Noguera, G. (2012). Accounting for Intermediates: Production Sharing and Trade in Value Added. *Journal of International Economics*, 86 (2), 224–36.

Kee, H. L., and Tang, H. (2016). Domestic Value Added in Exports: Theory and Firm Evidence from China. *American Economic Review*, 106 (6), 1402–36.

Kimura, F., Takahashi, Y., and Hayakawa, K. (2007). Fragmentation and Parts and Components Trade: Comparison between East Asia and Europe. *The North American Journal of Economics and Finance*, 18 (1), 23–40.

Koopman, R., Powers, W., Wang, Z., and Wei, S.-J. (2010). Give Credit Where Credit Is Due: Tracing Value Added in Global Production Chains. NBER Working Paper No. 16426.

Koopman, R., Wang, Z., and Wei, S. J. (2008). How Much of Chinese Exports is Really Made in China? Assessing Domestic Value-Added when Processing Trade is Pervasive. NBER Working Paper No. 14109.

Koopman, R., Wang, Z., and Wei, S. J. (2014). Tracing Value-Added and Double Counting in Gross Exports. *American Economic Review*, 104 (2), 459–94.

Kraemer, K. L., Linden, G., and Dedrick, J. (2011). Capturing Value in Global Networks: Apple's iPad and iPhone. Unpublished work. (Retrieved on October 1, 2020, http://economiadeservicos.com/wp-content/uploads/2017/04/value_ipad_iphone.pdf).

Lawrence, R. Z. (2015). Recent Declines in Labor's Share in US Income: A Preliminary Neoclassical Account. NBER Working Paper No. 21296.

Lawrence, R. Z., Slaughter, M. J., Hall, R. E., Davis, S. J., and Topel, R. H. (1993). International Trade and American Wages in the 1980s: Giant Sucking Sound or Small Hiccup? Brookings Papers on Economic Activity. *Microeconomics*, 1993 (2), 161–226.

Leontief, W. W. (1936). Quantitative Input and Output Relations in the Economic Systems of the United States. *Review of Economics and Statistics*, 18 (3), 105–25.

Levinsohn, J., and Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies*, 70 (2), 317–41.

Lin, J.T., Liang, X., and Wan, Y. (2001). *Telecommunications in China: Development and prospects*. Nova Publishers.

Linden, G., Kraemer, K. L., and Dedrick, J. (2009). Who Captures Value in a Global Innovation Network? The Case of Apple's iPod. *Communications of the ACM*, 52 (3), 140–44.

Los, B., Timmer, M. P., and de Vries, G. J. (2015). How Global are Global Value Chains? A New Approach to Measure International Fragmentation. *Journal of Regional Science*, 55 (1), 66–92.

Lu, Y., Shi, H., Luo, W., and Liu, B. (2018). Productivity, Financial Constraints, and Firms' Global Value Chain Participation: Evidence from China. *Economic Modelling*, 73, 184–94.

Manova, K., and Yu, Z. (2017). Multi-Product Firms and Product Quality. *Journal of International Economics*, 109, 116–37.

Mayer, T., Melitz, M. J., and Ottaviano, G. I. P. (2014). Market Size, Competition, and the Product Mix of Exporters. *American Economic Review*, 104 (2), 495–536.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71 (6), 1695–725.

Melitz, M. J., and Ottaviano, G. I. (2008). Market Size, Trade, and Productivity. *Review of Economic Studies*, 75 (1), 295–316.

Melitz, M. J., and Redding, S. J. (2014). Heterogeneous Firms and Trade. NBER Working Paper No. 18652.

Meng, B., Fang, Y., Guo, J., and Zhang, Y. (2017). Measuring China's Domestic Production Networks through Trade in Value-added Perspectives. *Economic Systems Research*, 29 (1), 48–65.

Meng, B., Yamano, N., and Webb, C. (2011). Application of Factor Decomposition Techniques to Vertical Specialisation Measurements. IDE Discussion Paper 276.

Michaels, G., Natraj, A., and Van Reenen, J. (2014). Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years. *Review of Economics and Statistics*, 96 (1), 60–77.

Miller, R. E., and Blair, P. D. (2009). *Input-output Analysis: Foundations and Extensions*. Cambridge University Press.

Mion, G., and Zhu, L. (2013). Import Competition from and Offshoring to China: A Curse or Blessing for Firms? *Journal of International Economics*, 89 (1), 202–15.

Nagengast, A. J., and Stehrer, R. (2016). The Great Collapse in Value Added Trade. *Review of International Economics*, 24 (2), 392–421.

Ng, F., and Yeats, A. (1999). *Production Sharing in East Asia: Who Does What for Whom, and Why?* The World Bank.

Olley, G., and Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 64 (6), 1263–97.

Pei, J., Oosterhaven, J., and Dietzenbacher, E. (2012). How Much Do Exports Contribute to China's Income Growth? *Economic Systems Research*, 24 (3), 275–97.

Pierce, J. R., and Schott, P. K. (2016). The Surprisingly Swift Decline of US Manufacturing Employment. *American Economic Review*, 106 (7), 1632–62.

Regis, P. J. (2018). The Extensive and Intensive Margins of Exports of Firms in Developing and Emerging Countries. *International Review of Economics and Finance*, 56, 39–49.

Reijnders, L. S., Timmer, M. P., and Ye, X. (2016). Offshoring, Biased Technical Change and Labor Demand: New Evidence from Global Value Chains. *GGDC Research Memorandum*, 164.

Rodrik, D. (2006). What's so Special about China's Exports? *China and World Economy*, 14 (5), 1–19.

Schott, P. K. (2008). The Relative Sophistication of Chinese Exports. *Economic Policy*, 23 (53), 5–49.

Steinberg, C., and Nakane, M. (2011). To fire or to hoard? Explaining Japan's labor market response in the great recession. IMF Working Papers, 1–29.

Stolper, W. F., and Samuelson, P. A. (1941). Protection and Real Wages. *Review of Economic Studies*, 9 (1), 58–73.

Tan, Z. A. (2002). Product Cycle Theory and Telecommunications Industry—Foreign Direct Investment, Government Policy, and Indigenous Manufacturing in China. *Telecommunications Policy*, 26 (1–2), 17–30.

Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. J. (2015). An Illustrated User Guide to the World Input-Output Database: The Case of Global Automotive Production: User Guide to World Input-Output Database. *Review of International Economics*, 23 (3), 575–605.

Timmer, M. P., Erumban, A. A., Los, B., Stehrer, R., and de Vries, G. J. (2014). Slicing Up Global Value Chains. *Journal of Economic Perspectives*, 28 (2), 99–118.

Timmer, M., Los, B., Stehrer, R., and de Vries, G. (2016). *An Anatomy of the Global Trade Slowdown Based on the WIOD 2016 Release*. Groningen Growth and Development Centre, University of Groningen.

Topalova, P., and Khandelwal, A. (2011). Trade Liberalization and Firm Productivity: The Case of India. *Review of Economics and Statistics*, 93 (3), 995–1009.

Upward, R., Wang, Z., and Zheng, J. (2013). Weighing China's Export Basket: The Domestic Content and Technology Intensity of Chinese Exports. *Journal of Comparative Economics*, 41 (2), 527–43.

UNCTAD (2013) Global Value Chains and Development: Investment and Value Added Trade in the Global Economy (Retrieved on October 1, 2020, https://unctad.org/system/files/official-document/wir2013_en.pdf).

UNCTAD (2015), Key Statistics and Trends in International Trade 2015. United Nation Conference on Trade and Development Report. (Retrieved on October 1, 2020, https://unctad.org/system/files/official-document/ditctab2015d1_en.pdf).

Urata, S., and Baek, Y. (2020). The Determinants of Participation in Global Value Chains: A Cross-Country, Firm-Level Analysis. ADBI Working Paper Series No.1116.

Van Beveren, I. (2012). Total Factor Productivity Estimation: A Practical Review. *Journal of Economic Surveys*, 26 (1), 98–128.

Wang, Z., Wei, S. J., Yu, X., and Zhu, K. (2018). Re-examining the Effects of Trading with China on Local Labor Markets: A Supply Chain Perspective. NBER Working Paper No. w24886.

Wang, Z., Wei, S. J., and Zhu, K. (2013). Quantifying International Production Sharing at the Bilateral and Sector Levels. NBER Working Paper No. 19677.

Wolszczak-Derlacz, J., and Parteka, A. (2018). The Effects of Offshoring to Low-wage Countries on Domestic Wages: A Worldwide Industrial Analysis. *Empirica*, 45 (1), 129–63.

WTO, and IDE-JETRO. (2011). Trade Patterns and Global Value Chains in East Asia: From Trade in Goods to Trade in Tasks. World Trade Organisation, Geneva, IDE-JETRO.

Xing, Y., and Detert, N. C. (2010). How the iphone Widens the United States Trade Deficit with the People's Republic of China. ADBI Working Paper No. 257.

Yamano, N., and Webb, C. (2018). Future Development of the Inter-Country Input-Output (ICIO) Database for Global Value Chain (GVC) and Environmental Analyses. *Journal of Industrial Ecology*, 22 (3), 487–8.

Yang, lianling, and Yang, C. (2017). Changes in Domestic Value Added in China's Exports: A Structural Decomposition Analysis Approach. *Journal of Economic Structures*, 6 (1), 18.

Yu, M. (2015). Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms. *Economic Journal*, 125 (585), 943–88.

Zhang, W., and Igel, B. (2001). Managing the Product Development of China's SPC Switch Industry as an Example of CoPS. *Technovation*, 21 (6), 361–68.

Zhu, H. L. (2019). A Quantitative Analysis of Global Value Chains: Why has Domestic Value-Added of China's Exports Increased? *International Journal of Economic Policy Studies*, 13 (2), 403–23.

Zhu, H. L. (2020). The Impact of Imported Intermediate Inputs on the Skill Structure of Labor Demand. *Journal of International Trade and Economic Development*. Advance online publication.

URL List

1. Handel Jones (2014) China needs a semiconductor industry. China Daily USA, (Retrieved on July 1, 2019, http://usa.chinadaily.com.cn/epaper/2014-10/07/content_18701860.htm).
2. Pwc (2016) China's impact on the semiconductor industry: 2016 update. Pwc, (Retrieved on October 1, 2020, https://www.pwc.com/gx/en/technology/chinas-impact-on-semiconductor-industry/assets/china-impact-of-the-semiconductor-industry-2016-update.pdf).
3. Tomohiro Otsuki (2019). Revealing the Iron Law of Apple's supply chains: Goodbye to 20 companies every year (in Japanese). Nikkei Xtech, (Retrieved on October 1, 2020, https://xtech.nikkei.com/atcl/nxt/mag/ne/18/00008/00022/).
4. Businesswire (2016). Revenue Growth Sounding Strong for Suppliers of Packaged MEMS Microphones, Latest Ranking from IHS Markit Reveals. Businesswire, (Retrieved on October 1, 2019, www.businesswire.com/news/home/20161018006400/en/Revenue-Growth-Sounding-Strong-for-Suppliers-of-Packaged-MEMS-Microphones-Latest-Ranking-From-IHS-Markit-Reveals).
5. Peter Clarke (2016). Apple win lifts Goertek up MEMS microphone ranks. HIS Markit, (Retrieved on October 1, 2019, https://www.eenewsanalog.com/news/apple-win-lifts-goertek-mems-microphone-ranks-0).
6. Sarah Mishkin (2013) Chinese companies move into supply chain for Apple components. Financial Times, (Retrieved on October 1, 2019, https://www.ft.com/content/d70fca52-2691-11e3-9dc0-00144feab7de).
7. The Wall Street Journal (Retrieved on October 1, 2019, https://www.wsj.com/market-data).
8. The Eora Global Supply Chain Database (Retrieved on October 1, 2019, https://worldmrio.com/).

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