Exports, income and regional inequality in China: value chain analyses
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Exports, Income and Regional Inequality in China: 
Value Chain Analyses

Yuwan Duan
Exports, Income and Regional Inequality in China: Value Chain Analyses

PhD thesis

to obtain the degree of PhD at the University of Groningen on the authority of the Rector Magnificus Prof. C. Wijmenga and in accordance with the decision by the College of Deans.

This thesis will be defended in public on

Thursday 14 January 2021 at 11.00 hours

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DUAN, Yuwan

November 14, 2020

Beijing, China
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CHAPTER 1

Introduction

The main losers in today’s very unequal world are not those who are too much exposed to globalization. They are those who have been left out.

Kofi Annan

Former secretary general of the United Nations, 2000

Adopting a value chain perspective, this thesis investigates the effects of China’s exports on three variables that are related to income. First, the import content of China’s exports and what determines the changes therein.¹ Second, the amount of national income that is exported (i.e. embodied in foreign final consumption). Third, China’s regional GDP and regional income inequality. In doing so, I take full consideration of three typical features of China’s exports. These are: (a) the large scale of processing exports; (b) the important role of Foreign Invested Enterprises (FIEs) in exports; and (c) the uneven distribution of export activities across China’s regions. These characteristics seriously influence the income effect of China’s exports and its dynamics. This thesis therefore takes them into full account. The outline of the research reported in Chapters 2 – 4 is given in Section 1.3. Before that, however, Section 1.1 briefly sketches the research setting. That is, it introduces the general patterns in global trade and the role of China in particular. Section 1.2 then describes the three typical characteristics of China’s exports (a - c) in more detail.

1.1 The global trade pattern and the role of China

Figure 1.1 shows the increase in the world average ratio of exports (for goods and services) to GDP since 1971. The value was only 0.14 in 1971, which increased to 0.26

¹ The import content of the exports is related to income because its counterpart is the amount of domestic value added that is embodied in the exports.
in 2000, rose further to 0.31 in 2008, after which it declined to 0.29 in 2015. In the period of 45 years, we see that the growth rate of the exports (given by the dashed line) is negative only twice. In 1975 due to the oil crisis and in 2009 due to the financial crisis, which sent many countries into a recession and led to a substantial fall in international trade (Sturgeon and Memedovic, 2010).

The exports-to-GDP ratio rebounded to the level before the crisis by 2011, but started to decrease again along with the overall weakness in global economic activity in the last few years (Timmer et al., 2016).

**Figure 1.1 The trade of goods and services in the world economy**

![Graph showing trade of goods and services in the world economy](image)

Notes: The data are from the World Development Indicators (World Bank, 2019). In some years (e.g., 1978, 1982, 1983, 1986, 1991, 1993, and 2001) the exports-to-GDP ratio fell whereas the exports showed positive growth. This is because GDP grew more than the exports.

What cannot be seen in Figure 1.1 is that the globalization in recent decades is quite different from earlier globalization. This is because of the fragmentation where production processes became sliced up into many stages. These stages were often located in different countries or regions instead of in a single region and intermediates crossed several national boundaries before ending up in the final product (Hummels et al, 2001). This development has become known as “the second wave of unbundling” or the “global value chain (GVC) revolution” (Baldwin and Lopez-Gonzalez, 2015). Under this new way of trade, the rich-nation firms relocated part of the production to lower-cost developing countries, which opened a new industrialization path for these developing countries. According to Baldwin (2011, p. 2): “in less than a decade, joining
a supply chain transmuted several East Asian industries from uncompetitive, tariff-
sheltered relics into world-class exporters”. This arose the question how international
trade contributed to the economic development of developing countries in a world
characterized by GVCs. In this respect, China is an ideal object of study given its
emergence as the “World’s Factory” after entering the WTO and its growing importance
in the world economy.

Figure 1.2 sketches the development of China’s trade from 1995 onwards. It shows
the country’s integration into the global trading system. Following China’s 2001 WTO
accession, its international trade has boomed. In nominal terms, the export volume
increased by a factor 10 between 2000 and 2018. This outpaced the three-fold expansion
of overall global trade during this period. As a result, the share of China’s merchandise
exports in the global trade rose from 2.9% in 1995 to 12.7% in 2018, as shown in Figure
1.2.

Figure 1.2 China’s role in world GDP and trade (unit: %)

![chart showing the share of China's merchandise exports and GDP in the world]

Note: The data are from the World Development Indicators (World Bank, 2019)

Figure 1.3 zooms in on five broader industries: “Food, textile, and wood”; “Paper”;
“Chemical products”; “Metal products and nonmetallic mineral products”; and
“Machinery and equipment”.¹ The figure depicts China’s export shares in the world

¹ The five-industry classification for manufacturing is an aggregation of the industries in the WIOD 2016 release. In particular: “Food, textile and wood” includes C10-C12, C13-C15, and C16; “Paper” is an aggregate industry of C17 and C18; “Chemical products” includes C19-C22; “Metal products and nonmetallic mineral products” includes C23-C25; and “Machinery and equipment” is an aggregate industry of C26-C30.
trade by industry from 2000 to 2014. It shows the increased roles of China in the world
exports of all five industries. China’s increased importance in the exports of
“Machinery and equipment” is remarkable, with the export share rising from 3.4% in
2000 to 19.2% in 2014.

Figure 1.3 The share of China’s exports in world trade by industry (unit: %)

![Graph showing the share of China's exports in world trade by industry from 2000 to 2014.]

Note: Author’s calculation based on WIOD data (Timmer et al., 2016).

Not only the sizes of the export volumes have grown enormously, China’s export
composition has also undergone substantial changes. Figure 1.4 shows the export shares
of the five industries in China’s total merchandise exports in 2000 and 2014. It is
observed that China’s export composition significantly changed from labor intensive
industries (Food, textile, and wood) towards high-tech industries (Machinery and
equipment). The developments summarized in Figure 1.3 (changes in export volumes)
and Figure 1.4 (changes in export composition) raise the questions how China’s exports
contributed to its economic development and how this contribution changed over time?
This thesis aims to answer these questions and investigates the income effects of China’s exports and the dynamics in these effects. More specifically, using a value chain perspective, this thesis studies the export effects on three variables that are related to income. The relationship between exports and economic growth has been examined thoroughly in the literature (Lewer and Van den Berg, 2003). However, there are two shortcomings.

First, most existing studies ignore the indirect effects of exports on income. These indirect effects are due to the production linkages between industries which exist because the production in each industry requires intermediate inputs from upstream industries. A positive demand shock for final products will therefore propagate upstream and affect the production in industries that have to meet the demand for extra intermediate inputs. Consequently, value added (and thus GDP, which equals the sum of values added in all industries) will be affected and the effects will be different across industries. For instance, as shown in Chinese official input-output table in 2012 (NBS, 2015), production in the textiles industry uses more intermediate inputs from the chemistry industry than does production in the agricultural industry. As a consequence, a positive shock in foreign demand (i.e. exports) for textiles will increase—through the production linkages of the input-output model—the value added of the chemistry industry more than an equal shock in the agriculture industry.
This example also shows the second shortcoming. That is, not only a change in the export volume but also a change in the composition of the exports bundle will cause changes in GDP and the composition of the industry contributions. Most macroeconomic studies that investigated the impact of exports on economic development, however, focused only on aggregate exports and ignored the composition of the exports. Adopting a value chain perspective, this thesis takes both shortcomings (i.e. indirect effects and composition effects) into full consideration.

1.2 The role of exports in China’s economy: stylized facts

With the booming of China’s exports, its economy has also experienced unprecedented growth with an average annual growth rate of 9.2% from 2000 to 2018. During the same period, world GDP grew only 2.8% per year. To illustrate the role of exports in China’s economy, Figure 1.5 gives China’s exports-to-GDP ratio from 1995 to 2018. It shows that the ratio has increased since 2001 and reached a peak of 0.36 in 2006. After that, the ratio has declined and eventually fell to 0.20 in 2018. The decline was gradual except for the years following the global financial crisis and may well be the result (at least partly) of China’s policy of stimulating domestic consumption and of increased foreign trade protectionism in recent years.

China’s international trade has several unique characteristics. Three of its most salient features are: the large amount of processing exports; the important role of FIEs in exports; and the uneven distribution of export activities across China’s regions.

First, China’s trade has been dominated by processing trade for years. As Figure 1.6 shows, China’s processing exports accounted for more than half of China’s total merchandise exports between 1996 and 2007. One of the key reasons why processing trade flourished in China is the country’s biased policy favoring this type of trade. For instance, materials imported into China are exempted from tariffs if they are used for processing trade. This policy leads to more imported inputs in the production of

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2 Both world and Chinese GDP growth rates are in real terms and are taken from the World Development Indicators (World Bank, 2019).
3 For example, in 2018 the U.S. enacted several waves of tariff increases on specific products and countries including China, Mexico, and some European countries. Meanwhile, non-tariff barriers (NTBs) have risen after the Global Financial Crisis in 2008 (WTO, 2012). China suffered from increased NTBs in other countries in recent years.
processing exports than in other types of production, such as the production of ordinary exports (Yang et al., 2015). As a consequence, an RMB of processing exports usually generate much less domestic value added (DVA) than an RMB of ordinary exports (Koopman et al, 2011; Chen et al., 2012; Ma et al., 2015; Kee and Tang, 2016).

Figure 1.5 The ratio of exports (goods and services) to GDP, China

![Graph showing the ratio of exports to GDP from 1995 to 2018.]

Note: The data are from the World Development Indicators (World Bank, 2019)

Figure 1.6 Processing exports and FIEs’ exports as a share of China’s merchandise exports (unit: %)

![Graph showing the share of processing exports and FIEs’ exports from 1995 to 2018.]

Note: The data are from China’s National Bureau of Statistics (NBS: http://data.stats.gov.cn/english/).

However, after decades of rapid trade growth, the share of processing exports in China declined slowly but persistently in the last two decades. A likely cause is China’s policy change. Processing exports of several commodities groups was prohibited or
restricted, in order to steer China’s export structure away from “resource-dependent” products. Another possible reason was China’s rapidly rising labor costs since the mid-2000s. They increased the production costs of processing and assembly activities in China and forced foreign enterprises to move them partly outside China. Despite this decline, the share of processing exports in China was still up to 33.5% in 2017 (Figure 1.6). Because processing exports depend largely on imported products and embody relatively little DVA, the decreasing processing export share seriously impacted the overall DVA content of China’s exports.

Second, there is a strong link between China’s inward foreign direct investment (FDI) flows and exports. China is the largest recipient of FDI in the world since 2014. The inward FDI flows into China in 2016 totaled 133.7 billion US$, which constituted 7.7% of the world’s total FDI. These foreign investments are closely related to China’s export activities. The share of FIEs’ exports in China’s merchandise exports was 58.3% in 2005 (and slowly declined to 43.2% in 2017). The role of FIEs is especially remarkable in processing exports (their exports were 83.3% of China’s processing exports in 2017) (Figure 1.6). The reason to focus on FIEs (next to processing exports) is that the value added of FIEs contains profits, part of which the FIEs can repatriate. These profit flows then add to the national income (NI) in the home country. So, the profits are part of China’s DVA but not always of China’s NI. As a consequence, Chinese DVA contained in its exports is not a good proxy for NI contained in exports. Because the profit flows are based on ownership, NI effects of exports cannot be analyzed by looking at processing exports but require looking at FIEs. Figure 1.6 shows that the share of FIEs’ exports in merchandise exports declined since 2007.

The third remarkable feature of China’s exports is its very unbalanced distribution across domestic regions. The map in Figure 1.7 gives the exports per capita at the province level in 2018. It shows a large heterogeneity across provinces with the highest exports per person (7468 US$) in Shanghai and the lowest (55 US$) in Qinghai. Most of China’s exports are concentrated in coastal provinces, especially Guangdong, Jiangsu, and Zhejiang. In 2018, these three provinces were responsible for 58.4% of China’s total merchandise exports. The other coastal provinces accounted for 25.6%

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4 The data are from the United Nations Conference on Trade and Development (UNCTAD) database.
and the inland provinces only accounted for 16.0%. The processing exports are even more concentrated in a few provinces. In 2012, 60.2% of the processing exports were from Guangdong, Shandong, and Jiangsu, and only 12.1% from the inland provinces.6

Figure 1.7 Export per capita in China at province level, 2018 (unit: US$/person)

Note: The data are from NBS (2019).

Figure 1.8 plots the GDP per capita against the ratios of exports to GDP at the province level in 2018. It suggests a positive correlation between exports and regional income. In particular, the coastal provinces are more actively participating in the globalization (reflected by larger export-to-GDP ratios) and have higher incomes than the inland provinces. This raises the question whether and how exports contributed to regional inequality, and whether processing exports and non-processing exports have exerted different effects on the regional disparity. China’s high regional inequality makes the questions even more significant (Xie and Zhou, 2014). The analysis in this

5 The data are from NBS (2019). The other coastal provinces are Fujian (FJ), Guangxi (GX), Hebei (HB), Hainan (HN), Liaoning (LN), Shanghai (SH), Shandong (SD), and Tianjin (TJ). The inland provinces include Anhui (AH), Beijing (BJ), Chongqing (CQ), Gansu (GS), Guizhou (GZ), Henan (HA), Hubei (HB), Heilongjiang (HL), Hunan (HN), Inner Mongolia (IM), Jilin (JL), Jiangxi (JX), Ningxia (NX), Qinghai (QH), Sichuan (SC), Shaanxi (SN), Shanxi (SX), Xinjiang (XJ), Xizang (XZ), and Yunnan (YN). The letters in parentheses give the abbreviation for each province, which are used as province labels in Figure 1.8. The abbreviations for Guangdong, Jiangsu, and Zhejiang are respectively GD, JS, and ZJ.

6 The data are from China’s Customs.
thesis follows a value chain perspective. This allows us to take full consideration of the indirect income effects of the coastal exports on the inland regions, which occurs when the inland regions provide materials and components to the export production in the coastal regions.

Figure 1.8 China’s regional exports and GDP per capita in 2018

Note: The data (for exports, GDP and population) are from NBS (2019).

1.3 Outline of the thesis

This thesis aims to investigate the effects of exports in China’s economy by taking full consideration of the three typical characteristics of China’s international trade and their dynamics. In doing so, it attempts to contribute both methodologically and empirically.

Chapter 2 deals with Vertical Specialization (VS). With the falling trade and communication cost, production processes have been sliced up into many sequential stages often located in many countries with each country specializing in particular stages. This process is known as vertical specialization in trade as proposed by Hummels et al. (2001). Countries rely on imports of intermediate goods to produce exports. As a result, the gross exports of a country do not necessarily reflect economic
growth. This is because only the domestic value added (and not the imports, which is foreign value added) that is embodied in the exports contributes to its GDP.

Hummels et al. (2001) proposed to measure the extent of vertical specialization by the VS share which calculates the average imports embodied in one dollar of exports. A larger VS share implies more dependence of a country’s exports on imported inputs and a smaller DVA share in the exports. Along with the falling trade cost, the world economy became more and more interconnected across countries. As a result, most of the countries experience increasing VS shares over time. However, as an exception, China has seen a decrease in the VS share since 2005. It is important to know why this happened because different answers have different policy implications. The first possible cause is the decreasing share of processing exports in China, which lowers the overall dependence of export production on imported inputs. If this is the case, the decreasing VS shares suggest that the “world’s factory” is moving out of China, in the sense of a shift from import-intensive processing exports to ordinary exports that depend more on domestic inputs. Changes in the input structure are another possible cause for the decreasing VS shares: the production of exports has become less dependent on imports and relies, instead, more on domestic inputs. In this case, decreasing VS shares suggest that China’s role in international fragmentation has been upgraded. This would change the perception that China always resides at the lower end of the global production chain and obtain limited DVA from its exports (Koopman et al., 2012).

Chapter 2 provides annual measurements of China’s VS share during the period 2000-2012. The calculations are based on special input-output (IO) tables that distinguish processing trade from other production. A structural decomposition analysis (SDA) approach is applied to further investigate the major drivers of the VS share changes from 2002 to 2012. For this, I develop a new decomposition, which decomposes the VS share change into 14 components and separates the contribution of the different production types. It distinguishes substitution: between primary and intermediate inputs; between domestically supplied and imported inputs; and between inputs provided by Domestic Enterprises (DEs) and by FIEs. The decomposition provides a much more detailed anatomy of the changes in China’s input structure. The substitution of imported intermediates with domestically produced intermediates was
the main driver for China’s declining VS share. The findings suggest an upgrade of China’s role in the global production network instead of moving the “world’s factory” out of China.

Chapter 3 investigates the NI content in Chinese exports and its dynamics from 2002 to 2012. Different from value added, which accrues to the country where the production factors are employed, NI accrues to the country of which the owners of these production factors are citizens. Given the large share of FIEs in Chinese gross exports, a portion of DVA embodied in exports is owned by foreigners and not part of China’s NI. As shown in Chapter 2, the DVA share in China’s exports has increased quickly since the turn of the millennium. Meanwhile, inward FDI also has undergone a substantial increase during this period. The dynamics of DVA shares and of FDI activities call for a longitudinal analysis of NI contained in Chinese exports. This issue is significant given the fact that NI is more relevant for welfare than DVA.

The chapter splits the DVA by ownership of production factors. By adopting the special IO tables that distinguish the production of processing exports from other production, it quantifies the NI as well as the foreign income generated by China’s exports in 2002, 2007, and 2012. After that, an SDA is applied to explore the underlying drivers behind the changes of the NI share in China’s exports. This share increased only slightly from 2002 and 2007, from which it is concluded that the considerable rise in the DVA share in exports mainly accrued to NIs abroad. From 2007 to 2012, however, the dynamics of NI and DVA in exports show a completely different pattern: the increased DVA share in exports mainly accrued to China and increased its NI. Further decompositions show that this difference is mainly due to changes of the capital income share in value added, which remarkably rose before the crisis but substantially dropped after the crisis.

Chapter 4 constructs new interregional input-output tables for China, which explicitly differentiate the production of processing exports from other production at the regional level. These are the IRIOP tables. Processing exports comprised a large part of China’s exports, with an extremely uneven distribution over the domestic regions. Processing exports heavily rely on imported materials and only generate limited domestic activities compared with other production. The literature proves that studies failing to separate processing exports from other production will bias the results.
For example, the contribution of China’s exports to economic growth is inflated (Chen et al., 2012; Pei et al., 2012), the damage of international trade to China’s environment is overestimated (Dietzenbacher et al., 2012), and China’s VS share is underestimated (Yang et al., 2015). We expect that the traditional studies on China’s regional growth give misleading conclusions because they use data that fail to separate processing exports. To properly answer this question, we must construct interregional input-output (IRIO) tables that differentiate the production of processing exports from other production.

These tables are termed IRIOP tables. They are constructed in Chapter 4 for 2002, 2007, and 2012, and they have 17 sectors and eight regions. The availability of consistent and reliable data is often regarded as a major barrier to construct a new IO table (Peters et al., 2011). For IRIOP tables, four types of data sources are used: the national IO tables that distinguish production of processing exports from other production at national level (NIOP tables); the traditional IRIO tables; international trade statistics; and the Regional Economic Accounts (REA). However, these data sources conflict with each other. The inconsistencies between the data sources are solved on the basis of certain principles (such as giving the highest priority to the most accurate trade statistics and to the official regional account statistics, and choosing less detailed industry classification in the available IO tables to avoid making additional assumptions to split some industries). After that, I construct the tables step by step by using a semi-survey method, based on a combination of survey data, proportionality assumptions, and RAS procedures. The chapter explicitly describes the data processing, the underlying construction principles and the construction methodology step by step.

Empirically, I investigate whether separating the production of processing exports from ordinary production matters when studying the contribution of exports to regional value added. I compare the empirical results computed with the new tables with the results obtained from the traditional interregional IO tables (which do not single out

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7 Under these principles, when data conflict, we give the highest priority to data from China’s Customs and to the REA. The IRIOP tables are compiled on the basis of the NIOP tables and the traditional IRIO tables. We use the NIOP tables as a benchmark and distribute the two types of production (production of processing exports and other production) over the different regions to construct the IRIOP tables. Note that the industry classifications in the NIOP tables and the traditional IRIO tables are different. The former include 42 industries, while the latter include 17 industries. We have aggregated the 42 industries in the NIOP tables to match the 17 IRIO industries. By doing this, we avoid having to make additional assumptions to disaggregate some of the IRIO industries to match the NIOP industries.
processing trade). I find that the contribution of regional exports to China’s GDP is significantly overestimated if processing trade is not properly included in the models.

Chapter 5 proposes and implements an accounting framework based on value chains to quantify the contributions of exports to interregional labor income inequality. A distinction is again made between processing exports and ordinary exports, and the new IRIOP tables of Chapter 4 were used. The method fully accounts for a region’s indirect exports, which arise through the provision of materials, components, and services to export production activities in other regions.

China’s economy faces a serious regional inequality with the coastal regions growing much more than the inland regions. The unequal income distribution is not only an important economic phenomenon but also a political challenge. The Chinese government attaches much importance to reduce regional inequality. At the 19th National Congress of the Communist Party of China, President Xi stated that “There are still large disparities in development between rural and urban areas, between regions, and in income distribution”. He emphasized that “we will strengthen measures to reach a new stage in the large-scale development of the western region; deepen reform to accelerate the revitalization of old industrial bases in the northeast and other parts of the country; help the central region rise by tapping into local strengths; and support the eastern region in taking the lead in pursuing optimal development through innovation. To this end, we need to put in place new, effective mechanisms to ensure the coordinated development of different regions.” 8 Therefore, investigating the relation of globalization and regional inequality is significant for China’s future sustainable development and has important policy implications.

Empirically, I find that processing exports contribute little, but the DVA embodied in processing exports is unequally distributed among regions. Rather, ordinary exports predominantly contribute to China’s regional inequality. The substantial decline of regional inequality in the period 2002-2012 was not due to changes in exporting activities. Even though the DVA embodied in exports (both processing and ordinary) was distributed more evenly over the regions, the growth in exports still had an inequality-increasing effect. The increased levels of domestic final demands and the changes in ordinary production—which become more domestically fragmented, with

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the inland regions increasingly involved—are the main reasons for the declining regional inequality. In this regard, the outcomes are in line with China’s recent policy of stimulating domestic demand to decrease regional inequality.

Chapter 6 summarizes the main findings of this thesis and discusses its limitations.
CHAPTER 2
Why Has China’s Vertical Specialization Declined?  

2.1 Introduction

Recent economic globalization is characterized by international fragmentation. This has led to the rapid growth of trade in components and parts (Yi, 2003). To measure a country’s involvement in international fragmentation, Hummels et al. (2001, hereafter HIY) proposed the concept of “vertical specialization” (VS), which is defined as the imports embodied in one unit of exports. The VS share is an important indicator to measure the structural interdependence of the world economy (Amador and Cabral, 2009). A larger VS share implies more in-depth involvement in international fragmentation, that is, a higher dependence of a country on imported inputs for its export production. From another perspective a higher VS share implies less domestic value added (DVA) is generated by the exports. The VS share thus reflects how much a country ‘earns’ on its exports, and its changes therefore indicates a country’s economic development pattern. A large body of literature has found that in past decades the VS share has increased not only for the world’s average but also in most of the developed countries. These include the United States, Germany (Hummels et al., 2001), the United Kingdom, Canada, France, Australia (Chen et al., 2005), and South Korea (Chen and Chang, 2006).  

China, as one of the most important engines for the recent trade boom, has become a popular object of study for international economists. As a consequence, China’s VS share has been thoroughly measured. The literature (e.g., Ping, 2005; Hwang et al., 2011)

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1 This chapter was originally published in Economic Systems Research, vol. 30, pp. 178-200, 2018. (Jointly written with Erik Dietzenbacher, Xuewei Jiang, Xikang Chen, and Cuihong Yang).
2 In contrast, Chen et al. (2005) found that the VS share of Japan and Denmark has declined for the period from 1985 to 1995. In general, there is strong support for the increase in VS in the last decades. Amador and Cabral (2009) observed a strong increase of VS activities in the world’s main areas from 1967-2005. Using the WIOD data, Johnson (2014) reported that the ratio of DVA to exports decreased from 1995 to 2008 for 18 of the top 20 exporting countries, implying increasing VS shares. Los et al. (2015a) found that the share of foreign value added (i.e., from outside the country-of-completion) in almost all final goods has increased since 1995, implying an increase in global fragmentation.
documents that prior to 2005, China’s VS share rose sharply. Ping (2005) showed that it soared from 14% in 1992 to 22% in 2002, an increase that had previously taken most OECD countries about 20 years to achieve. An important reason for this sharp increase was that China’s trade became dominated by processing trade, which was triggered by a very biased policy.¹ For example, materials imported into China were exempted from tariffs if they were used for processing trade. This policy led to an increase of imported intermediate inputs in the production of processing exports rather than in other types of production, including the production of ordinary exports (Yang et al., 2015). However, standard input-output (IO) tables do not reflect the appropriate role of processing trade, and surprisingly low levels of VS have thus been reported. Therefore, special IO tables have been constructed that separate processing exports from other exports (Dean et al., 2011; Yang et al., 2015). Using these special tables revealed much higher levels of VS.

After decades of rapid trade growth, the policy regarding processing trade changed in the mid-2000s. In 2006, the Ministry of Commerce designated several commodities groups for which processing trade became prohibited or restricted.² Meanwhile, China’s minimum wage policy reform in 2004 has effectively increased China’s labor costs.³ This has caused some multinational enterprises, which use labor costs as an important determinant of their location, to move their processing and assembly operations to countries where labor is cheaper than in China. As a result, the share of processing exports in total exports declined from 55.3% in 2002 to 34.1% in 2016.⁴ This decrease in the share of processing exports suggests an overall decline in the VS share.⁵ We ask, however, whether or not other causes have also played a role.

¹ Processing trade refers to the business activity of importing all, or part of, the raw and auxiliary materials, parts and components, accessories, and packaging materials from abroad in bond, and re-exporting the finished products after processing or assembly by enterprises within mainland China. Processing trade in this thesis includes two types. (1) Processing with Imported Materials (PIM): business enterprises in China make a foreign exchange payment for imported raw and auxiliary materials, parts and components, accessories, and they export the finished products after processing or assembly. (2) Processing & Assembling (P&A): business enterprises do not make a foreign exchange payment for the imports, but just charge the foreign party a processing fee.
² In 2015, processing exports were prohibited for 1862 commodities, accounting for 14% of all commodities at ten-digit Harmonized System codes (Announcement No. 59 of 2015 of the Ministry of Commerce, PRC; see: http://www.mofcom.gov.cn/article/b/c/201501/201501006635077.shtml). HKTDC (2007) reports that China’s processing trade policy changes reduced the processing trade of products with low pollution, high energy and resource consumption.
³ Minimum wages were first introduced in China in 1993. They really took effect, however, only after 2004 when the minimum-wage coverage was extended to migrant workers and the penalties in case of violation were dramatically increased. Each province, municipality, autonomous region, and even district sets its own minimum wage according to both local conditions and national guidelines (Mayneris et al., 2014).
⁴ The data are from the China’s National Bureau of Statistics.
⁵ Koopman et al. (2012) and Yang et al. (2015), report that China’s VS share declined from 2002 to 2007, but they fail to explain why this happened. The focus of their work was to propose new VS share measurements based on the
This question is important because different answers have different policy implications. If the decline in the share of processing exports is the main driver, the decreasing VS shares suggest that the “world’s factory” is moving out of China. On the other hand, the decreasing VS shares may have been caused by changes in the input structure. The production of exports has become less dependent on imports and relies, instead, more on domestic inputs. In this case, decreasing VS shares suggest that China’s role in the global value chains (GVCs) has been upgraded. This would change the perception that China will always reside at the lower end of the global production chain and obtain limited DVA from its exports (Koopman et al., 2012).

This chapter first provides annual measurements of China’s VS share during the period 2000-2012, based on the special IO tables that distinguish processing trade from other production. Next, we apply a structural decomposition analysis (SDA) to investigate the major drivers of the changes in China’s VS share from 2002 to 2012. To this end, a new decomposition is developed. It decomposes the VS share change into 14 components. The new decomposition measures the contribution of the three different production types separately and splits changes in their production technologies into smaller components. It distinguishes substitution: between primary and intermediate inputs; between domestically supplied and imported inputs; and between inputs provided by Domestic Enterprises (DEs) and by Foreign Invested Enterprises (FIEs). Compared with existing decompositions (Pei et al., 2012), our decomposition provides a much more detailed anatomy of the changes in China’s input structure.

We find that since 2005, China’s VS share has reversed its upward trend and declined steadily. The decomposition results show that the main driver is changes in the input structure, especially the substitution of imported intermediates by domestically produced intermediates. This implies that China’s declining VS share is to a large extent the result of the upgrading of China’s production all along the GVCs. However, simultaneous changes in the composition of the export bundle have increased China’s VS share from 2002 to 2007. This is surprising because the share of processing exports, which depend more on imports than nonprocessing exports, has declined dramatically.

IO tables that distinguish the production of processing exports from other production. Using these tables, Chen et al. (2012) documented that the DVA content in China’s exports increased for 2002-2007. Kee and Tang (2016) did so for 2000-2007, using firm- and customs transaction-level data. This implies that the counterpart of the share of DVA (i.e., the VS share) declined.
in this period. It appears that this is due to the change in the commodity composition of the exports toward capital-intensive products. After the 2008 global financial crisis, changes in the commodity composition of exports have decreased the VS share from 2007 to 2012.

2.2 Measurement of the VS share

2.2.1 Overview

The empirical literature suggests a range of different methods to quantify the degree of VS. In summary, the main approaches can be classified into two types: one using international trade statistics, the other employing IO tables. When using international trade statistics, one of the widely accepted methods is to measure the components or materials that are imported (or exported) to be processed and then re-exported (re-imported) again (Swenson, 2005; Helg and Tajoli, 2005). Also purchased goods by multi-national enterprises from foreign affiliate (Lawrence, 1994; Slaughter, 1995) and the measurement of trade in intermediate goods, parts, and components (Yeats, 1998) have been frequently used. The advantage of these methods is that they rely only on international trade statistics, implying high accessibility of the data and comparability across countries. On the other hand, however, these methods do not provide accurate measurements of VS. The first two methods undervalue the degree of VS, as they cannot capture VS activities beyond pure, direct (i.e., without any intermediate steps) processing trade or outsourcing, and the third method relies too heavily on the product classification (Amador and Cabral, 2009).

Compared with the approaches based on international trade statistics, approaches using IO tables reflect the complex relationships among industries and thus provide an appropriate tool for quantifying the degree of VS. A key advantage of using IO tables is that the arbitrariness of dividing goods into ‘intermediate’ goods and ‘final’ goods is avoided (Amador and Cabral, 2009). Besides, IO tables also allow us to derive the VS of a single sector (Hummels et al., 2001). Based on IO data, some literature directly uses the intermediate imports to obtain the degree of VS. For example, Feenstra and Hanson (1996, 1999) use the share of imported intermediate inputs in an industry’s total
non-energy input purchases to measure the outsourcing level. However, this method cannot distinguish whether the intermediate imports are used for domestic production or for producing exports, which will affect the measurement of the VS.

By now, the most popular approach to measure the VS based on IO tables is the HIY method proposed by Hummels et al. (2001). It measures the value of the total imports necessary to produce one unit (e.g., a dollar) of exports. The HIY method has been extended into two directions. The first is the extension from using national input-output (NIO) tables to the multi-country input-output (MRIO) tables. Koopman et al. (2014) measure the VS by separately calculating the foreign value added in the intermediate goods exports of a country, in the final goods exports of this country, and in the double counted terms.6 The second extension was developed because the HIY method gave very biased estimates for China’s VS share due to the prevalence of processing exports (Dean et al., 2011; Koopman et al., 2012; Yang et al., 2015). For example, Yang et al. (2015) constructed the tripartite IO table that distinguishes between: production for domestic use; production of processing exports; and production of nonprocessing exports and other production of FIEs. They showed that adapting the HIY approach for the tripartite IO table offers more accurate estimates for China’s VS share than applying HIY to the standard IO table. Therefore, this chapter will adopt the tripartite IO tables. As a robustness check, we will also apply the original HIY approach to standard NIO tables, and apply the method in Koopman et al. (2014) to MRIO tables.

2.2.2 The traditional HIY method

The traditional HIY method is applied to a standard NIO table with \( n \) industries. The \( n \times n \) matrix \( A \) gives the domestic input coefficients, with element \( a_{ij} \) indicating the output from industry \( i \) that is used as intermediate input by industry \( j \) per unit of its output. The matrix with import coefficients is given by \( A^M \) and its element \( a_{ij}^M \) denotes the imports of good \( i \) used as intermediate input by industry \( j \) per unit of its output. Here, \( \mathbf{e} \) is the column vector of industry exports. Let \( \mathbf{u} \) denote the

---

6 “Double-counted terms” in Koopman et al. (2014) refers to the trade value that is accounted by customs more than once due to multiple border crossing of intermediate goods.
summation vector, i.e., \( \mathbf{u} = (1, ..., 1)' \), where a prime is used to indicate transposition of a vector or matrix. Then, according to Hummels et al. (2001), the direct VS share for total exports is formulated as:

\[
d_{VS} = \frac{\mathbf{u}' \mathbf{A} \mathbf{e}}{\mathbf{u}' \mathbf{e}}. \tag{2.1}
\]

However, export production requires not only imported inputs (i.e., the direct effect), but also domestic inputs, whose production requires imported inputs (i.e., the indirect effects). The total amount of imports that are necessary to produce the vector of exports includes both the directly and the indirectly imported inputs. It is measured by employing the Leontief inverse \( \mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} \), where \( \mathbf{I} \) is the identity matrix of appropriate dimension. The total VS share for exports is given by:

\[
v_{VS} = \frac{\mathbf{u}' \mathbf{A} \mathbf{L} \mathbf{e}}{\mathbf{u}' \mathbf{e}}. \tag{2.2}
\]

Deducting the direct VS share from the total VS share yields the indirect VS share, which reflects the imports indirectly required for the exports. Throughout the rest of this chapter, the term VS share will indicate the total VS share.

### 2.2.3 The tripartite method

Before we outline the method of Yang et al. (2015), we provide a brief description of China’s tripartite IO table. The tripartite table is an extension of the standard NIO table where production is divided into the following three types. Production of DEs to satisfy domestic demand (indicated by D), production for processing exports (indicated by P), and the combination of production for nonprocessing exports and production of FIEs to meet domestic needs (indicated by N). The form of the tripartite table is shown in Table 2.1.
Table 2.1 The schematic outline of China’s tripartite input-output table

<table>
<thead>
<tr>
<th></th>
<th>Intermediate use</th>
<th>Final use</th>
<th>TOT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( D )</td>
<td>( P )</td>
<td>( N )</td>
</tr>
<tr>
<td>( D )</td>
<td>( Z^{DD} )</td>
<td>( Z^{DP} )</td>
<td>( Z^{DN} )</td>
</tr>
<tr>
<td>( P )</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( N )</td>
<td>( Z^{ND} )</td>
<td>( Z^{NP} )</td>
<td>( Z^{NN} )</td>
</tr>
<tr>
<td>( IMP )</td>
<td>( Z^{MD} )</td>
<td>( Z^{MP} )</td>
<td>( Z^{MN} )</td>
</tr>
<tr>
<td>( VA )</td>
<td>( (v^D)' )</td>
<td>( (v^P)' )</td>
<td>( (v^N)' )</td>
</tr>
<tr>
<td>( TOT )</td>
<td>( (x^D)' )</td>
<td>( (x^P)' )</td>
<td>( (x^N)' )</td>
</tr>
</tbody>
</table>

Notes: \( D \) = production by domestic enterprises (DEs) for domestic use only; \( P \) = production of processing exports; \( N \) = production of non-processing exports and production of FIEs to meet domestic demand; \( DFD \) = domestic final demands; \( EXP \) = exports; \( TOT \) = gross industry outputs (and total imports in the row \( IMP \)); \( IMP \) = imports; and \( VA \) = value added. The IO table is expressed in monetary units. \( Z^{ij} \) indicates the intermediate deliveries from each sector in production type \( S = (D, N) \) to each sector in production type \( T = (D, P, N) \). \( v^T \) gives the value added of each sector in production type \( T \), while \( x^T \) gives the output of each sector in production type \( T \). Finally, \( f^T \) gives each sector’s products in production type \( T \) used for domestic final demand purposes.

The domestic input matrix and the Leontief inverse now become partitioned 3\(n\) \times 3\(n\) matrices:

\[
A = \begin{pmatrix}
A^{DD} & A^{DP} & A^{DN} \\
A^{ND} & A^{NP} & A^{NN}
\end{pmatrix}
\quad \text{and} \quad
L = (I - A)^{-1} = \begin{pmatrix}
L^{DD} & L^{DP} & L^{DN} \\
L^{ND} & L^{NP} & L^{NN}
\end{pmatrix},
\]

where, for example, element \( a^{DP}_{ij} \) (of \( A^{DP} \)) indicates the output from industry \( i \) of \( D \) that is used as intermediate input in the industry \( j \) that produces \( P \) (per unit of its output). Notice that products of \( P \) are never used for domestic use by definition, and, therefore, the partitions of their intermediate use are zero (i.e., \( A^{PD} = A^{PP} = A^{PN} = 0 \)). The import matrix and export vector become \( A^M = (A^{MD} \ A^{MP} \ A^{MN}) \) and \( e = \begin{pmatrix}
e^P \\
e^N
\end{pmatrix} \),

where, for example, \( A^{MP} \) indicates the import coefficients of the production of \( P \). \( e^P \) and \( e^N \) are the vectors of processing exports and of nonprocessing exports. Note that \( e^D = 0 \) because products of \( D \) are only for domestic use. In the same fashion, we have in the tripartite table that \( f^P = 0 \) because \( P \) producers are only allowed to produce exports and do not deliver anything domestically.

Then according to Yang et al. (2015), the direct VS share and the total VS share in the tripartite table can be formulated as:

\[
d_{VS} = \frac{u'A^M e}{u'e} = \frac{u'AMPe + u'AMNe^N}{u'e^P + u'e^N}, \quad (2.3)
\]
\[ v_S = \frac{u'\Delta L e}{u'e} = \frac{u'A^M_D L^D P^e + L^{D^N} e^N + u'A^M_P e^P + u'A^M_N (L^{N^P} e^P + L^{N^N} e^N)}{u'e^P + u'e^N} \] (2.4)

Furthermore, by using counterfactual cases, one can also calculate the VS share for processing and nonprocessing exports separately. For example, if all the nonprocessing exports \( e^N \) are set to zero, then Equation 2.4 yields the VS share of processing exports.

Note that the only difference between the traditional HIY method and the tripartite method is that they are implemented with different IO tables. However, this difference can result in great gaps in the estimates of the VS shares. Yang et al. (2015) found that estimates of the VS share based on the tripartite method were almost 50% larger than those from the HIY method.\(^7\)

### 2.3 Estimation of China’s annual VS shares

In this section, we calculate China’s VS shares by applying the tripartite method. However, currently there are only three tripartite tables available. They are for the benchmark years 2002, 2007 and 2012 and were jointly compiled by China’s National Bureau of Statistics (NBS) and the Chinese Academy of Sciences (CAS).\(^8\) Equation 2.4 yields the VS shares, which are 44.9% in 2002, 40.9% in 2007, and 33.1% in 2012.\(^9\)

---

\(^7\) Yang et al. (2015) compared the VS shares between the traditional HIY method (applied to the aggregated tripartite tables) and the tripartite method. They also showed that the traditional HIY results are equivalent to a weighted average of the VS shares of the three types of production in the tripartite table, weighted by their output shares (instead of their export shares). As domestic production has a very large share in gross output, its low import dependence then leads to the underestimation of the VS share when the traditional HIY method is applied.

\(^8\) See Lau et al. (2010) and Chen et al. (2012) for compilation details. It is worth noting that in line with the System of National Accounts 2008, only the processing fees of P&A activities are included in the outputs and exports in the official NIO tables in and after 2007, while the imported materials (P&A imports) are not. However, in the tripartite tables all imports for processing exports are recorded as intermediate inputs of the processing industry, to reflect its underlying technology. Subtracting the P&A imports from the corresponding items in the tripartite table makes the table almost consistent with the official NIO table. The tripartite tables are different from the IO tables in Ma et al. (2015) and Jiang et al., (2015a,b), which distinguish four types of production: processing exports of DEs, other production of DEs, processing exports of FIEs, other production of FIEs. Since Ma et al. (2015) show that the VS share of exports of DEs within the same trade mode (e.g., processing trade, nonprocessing trade) is very close to that of FIEs. Therefore, our tripartite IO tables, which only separate the processing exports from other production, are enough to provide accurate estimates of VS share in China.

\(^9\) The results in 2002 and 2007 for all exports have also been reported in Yang et al. (2015). Also Koopman et al. (2012) used IO tables that singled out processing exports and found VS shares of 46.1% in 2002 and 39.4% in 2007. The differences between the findings of Koopman et al. (2012) and ours are due to the different methods of separating processing exports from other production. Our tripartite tables rely heavily on survey data, while the bipartite tables of Koopman et al. (2012) rely more on quadratic programming.
Although these results suggest a trend of declining VS shares, care should be taken because this conclusion is based on only three observations. It is possible that the VS share always fluctuated around the same value but still shows a decrease between 2002 and 2007 and between 2007 and 2012. A more detailed examination of the time pattern of China’s VS share requires a series of annual estimates.

To this end, we have roughly constructed the tripartite tables for non-benchmark years based on customs trade data, industrial statistics and the tripartite tables in benchmark years, and then calculate the VS shares by using Equation 2.4. However, due to space limit, the full estimation procedure for VS shares in non-benchmark years is given in Appendix 2.1. It is worth to note that due to a lack of data, we only estimate the VS shares of merchandise trade for non-benchmark years. Ignoring trade in services will not affect our findings very much for the following two reasons. First, Chinese trade is dominated by trade in merchandise, which accounts for about 90% of total trade value. Second, by definition, processing trade only exists in merchandise trade. For trade in services, it is therefore unnecessary to distinguish processing trade from nonprocessing trade.

Figure 2.1 presents our estimates of China’s VS shares based on the tripartite tables—indicated by “Tripartite estimates (excluding services)”—from 2000 to 2012. The estimates show that China’s VS share rose from 2001 to 2004, albeit slowly, with an average annual growth rate of 1.3%. It reached a peak of 52.0% in 2004 and then began to slide downwards, declining on average by 1.8% annually from 2005 to 2012.

In the benchmark years our tripartite estimates for merchandise exports (i.e., excluding services) are close to but slightly higher than the results for all exports (including services). As a comparison, we have also applied the HIY method to China’s standard NIO tables. These are derived by aggregating the three production types in the tripartite tables, which are available only for the benchmark years (HIY estimates). The HIY estimates (in Figure 2.1) are significantly lower than the tripartite estimates (including services). This outcome is fully consistent with the findings of Dean et al. (2011) and Yang et al. (2015) that using NIO tables leads to biased estimates for the VS share. In contrast to the tripartite estimates that show decreasing VS shares, the HIY estimates remained about constant between 2002 and 2012. This further indicates the importance of separating the processing exports from other production.
As a robustness check, we have estimated China’s VS shares by using the NIO tables and MRIO tables from the World Input-Output Databases (WIOD) and the OECD-TiVA database (WIOD estimates and OECD-TiVA tripartite estimates, respectively). Equation 2.2 has been applied to the NIO tables and the method in Koopman et al. (2014) to the MRIO tables.\textsuperscript{10} Except for covering different time periods, another significant difference between WIOD and OECD-TiVA is that the OECD-TiVA tables separate China’s production of processing exports from other production, whilst WIOD tables do not.\textsuperscript{11} For a clear comparison, we also re-estimate the VS shares by firstly aggregating the processing exports and nonprocessing production together in OECD-TiVA IO tables (OECD-TiVA aggregate estimates, hereafter).

The results in Figure 2.1 all indicate a decline of China’s VS share in recent years. The WIOD estimates are in line with the tripartite estimates and show that the VS share first increased gradually and slowly declined after 2006 (except for the additional dip in 2009).\textsuperscript{12} Both OECD-TiVA tripartite estimates and OECD-TiVA aggregate estimates show similar trends with WIOD estimates, although with fewer observations. However, the OECD-TiVA aggregate estimates are much lower than OECD-TiVA estimates. This further verified our results that the IO tables which fail to separate processing exports from other productions will seriously underestimate the China’s VS share. Still some other differences are observed between the levels of the VS shares for the various estimates. Though all tables (WIOD, OECD-TiVA, and tripartite) used the official NBS IO tables as underlying data, they have been adapted in a different way and therefore yield different results.

Figure 2.1 also shows that the MRIO estimates are always very similar but slightly lower than the NIO estimates from the same database. The possible reason is that compared with the NIO estimates, the MRIO estimates exclude the domestic content

\textsuperscript{10} Koopman et al. (2014) argue that for MRIO models the VS share of country $s$ can be calculated as $1 - (c_{s}^{T}\mathbf{B}_{s}s_{s}^{T})/(u^{T}e_{s}^{T})$, where $c_{s}$ is the row vector of value added coefficients of country $s$, $e_{s}$ is the column vector of exports in country $s$, $\mathbf{B}_{s}$ is the partition of the Leontief inverse $\mathbf{B} = (\mathbf{I} - \mathbf{A})^{-1}$ that corresponds to country $s$, where $\mathbf{A}$ is the world intermediate input coefficient matrix.

\textsuperscript{11} WIOD provides annual tables that cover the entire period 2000-2012 (Dietzenbacher et al., 2013) but the OECD-TiVA tables are (in this period) only available for 2000, 2005, and 2008-2011.

\textsuperscript{12} The dip may have been caused by the global financial crisis in 2008, which resulted in a collapse of global trade. As Bems et al. (2011) documented, the decline in demand during the crisis was the largest in sectors with a large vertical specialization. As a result, the VS share decreased rapidly in 2009 and recovered slightly in 2010. Johnson and Noguera (2016) found that the VAX ratio (i.e., the ratio of value added exports to gross exports) for China steadily increased from 2005 to 2010. Their result implies a steady decrease of foreign value added in China’s exports during this period, which is entirely in line with our tripartite estimates.
that returns to the source country. Nevertheless, both estimates show similar trends over time.

**Figure 2.1 Estimates of China’s VS shares from 2000 to 2012**

The continuous decline of VS shares in China is somewhat surprising. The deepening of international fragmentation implies that cross-border supply chains have become more prevalent and production has become more dependent on imported intermediates. It seems that in recent years China is an exception to the global tendency of countries participating more and more actively in globalization. In past decades, China’s low labor and land costs have generated large amounts of labor-intensive processing activities. As a result, China became the famous “world’s factory”. Parts and components were imported and re-exported again after very simple assembling or processing activities had been conducted. However, the declining VS share points to a change in this situation. To better understand the implications of the declining VS share, we will investigate the underlying drivers of this decrease in the next section.

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13 See Koopman et al. (2014) for details.
2.4 Decomposition of the VS share

Several factors are expected to have contributed to the decline of the VS share. On the one hand, Figure 2.1 shows similarities in the trends of the VS share and the processing exports share. This suggests that the decreasing share of processing exports (with large import dependence) may be the main driver of the decreasing VS shares. If so, the decreasing VS shares simply suggest that the “world’s factory” is moving out of China. On the other hand, the decreasing VS shares may be caused by changes in the input structure. The production of exports has become less dependent on imports and relies, instead, more on domestic inputs. In this case, decreasing VS shares suggest that China’s role in the GVCs has been upgraded. The tripartite IO table distinguishes three types of production: D (DEs production to satisfy domestic demand), P (production for processing exports), and N (production for nonprocessing exports and production of FIEs to meet domestic needs). It allows us to investigate how much each type of production contributed to the decline of China’s VS share. Answering this question not only provides insight into the pattern of China’s economic development, but also has important policy implications. This is because upgrading China’s role in the GVCs is an important target clearly indicated in the country’s ten-year national plan “Made in China 2025”.

To answer the question how much each type of production contributed to the decline of China’s VS share, we develop a new decomposition. It splits the change in the VS share into the contributions by each of its 14 drivers. The new decomposition allows us to capture the contribution to the VS share change of different production types as well as of substitutions among different inputs. The decomposition enables us to provide a detailed analysis of the pattern of China’s economic development.

2.4.1 A brief introduction to structural decomposition analysis

We start this subsection with a brief description of SDA, which has been widely used to break down the change in one variable into the changes of its independent determinants. Decompositions are not unique. In the case of $n$ independent determinants,
the number of equivalent decompositions is \( n! \). Because it is computationally burdensome to calculate all of the \( n! \) decompositions, several shortcuts have been proposed.\(^{14}\) Among them, Dietzenbacher and Los (1998) suggest using the average of the two so-called polar decompositions, and they show that this average provides a good approximation of the average of all \( n! \) decompositions.

The idea of two polar decompositions can be illustrated by using an SDA model with two determinants as an example. That is, \( y = Bf \), where \( B \) and \( f \) can change independently from each other. Subscripts 0 and 1 denote the beginning year and the end year. The change in \( y \) can then be ascribed to the changes in \( B \) and \( f \) as follows:

\[
\Delta y = B_1 f_1 - B_0 f_0 \\
= B_1 f_1 - B_1 f_0 + B_1 f_0 - B_0 f_0 = B_1 (\Delta f) + (\Delta B)f_0 \quad \text{(one polar)} \quad (2.5a) \\
= B_1 f_1 - B_0 f_1 + B_0 f_1 - B_0 f_0 = B_0 (\Delta f) + (\Delta B)f_1 \quad \text{(counter polar)} \quad (2.5b) \\
= 0.5(\Delta B)(f_0 + f_1) + 0.5(B_0 + B_1)(\Delta f). \quad \text{(average)} \quad (2.5c)
\]

Equations 2.5a and 2.5b are the polar decompositions using different weights, and Equation 2.5c takes the average of the two polar decompositions and provides the final result.

2.4.2 Overall decomposition of the changes in the VS share

To derive the decomposition formula for VS share, we start with Equation 2.4. Among the determinants are the matrices with import coefficients (\( A^M \)) and with domestic input coefficients (\( A \)). Although they are not fully dependent on each other, they are very closely related.\(^{15}\) First, intermediate inputs are determined by factors such as the level of primary inputs and the production technology. This holds for import and for domestic input coefficients. Second, there is sufficient evidence for the substitution of imported

\[^{14}\text{For example, Sun (1998) and Sun and Ang (2000) propose to split the interaction terms equally over the determinants. His approach yields exactly the same results as the average of the } n! \text{ different outcomes, which was proposed by Dietzenbacher and Los (1998).}\]

\[^{15}\text{According to Dietzenbacher and Los (2000), full dependency occurs if one determinant cannot change without corresponding changes in another determinant.}\]
and domestically produced intermediates (e.g., Kee and Tang, 2016). In order to solve this dependency problem, the input structure will be decomposed into four parts: substitution between primary and intermediate inputs (e.g., greater amounts of capital increased the efficiency of production, so that fewer intermediates are required per unit of output), substitution between intermediate inputs (e.g., replacing steel with plastic), substitution between imported and domestically produced intermediates, and substitution between domestically produced intermediates provided by DEs and by FIEs.

\[ A^T = A^{D*} + A^{N*} + A^M \] (with \( n \times 3n \) dimension) indicates the total input coefficients (i.e., the total amount of intermediate inputs required per unit of output, irrespective of their source), with \( A^{D*} = (A^{DD} \ A^{DP} \ A^{DN}) \) and \( A^{N*} = (A^{ND} \ A^{NP} \ A^{NN}) \) indicating the input coefficients of intermediates sourced from DEs and from FIEs. Note that production for processing exports does not deliver anything domestically. Further we define \( A^H = A^{D*} + A^{N*} \) (with \( n \times 3n \) dimension) for the aggregate domestic input coefficients.

We denote the value-added ratios by \( c_j \). Then, there is full dependency because

\[ u'A^T = u' - c'. \] (2.6)

The changes in \( c' \) reflect the substitution between primary inputs and intermediate inputs. Following Equation 2.6, we rewrite \( A^T \) as the product of its level and its structure:

\[ A^T = A^K(1 - \hat{c}), \] (2.7)

where \( A^K = A^T(1 - \hat{c})^{-1} \) is the matrix with normalized total intermediate input coefficients. They provide the mix of intermediate inputs in each industry. Changes in \( A^K \) therefore represent the inter-sector substitution between intermediate inputs.

To distinguish between imported and domestically produced intermediates, we introduce the \( n \times 3n \) matrix \( R \) with the share of imports in total intermediates. That is, \( r_{ij} = \alpha_{ij}^M/\alpha_{ij}^T \). We then have
\[ A^M = A^T \odot R, \]  
\[ (2.8) \]

where the Hadamard product \( \odot \) indicates cell-by-cell multiplication. The changes in \( R \) represent the substitution between imports and domestic intermediates. For example, an increase in the elements of \( R \) implies a substitution of domestically produced intermediates by imported intermediates. In the same way, we have the matrix with domestic input coefficients

\[ A^H = A^T - A^M = A^T \odot (U - R), \]  
\[ (2.9) \]

where \( U \) is a \( n \times 3n \) matrix with all elements equal to 1.

Domestic intermediates \( (A^H) \) are provided by DEs \( (A^{D*}) \) or by FIEs \( (A^{N*}) \). We define the \( n \times 3n \) matrix \( S \) as follows \( s_{ij} = a_{ij}^{D*}/a_{ij}^H \), which gives the shares of domestic intermediates that are provided by DEs. Combining with Equation 2.9, we have

\[ A^{D*} = A^H \odot S = A^T \odot (U - R) \odot S, \]  
\[ (2.10) \]

\[ A^{N*} = A^H - A^{D*} = A^T \odot (U - R) \odot (U - S). \]  
\[ (2.11) \]

The changes in \( S \) measure the substitution between intermediate inputs provided by DEs and FIEs. An increase in \( S \) indicates a substitution of FIE products with DE products. Together with \( R, S \) sheds further light on the substitution of imports and products of DEs and FIEs. For example, a simultaneous decline in \( R \) and \( S \) implies that FIE products, rather than DE products, have been substituted by imported intermediate inputs.

Substituting Equations 2.7, 2.8, 2.10, and 2.11 into Equation 2.4 yields

\[ v_S = u'(A^T \odot R) \left[ I - \begin{pmatrix} A^{D*} \\ 0 \\ A^{N*} \end{pmatrix} \right]^{-1} \bar{e} \]

\[ = u'[\begin{pmatrix} A^K(I - \hat{e}) \end{pmatrix} \odot R] \left[ I - \begin{pmatrix} [A^K(I - \hat{e})] \odot (U - R) \odot S \\ 0 \\ [A^K(I - \hat{e})] \odot (U - R) \odot (U - S) \end{pmatrix} \right]^{-1} \bar{e}, \]  
\[ (2.12) \]
where $\bar{e} = e / (u'e)$ gives the vector with the export structure. Equation 2.12 expresses the VS share as a function of five independent determinants. To summarize, changes in $A^K$ indicate the substitution among intermediate inputs, changes in $c$ represent the substitution between intermediate inputs and primary inputs, changes in $R$ represent the substitution between imported and domestically produced intermediates, and changes in $S$ indicate the substitution between intermediates provided by FIEs and DEs. These four components reflect changes in the input structure of production. Finally, changes in $\bar{e}$ are export composition changes.

2.4.3 Decomposing the VS share by production type

In order to examine how much each of the three production types ($D$, $P$, and $N$) contributes separately to the change in the VS share, we split Equation 2.12. For the $3n$-element vector $c'$ we have $c' = ((c^D)' (c^P)' (c^N)')$. Similarly, for the following $n \times 3n$ matrices we have $A^K = (A^{KD} A^{KP} A^{KN})$, $R = (R^D R^P R^N)$, and $S = (S^D S^P S^N)$. This yields for Equation 2.12,

$$[A^K (I - \bar{c})] \otimes R$$

$$= [A^{KD} (I - \bar{c}^D) \otimes R^D A^{KP} (I - \bar{c}^P) \otimes R^P A^{KN} (I - \bar{c}^N) \otimes R^N] \quad (2.13)$$

and

$$\begin{bmatrix} A^{D*} \\ A^{N*} \end{bmatrix} = \begin{bmatrix} \Omega^{DD} & \Omega^{DP} & \Omega^{DN} \\ 0 & 0 & 0 \\ \Omega^{ND} & \Omega^{NP} & \Omega^{NN} \end{bmatrix} \quad (2.14)$$

with, for example, $\Omega^{DP} = A^{KP} (I - \bar{c}^P) \otimes (U - R^P) \otimes S^P$ and $\Omega^{NP} = A^{KP} (I - \bar{c}^P) \otimes (U - R^P) \otimes (U - S^P)$.

We can now ascribe the change in the VS share into the contribution of the changes in 13 independent components. These are: the structure of intermediate inputs for each of the three production types ($A^{KD}$, $A^{KP}$, and $A^{KN}$), the value added ratios ($c^D$, $c^P$, and $c^N$), the shares of imported intermediates ($R^D$, $R^P$, and $R^N$), the shares of the domestic intermediates provided by DEs ($S^D$, $S^P$, and $S^N$), and the export structure ($\bar{e}$).
Note that our decomposition fails to disentangle the effect of changes in the export structure $\bar{e}$ by production type. Because the structure is defined in terms of export shares, $\bar{e}^p \equiv e^p / u'(e^p + e^N)$ and $\bar{e}^N \equiv e^N / u'(e^p + e^N)$ are highly dependent on each other, as $u'\bar{e}^p + u'\bar{e}^N = 1$. We define $t^p = u'\bar{e}^p$ as the share of all processing exports in total exports. The share of nonprocessing exports is then given by $1 - t^p$. We further define the commodity mix of processing exports as $q^p = \bar{e}^p / t^p$ and the commodity mix of nonprocessing exports as $q^N = \bar{e}^N / (1 - t^p)$. This implies that the export vector can be written as

$$\bar{e} = \begin{pmatrix} 0 \\ \bar{e}^p \\ \bar{e}^N \end{pmatrix} = \begin{pmatrix} 0 \\ t^p q^p \\ (1 - t^p) q^N \end{pmatrix}.$$  

We would like to split $\bar{e}$ into just two components: changes in the processing exports and changes in the nonprocessing exports. This implies that the change in $t^p$ must partly be ascribed to changes in processing exports and partly to changes in nonprocessing exports. If the change in $t^p$ is fully ascribed to changes in processing exports we have

$$\Delta \bar{e} = \left[ \begin{pmatrix} 0 \\ t^p q^p \\ (1 - t^p) q^N \end{pmatrix} - \begin{pmatrix} 0 \\ t^0 q^p_0 \\ (1 - t^0) q^N_0 \end{pmatrix} \right] + \left[ \begin{pmatrix} 0 \\ t^0 q^p_0 \\ (1 - t^0) q^N_0 \end{pmatrix} - \begin{pmatrix} 0 \\ t^0 q^p_0 \\ (1 - t^0) q^N_0 \end{pmatrix} \right]$$

(2.15a)

The first bracketed expression gives the changes in the processing exports and includes the change in $t^p$, the second bracketed term gives the changes in nonprocessing exports and covers only the changes in $q^N$. In the same fashion, including the change in $t^p$ in the changes in nonprocessing exports and leaving only the changes in $q^p$ for the changes in processing exports, yields
\[ \Delta \bar{e} = \left[ \left( \frac{0}{t_0^p q_0^p} \right) - \left( \frac{0}{t_0^p q_0^p} \right) \right] + \left[ \left( \frac{0}{t_1^p q_1^p} \right) - \left( \frac{0}{t_0^p q_1^p} \right) \right] \]  

(2.15b)

Note that Equations 2.15a and 2.15b are each a “polar” decomposition, their corresponding “mirror images” are given in Equations 2.15c and 2.15d below.

\[ \Delta \bar{e} = \left[ \left( \frac{0}{t_1^p q_1^p} \right) - \left( \frac{0}{t_0^p q_0^p} \right) \right] + \left[ \left( \frac{0}{t_1^p q_1^p} \right) - \left( \frac{0}{t_0^p q_1^p} \right) \right] \]  

(2.15c)

\[ \Delta \bar{e} = \left[ \left( \frac{0}{t_1^p q_1^p} \right) - \left( \frac{0}{t_0^p q_0^p} \right) \right] + \left[ \left( \frac{0}{t_1^p q_1^p} \right) - \left( \frac{0}{t_0^p q_1^p} \right) \right] \]  

(2.15d)

The change in processing exports, for example, is obtained as the average of the bracketed terms listed first in 2.15a – 2.15d.

Summarizing, it follows from Equations 2.12 and 2.5 that

\[ \Delta \nu_s = \frac{1}{2} u' [\Delta (A^M L)] (\bar{e}_0 + \bar{e}_1) + \frac{1}{2} u' (A^M_0 L_0 + A^M_1 L_1) (\Delta \bar{e}) \]  

(2.16)

when \( \Delta \bar{e} \) is split into two components (changes in processing exports and changes in nonprocessing exports) using Equations 2.15. \( \Delta (A^M L) \) is split into 12 components \( (A^{KD}, A^{KP}, A^{KN}, c^D, c^P, c^N, R^D, R^P, R^N, S^D, S^P, \text{ and } S^N) \) on the basis of Equations 2.13 and 2.14. Details of the decomposition of \( \Delta (A^M L) \) are given in Appendix 2.2 and Table 2.2 summarizes the components of the decomposition.

Adding the appropriate components gives us the total effect on the VS share of all of the changes related to each of the three production types. That is,

\[ E(D) = E(A^{KD}) + E(c^D) + E(R^D) + E(S^D) \]  

(2.17a)

\[ E(P) = E(A^{KP}) + E(c^P) + E(R^P) + E(S^P) + E(\bar{e}^P) \]  

(2.17b)
\[ E(\text{NP}) = E(\textbf{A}^{KN}) + E(\textbf{c}^N) + E(\textbf{R}^N) + E(\textbf{S}^N) + E(\textbf{e}^N) \]  

\[ (2.17c) \]

Table 2.2 Summary of the components in the structural decomposition analysis

<table>
<thead>
<tr>
<th>Effects</th>
<th>The change in VS share due to changes in:</th>
</tr>
</thead>
<tbody>
<tr>
<td>( E(\textbf{A}^{KD}), E(\textbf{A}^{KP}), E(\textbf{A}^{KN}) )</td>
<td>the structure of intermediate inputs in the production of ( D, P, N )</td>
</tr>
<tr>
<td>( E(\textbf{c}^D), E(\textbf{c}^P), E(\textbf{c}^N) )</td>
<td>the value added ratios for the production of ( D, P, N )</td>
</tr>
<tr>
<td>( E(\textbf{R}^D), E(\textbf{R}^P), E(\textbf{R}^N) )</td>
<td>the shares of imported intermediate inputs in total intermediate inputs for the production of ( D, P, N )</td>
</tr>
<tr>
<td>( E(\textbf{S}^D), E(\textbf{S}^P), E(\textbf{S}^N) )</td>
<td>the shares of domestic intermediate inputs that are provided by DEs in the production of ( D, P, N )</td>
</tr>
<tr>
<td>( E(\textbf{e}^P), E(\textbf{e}^N) )</td>
<td>the structures of processing and non-processing exports</td>
</tr>
</tbody>
</table>

Notes: \( D = \) production by DEs for domestic use only; \( P = \) production of processing exports; \( N = \) production of non-processing exports and production of FIEs to meet domestic demand.

2.5 Empirical results

2.5.1 The aggregate results

This section presents and discusses the results of decomposing the change of China’s VS share from 2002 to 2007 and from 2007 to 2012.\(^{16}\) The main reason we choose these two periods is that they are the most recent years for which full tripartite IO tables are available. Although we also derived tripartite IO tables for all non-benchmark years from 2000 to 2012, they cannot provide the full picture if used in an SDA because the estimation is rather crude due to lack of data. This decomposition also allows us to compare China’s trade development before and after the financial crisis. The tripartite tables for the three years include 42 sectors but the sector classifications differ slightly. In order to ensure a consistent sector classification, we aggregated the 42 sectors into 40 sectors (see Appendix 2.3). A final remark is that the decomposition of the VS share is based on current priced IO tables, because they are the only ones available.

\(^{16}\) Pei et al. (2012) also used the same tripartite tables in their SDA. However, they focus on the contribution of imports on China’s GDP growth. Also their decompositions are completely different from ours.
Nevertheless, Section 2.5.4 presents a robustness check of our SDA results using crudely estimated tripartite tables in constant prices.\footnote{Ideally, one would like to do the SDA with IO tables in constant prices. However, constructing an accurate constant price table requires considerable price information, for example, the price indexes for each transaction between producers as well as from producers to domestic or foreign consumers. Most of the price information is not available at sectoral level in China. Therefore, estimating tables in constant prices would introduce many new biases as the lack of data requires us to make assumptions, which are somewhat crude. Therefore, we present the current price based SDA results in the main section. Since all of the components in our decomposition are ratios, we expect that the price change effect is relatively small. Still, we also try our best to compile the constant price IO tables and treat the constant price based SDA results as robustness check in subsection 3.4.}

Table 2.3 provides the results for the 14 components listed earlier in Table 2.2. Table 2.3 also provides the aggregate results for the three types of production (i.e., taking the column sums) and for each factor (i.e., taking the row sums, which reflect a component’s contribution over the production types). All of the results are given as absolute changes (i.e., percentage point changes). The VS share decreased by 4.0 percent from 44.9% in 2002 to 40.9% in 2007 and by 7.8 percent from 2007 to 33.1% in 2012. However, the reasons for the decreases are different in the two periods.

<table>
<thead>
<tr>
<th>Component</th>
<th>2002 to 2007 (unit: %)</th>
<th></th>
<th>2007 to 2012 (unit: %)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A\textsuperscript{k}</td>
<td>0.3</td>
<td>0.3</td>
<td>0.9</td>
<td>1.5</td>
</tr>
<tr>
<td>c</td>
<td>1.0</td>
<td>-0.6</td>
<td>-1.2</td>
<td>-0.8</td>
</tr>
<tr>
<td>R</td>
<td>0.7</td>
<td>-4.5</td>
<td>-3.1</td>
<td>-6.9</td>
</tr>
<tr>
<td>S</td>
<td>0.3</td>
<td>-0.6</td>
<td>0.2</td>
<td>-0.1</td>
</tr>
<tr>
<td>\bar{e}</td>
<td>--</td>
<td>1.6</td>
<td>0.7</td>
<td>2.3</td>
</tr>
<tr>
<td>Sum</td>
<td>2.3</td>
<td>-3.8</td>
<td>-2.5</td>
<td>-4.0</td>
</tr>
</tbody>
</table>

Notes: D = production by DEs for domestic use only; P = production of processing exports; N= production of non-processing exports and production of FIEs to meet domestic demand; DEs = domestic enterprises; FIEs= foreign invested enterprises.

The results show how the VS share would have changed due to changes in a particular component, assuming all other components would have remained constant. For example, the second row (c) in Table 2.3 indicates that the changes in the value added ratios of production of P have decreased the VS share by 0.6 percent, which equals 15% of the total decrease in the VS share from 2002 to 2007. The changes in all value added ratios have contributed 20% to the decrease of the VS share (i.e., a decrease of 0.8 percent). The second column sum indicates that all changes in the production of
P have decreased the VS share from 2002 to 2007 by 3.8 percent.

With respect to the aggregate results for the factors, Table 2.3 shows that the changes in the import shares of intermediate inputs (\(R\)) played the most important role in the decline of the VS share in both periods. The substitution of imported intermediate inputs by domestically produced inputs has been the main driver of the VS share decline. The second important driver was the changes in the export structure (\(E\)), but the contributions to the VS share’s change had opposite signs before and after the crisis. The share of the import-intensive processing exports in total exports has declined substantially since 2002 (see Figure 2.1). One would therefore expect this to cause a decline in China’s VS share. However, the changes in export structure have significantly increased, rather than decreased, the VS share in China from 2002 to 2007. The consequence of this finding is that the mix of exported goods must have changed in favor of more import-intensive products. When we combine this information with the analysis in Section 2.3.2, the decomposition result indicates that the decreasing VS shares suggest an upgrade of China’s role in the GVCs, rather than the “world’s factory” moving out of China.

For the different production categories, changes in the production of \(P\) are the largest contributor to the decline of the VS share from 2002 to 2007. They are followed by changes in the production of \(N\), which became the largest contributor in the period 2007-2012. It should be noted that more than 80% of the processing exports in China were produced by FIEs and more than 75% of the output of \(N\) were domestic products produced by FIEs. As a consequence, FIEs played a significant role in the decline of China’s VS share. The reduction in the VS share brought about by them was partly offset by changes in the production of \(D\). The size of the effect (i.e., an increase in the VS share of 2.3% for 2002-2007 and 1.2% for 2007-2012) is remarkably large, given that the production of \(D\) is only indirectly involved in the exports.

### 2.5.2 Changes in the input structure

#### 2.5.2.1 A comparison of the input structures

All of the factors listed in Table 2.3, except the export structure, reflect changes in the
input structure of Chinese production. Figure 2.2 gives the aggregate input structures (i.e., all 40 industries have been aggregated into one) in 2002, 2007, and 2012 for each production type. These average input coefficients show how the direct deliveries among different production types have changed. For example, the production of 100 Rmb $N$ required in 2012, on average, 48.3 Rmb of inputs from products of $D$, 17.2 Rmb of inputs from products of $N$, 7.4 Rmb of imports, and generated 27.1 Rmb of value added.

**Figure 2.2. Aggregate input structure in 2002, 2007, and 2012 (unit: %)**

![Diagram showing input structure percentages for D, P, and N in 2002, 2007, and 2012.]

Notes: D = production by DEs for domestic use only; P = production of processing exports; $N$ = production of non-processing exports and production of FIEs to meet domestic demand; M = imports.

The Chinese input structure shows several characteristics. First, huge differences exist between the three production types. The value added ratio of $D$ is much higher than that of $N$, which in turn is larger than that of $P$. Second, when it comes to the use of imported inputs the opposite situation occurs. Production of $P$ has an extremely high dependence on imported intermediates, while production of $D$ and $N$ does not. This implies that production of $D$ and $N$ largely depends on domestically produced intermediate inputs, which are produced by DEs as shown by “From products of D” and by FIEs as shown by “From products of N”, as witnessed in Figure 2.2.

Looking at the input structure, several substantial changes have taken place over time. This particularly holds for the production of $P$ and $N$. Their input structures show large shifts from using imported intermediates toward using domestic intermediates in
both periods. However, the shift is more toward inputs produced by DEs in production of \( P \) and more to inputs produced by FIEs in production of \( N \). The share of inputs from DEs (i.e., from \( D \)) in production of \( P \) has increased rapidly from 3.3% in 2002 to 18.2% in 2007, and then fallen slightly to 16.8% in 2012. The share of inputs from FIEs (i.e., from \( N \)) in production of \( N \) has increased from 8.6% in 2002 to 12.9% in 2007 and then to 17.2% in 2012. In contrast, production of \( D \) shifted from using primary inputs to using intermediate inputs, especially intermediates provided by FIEs and imports.

### 2.5.2.2 Substitution of imported intermediates by domestically produced inputs

We have seen that changes in the shares of imported intermediates (\( R \)) are the main contributor to the decline of China’s VS share. If only \( R \) had changed as it actually did and everything else had remained constant, China’s VS share would have dropped by 6.9 percent from 2002 to 2007 and by 4.2 percent from 2007 to 2012. Imported intermediates have been substituted by domestic intermediates, which is the main driver of China’s declining VS share. This finding resonates with the conclusion of Kee and Tang (2016). Using firm-level data from 2000 to 2007, they find a within firm substitution of imported materials by domestically produced materials. As we see in Table 2.3 and Figure 2.2, the case is very clear for the production of \( P \) and \( N \), which led to a decrease in the VS share of \( 4.5 + 3.1 = 7.6 \) percent from 2002 to 2007 and of \( 1.1 + 4.1 = 5.2 \) percent from 2007 to 2012.

Then, another intriguing question is whether the imports are substituted by products of DEs or those of FIEs. Theories on international trade yield different outcomes and, depending on the reasoning, state that imported materials are substituted by products from FIEs or from DEs. On the one hand, according to Mundell (1957), foreign direct investment (FDI) is a substitute for imports. Certain products that were originally imported are now produced by FIEs in the host country. In this case, the substitution of imports by domestic intermediates is just a direct consequence of foreign producers shifting their plant locations (Pugel, 2012). On the other hand, substitution of imports by DEs’ products occurs when DEs improve their production technology and product quality. This may happen, for example, through technology spillovers from FDI.
or increased R&D investments (Wang, 2014; Liu, 2008).

The first line of reasoning hypothesizes that imports are substituted by domestic products of FIEs. The second line arrives at the substitution of imported intermediates with domestic products by DEs.

For production of $P$, Table 2.3 shows that the change in the shares of inputs provided by DEs in total domestic intermediates ($S$) has decreased the VS share by 0.6% from 2002 to 2007. Given the fact that production of $N$ typically depends more on imports than production of $D$, this decomposition result reveals that the imported intermediates are mainly substituted by DEs’ products in the production of $P$ from 2002 to 2007. In the period 2007 to 2012 the change in $S$ has increased the VS share by 0.1%. A similar line of reasoning suggests that imported intermediates have been mainly substituted with FIEs’ products (i.e., from $N$) from 2007 to 2012. For the production of $N$, the imports are mainly substituted by FIEs’ products in both periods. All of our findings are confirmed by Figure 2.2. Returning to the theories, the results for production of $P$ are in line with the upgrading of DEs’ products. The results for production of $N$ are in line with a larger role of FIEs in supplying intermediates on the domestic market. This stronger role of FIEs is also related to the FIEs’ market strategy, which shows a shift from exports to sales in China’s domestic market. Figures from the NBS state that the share of domestic sales in FIEs’ manufacturing output has increased from 58.6% in 2007 to 70.3% in 2015.

The tripartite tables also provide detailed sectoral input information for each production type, which allows us to further investigate which kind of imported inputs are substituted in export production. It shows that over the period 2002-2007, imported intermediates across all manufacturing products are partially substituted by products of DEs for the production of $P$. Manufacture imports except imports of Non-metallic mineral products (13), Metals smelting and pressing (14), Metal products (15), are partially substituted by products of DEs and FIEs in production of $N$ from 2002 to 2007. From 2007 to 2012, in export production, the substitution mainly focuses on the imports of Manufacture of food products and tobacco processing (6), Chemicals (12), Non-metallic mineral products (13), and Equipment and machinery (16-20), which are partially substituted by the intermediates provided by DEs as well as FIEs.

Overall, our decomposition shows that China’s decreasing VS share is largely a
combination of DEs’ product upgrading and expansions of FIEs in the domestic market. As Duan et al. (2012) documented, a large part of FIEs’ profits do not belong to national income. China should therefore focus particularly on improving the competitiveness of intermediates provided by DEs. Our results also imply an increase in the competitiveness of domestic products, which contributed significantly to China’s upgrading in the GVCs. As the existing literature shows, this may be highly related with China’s increasing Research and Development (R&D) investment (Wang, 2014), increasing human capital (Li et al., 2013), and the spillover effect of the FDI to DEs (Liu, 2008; Zhang, 2014).

2.5.3 The export structure

Changes in the export structure ($\bar{e}$) is the second most important factor impacting the VS share changes. They have increased China’s VS share with 2.3 percent from 2002 to 2007, but decreased it with 3.0 percent from 2007 to 2012 (see Table 2.3). At first glance, this result seems somewhat counterintuitive because the share of processing exports in total exports, which depend much more on imports than nonprocessing exports, had undergone a considerable decline in both periods. One would therefore have expected that changes in $\bar{e}$ have decreased the VS share. But, this is not what happened in the period 2002-2007. A logical consequence is that in this period import-intensive products must have gained additional weight in the bundle of exports. To test this, we further decompose $\bar{e}$ into the trade mode ($w$) and the commodity composition of the exports ($q$). The trade mode indicates the share of processing exports in the total exports of each good, while the commodity composition gives the share of the exports of a good (no matter whether processing exports or nonprocessing exports) in national aggregate exports. Then the SDA further allows us to distinguish the VS share changes due to the changes in trade mode from those due to the changes in the export commodity composition (see Appendix 2.4 for analytical details). Table 2.4 provides the results.

As anticipated, the change in trade mode (i.e., decline in the share of processing exports) decreased the VS share in both periods. This result is overpowering, however, by the effect of the changes in the commodity composition of the exports, which has
substantially increased the VS share from 2002 to 2007 and decreased the VS share from 2007 to 2012. Therefore, the export structure changes have increased VS share from 2002 to 2007 instead of reducing it.

Table 2.4 Contributions of changes in trade mode and in commodity composition to the change in VS share (unit: %)

<table>
<thead>
<tr>
<th></th>
<th>2002 to 2007</th>
<th>2007 to 2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trade mode</td>
<td>-2.6</td>
<td>-1.0</td>
</tr>
<tr>
<td>Commodity composition</td>
<td>4.9</td>
<td>-2.0</td>
</tr>
<tr>
<td>Total</td>
<td>2.3</td>
<td>-3.0</td>
</tr>
</tbody>
</table>

To provide more detailed insight into the changes, Table 2.5 gives the export shares, distinguishing between processing and nonprocessing exports, for the 10 largest exporting industries in China in 2002, 2007, and 2012. For example, the processing exports of Computers and other electronic equipment constituted 13.8% of all Chinese exports in 2002. A shift of exports from labor-intensive industries (industries 6-10) and services to capital-intensive industries is observed from 2002 to 2007. More specifically, the export share of Equipment and machinery (industries 16-20) has increased from 33.8% to 43.8% from 2002 to 2007. Since the labor-intensive industries and services usually have much lower VS shares than the capital-intensive industries (Yang et al., 2015), changes in the commodity composition eventually increased the import dependence of China’s exports from 2002 to 2007. Differently, in the period 2007 to 2012, China’s export share of services has substantially increased from 13.0% to 17.8%, which has decreased the VS share. All of these changes indicate an improvement of China’s export commodity composition to products with a higher value added ratio and more advanced technology.
Table 2.5 The export shares of the top 10 export industries (as % of total exports)

<table>
<thead>
<tr>
<th>Industry ID</th>
<th>2002</th>
<th></th>
<th>2007</th>
<th></th>
<th>2012</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P$</td>
<td>$NE$</td>
<td>$P$</td>
<td>$NE$</td>
<td>$P$</td>
<td>$NE$</td>
</tr>
<tr>
<td>Computers and other electronic equipment</td>
<td>13.8</td>
<td>2.3</td>
<td>20.9</td>
<td>2.8</td>
<td>18.9</td>
<td>2.9</td>
</tr>
<tr>
<td>Electric equipment and machinery</td>
<td>4.4</td>
<td>2.2</td>
<td>4.2</td>
<td>3.0</td>
<td>4.0</td>
<td>3.8</td>
</tr>
<tr>
<td>Instruments, meters, cultural and office machinery</td>
<td>4.4</td>
<td>0.4</td>
<td>3.2</td>
<td>0.7</td>
<td>0.7</td>
<td>0.6</td>
</tr>
<tr>
<td>Wearing apparel, leather, furs, and related products</td>
<td>4.2</td>
<td>4.8</td>
<td>2.0</td>
<td>4.2</td>
<td>1.8</td>
<td>6.1</td>
</tr>
<tr>
<td>Chemicals</td>
<td>2.8</td>
<td>4.2</td>
<td>2.7</td>
<td>4.7</td>
<td>2.3</td>
<td>5.2</td>
</tr>
<tr>
<td>Textile goods</td>
<td>2.5</td>
<td>6.3</td>
<td>1.4</td>
<td>6.9</td>
<td>0.6</td>
<td>3.3</td>
</tr>
<tr>
<td>Common and special equipment</td>
<td>1.6</td>
<td>2.6</td>
<td>1.9</td>
<td>3.9</td>
<td>2.9</td>
<td>4.9</td>
</tr>
<tr>
<td>Metal products</td>
<td>1.6</td>
<td>1.9</td>
<td>1.2</td>
<td>2.4</td>
<td>0.8</td>
<td>2.4</td>
</tr>
<tr>
<td>Transport equipment</td>
<td>1.1</td>
<td>1.1</td>
<td>1.4</td>
<td>1.9</td>
<td>2.3</td>
<td>2.3</td>
</tr>
<tr>
<td>Paper, printing and record medium reproduction</td>
<td>2.3</td>
<td>0.9</td>
<td>1.6</td>
<td>1.0</td>
<td>3.3</td>
<td>1.0</td>
</tr>
<tr>
<td>Labor-intensive industries (6-10)</td>
<td>8.4</td>
<td>14.4</td>
<td>4.6</td>
<td>14.2</td>
<td>3.2</td>
<td>13.3</td>
</tr>
<tr>
<td>Equipment and machinery (16-20)</td>
<td>25.2</td>
<td>8.6</td>
<td>31.6</td>
<td>12.2</td>
<td>28.9</td>
<td>14.2</td>
</tr>
<tr>
<td>Service (27-40)</td>
<td>-</td>
<td>21.2</td>
<td>-</td>
<td>13.0</td>
<td>-</td>
<td>17.8</td>
</tr>
<tr>
<td>All industries</td>
<td>48.1</td>
<td>51.9</td>
<td>45.7</td>
<td>54.3</td>
<td>39.5</td>
<td>60.5</td>
</tr>
</tbody>
</table>

Notes: $P = \text{processing exports}$; $NE = \text{non-processing exports}$. Here, the labor-intensive industries includes Manufacturing of food products and tobacco processing, Textile goods, Wearing apparel, leather, furs, and related products, Sawmills and furniture; The equipment and machinery includes Common and special equipment, Transport equipment, Electric equipment and machinery, Computers and other electronic equipment, Instruments, meters, cultural and office machinery.

2.5.4 A robustness check

In the analysis above we have decomposed the changes in the VS share using the tripartite tables in current prices. However, when making intertemporal comparisons, it is customary to deflate IO tables and compare transactions in constant prices. In this subsection we check the robustness of our decomposition results. We first transform the 2007 and 2012 Chinese tripartite tables into tables in 2002 prices and then redo the entire analysis. To estimate the IO tables in constant prices, we follow the research of
Pei et al. (2012) and use the so called double-deflation method.\textsuperscript{18} Applying the same decomposition procedure as before for the tripartite tables in current prices yields results for the constant priced tripartite tables listed in Table 2.6. It appears that the results are consistent with those in Table 2.3 with slight differences in the magnitudes.

| Table 2.6 The decomposition of China’s VS share on constant price IO tables (unit:%) |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
|                                 | 2002 to 2007    | 2007 to 2012    |
|                                 | D | P | N | sum | D | P | N | sum |
| $A^K$                           | 0.3 | 0.3 | 1.0 | 1.6 | 0.1 | -0.7 | -0.5 | -1.1 |
| c                               | 1.0 | -0.9 | -1.3 | -1.3 | 0.0 | 0.2 | 0.7 | 0.9 |
| R                               | 0.7 | -4.5 | -3.1 | -7.0 | 0.9 | -1.1 | -4.0 | -4.2 |
| S                               | 0.3 | -0.6 | 0.2 | -0.1 | 0.2 | 0.1 | 0.1 | 0.4 |
| $\bar{e}$                       | 0.0 | 1.8 | 0.8 | 2.6 | 0.0 | -0.6 | -2.4 | -3.0 |
| Sum                             | 2.3 | -3.9 | -2.5 | -4.1 | 1.2 | -2.1 | -6.1 | -7.0 |

Notes: $D =$ production by DEEs for domestic use only; $P =$ production of processing exports; $N =$ production of non-processing exports and production of FIEEs to meet domestic demand; DEEs = domestic enterprises; FIEEs = foreign invested enterprises.

2.6 Conclusion

This chapter presented the annual estimates for China’s vertical specialization (VS) share from 2000 to 2012 using the tripartite input-output (IO) tables. We found that China’s VS share changed its upward trend and declined steadily since 2005, implying a decreased dependence of China’s exports production on imports. To explore what might have caused such a decline of the VS share, we developed a new structural decomposition to quantify the contribution of the main factors to the overall change in China’s VS share. The decomposition allowed us to capture the contribution of different production types as well as the substitution among different inputs to the VS share change. We eventually decomposed the changes in China’s VS share between 2002 and

\textsuperscript{18} WIOD provides detailed price information at industry level for 40 countries including China. However, it only covers the period from 1995 to 2009 and the industry classification is very different from that in the tripartite tables. Instead, the output price from the NBS was used for the deflation. In details, price index for the agricultural sector is proxied by the producer price index (PPI) of agricultural products. The ex-factory price indexes from NBS for secondary industries are adopted to match the IO sector classification. Price index for construction is proxied by the price index of fixed capital investments. Similarly, the consumer price index of different categories is used to proxy the price index for the tertiary industries (all data are from NBS).
2007 and between 2007 and 2012 into the effects of 14 components.

We found that the substitution of imported intermediates with domestically produced intermediates was the main driver for China’s declining VS share. This substitution effect was observed for the production of processing exports and for the production of nonprocessing exports and the production of foreign invested enterprises to meet domestic demand. The findings suggest an upgrade of China’s role in the GVC instead of moving the “world’s factory” out of China, as suggested by the declining shares of processing exports in total exports. The results imply that improving the quality and competitiveness of domestic intermediates may be an efficient way to upgrade a country’s role in the GVC. To this end, more research & development inputs and FDI inflows to high-technology industries should be further encouraged.

Another interesting finding that has initially caused some surprise is that the changes in exports have increased China’s VS share in the period 2002 to 2007 but decreased it from 2007 to 2012. The share of processing exports, which is highly dependent on imports, has declined continuously since 2005. One would therefore have expected that the changes in the shares of processing exports in total exports would have decreased the VS share in both periods. The increase in the first period (2002 to 2007) was due to changes in the commodity composition of the exports. In the period 2002 to 2007, China changed to exporting more capital-intensive products, which depend more on imported intermediates. This indicates that also adjusting the commodity composition of the exports may be effective to move up the GVC.

China’s path is of interest to other developing countries (such as South Asian and Sub-Saharan African countries) that seek to increase their involvement in GVCs or achieve a higher position in the GVC. China’s development has been to first participate in GVCs by carrying out simple assembly and processing tasks (processing trade). The second step has been to actively move up the GVC by (i) increasing the domestic inputs in the production of exports, and (ii) adjusting the export commodity composition. This followed from learning-by-doing and the spillover effects of FDI inflows.
Appendix

Appendix 2.1

Estimation of VS Shares in non-benchmark years

This appendix describes the estimation procedure of the VS shares for non-benchmark years based on the tripartite tables.

Ideally, the tripartite tables should be completely updated for each non-benchmark year. However, it’s not practical due to data limitations. As we previously discussed, the VS share includes the direct VS share and the indirect VS share. The former is by far the dominant part, which accounts for 91% of the total VS share in 2002 (Yang et al., 2015). Accordingly, we will concentrate on updating the information that is necessary for calculating this direct VS share. That is, the vector with exports \( \mathbf{e} \) and the matrix with import coefficients \( \mathbf{A}^M \) (see Equation 2.3). The data processing is therefore focused on estimating \( \mathbf{e} \) and \( \mathbf{A}^M \) for non-benchmark years. After that, together with the domestic input coefficients \( \mathbf{A} \) in the benchmark years, the total VS shares will be calculated.

To this end, the statistics from China’s Customs are essential. These provide detailed annual trade data for both exports and imports. The data are not only by commodity (at the 8-digit level under the Harmonized Commodity Description and Coding System (HS)), but also by trade mode (e.g., processing trade, non-processing trade) and by firm type (e.g., DEs, FIEs). In addition, annual industry outputs \( \mathbf{x}^f \) of FIEs and \( \mathbf{x}^d \) of DEs are available from the NBS.

The updating process follows three steps. First, we estimate the outputs at industry level in the tripartite tables for each non-benchmark year. To this end, all annual trade data from the Customs are regrouped into the industry classification used by the NBS for IO tables. For the tripartite tables, this yields the vectors of processing exports \( \mathbf{e}^p \), non-processing exports \( \mathbf{e}^N \), processing imports \( \mathbf{m}^p \), non-processing imports, and exports of FIEs \( \mathbf{e}^f \).

The industry outputs are obtained as follows. By definition, \( \mathbf{e}^p \) is also the output of \( \mathbf{P} \), i.e., \( \mathbf{x}^p = \mathbf{e}^p \). The exports of DEs are obtained by subtracting \( \mathbf{e}^f \) from the total exports, which yields \( \mathbf{e}^p + \mathbf{e}^N - \mathbf{e}^f \). Then, subtracting the exports of DEs from the
outputs of DEs yields the output for the D. That is, $x^D = x^d - (e^p + e^N - e^f)$. Finally, the sum of domestic sales of FIEs (i.e. $x^f - e^f$) and all non-processing exports yields the output of the N, i.e., $x^N = (x^f - e^f) + e^N$.

Second, we estimate the row sums (to be used in the next step of the procedure) for the import matrices in non-benchmark years. According to China’s trade policy, processing imports are only allowed to be used to produce P. The vector $m^P$ with processing imports thus gives the row sums of the import matrix of production of P. For other (or non-processing) imports, we separate the parts used for intermediate use (in production of D and N, $m^{N+D}$) and the parts used for final demand by using a combination of Chinese Customs’ import statistics and the United Nations Broad Economic Categories (UN BEC) classification. $m^{N+D}$ provides the row sums for the sum of the import matrices of D and N.

Third, we extrapolate the import matrices to non-benchmark years. The extrapolation is based on the import coefficient matrices ($A^{MD}$, $A^{MP}$, and $A^{MN}$) in the nearest benchmark year. Specifically, the estimation for years 2000-2005 is based on the import matrices of 2002, the estimation for the years 2006-2009 (excluding 2007) is based on the import matrices of 2007, and the estimation for 2011-2013 is based on the import matrices of 2012. The year 2000 as an example. Subscript 00 is adopted to indicate the variables in 2000, while subscript 02 is for variables in 2002. Initial import matrices of 2000 are obtained by multiplying the import coefficient matrices of 2002 with the outputs of 2000. That is:

$$Z_{00}^{MD} = A_{02}^{MD} \hat{x}_{00}^D,$$  \hspace{1cm} (A2.1.1a)
$$Z_{00}^{MP} = A_{02}^{MP} \hat{x}_{00}^P,$$  \hspace{1cm} (A2.1.1b)
$$Z_{00}^{MN} = A_{02}^{MN} \hat{x}_{00}^N,$$  \hspace{1cm} (A2.1.1c)

where a “hat” is used to indicate a diagonal matrix.

Then we adjust the initial import matrices in Equations A2.1.1b because their row sums do not equal $m^P$ and $m^{N+D}$ obtained from the import statistics for 2000.

---

19 The NBS and the Chinese Academy of Sciences have also compiled the tripartite tables for 2010, which directly provides the import matrix in this year.
Therefore, we need to calibrate the estimates to make them consistent with the known row sums. To do so, we reallocate the row sums of 2000 in each row of the initial estimate of the import matrix, keeping the proportions within each row constant. This procedure is formulated as:

\[
\begin{align*}
Z^{MD}_{00} &= (\mathbf{k}^{N+D}_{00})^{-1}\mathbf{m}_{00}^{N+D}\mathbf{Z}_{00}^{MP}, \\
Z^{MP}_{00} &= (\mathbf{k}^{P}_{00})^{-1}\mathbf{m}_{00}^{P}\mathbf{Z}_{00}^{MP}, \\
Z^{MN}_{00} &= (\mathbf{k}^{N+D}_{00})^{-1}\mathbf{m}_{00}^{N+D}\mathbf{Z}_{00}^{MN},
\end{align*}
\]  

(A2.1.2a) \hspace{2cm} (A2.1.2b) \hspace{2cm} (A2.1.2c)

where \( \mathbf{k}^{P}_{00} = \mathbf{Z}_{00}^{MP} \mathbf{u} \) and \( \mathbf{k}^{N+D}_{00} = \mathbf{Z}_{00}^{MD} \mathbf{u} + \mathbf{Z}_{00}^{MN} \mathbf{u} \), indicating the row sums of the initial estimates of the import matrices.

Equations A2.1.2b provide estimates of the import matrices in 2000, in which the row sums equal the known trade statistics. From Equation A2.1.2b we straightforwardly obtain the import coefficients matrices for each year. Combining these import coefficients matrices with the Leontief inverse in the benchmark years, the VS shares for non-benchmark years are obtained.
Appendix 2.2

The full decomposition

From Equations 2.12-2.14 in the main text, the VS share can be denoted as a function with 13 variables, that is, \( f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}) \).

Then, one of the polars of the decomposition of the VS share change is as follows:

\[
\Delta v_s = v_{s1} - v_{s0} \\
= f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1a
\]

\[
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1b
\]

\[
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1c
\]

\[
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1d
\]

\[
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1e
\]

\[
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1f
\]

\[
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1g
\]

\[
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1h
\]

\[
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1i
\]

\[
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1j
\]

\[
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) + \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_1) - \\
f(A^{KD}, A^{KP}, A^{KN}, c^D, c^p, c^N, R^D, R^P, R^N, S^D, S^P, S^N, \bar{e}_0) \\
A.2.1k
\]
\[ f(A_0^{KD}, A_0^{KP}, A_0^{KN}, c_0^D, c_0^p, c_0^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.11) \]

\[ + f(A_0^{KD}, A_1^{KP}, A_0^{KN}, c_0^D, c_0^p, c_0^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) - \]

\[ f(A_0^{KD}, A_0^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.1m) \]

The other polar is obtained as the mirror image of the decomposition above:

\[ \Delta \nu s \]

\[ = f(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) - \]

\[ f(A_1^{KD}, A_0^{KP}, A_1^{KN}, c_0^D, c_0^p, c_0^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2a) \]

\[ +f(A_1^{KD}, A_1^{KP}, A_2^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) - \]

\[ f(A_1^{KD}, A_1^{KP}, A_0^{KN}, c_0^D, c_0^p, c_0^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2b) \]

\[ +f(A_2^{KD}, A_1^{KP}, A_2^{KN}, c_2^D, c_2^p, c_2^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2c) \]

\[ f(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2d) \]

\[ +f(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2e) \]

\[ f(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2f) \]

\[ +f(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2g) \]

\[ f(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2h) \]

\[ f(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2i) \]

\[ f(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2j) \]

\[ f(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2k) \]

\[ f(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^p, c_1^N, R_0^D, R_0^p, R_0^N, S_0^D, S_0^p, S_0^N, \bar{e}_1) \quad (A2.2.2l) \]
+ \mathbf{f}(A_1^{KD}, A_1^{KP}, A_1^{KN}, c_1^D, c_1^P, R_1^D, R_1^P, R_1^N, S_1^D, S_1^P, e_1) - \\
\mathbf{f}(A_1^{KD}, A_1^{KP}, A_1^{KN}, A_1^{nP}, A_1^{nN}, c_1^D, c_1^P, R_1^D, R_1^P, R_1^N, S_1^D, S_1^P, e_0)

(A2.2.2m)

Then, the final decomposition is given by the average of the corresponding terms:

E(\mathbf{A}^{KD})=[(A2.2.1a)+(B-2a)]/2; \quad E(\mathbf{A}^{KP})=[(A2.2.1b)+(A2.2.2b)]/2;

E(\mathbf{A}^{KN})=[(A2.2.1c)+(A2.2.2c)]/2; \quad E(\mathbf{c}^D)=[(A2.2.1d)+(A2.2.2d)]/2;

E(\mathbf{c}^P)=[(A2.2.1e)+(A2.2.2e)]/2; \quad E(\mathbf{c}^N)=[(A2.2.1f)+(A2.2.2f)]/2;

E(\mathbf{R}^D)=[(A2.2.1g)+(B-2g)]/2; \quad E(\mathbf{R}^P)=[(A2.2.2h)+(A2.2.2h)]/2;

E(\mathbf{R}^N)=[(A2.2.1i)+(A2.2.2i)]/2; \quad E(\mathbf{S}^D)=[(A2.2.1j)+(A2.2.2j)]/2;

E(\mathbf{S}^P)=[(A2.2.1k)+(A2.2.2k)]/2; \quad E(\mathbf{S}^N)=[(A2.2.1l)+(A2.2.2l)]/2;

E(\mathbf{e})=[(A2.2.1m)+(A2.2.2m)]/2.
Appendix 2.3

Sector specifications of the Chinese input-output tables

<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>1</td>
<td>Agriculture</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>Coal mining, washing and processing</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>Crude petroleum and natural gas products</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>Metal ore mining</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>Non-ferrous mineral mining</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>Manufacturing of food products and tobacco processing</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>7</td>
<td>Textile goods</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>8</td>
<td>Wearing apparel, leather, furs, and related products</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>9</td>
<td>Sawmills and furniture</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>10</td>
<td>Paper and products, printing and other reproduction</td>
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</tr>
<tr>
<td>11</td>
<td>Petroleum processing, coking and nuclear fuel processing</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>12</td>
<td>Chemicals</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>13</td>
<td>Non-metallic mineral products</td>
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<td>Metal smelting and pressing</td>
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<td>14</td>
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<td>15</td>
<td>Metal products</td>
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<tr>
<td>16</td>
<td>Common and special equipment</td>
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<td>16</td>
</tr>
<tr>
<td>17</td>
<td>Transport equipment</td>
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</tr>
<tr>
<td>18</td>
<td>Electric equipment and machinery</td>
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<td>18</td>
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<tr>
<td>19</td>
<td>Computers and other electronic equipment</td>
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<tr>
<td>20</td>
<td>Instruments, meters, cultural and office machinery</td>
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<td>21</td>
<td>Other manufacturing products</td>
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<td>Scrap and waste</td>
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</tr>
<tr>
<td>23</td>
<td>Electricity and heating power production and supply</td>
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<td>Gas production and supply</td>
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<td>Water production and supply</td>
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<td>26</td>
<td>Construction</td>
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<td>26</td>
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<td>27</td>
<td>Transport and warehousing</td>
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<td>28</td>
<td>Post</td>
<td>28</td>
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<tr>
<td>29</td>
<td>Information communication, computer services and software</td>
<td>29</td>
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</tr>
<tr>
<td>30</td>
<td>Wholesale and retail trade</td>
<td>30</td>
<td>30</td>
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<td>31</td>
<td>Accommodation, eating and drinking places</td>
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<td>32</td>
<td>Finance and insurance</td>
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<td>Real estate</td>
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<td>Renting and commercial services</td>
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<td>Health services and social welfare</td>
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<td>39</td>
<td>Culture, sports and amusement</td>
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<td>40</td>
<td>Public management and social administration</td>
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<td>42</td>
</tr>
</tbody>
</table>

Notes: The IO codes are from the 42-sector benchmark classification scheme as released by NBS of China.
Appendix 2.4

A parallel decomposition of the export structure

For each good $j$, the trade mode is measured by the proportion of processing exports in the total exports of this good, i.e. $w_j = e_j^p / (e_j^p + e_j^N)$. The commodity mix gives the share of the exports of good $j$ in aggregate exports, i.e. $q_j = (e_j^p + e_j^N) / \sum_{j=1}^{n}(e_j^p + e_j^N)$. Note that we have $q = \bar{e}^p + \bar{e}^N$. This yields

\[
\bar{e} = \begin{pmatrix} 0 \\ \bar{e}^p \\ \bar{e}^N \end{pmatrix} = \begin{pmatrix} 0 \\ \hat{\Psi}q \\ (1 - \hat{\Psi})q \end{pmatrix} = \Psi q.
\]

(A2.4.1a)

Part of Equation 2.16 is $u'(A_0^M L_0 + A_1^M L_1)(\Delta \bar{e})/2$ and it follows from Equation 2.18 that $\Delta \bar{e} = \Psi_1 q_1 - \Psi_0 q_0 = (\Psi_1 + \Psi_0)\Delta q/2 + \Delta \Psi(q_1 + q_0)/2$. The effects of changes in the trade mode structure and in the commodity mix of the exports to the VS share change are given by

\[
E(w) = 0.25u'(A_0^M L_0 + A_1^M L_1)(\Delta \Psi)(q_1 + q_0)
\]

(A2.4.1b)

\[
E(q) = 0.25u'(A_0^M L_0 + A_1^M L_1)(\Psi_1 + \Psi_0)(\Delta q)
\]

(A2.4.1c)
CHAPTER 3
How Much Did China’s Emergence as “The World’s Factory” Contribute to its National Income?

3.1 Introduction

Major improvements in information and communication technology, together with trade liberalization and continued reductions in transportation costs, have changed the nature of international trade. Global Value Chains (GVCs) have emerged: the production of consumer goods has become fragmented into several stages that take place in multiple countries, frequently spread over multiple continents (see, e.g. Timmer et al., 2014; Johnson, 2014; Johnson and Noguera, 2017; and Antràs, 2020). China has played a prominent role in these changes. Fueled by its membership of the World Trade Organization since 2001, its well-educated but relatively low-wage workforce and state-led promotion of foreign direct investment (FDI) in processing export activities, China became a central player in the network of GVCs. As the “Factory of the World”, it first exported products like toys and apparel and at a later stage diversified its exports towards higher-end products like consumer electronics (see, e.g., Hanson, 2012).

In this period, Chinese standards of living have improved considerably. It is widely believed that its export performance has played a crucial role in this development (Erten and Leight, 2019; Tombe and Zhu, 2019). We aim to quantify the contribution of nationwide exports to the growth in China’s Gross National Income (GNI) in the period 2002-2012. We adopt an accounting approach, which implies that we do not consider long-run effects due to learning-from-exporting (Bernard and Jensen, 1999; Blalock and Gertler, 2004) or learning-from-inward FDI (Javorcik, 2004; Javorcik and Spatareanu, 2008), which are notoriously hard to estimate. Still, just measuring the part of China's GNI attributable to exporting is a challenge. We have to address two major issues: (i) the value of Chinese gross exports is not a good proxy for Chinese value added in its exports, because China imports a lot of intermediate goods and services to produce its exports; and (ii) Chinese value added contained in its exports is not a good
proxy for national income due to exports, given the prominence of foreign-owned economic activity in the Chinese economy. 1

First, intensive participation in GVCs implies that the value of Chinese gross exports is not a good proxy for China’s value added induced by exports. The value of gross exports is composed of this “domestic value added” (DVA) in exports and the value of imported intermediate inputs required to produce these exports. Several studies have demonstrated that China generated little DVA per unit of exports in the early stages of its WTO membership (see, e.g., Dean et al., 2011; Koopman et al., 2012; Ma et al., 2015; and Kee and Tang, 2016). This was partly due to the active promotion of the processing exports activities mentioned above. By design, these rely heavily on imports, rather than on materials, parts and components, and services supplied by domestic firms. The accumulated empirical evidence suggests that DVA’s share in China’s exports started to increase quickly (Dean et al., 2011; Chen et al., 2012; Upward et al., 2013; Kee and Tang, 2016; and Tang et al., 2020). Kee and Tang (2016), who analyzed firm-level data, attributed the marked change to the development of technological and organizational capabilities in China, as a consequence of which firms can produce previously imported intermediate inputs in-house, or source these from domestic suppliers. Van Assche and van Biesenbroeck (2018) found evidence for similar trends in the processing exports sector in specific. Using Chinese customs data, they show that Chinese activities have shifted from the "Pure Assembly" to the "Import & Assembly" type of export processing, which implies that export processing firms in China have become active in a much broader range of activities than before, including logistics and quality control.

The second problem is related to the difference between DVA and national income (or, at the economy-wide level, between GDP and GNI). Value added is assigned to the country in which production factors are employed, whereas income is assigned to the country of which the owners of these production factors are citizens. Living standards in China are determined by Chinese GNI rather than by Chinese GDP. China's export promotion policies attracted a lot of inward FDI as a consequence of the attractiveness

1 The part of GDP that is embodied in exports is often termed ‘domestic value added (DVA) in exports’, and contributions of industries to GDP are often termed ‘value added’. In the same fashion, we use the terms ‘national income in exports’ for the part of GNI that is embodied in exports and ‘national income by industry’ for the contribution of industries in GNI.
of its processing exports regulations. Duan et al. (2012) report that slightly more than 80% of all processing exports in 2007 were accounted for by foreign-invested enterprises (FIEs, including wholly foreign-owned firms, equity joint ventures and contractual joint ventures), while this share was close to 55% if all exports are considered (Tang et al., 2020). The value added of these firms contains profits, which the FIEs can repatriate. Duan et al. (2012) find that close to 15% of China’s DVA in exports does not add to its GNI. Ma et al. (2015), using slightly different data (for 2007 as well), arrive at a share of 12%. Since 2006, however, the share of FIEs in the value of Chinese gross exports has slightly declined.

The dynamics of DVA shares and of FIE shares in exports call for a longitudinal analysis of national income contained in Chinese exports. How did China’s export-promoting policies affect national income in the period of rapid international fragmentation of production processes leading to the global production network? After having addressed this question, we will decompose the changes to obtain insights into the empirical magnitudes of various drivers of change. The data needed to conduct such a study are basically those used by Duan et al. (2012) and Ma et al. (2015) for 2007. These are high-quality input-output (IO) tables that explicitly make the distinction between the processing exports parts of industries and regular parts of these industries are required to arrive at meaningful results. Our focus on changes over time implies that such tables are needed for multiple years. We use the so-called tripartite input-output tables for 2002, 2007, and 2012 (the latest year for which the source data are available) constructed by Chen et al. (2012), Yang et al. (2015) and Chen et al. (2020). Next to these tripartite input-output tables, the estimation of GNI in Chinese exports requires data on investment by firms categorized by ownership (e.g. domestic enterprises vs. FIEs) and assumptions on returns to capital.

The chapter proceeds as follows. Section 3.2 explains the IO framework that we adopt to measure the Chinese value added due to Chinese exports, and the methodology to account for the differences between national income and this value added in exports.

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2 Wholly foreign-owned firms are established with exclusive investment from foreign investors or investors based in Hong Kong, Macao or Taiwan (HMT). Joint Venture Enterprises and contractual joint ventures are jointly established by foreign or HMT investment with enterprises in mainland China, in accordance with the relevant laws. The sharing of investment, profits and risks is stipulated under contract. See also Zhang and Song (2001) and Zhang (2005). Tang et al. (2020) have estimated the ratio of domestic value-added to gross exports for different firm types in China, including State-Owned Enterprises, Foreign-Owned Enterprises, Large Private Enterprises, and Small and Medium Enterprises. However, they did not study the implications of exports for national income.
Section 3.3 gives a detailed description of the data sources. Section 3.4 provides the empirical results. In section 3.5, we quantify the contributions of changes in several exogenous variables to see which tendencies have had the most important effects on changes in the share of Chinese GNI in its exports in the decade between 2002 and 2012. Section 3.6 focuses on the relative importance of exports in generating China’s GNI in the same period. Section 3.7 concludes.

3.2 Methodology

3.2.1 Deriving national income in exports from a tripartite input-output table

Input-output tables have proven to be a useful vehicle for analyses of the dynamics of growth. Such tables provide quantitative descriptions of the production technologies of the industries of which the economy consists. One of the major assumptions of input-output models based on such tables is that the production technology used to produce a given unit of output of an industry is not dependent on the use of the output. That is, the domestic intermediate input requirements, the imported intermediate input requirements and the payments to production factors are assumed to be identical for the products of an industry, irrespective of whether they are used as intermediate inputs by downstream industries, as consumption goods, as capital goods or as exported products. For countries like Mexico and China, however, this assumption tends to be violated to a much larger extent than elsewhere. This is due to the prevalence of processing exports activities. These activities (which are present in several manufacturing industries) are exempted from tariffs on imported inputs, provided that the output is only sold abroad. The ensuing differences in the relative prices of imported and domestic inputs faced by a processing exports producer and a regular firm in the same industry cause differences in input mixes. Furthermore, processing exports firms are more often foreign-owned than regular producers, which is reflected in differences in the technologies available to both types of producers. Considerable evidence exists that studies that cannot separate China’s processing exports activities from other production activities (e.g. production for domestic use) will lead to biased estimates of factor contents of exports (see, e.g.,
Dean et al., 2011, Koopman et al., 2012, and Pei et al., 2012).  

To reduce this aggregation bias, Chen et al. (2012) developed a tripartite input-output table for China, in which all industries have been split into three ‘subindustries’: a subindustry for production of Domestic Enterprises (DEs) to meet domestic demand (hereafter ‘domestic production’), production for processing exports (hereafter ‘processing exports’), and a subindustry in which production for ordinary exports and production of FIEs for domestic use (hereafter ‘ordinary exports and other’) are merged. The structure of such a tripartite table is shown in Figure 3.1.

Figure 3.1 Schematic outline of China’s tripartite input-output table.

<table>
<thead>
<tr>
<th>Supply</th>
<th>Intermediate use</th>
<th>Final use</th>
<th>TOT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>$Z^{DD}$</td>
<td>$Z^{DN}$</td>
<td>$f^D$</td>
</tr>
<tr>
<td>P</td>
<td>0</td>
<td>0</td>
<td>$e^P$</td>
</tr>
<tr>
<td>N</td>
<td>$Z^{ND}$</td>
<td>$Z^{NN}$</td>
<td>$f^N$</td>
</tr>
<tr>
<td>IMP</td>
<td>$Z^{MD}$</td>
<td>$Z^{MP}$</td>
<td>$f^M$</td>
</tr>
<tr>
<td>VA</td>
<td>$(v^b)'$</td>
<td>$(v^p)'$</td>
<td>$(v^N)'$</td>
</tr>
<tr>
<td>TOT</td>
<td>$(x^D)'$</td>
<td>$(x^P)'$</td>
<td>$(x^N)'$</td>
</tr>
</tbody>
</table>

Notes: D: domestic production subindustries; P: processing exports subindustries; N: ordinary exports and other subindustries; DFD: domestic final demand; EXP: exports; TOT: gross output; IMP: imports; and VA: value added. The table is expressed in monetary units.

Given that each industry is divided into three subindustries, the numbers of rows and columns of the intermediate deliveries block $Z$ are three times as large as in an ordinary IO table. The subscript $D$ refers to domestic production, while $P$ indicates processing exports, and $N$ represents ordinary exports and other subindustries. The rows correspond to subindustries that sell to (at most) three categories of users, which are represented by the columns: subindustries (of the three types) that purchase the output of the row subindustry as intermediate inputs, Chinese households and firms that use this output as consumption products and capital goods, respectively (domestic final demand, $DFD$) and foreign buyers (exports, $EXP$). The block labeled $IMP$ contains

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3 See also Duan et al. (2018), for similar findings regarding the degree of vertical specialization.

4 Yang et al. (2015) provides detailed information about the data for ‘ordinary exports and other’. It should be noted that DEs can be partly owned by foreigners, if they invested in the enterprise after it was established using Chinese assets only.

5 The industry classification of the national input-output tables is presented in Appendix 2.1.
imports. Each row in this block corresponds to a selling industry. The row labeled $VA$ contains the value added in all subindustries of all three types. The double-entry bookkeeping identity ensures that the sum over all elements in each of the subindustry rows ($TOT$) is equal to the sum over all elements in the corresponding column.

As is reflected in Figure 3.1, the split of industries in the $D$, $P$, and $N$ types implies that some blocks of the input-output table exclusively contain zeros. The output of domestic production activities is by definition only sold to domestic users, so the export vector for the $D$ rows consists of zeros. Furthermore, the intermediate use and domestic final use parts of the $P$ rows contain zeros, since processing exports are only allowed to produce for foreign markets.

The matrix with domestic intermediate input coefficients $A$ can be obtained as $A = Z\tilde{x}$, in which $\tilde{x}$ indicates the diagonal matrix with the elements of the vector $x$ (which contains the elements of $x^D$, $x^P$ and $x^N$) on the main diagonal:

$$
A = \begin{pmatrix}
A^{DD} & A^{DP} & A^{DN} \\
0 & 0 & 0 \\
A^{ND} & A^{NP} & A^{NN}
\end{pmatrix}
$$

Each block $A_{ST}$ indicates the cost shares of output from each subindustry in $S$ in the value of the output of each subindustry in $T$, with $S = D, P, N$ and $T = D, P, N$. This implies that the Leontief inverse for the tripartite table is given by

$$
L = (I_m - A)^{-1} = \begin{pmatrix}
L^{DD} & L^{DP} & L^{DN} \\
0 & I & 0 \\
L^{ND} & L^{NP} & L^{NN}
\end{pmatrix}
$$

in which $I$ stands for the identity matrix and $m$ represents the number of industries.

As mentioned, the input-output table depicted in Figure 3.1 contains information on value added created in each of the subindustries. The cells in the row $VA$ contain value added that partly contributes to GNI (e.g., wages paid to Chinese workers and compensation of capital owned by Chinese investors) and partly not (e.g., wages paid to non-residents and profits accruing to foreign capital owners). If we denote the column vector with value added-to-gross output ratios by $w$, we could split these ratios as $w = w^n + w^f$, with
\[ \mathbf{w}^n = \begin{pmatrix} w^{nD} \\ w^{nP} \\ w^{nN} \end{pmatrix} \quad \text{and} \quad \mathbf{w}^f = \begin{pmatrix} w^{fD} \\ w^{fP} \\ w^{fN} \end{pmatrix} \]

\(\mathbf{w}^n\) and \(\mathbf{w}^f\) represent the vector of national income-to-gross output ratios and the vector of foreign income-to-gross output ratios by industry, respectively. Below, we will explain our approach to estimating these splits of the elements in \(\mathbf{w}\) into the elements of \(\mathbf{w}^n\) and \(\mathbf{w}^f\).

Armed with these definitions and assuming constant returns to scale production functions and homogeneous production techniques within subindustries, we can compute national income induced by the three types of final demand: domestic final demand \((f^D)\), processing exports \((e^P)\), and ordinary exports \((e^N)\):

\[
\begin{align*}
ni^D &= (w^{nD}L^{DD} + w^{nN}L^{ND})f^D \\
ni^P &= (w^{nD}L^{DP} + w^{nP} + w^{nN}L^{NP})e^P, \\
ni^N &= (w^{nD}L^{DN} + w^{nN}L^{NN})e^N
\end{align*}
\] (3.1-3.3)

Equation 3.1 gives the GNI generated by domestic final demand. Subindustries in the domestic production sector and the ordinary exports sector contribute to this. Not only subindustries producing final products add to this part of national income, but also subindustries supplying intermediate inputs to these Chinese producers of final products, subindustries supplying to these ‘first-tier suppliers’, etc. This is reflected by the blocks of the Leontief inverse \(L\) in Equation 3.1. In a similar vein, Equation 3.2 shows that all three types of subindustries create GNI due to exports of the output of processing exports activities. The domestic and ordinary exports subindustries only contribute via upstream activities (delivering intermediate inputs), while the processing exports industries only create GNI in the last stage of production of the exported products. These subindustries do not deliver any intermediate inputs, as was reflected already by the row with zeros in the matrix with intermediate input coefficients, \(A\). Equation 3.3 indicates the GNI that can be attributed to ordinary exports. The sum of Equations 3.2 and 3.3 yields the national incom in total exports. The sum of \(ni^P\) and \(ni^N\) will be lower than the sum of the elements in the gross exports vectors \(e^P\) and \(e^N\),
since our approach takes into account that such gross exports also contain imported value added and value added that is income earned by foreign firms. Both aspects are important given China’s strong involvement in the global production network.

3.2.2 Estimating national income and foreign income shares in domestic value added

We now turn to splitting value added into national and foreign income. We have to estimate the shares of national income in value added by (sub)industry ourselves, since such data is not available. Value added in China's input-output tables consists of three parts: (1) taxes, (2) labor income, and (3) capital income, which includes depreciation of fixed assets and profits. Taxes are paid to the Chinese government and are therefore part of China’s GNI. We assume that all labor income contributes to GNI, neglecting the small part earned by foreign employees.\(^6\) Hence, we only focus on splitting capital income, since a substantial part of capital income in China consists of returns on foreign capital.

China’s Balance of Payments (BOP) provides information about the profits on foreign investment in China. However, the headline figure seriously underestimates the true profits on inward FDI, due to China’s incomplete statistics on retained earnings on foreign investment.\(^7\) In re-estimating income on foreign capital, we use an improved version of the method proposed by Duan et al. (2012).\(^8\)

We proceed along the lines depicted in Figure 3.2 for the case of production of processing exports. The same procedure applies to the other two cases (i.e. production of domestic outputs and production of ‘ordinary exports and other’). The data we use and the assumptions we make will be discussed in the next section. First, we divide the output of each subindustry into output of FIEs and output of DEs. For the domestic

\(^6\) According to the United Nations Global Migration Database, in 2013 the share of foreigners in the total number of people living in China amounted to only 0.06%.

\(^7\) According to the International Monetary Fund (2009), the item Profit from Investment in the BOP should include all profits created by foreign investment, irrespective of whether these remain in the host country or not. Yao’s (2008) rough estimate indicates that the real profits of inward FDI in China for 2004-2006 were about four times the value shown in the official BOP statistics.

\(^8\) Duan et al. (2012) assumed that enterprises with foreign investment (FIEs) and domestically-owned enterprises (DEs) have identical capital income to output ratios, which is an implausible assumption (see, e.g. data in NBS, 2008).
production subindustries, this is trivial: by definition, these only consist of Chinese firms and almost all capital income accrues to China. Next, we estimate the capital income of both types of enterprises. We then continue by splitting these capital income levels into foreign capital income and national capital income, and add the respective results for FIEs and DEs to arrive at initial estimates of aggregate foreign capital income and national capital income (in processing exports and in ordinary exports and other separately). These initial estimates might not add up to total capital income as documented in the tripartite input-output tables, because the underlying data are not necessarily consistent with each other. Therefore, a final reconciliation step is needed to ensure that the foreign-owned capital income and national capital income data can be used in an IO framework.

A detailed, mathematical exposition of the methods underlying the procedure depicted in Figure 3.2 can be found in Appendix 3.1.

Figure 3.2 Capital income decomposition procedure for production of processing exports

Note: NCI=National capital income; FCI= foreign capital income.

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9 By definition, the DEs are established by using Chinese assets. However, in reality, after the establishment of a DE, it is allowable to receive a small fraction of foreign investment without changing the registration type. Therefore, there is some foreign capital invested in DEs. In 2007, for example, the foreign capital accounted for 1.2% of all capital invested in DEs in the industrial sector (including Mining, Manufacturing, and Supply of electricity, heat, gas and water).
3.3 Data\textsuperscript{10}

Tripartite input-output tables for China, which were jointly compiled by the National Bureau of Statistics of China (NBS) and the Chinese Academy of Sciences (CAS), are one of our key data sources. Currently, the tripartite tables are available for the years of 2002, 2007, and 2012. These years mark the rapid emergence of China as the “Factory of the World”, after it became a member of the WTO in 2001. Details of the procedures adopted by NBS and CAS to construct the tables have been provided by Chen et al. (2012). Due to limited industry detail in the data required to split capital income according to Figure 3.2, we have to sacrifice some detail in the input-output data: we aggregated the 42 industries in the tripartite input-output tables into 30 industries. These include 5 natural resources industries (i.e., agriculture and mining), 16 manufacturing industries, 4 industries related to construction and utilities, and 5 services industries (see Appendix 3.2 for details). All data represented by the matrices and vectors depicted in Figure 3.1 are contained in these tables.

The tripartite input-output tables for China are also the source for the capital income shares in value added for all subindustries, as used in the last step of the procedure outlined in Figure 3.2. The simplified Figure 3.1 contains a single row for value added (the vectors $\mathbf{v}$), but the actual tables contain several rows, and a row with capital income is one of these. The capital income shares are simply computed as the ratios between capital income and total value added in each sector. These do not provide information on the split between national capital income and foreign capital income, though.

In the first step (see also Figure 2.2), we compute the output shares of FIEs in each subindustry, which is not possible on the basis of input-output data only. For subindustries of the domestic production type, the FIE’s share in output is zero, because the definition of domestic production implies that only DEs are active in these subindustries. Hence, we only need to estimate the proportion of FIE output in total output of the processing exports and the ordinary exports and other subindustries. To this end, we employ export statistics from China’s Customs Office (also used by Brandt

\textsuperscript{10} See Appendix 3.3 for a summary table of the data sources described in this section.
et al., 2017), which are not only classified by commodity (at the 8-digit HS level), but also by trade regime (e.g. processing exports, ordinary exports) and by enterprise type (FIEs and DEs). We use concordance tables (provided by NBS) between the HS 8-digit commodities and the input-output classifications to split processing exports and ordinary exports of goods into exports of FIEs and exports of DEs. Since statistics for services exports are of relatively poor quality, we have to adopt a rough approximation procedure. We assume that the export shares of FIEs are identical to the shares of FIEs in total domestic sales by services industries. Given that exports of services amounted to just 10.9% and 8.5% of the total Chinese exports value in 2002 and 2012, respectively, our results for the national income attributed to all exports will probably not be very sensitive to this crude assumption.

In the second step, we estimate the capital income-output ratios at subindustry level, for which we employ various data. To compute capital income of FIEs and DEs, we add ‘depreciation of fixed assets’ to ‘operating profits’. For manufacturing industries, these data and (and the output data as well) are sourced from the annual China Industry Economy Statistical Yearbook. For services and construction, data on ‘operating income’ are used to capture the output of FIEs and DEs, which together with capital income data is taken from China’s Economic Census Statistics Yearbook (NBS, 2006; 2010). We then straightforwardly compute the capital income to output ratios by dividing the capital income by output in each subindustry. For agriculture, facing a lack of more sophisticated data, we obtain the capital income-output ratio from the tripartite tables: we take the capital income-output ratio of the domestic production subindustry as a proxy of that of DEs, while we use the capital income-output ratio of the ordinary exports and others subindustry as estimate of that of FIEs.

Finally, to estimate the foreign-owned capital shares in DEs and FIEs in the third step of Figure 3.2’s procedure, we use data related to ‘paid-in capital’ (the asset value of firms). In China’s statistics, six categories of paid-in capital are present. Four of these relate to assets financed by various types of Chinese shareholders. The remaining

\[11\] The use of ‘operating income’ (which measures the total sales of a service sector) is in accordance with the method described in the Compilation of Chinese Input Output Table 2007 (NBS, 2009).

\[12\] Paid-in capital refers to the total value of assets actually invested by shareholders. These assets can be currency, physical assets (e.g., equipment, plants) and intangible assets (e.g., technology, patents). Paid-in capital represents the property right of investors to the enterprise, and its composition is the main basis for profits distribution among investors. See: http://www.stats.gov.cn/tjzl/tjzbs/t200201327_14284.htm
two (HMT paid-in capital and foreign paid-in capital) indicate the value of assets sourced from Hong Kong, Macao and Taiwan and from foreign regions, respectively.\textsuperscript{13} We employ the aggregate shares of HMT and foreign paid-in capital in total paid-in capital to measure the foreign-owned capital shares in DEs and FIEs. The paid-in capital data for both FIEs and DEs are taken from the \textit{China Industry Economy Statistical Yearbook} (NBS, 2003, 2008, 2013) for manufacturing industries, and from \textit{China’s Economic Census Statistics Yearbook} (NBS, 2006, 2010) for services industries.\textsuperscript{14}

For the agriculture and construction industries, paid-in capital data are not available. Hence, we use the share of foreign-owned capital in ‘registered capital’ of FIEs to estimate the foreign-owned capital share of FIEs in these industries. Registered capital refers to the total value of assets invested by shareholders at the time an enterprise has just been established. Consequently, registered capital data will yield biased statistics if compared to the true capital stock, if the origin of later investments is different from the initially provided assets. However, according to Chinese regulation, differences between paid-in capital and registered capital must remain below 20%, otherwise the registered capital data must be updated to conform with paid-in capital, so our estimates cannot be very inaccurate. The registered capital data come from the \textit{China Statistical Yearbook}. For DEs in agriculture and construction, we do not have meaningful data on ownership and assume that capital stocks are fully owned by Chinese.

We should note that the national income concept in this chapter and GNI published by the NBS are slightly different from each other, in two respects. First, we only focus on the part of GNI generated on Chinese territory, ignoring the part of GNI due to Chinese outward FDI. Second, GNI as published by the NBS is obtained as the sum of GDP and the net inflow of labor compensation and investment income to China, as documented in China’s BOP statistics. However, as mentioned above, China’s BOP accounts underestimate the true profits of inward foreign investment severely (Yao, 2008). This leads to our three-step estimation of the returns to inward foreign

\textsuperscript{13} The six categories are state paid-in capital, collective paid-in capital, corporation paid-in capital, individual paid-in capital, HMT paid-in capital, and foreign paid-in capital.

\textsuperscript{14} The statistics on DEs and FIEs only cover enterprises with annual sales of 5 million RMB or above. We use the foreign-owned capital shares in these large enterprises as proxies for those of all enterprises here. We use data from the \textit{China Census Economic Yearbook 2004} (NBS, 2006) to conduct the estimations for services industries for 2002, and use the \textit{China Census Economic Yearbook 2008} (NBS, 2010) for the estimations for 2007 and 2012.
investment above, which provides a better estimation on national income but also causes divergence from the official statistics.

3.4 Results: National income in China’s exports

3.4.1 Aggregate national income in exports

Using the methodology set forth in section 3.2, we estimate the contents of exports by the two types of subindustries that sell abroad, in 2002, 2007 and 2012. We present the results in Table 3.1. The first column (DVA) gives the share of domestic value added in exports.\textsuperscript{15} DVA is split into a part that contributes to Chinese national income (the second column) and in a part that consists of foreign income (the fourth column). The third column gives the shares of national income in DVA in exports. Finally, we define the foreign content of exports (in the sixth column) as the sum of foreign income and imported content (fifth column) in exports. By definition, the sum of the DVA share and the imported content share is equal to 1, as is the sum of the national income share and the foreign content share (that is, (1)+(5)=100 and (2)+(6)=100 in each row).

A first important finding is that the national income shares in exports were not only considerably lower than the DVA shares in exports, but also developed differently over the decade in which China became a major player in the global production network. In the early stages, from 2002 to 2007, the DVA share in exports increased rapidly by 3.8 percentage points (from 55.4% to 59.2%), reflecting a reduced dependence on imported intermediate inputs. The national income share, however, grew only marginally (0.7 percentage points, from 50.6% to 51.3%) over the same period.\textsuperscript{16} Several tendencies can have contributed to these changes: (1) exporting firms may have substituted imported intermediate inputs by inputs produced in China by (partly) foreign-owned establishments, (2) such FIEs may have started producing previously imported inputs in-house, or (3) exports by FIEs may have grown faster than exports by DEs.

\textsuperscript{15} This indicator is called VAX-D in the taxonomy of value added in exports indicators proposed by Los and Timmer (2018).

\textsuperscript{16} Duan et al. (2012) arrived at a 0.6 percentage point lower estimate for the national income share in exports for 2007. We argue that our result reported here is slightly more accurate (see footnote 7).
In the second sub-period, the DVA share in exports rose even more (7.5 percentage points from 2007 to 2012, as compared to 3.8 percentage points from 2002 to 2007). In contrast to the first sub-period, however, it was now accompanied by a substantial rise of the national income share (from 51.3% in 2007 to 58.7% in 2012). Whereas in the first sub-period more than 80% of the gains in DVA went to capital owners abroad, this was less than 5% in the second sub-period. This fundamental difference between the early and the later sub-period is clearly reflected in the evolution of the national income to DVA in exports ratio, which declined considerably over 2002-2007 but rebounded somewhat after 2007. This result suggests that previously imported intermediate inputs were substituted by products from Chinese firms and/or were produced in-house by such firms. The mirror image of the changes in national income shares in exports is given by the foreign contents of exports. Over the decade considered, the role of foreign firms in the value chains of Chinese exports has declined considerably, by as much as about 8 percentage points.

Table 3.1 Value composition of exports (2002-2012), in %

<table>
<thead>
<tr>
<th></th>
<th>DVA National income</th>
<th>National income to DVA ratio (3)=(2)/(1)</th>
<th>Foreign income (4)</th>
<th>Import content (5)</th>
<th>Foreign content (6)=(4)+(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002 Total exports</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Processing exports</td>
<td>55.4</td>
<td>50.6</td>
<td>91.3</td>
<td>4.8</td>
<td>44.6</td>
</tr>
<tr>
<td>Ordinary exports</td>
<td>30.6</td>
<td>26.1</td>
<td>85.3</td>
<td>4.5</td>
<td>69.4</td>
</tr>
<tr>
<td>Domestic production</td>
<td>78.5</td>
<td>73.2</td>
<td>93.2</td>
<td>5.3</td>
<td>21.5</td>
</tr>
<tr>
<td>2007 Total exports</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Processing exports</td>
<td>59.2</td>
<td>51.3</td>
<td>86.7</td>
<td>7.9</td>
<td>40.8</td>
</tr>
<tr>
<td>Ordinary exports</td>
<td>36.6</td>
<td>29.4</td>
<td>80.3</td>
<td>7.2</td>
<td>63.4</td>
</tr>
<tr>
<td>Domestic production</td>
<td>78.1</td>
<td>69.7</td>
<td>89.2</td>
<td>8.4</td>
<td>21.9</td>
</tr>
<tr>
<td>2012 Total exports</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Processing exports</td>
<td>66.9</td>
<td>58.7</td>
<td>87.8</td>
<td>8.2</td>
<td>33.1</td>
</tr>
<tr>
<td>Ordinary exports</td>
<td>39.6</td>
<td>35.7</td>
<td>90.3</td>
<td>3.9</td>
<td>60.4</td>
</tr>
<tr>
<td>Domestic production</td>
<td>84.7</td>
<td>73.7</td>
<td>87.0</td>
<td>11.0</td>
<td>15.3</td>
</tr>
</tbody>
</table>

Notes: Values for domestic production relate to the composition of final output for domestic use (rather than exports) and have been included for reference only. Values for ordinary exports and other relate to the exports of this type of subindustries.

Secondly, we find that the observed trends are different for exports from the two
types of exporting subindustries. The national income share of ordinary exports in 2012 was almost the same as in 2002, although it had been slightly lower in 2007. This share was still much higher than for processing exports (but still lower than the national income share in the final output of domestic production subindustries), 73.7% vs. 35.7%.\textsuperscript{17} For processing exports, however, the national income share grew rapidly, from 26.1% to 35.7%.

In Section 3.5, we will dig deeper into the sources of these changes. Before turning to that, we first study whether the trends revealed in Table 3.1 for the aggregate Chinese economy were trends that can be observed across the board, or are the reflection of marked changes in the value chains of a limited number of exported products.

### 3.4.2 National income in exports by specific industries

Table 3.2 presents results for total exports by a selected number of industries and by a few aggregates of industries.\textsuperscript{18} The results reveal that Chinese national income as a share of the export value has increased for almost all industries over the decade spanned by 2002 and 2012. Despite this common pattern, the magnitudes of these shares still varies considerably, even if only major exporting industries are considered. In exports of electronics equipment, the national income share was still lower than 40% in 2012, despite a rapid increase from a share below 20% in 2002.\textsuperscript{19} At the other end of the spectrum, about three quarters of the value of exported textiles and clothing products consisted of value added that contributed to national income.

A broader comparison of the national income share in exports by the labor-intensive industries (6-9) aggregate and the machinery industries (16-20) tells an interesting story. Chinese owners and workers captured a relatively large share of the export value of the labor-intensive industries in 2002 already (61.8%), while the corresponding share for machinery was much lower at the time (only 29.2%). In both sub-periods, however, the national income share in machinery exports rose faster than

\textsuperscript{17} 'National income share in final output of domestic production' indicates the part of GNI that is embodied in one unit of final output of domestic production.

\textsuperscript{18} Table 3.3 lists results for selected industries of specific interest, full results are given in Appendix 3.4.

\textsuperscript{19} In their seminal case study for iPods exported in 2005, Dedrick et al. (2010) estimated a Chinese NI share smaller than 4%.
for labor-intensive products. This convergence confirms the impression that Chinese firms have managed to become more competitive within value chains for sophisticated final products. Still, Timmer et al. (2019) find that the wide-spread notion that China is mainly active in ‘low value added’ activities in global value chains of ‘high-end’ products is still accurate. The national income to DVA in exports ratios for the labor-intensive industries aggregate and the machinery industries aggregate suggest that changes in the importance of foreign income relative to total income have played a minor role in this convergence: the gap between the national income to DVA ratios of both aggregates narrowed over time, but it was relatively modest in 2002 already.20 High-tech machinery exports require considerably less imports than before, and our results do not provide reason to believe that this improvement has only been attained by foreign-owned firms. This substitution process was much weaker in labor-intensive industries.

Table 3.2 National income shares in exports (2002-2012), selected industries, in %

<table>
<thead>
<tr>
<th>Industry</th>
<th>National income in exports</th>
<th>National income to domestic value added (DVA) ratio</th>
<th>Share of national income generated by all exports</th>
</tr>
</thead>
<tbody>
<tr>
<td>7. Textiles</td>
<td>64.4</td>
<td>72.7</td>
<td>75.0</td>
</tr>
<tr>
<td>8. Clothes</td>
<td>56.7</td>
<td>66.5</td>
<td>73.5</td>
</tr>
<tr>
<td>12. Chemicals</td>
<td>49.4</td>
<td>38.9</td>
<td>57.4</td>
</tr>
<tr>
<td>16. Machinery</td>
<td>48.3</td>
<td>50.5</td>
<td>56.9</td>
</tr>
<tr>
<td>18. Electrical machinery</td>
<td>36.3</td>
<td>39.8</td>
<td>47.2</td>
</tr>
<tr>
<td>19. Electronic equipment</td>
<td>18.4</td>
<td>31.3</td>
<td>38.8</td>
</tr>
<tr>
<td>27. Trade</td>
<td>68.0</td>
<td>71.6</td>
<td>74.0</td>
</tr>
<tr>
<td>30. Other services</td>
<td>66.1</td>
<td>69.2</td>
<td>70.6</td>
</tr>
<tr>
<td>Energy and Materials</td>
<td>61.4</td>
<td>44.1</td>
<td>51.1</td>
</tr>
<tr>
<td>Labor-intensive machinery</td>
<td>61.8</td>
<td>68.8</td>
<td>74.0</td>
</tr>
<tr>
<td>Machinery</td>
<td>29.2</td>
<td>37.2</td>
<td>45.9</td>
</tr>
<tr>
<td>Aggregate economy</td>
<td>50.6</td>
<td>51.3</td>
<td>58.7</td>
</tr>
</tbody>
</table>

Notes: Exports of wholesale and retail trade include trade margins of exported products; exports of transportation include transportation margins for merchandise exports. Results relate to total exports, aggregated over processing exports and ordinary exports sub-industries.

20 A lot of heterogeneity is hidden in the aggregates. Within the machinery aggregate, for instance, the share of national income in DVA has increased considerably for electronics exports, while it declined for exports of several other types of machinery.
Appendix 3.4 shows that only four out of 30 industries experienced changes causing a decline of national income shares in exports in the analyzed decade. These are mainly clustered in what we label energy and materials industries. The national income share in exports of the aggregate of these industries (2-5, 11, 22-24) decreased by 10.3 percentage points. The national income to DVA ratio for this industry aggregate did not change very much over time (see the second set of columns in Table 3.2), which implies that China’s energy and materials exports became increasingly dependent on imported inputs (in particular between 2002 and 2007). We can think of two potential causes. One relates to changes in relative prices, rather than to changes in quantities. The price of crude oil (an important imported input for these industries) increased considerably in this period. The other potential cause is the energy sector liberalization that took place in the early 2000s (Bas and Causa, 2013). Besides private firms, foreign investors were encouraged to get involved in this sector. This exerted a downward pressure on the DVA in exports since FIEs usually use more imported inputs in their production processes than DEs.

The rightmost panel of Table 3.2 shows the shares of exports by industries in all national income induced by exports. Not surprisingly, the labor-intensive industries aggregate has become less important as a generator of GNI via its exports (its share went down by 7.2 percentage points). Over the same period, the machinery aggregate became responsible for an increasing share of China’s national income attributable to exports: its share went up from less than 20% in 2002 to more than a third in 2012. This increase mainly took place in the 2002-2007 period, which is the period in which value chains for various types of machinery became internationally fragmented (see Los et al., 2015a).

3.4.3 Sensitivity analyses
3.4.3.1 Round-tripping of FDI

A major concern regarding Chinese FDI flows data is that part of these might reflect so-called “round-tripping”. This phenomenon relates to capital invested by Chinese
investors in the form of FDI through special-purpose entities outside Mainland China, primarily in order to take advantage of preferential fiscal incentives offered to foreign investors (Wei, 2005). Since this capital originates from Chinese firms, reported FDI flows into China are inflated. We investigate the sensitivity of the results presented in the previous subsection to adding the returns to round-tripped Chinese investments to Chinese GNI.

In the existing literature, estimates of the magnitude of round-tripping vary substantially, which is understandable given that firms use this ‘trick’ to deceive authorities. The most popular estimate is from the World Bank, which suggests that a quarter of China’s total FDI inflows reflect round-tripping (World Bank, 2002). Xiao (2004) is among the few studies providing details about the method and data used, arriving at a share of 33.9% for the 1998-2002 period. Using the same method, Han's (2011) more recent study focused on FDI from Hong Kong in specific and estimated that about 15.5% of its 1998-2002 FDI into China related to round-tripping. Given the uncertainty about the true magnitude of round-tripping of Chinese FDI, we will assess our results based on three scenarios. In the first of these, we assume that round-tripped investment accounted for a quarter of China’s total foreign capital in 2002, 2007 and 2012. Since Broadman and Sun (1997) and Davies (2012) argue that the relative magnitude of round-tripping of FDI gradually decreased as a result of Chinese policy adjustments, we assume in scenario 2 that the proportion of round-tripped capital in official FDI figures decreased to 20% in 2007 and 15% in 2012. In scenario 3, we adopt the estimates by Xiao (2004) and Han et al. (2012) and assume shares of 33.9% in 2002, and 15.5% in 2007 and 2012. In the absence of both industry-level estimates, we assume that these percentages apply to all industries.

We assume that round-tripped investment generated rates of return identical to those on ‘truly foreign’ capital, which implies that the proportion of income from round-tripped investment in foreign income is the same as the proportion of round-tripped FDI in total FDI. Based on the foreign income figures that we reported in Table 3.1, we

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21 Other estimates in the literature for the early period considered in this chapter range from 10%-15% to 37% (see, e.g. UNCTAD, 2003; Wei, 2005).
22 These policy adjustment included the elimination of an exemption from customs duties of imported capital equipment and the value added tax for FIEs in 1996 (Broadman and Sun, 1997), tighter reporting standards for special purpose entities established abroad by Chinese companies since 2006, and the abolition of some foreign investment incentives from 2008 (Davies, 2012). These policies significantly decreased the incentives for Chinese investors to invest in the form of FDI.
obtain the income in exports, which should not be part of foreign income due to round-tripping of investment. We deduct this income from foreign income and add it to national income. Our adjusted estimates of the national income share in exports are presented in Table 3.3.

**Table 3.3 National income shares in exports adjusted for round-tripping of FDI, in %**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>National income</td>
<td>Foreign income</td>
<td>National income</td>
<td>Foreign income</td>
<td>National income</td>
</tr>
<tr>
<td>2002</td>
<td>50.6</td>
<td>4.8</td>
<td>51.8</td>
<td>3.6</td>
</tr>
<tr>
<td>2007</td>
<td>51.3</td>
<td>7.9</td>
<td>53.3</td>
<td>5.9</td>
</tr>
<tr>
<td>2012</td>
<td>58.7</td>
<td>8.2</td>
<td>60.8</td>
<td>6.2</td>
</tr>
<tr>
<td>Change, 2002 to 2007</td>
<td>0.7</td>
<td>3.1</td>
<td>1.5</td>
<td>2.3</td>
</tr>
<tr>
<td>Change, 2007 to 2012</td>
<td>7.4</td>
<td>0.3</td>
<td>7.5</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Table 3.3 shows that the increase in the foreign income was still the most important contributor to the total increase of DVA in exports from 2002 to 2007, also after considering round-tripping of FDI. Still, the relative importance of increases in national and foreign income varies across scenarios. In contrast, the increase of the national income share in exports between 2007 and 2012 is roughly the same in all scenarios. Hence, the broad tendencies found in the baseline scenario are also found if we correct for Chinese investments into China via e.g. Hong Kong and Macau.

### 3.4.3.2 Round-tripping of imports

The round-tripping phenomenon is not limited to investment flows. China’s exports contain a considerable volume of products that are first exported and then returned to Mainland China for the purpose of currency arbitrage or tax credits receipts (Chao et al, 2001). This round-tripping of imports does not affect China’s trade balance, because it
is included both in total exports and in total imports. It might influence the national income share in exports, however, since it may affect the compositions of imported inputs and of exports. In this subsection, we assess the sensitivity of the results reported in Table 3.1 to stripping the official imports and exports figures from round-tripped imports.

As the true volume of round-tripping of imports is unknown, we specify two scenarios that should give some insights into the rough magnitudes of the changes in our results. The first scenario uses China’s re-imports data. In these data, re-imports are defined as products exported by China and subsequently imported by China via a third country (or regions like Hong Kong, Macau and Taiwan, or a “bonded zone”). In Chinese statistics, these flows are recorded as “China–China trade” (Liu, 2013). Re-imports accounted for 5.1% of China’s total imports in 2002, 9.0% in 2007, and 7.9% in 2012. These re-imports data provide a lower bound for the volume of round-tripping of imports. In addition, some round-tripped products are imported into China after having acquired formal status as “exported to a foreign area”. Given that experts believe that most of China’s round-tripping of exports goes through Hong Kong (Liu, 2013), we consider re-imports plus China’s imports from Hong Kong as an upper bound of the round-tripped trade volume in scenario 2. Imports from Hong Kong accounted for 3.6% of Chinese total imports in 2002, 1.3% in 2007, and 1.0% in 2012.

We take both the re-imports data and China’s import data from Hong Kong from the UN Comtrade Database, at HS-6 digit level. Using the UN Broad Economic Categories (BEC) classification, we split the imports and re-imports into three categories: for intermediate use, for final consumption, and for investment. Afterwards, these data are further regrouped to match the industry classification used for the tripartite input-output tables, based on an unpublished concordance between HS-6 digit commodities and the IO classification provided by the NBS.

Two adjustments of the tripartite tables are necessary to analyze the consequences of round-tripping of imports. First, we re-estimate the domestic intermediate coefficients, since the round-tripped imports for intermediate use should be considered as domestic inputs rather than as imported inputs. To this end, we first estimate the

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23 See http://comtrade.un.org/
intermediate coefficient matrix of round-tripped imports (\( A_r \)) by assuming proportionality between use of a round-tripped input and total use of this input (domestically sourced and imported).\(^{24}\) By adding this matrix to the original domestic input coefficients matrix, we obtain the adjusted domestic coefficient matrix, \( A + A_r \). Second, we adjust the exports column, since it includes round-tripped imports. Like input-output tables for most countries, the Chinese tables contain exports expressed in free on board (f.o.b.) prices, while imports are expressed in cost, insurance and freight (c.i.f.) prices. The latter include margins for international transport and trade, and are therefore higher. To correct for this, we apply a 10% discount to the value of round-tripped imports to obtain a value of round-tripped exports (denoted as \( e_r \)) that can be deducted from the exports column.\(^{25}\) Hence, considering the round-tripping of imports, the NI in total exports is given by

\[
ni_r^e = w^n'(I_{3m} - A - A_r)^{-1}(e - e_r) \quad (3.4)
\]

In this Equation, \((e - e_r)\) is a vector with \(3m\) elements, which implies that exports by processing trade subindustries and by ordinary exports subindustries are both taken into account. The results obtained using Equation 3.4 are presented in Table 3.4. The numbers for both scenarios reveal that the national income share in exports increase somewhat if round-tripping of imports is proxied by either one of our methods, but that the results do not change in a qualitative sense. While growth in foreign income accounted for most of the increase of DVA in exports from 2002 to 2007, the national income share increased much faster afterwards.

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\(^{24}\) See Appendix 3.5 for more details. This procedure is very similar to how imports of an intermediate product are attributed to using industries in the construction of the World Input-Output Database (WIOD, see Dietzenbacher et al., 2013). In WIOD this procedure is adopted for Use tables, in this study we apply it to input-output tables directly.

\(^{25}\) Fung and Lau (2003) also applied a 10% discount to convert c.i.f. prices to f.o.b. prices. We also assessed the sensitivity of our results by adopting discount rates ranging from 5% to 30%, but did not find economically significant differences.
Table 3.4 National income share in exports adjusted for round-tripping of imports, in %

<table>
<thead>
<tr>
<th>Year</th>
<th>Baseline Scenario</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>National income</td>
<td>Foreign income</td>
<td>National income</td>
</tr>
<tr>
<td>2002</td>
<td>50.6</td>
<td>4.8</td>
<td>52.6</td>
</tr>
<tr>
<td>2007</td>
<td>51.3</td>
<td>7.9</td>
<td>53.5</td>
</tr>
<tr>
<td>2012</td>
<td>58.7</td>
<td>8.2</td>
<td>59.9</td>
</tr>
<tr>
<td>Change, 2002 to 2007</td>
<td>0.7</td>
<td>3.1</td>
<td>0.9</td>
</tr>
<tr>
<td>Change, 2007 to 2012</td>
<td>7.4</td>
<td>0.3</td>
<td>6.4</td>
</tr>
</tbody>
</table>

Notes: Scenario 1: Round-tripped imports proxied by China’s re-imports; Scenario 2: Round-tripped imports proxied by China’s imports from Hong Kong.

3.5 Results: Accounting for changes in the national income share in exports

As discussed in the introduction, the dynamism of the Chinese economy has been reflected in many different types of changes, each of which had impacts on the extent to which its exports contribute to national income. In this section, we will use structural decomposition analysis (a technique related to shift-share analysis, extended to take input-output relations into account) to analyze which changes contributed most to the tendencies reported in the previous section. Knowing more about the relative importance of the multitude of changes in the recent past is not only interesting in itself, but might also be informative for speculations about what might happen in the future.

3.5.1 Decomposition methodology

We decompose changes in the national income share in exports, over the periods 2002-2007 and 2007-2012, respectively. With the data available to us, the change in this ratio can be split into contributions of five partial effects:26

26 The full mathematical details of the decomposition are provided in Appendix 3.6.
• Effects of changes in ratios of national income to value added;
• Effects of changes in value added to gross output ratios;
• Effects of changes in domestic input coefficients, mainly driven by changes in the origin of intermediate inputs;
• Effects of changes in the relative importance of export types (processing exports vs. ordinary exports);
• Effects of changes in the industry composition of exports;

For clarity, we first re-formulate the national income share in exports by combining Equations 3.2 and 3.3:

\[ n = w^r(I_{3m} - A)^{-1} \bar{e} \]  \hspace{1cm} (3.5)

in which the $3m \times 1$ vector $\bar{e} = e(u'v)$ measures the export composition, capturing the share of each commodity and export type in total exports. $u$ denotes the summation vector $u = (1, ..., 1)'$, with the prime indicating transposition. If the vector $d$ contains the ratios of national income in value added (the NIVA ratios, hereafter), the national income coefficients vector can be expressed as: $w_n = d \odot w$, with the Hadamard product $\odot$ indicating cell-by-cell multiplication.

Next, we further decompose $\bar{e}$ into the shares (at the product level) accounted for by the two trade types ($\bar{f}$) and the commodity composition of the exports ($\bar{q}$). That is,

\[ \bar{e} = \bar{f} \odot \bar{q} \]  \hspace{1cm} (3.6)

The commodity composition of exports is reflected in $\bar{q} = (0 \; q \; q)'$, with $q_j = e_j/(u'v)$. We indicate the share of processing exports in the total exports of each sector by $\bar{f} = (0 \; t \; u - t)'$, with $t_j = (e_j^p)/(e_j^p + e_j^N)$. The national income share in exports can now be represented as

\[ n = (d' \odot w')(I - A)^{-1}(\bar{f} \odot \bar{q}) \]  \hspace{1cm} (3.7)
Changes in this national income share ($\Delta n = n_t - n_{t-1}$) can then be expressed as

$$\Delta n = (\Delta d' \odot \mathbf{w}')(\mathbf{I} - \mathbf{A})^{-1}(\bar{\mathbf{f}} \odot \bar{\mathbf{q}}) + (d' \odot \Delta \mathbf{w}')(\mathbf{I} - \mathbf{A})^{-1}(\bar{\mathbf{f}} \odot \bar{\mathbf{q}})$$

$$+ (d' \odot \mathbf{w}')(\mathbf{I} - \Delta \mathbf{A})^{-1}(\bar{\mathbf{f}} \odot \bar{\mathbf{q}}) + (d' \odot \mathbf{w}')(\mathbf{I} - \mathbf{A})^{-1}(\Delta \bar{\mathbf{f}} \odot \bar{\mathbf{q}})$$

(3.8)

This equation expresses changes in the national income share in exports over time as a function of changes in the five independent determinants mentioned above: the first term on the right hand side of Equation 3.8 is the change due to changes in the NIVA ratios, the second term gives the change that can be ascribed to changes in the value added to gross output ratios, etc. The results depend on the weights. For the first term (related to $\Delta \mathbf{d}$), for instance, weights for $\mathbf{w}$, $\mathbf{A}$, $\bar{\mathbf{f}}$ and $\bar{\mathbf{q}}$ have to be chosen. These could be their values at $t$, at $t - 1$, or some average of these. We determined the weights in line with the popular polar decomposition approach introduced by Dietzenbacher and Los (1998).

3.5.2 Decomposition results

Table 3.5 presents the decomposition results. It is clear that the largest part of the growth in the national income share in exports in both periods was due to changes in the domestic input structure ($\Delta \mathbf{A}$). If only this determinant structure would have changed, the national income share would have grown by 10.7 percentage points over the entire 10-year period, which is 1.3 times its actual growth in that period. This positive effect reflects the increasing use of domestically sourced intermediate inputs in the production of exports. Appendix 3.7 confirms this: a substantial degree of substitution of imports by domestic inputs was observed. This finding is consistent with the conclusion of Duan et al. (2018), which concludes that the substitution of imports by domestic products is the major reason for China’s decreasing vertical specialization, and with the microeconomic evidence provided by Kee and Tang (2016).

Changes in the relative importance of trade types (processing exports and ordinary exports) are also an important positive contributor. From 2002 to 2012, these changes
alone led to an increase of the national income share by 4.4 percentage points. The share of processing exports in total exports decreased over time, from 48.0% in 2002, to 45.7% in 2007 and 39.5% in 2012.\(^{27}\) As already shown in Table 3.1, the national income share of processing exports has been much lower than that of ordinary exports.

**Table 3.5 Decomposition results of changes in the national income share in exports (in %-points)**

<table>
<thead>
<tr>
<th></th>
<th>NIVA ratio</th>
<th>Value added ratio</th>
<th>Input Structure</th>
<th>Trade types</th>
<th>Export composition</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002-2007</td>
<td>-1.9</td>
<td>-2.0</td>
<td>6.1</td>
<td>2.9</td>
<td>-4.4</td>
<td>0.7</td>
</tr>
<tr>
<td>2007-2012</td>
<td>0.7</td>
<td>-0.7</td>
<td>4.6</td>
<td>1.5</td>
<td>1.5</td>
<td>7.4</td>
</tr>
</tbody>
</table>

Between 2002 and 2007, these two positive effects were offset by the negative effects of changes in other determinants, including the overall decreasing NIVA ratios, the changes in value added ratios, and a changing commodity composition of exports. The net effect was a modest growth in the national income share in exports. In the 2007-2012 period, however, both the NIVA ratio and the export composition became determinants that contributed to increases of the national income share. The role of the export composition was especially prominent. It led to a 4.4 percentage point decline in the national income share from 2002 to 2007, but to a 1.5 percentage point increase from 2007 to 2012. This resonates well with the analysis in section 3.4.2. The export share of machinery products, which generate comparatively low national income, expanded rapidly before the crisis. From 2007 to 2012, however, the export share of services, which have high national income shares, has obviously increased (see Appendix 3.7). The NIVA ratios were another important determinant causing differences between the two sub-periods. Its levels decreased from 2002 to 2007, but increased from 2007 to 2012 (see Appendix 3.7). The major driver behind this are the changes in the capital income share in value added. The data from the tripartite tables indicate that capital income share in value added (aggregated over industries) rose from

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\(^{27}\) China’s rising labor costs led to a shift of manufacturing activities from China to other Asian countries where wages are lower, such as Vietnam, Bangladesh, and Indonesia. Moreover, the collapse in aggregate expenditure due to the crisis was most prominent for durable goods, see Bems et al. (2012). China’s machinery products, for example, are mainly exported as processing export.
37.3% to 44.2% during 2002-2007, but then fell back to 37.1% in 2012. Since foreign income is contained in capital income only, an increasing capital income share would, ceteris paribus, reduce the national income share in exports.

3.6 Dependence of China’s national income on exports

The final question we address is by how much total exports contributed to China’s GNI and how this changed over the period 2000-2012, relative to other final demand categories. It is widely believed that China’s exports contributed much to its economic growth (e.g., Lardy, 2007). However, some literature argues that China’s GDP dependence on exports is significantly lower than what is implied by conventional indicators, such as the exports-to-GDP ratio (He and Zhang, 2010, Pei et al., 2012). These differences in findings are strongly related to the limited DVA generated per unit of processing exports. We expect that the dependence of China’s GNI on exports is even lower, in view of the strong presence of foreign-owned firms in exporting activities (and processing exports in particular).

Table 3.6 documents the dependence of China’s GNI and GDP on the four categories of final demand, i.e. consumption, capital formation, processing exports, and ordinary exports. The rows ‘share in final demand’ present the share of each category in total final demand, while the rows ‘GNI dependence’ and ‘GDP dependence’ show the share of GNI and GDP induced by each of the final demand categories.28

As expected, China’s GNI has been less dependent on exports than its GDP. Processing exports, which accounted for 10.1% of final demand in 2002, only contributed 3.3% of GNI in that year.29 The relative contribution of exports to GNI increased substantially from 2002 to 2007, but decreased considerably after the crisis, most probably due to sluggish growth during the recovery phase in many of China’s most important export destinations.

28 The results have been obtained using Equations 3.1-3.3. The GNI figures in this section only relate to China’s national income generated by activities in China itself, excluding national income derived from activities abroad.

29 Our approach is an accounting approach. A full-blown economic model might include positive feedback effects from exports to consumption and capital formation, through exports-induced household income and reinvestments of retained corporate profits. A long-run perspective would also include the positive effects of knowledge spillovers from the activities of foreign-owned enterprises to domestic enterprises.
Table 3.6 Dependence of China’s GNI and GDP on final demand categories (%)

<table>
<thead>
<tr>
<th>Year</th>
<th>Share in final demand</th>
<th>GNI dependence</th>
<th>GDP dependence</th>
<th>Share in final demand</th>
<th>GNI dependence</th>
<th>GDP dependence</th>
<th>Share in final demand</th>
<th>GNI dependence</th>
<th>GDP dependence</th>
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<td>2007</td>
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<td>33.7</td>
<td>5.5</td>
<td>15.5</td>
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<td>2012</td>
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<td>36.9</td>
<td>8.6</td>
<td>13.2</td>
<td>100.0</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>2002-2007</td>
<td>29.7</td>
<td>37.2</td>
<td>8.9</td>
<td>24.1</td>
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<td>2007-2012</td>
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<td>43.0</td>
<td>2.2</td>
<td>9.0</td>
<td>100.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: GDP data in IO tables are slightly different from those in the Annual China Statistical Yearbook. GDP shares in this table relate to GDP figures in IO tables. The GNI shares are based on GNI generated inside China, which is different from GNI figure as published by the NBS (which includes earnings generated by Chinese activities abroad). The shares in some rows do not add up not 100 percent due to the ‘error column’ in Chinese IO tables, which NBS uses to balance them.

We then investigate the contributions of growth in each final demand category to Chinese GDP and GNI growth in 2002-2007 and 2007-2012. To do this, we first calculate the national income and DVA induced by each final demand category in 2002, 2007, and 2012 (equations 3.1-3.3). We then deflate the induced national income and DVA as well as the overall GNI and GDP in 2007 and 2012 into values in expressed in 2002 prices, using the GDP deflator. Finally, the contributions are computed as the ratio of changes in national income (DVA) induced by each final demand category to the overall changes in Chinese GNI (GDP). The results are depicted in the last panel of Table 3.6. Exports have contributed 33.0% of GNI growth and 34.8% of GDP growth from 2002 to 2007. This contribution was mainly ascribed to the rapid growth in export volume. However, these contributions dropped to 11.2% for GNI growth and 11.7% for GDP growth in 2007-2012, due to the stagnation of the exports after the 2008 financial crisis. The continued sluggish growth in Europe and the United States suggests that to achieve sustainable economic growth, the Chinese government might want to devote
more attention to improving the national income share in exports rather than only relying on the volume growth of exports (besides, of course, its efforts to achieve a healthy balance between fostering export growth and growth of domestic consumption, see e.g.. Los et al., 2015b).

3.7 Conclusions

This chapter presents a new input-output accounting method to assess the extent to which China’s widely discussed exports expansion implied growth of its national income. A yuan of exports does not imply a yuan of national income, due to two issues. First, the value of exports incorporates not only Chinese domestic value added (DVA), but also the value of the imports directly and indirectly needed to produce them. Second, Chinese value added includes capital income, part of which accrues to foreign owners. Both issues are more prominent for China than for many other countries, given that its remarkable export performance was fueled by an inflow of (partly) foreign-owned firms and the introduction of processing export zones, the activities in which relied strongly on imported parts and components.

We study the period 2002-2012, which largely coincides with the rise of China as the ‘Factory of the World’. The availability of the required data not just for these two years but also for 2007, allows us to consider two subperiods. We find that national income and DVA induced by exports experienced completely different dynamics before and after the global crisis. DVA in exports increased considerably in both subperiods. Between 2002 and 2007, this was mainly a reflection of increases in the profits of foreign investors, while the share of national income grew substantially from 2007 to 2012.

Our paper extends the work of Duan et al. (2012) and Ma et al. (2015) to a longitudinal context. Compared to their work, this chapter considers the changes in exports and their effects on GDP and GNI, rather than their levels at a specific point in time. We find that the dependence on other countries changed between 2002 and 2007 from depending on imported inputs to a dependence on domestic inputs produced using foreign capital. From 2007 to 2012 the dependence declined even further, but in this
period increasing shares of domestic inputs were produced in domestic enterprises with very limited foreign capital.

To study the relative importance of potential determinants of these different patterns, we relied on structural decomposition analysis, which is an accounting method that can be applied if two or more comparable input-output tables are available. The decade-long rise of DVA in exports has mainly been due to changes in the requirements of domestic intermediate inputs in the production processes of exports within processing exports and ordinary exports subindustries. Imported materials, parts and components were substituted by domestic inputs, which is in line with the microeconomic evidence suggesting increasing Chinese production capabilities as reported by Kee and Tang (2016). This effect was reinforced by a continued between effect. Processing exports became increasingly less prominent in China’s exports bundle. This matters because per yuan, ordinary exports contain much more DVA than processing exports.

The very slow growth of national income in exports in the early phase of China’s emergence as a hub in the global economy was mainly due to an unfavorable change in the mix of its export composition (away from products inducing much national income, to products relying mainly on imported inputs and activities of foreign-owned enterprises). Reductions in value added per unit of output and the ratio between national income and value added (related to increased shares of partially foreign-owned capital income in DVA) added to this. After 2007, the tendencies for the export composition and the national income per unit of value added were reversed, and the downward pressure exerted by falling value added to gross output ratios became much weaker. In sum, we find that China’s dependence on foreign countries in producing its exports initially shifted from a reliance on foreign products to a dependence on foreign capital. Only after 2007, a yuan of exports started to yield increasing contributions to national income. The analytical framework proposed in this chapter might be used to find out whether these stages in a process of export-led growth can also be observed for other countries, such as Mexico and Vietnam.

Despite these results, the relative contribution of exports to Chinese GNI increased substantially from 2002 to 2007, but fell seriously from 2007 to 2012. This is due to the extraordinary growth of its export volume before the crisis and the stagnation of the
exports afterwards. Given the non-sustainable nature of rapid export expansion, the Chinese government could, besides stimulating consumption by Chinese households, focus on having Chinese firms moving towards more value-adding activities in global value chains, to achieve steady long-run economic growth. The wave of foreign direct investment could well bring such long-run benefits. As observed at an early stage by Zhang and Song (2001), Zhang (2002) and Gao (2005), among others, China might well benefit from foreign profits when they are reinvested, further contributing to the technological capabilities and productivity growth of domestic firms.
Appendix

Appendix 3.1

Estimation of National Capital Income

To explain our estimation process of national capital income in more detail, we start at the industry level and begin with the introduction of some variables. We denote the proportions of foreign-owned capital in the capital stocks of DEs (domestic enterprises) and FIEs (foreign-invested enterprises) in industry $j$ by $k_{dj}$ and $k_{fj}$ respectively. The capital income-output ratio of DEs and FIEs in industry $j$ are labeled $r_{dj}$ and $r_{fj}$, respectively.

Taking processing exports as an example, the estimation process is as follows. Denote $s^p_j$ as the output share of FIEs in processing exports. Firstly, the processing exports of industry $j$ are divided into output of FIEs and output of DEs, that is, $x^p_j s^p_j$ and $x^p_j (1 - s^p_j)$ respectively. We assume that every unit of capital in a given industry receives the same compensation, regardless of the ownership of that unit. Accordingly, the total capital income in DEs is $x^p_j (1 - s^p_j)r_{dj}$, of which $x^p_j (1 - s^p_j)r_{dj}k_{dj}$ is foreign-owned capital income. Similarly, the total capital income in FIEs is $x^p_j s^p_j r_{fj}$, of which $x^p_j s^p_j r_{fj}k_{fj}$ is the foreign-owned capital income. Then the sum of foreign-owned capital income in DEs and FIEs yields the total foreign-owned capital income in processing exports:

$$c_{ij}^{pf} = x^p_j (1 - s^p_j) r_{dj}k_{dj} + x^p_j s^p_j r_{fj}k_{fj}. \quad (A3.1.1)$$

The total capital income in processing exports is given by the sum of capital income in FIEs and DEs:

$$c_{ij}^p = x^p_j (1 - s^p_j) r_{dj} + x^p_j s^p_j r_{fj}. \quad (A3.1.2)$$

The share of foreign-owned capital income in total capital income in the processing exports can then be obtained as the ratio between Equations A3.1.1 and
A3.1.2. Defining $\tau_j = \tau_{fj}/r_{dj}$ as the ratio of capital income-output ratio of FIEs to that of DEs, measuring the difference in capital requirements per unit of output between the two different firm types within processing exports industry $j$, and dividing numerator and denominator by $r_{dj}$, we obtain:

$$p^f_j = \frac{c^f_j}{c^p_j} = \frac{(1-s^p_j) k_{dj} + s^p_j r_{kjfj}}{1-s^p_j + s^p_j r_{kjfj}}.$$  

(A3.1.3)

Next, denote $c^p_j$ as the capital income share of processing exports $j$, which is derived from the tripartite tables and defined as the aggregate proportion of fixed asset depreciation and operating surplus in all value added $v^f_j$ (which is, given that all output of processing exports subindustries must be sold abroad, equal to value added due to exports). The adjusted foreign-owned capital income of processing exports $j$ can then be expressed as

$$v^f_j = c^p_j v^f_j p^f_j = c^p_j v^f_j \frac{(1-s^p_j) k_{dj} + s^p_j r_{kjfj}}{1-s^p_j + s^p_j r_{kjfj}}.$$  

(A3.1.4)

Given that we assume that all taxes and labor income contribute to national income, Equation A3.1.4 is the foreign income induced by processing exports subindustry $j$.\(^{30}\) Deducting the foreign income from the value added generates the national income. Hence, the foreign income coefficient and national income coefficient of processing exports $j$ are

$$w^f_j = \frac{v^f_j}{x_j} = c^p_j w^f_j \frac{(1-s^p_j) k_{dj} + s^p_j r_{kjfj}}{1-s^p_j + s^p_j r_{kjfj}}$$  

(A3.1.5)

and

$$w^n_j = \frac{v^n_j}{x_j} = \frac{v^f_j - v^f_j}{x_j} = w^f_j - c^p_j w^f_j \frac{(1-s^p_j) k_{dj} + s^p_j r_{kjfj}}{1-s^p_j + s^p_j r_{kjfj}}.$$  

(A3.1.6)

---

\(^{30}\) If the capital income-output ratios are equal for FIEs and DEs in all industries ($\tau_j = 1$), Equation A3.1.4 yields the formula adopted by Duan et al. (2012) to estimate foreign-owned capital income, i.e., $v^f_j = c^p_j v^f_j (k_{dj} - s^p_j k_{dj} + s^p_j k_{kjfj})$. 
Turning to matrix notation to generalize the results for processing exports subindustry \(j\) to all subindustries engaged in processing exports, the diagonal elements of the matrix in the left hand side of Equation A3.1.7 give the national income coefficients of processing exports subindustries

\[
\hat{\mathbf{w}}^{nP} = \hat{\mathbf{w}}^P - \hat{\mathbf{c}}^P \hat{\mathbf{w}}^P (\mathbf{k}_d - \hat{s}^P \hat{\mathbf{k}}_d + \hat{s}^P \hat{\mathbf{r}} \mathbf{k}_f) (\mathbf{I}_m - \hat{s}^P + \hat{s}^P \hat{\mathbf{r}})^{-1}.
\]  

(A3.1.7)

Bold symbols refer to vectors with the corresponding symbols in italics in Equations A3.1.1-A3.1.7 as elements: \(\mathbf{c}^P\) is the capital income share vector of processing exports; \(\mathbf{s}^P\) is the vector of FIEs’ output share in processing exports; \(\mathbf{k}_d\) refers to the vector of foreign-owned capital share in DEs, indicating the proportion of foreign-owned capital stock in total capital stock of DEs. \(\mathbf{k}_f\) is the vector of foreign-owned capital share in FIEs. \(\mathbf{r}\) shows the capital income-output ratio in FIEs relative to that of DEs. A hat indicates a diagonal matrix of with the elements of one of these vectors on the main diagonal.

By analogy, national income coefficients for subindustries in domestic production and ordinary exports and others can be expressed as:

\[
\hat{\mathbf{w}}^{nD} = \hat{\mathbf{w}}^D - \hat{\mathbf{c}}^D \hat{\mathbf{w}}^D (\mathbf{k}_d - \hat{s}^D \hat{\mathbf{k}}_d + \hat{s}^D \hat{\mathbf{r}} \mathbf{k}_f) (\mathbf{I}_m - \hat{s}^D + \hat{s}^D \hat{\mathbf{r}})^{-1} = \hat{\mathbf{w}}^D - \hat{\mathbf{c}}^D \hat{\mathbf{w}}^D \mathbf{k}_d
\]  

(A3.1.8)

and

\[
\hat{\mathbf{w}}^{nN} = \hat{\mathbf{w}}^N - \hat{\mathbf{c}}^N \hat{\mathbf{w}}^N (\mathbf{k}_d - \hat{s}^N \hat{\mathbf{k}}_d + \hat{s}^N \hat{\mathbf{r}} \mathbf{k}_f) (\mathbf{I}_m - \hat{s}^N + \hat{s}^N \hat{\mathbf{r}})^{-1}
\]  

(A3.1.9)

in which \(\mathbf{c}^D\) and \(\mathbf{c}^N\) represent the capital income shares in domestic production and in ordinary exports and others, respectively. \(\mathbf{s}^D\) and \(\mathbf{s}^N\) denote FIEs’ output shares in domestic production and in ordinary exports and others, respectively. As all domestic production subindustries exclusively consist of DEs, we have \(\mathbf{s}^D = \mathbf{0}\). We can then express the national income coefficients for all the three types of production in one formula. That is,
\[ \hat{w}^n = \hat{w} - c \hat{w} (\hat{k}_d - \hat{s} \hat{k}_d + \hat{s} \hat{r} \hat{k}_f) (I_{3m} - \hat{s} + \hat{s} \hat{r})^{-1} \]  

(A3.1.10)

with \( c = (c^D \quad c^p \quad c^N) \), \( s = (0 \quad s^D \quad s^N) \), \( \hat{k}_d = (k_d \quad k_d \quad k_d) \), \( \hat{k}_f = (k_f \quad k_f \quad k_f) \), and \( \hat{r} = (r \quad r \quad r) \).
### Appendix 3.2

#### Table A3.2.1 Industry classification in tripartite input-output tables

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<th></th>
<th></th>
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<tr>
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<td>Mining and Washing of Coal</td>
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<tr>
<td>3</td>
<td>Extraction of Petroleum and Natural Gas</td>
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<td>3</td>
</tr>
<tr>
<td>4</td>
<td>Mining of Metal Ores</td>
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<tr>
<td>5</td>
<td>Mining and Processing of Nonmetal Ores and Other Ores</td>
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<td>Manufacture of Foods and Tobacco</td>
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<td>Manufacture of Textile, Manufacture of Textile Wearing Apparel,</td>
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<tr>
<td></td>
<td>Processing of Foils and Fabrics, Textile and Clothing</td>
<td></td>
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<tr>
<td>8</td>
<td>Footwear, Caps, Leather, Fur, Feather(Down) and Its products</td>
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<td>9</td>
<td>Processing of Timbers and Manufacture of Furniture</td>
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<td>10</td>
<td>Papermaking, Printing and Manufacture of Articles for Culture, Education</td>
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<tr>
<td></td>
<td>and Sports Activities</td>
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<tr>
<td>11</td>
<td>Processing of Petroleum, Coking, Processing of Nuclear Fuel</td>
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<td>Manufacture of Nonmetallic Mineral Products</td>
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<td>Smelting and Rolling of Metals</td>
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<td>15</td>
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<td>Manufacture of General Purpose and Special Purpose Machinery</td>
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<td>17</td>
<td>Manufacture of Transport Equipment</td>
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<td>18</td>
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<td>Manufacture of Electrical Machinery and Equipment</td>
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<td>Manufacture of Communication Equipment, Computer and Other Electronic</td>
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<td>Equipment, Manufacture of Measuring Instrument</td>
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<td>and Machinery for Cultural Activity &amp; Office Work</td>
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<td>Water production and supply</td>
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Appendix 3.3

Data sources

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<td>The tripartite tables</td>
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<td>Output shares of FIEs ($s$)</td>
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<td>Non-processing exports of FIE</td>
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<td>Foreign capital shares in DEs and FIEs ($k_{d}$ and $k_{r}$)</td>
<td>Paid-in capital for industrial sectors</td>
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<td>Registered capital of FIEs in Agriculture and Construction</td>
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## Appendix 3.4

### National income shares in export

**Table A3.4.1 National income shares (2002 -2012), selected industries, in %**

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<tr>
<th>Industry</th>
<th>National income (NI) in exports</th>
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<td>2002</td>
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<tr>
<td>27</td>
<td>50.1</td>
</tr>
<tr>
<td>28</td>
<td>50.6</td>
</tr>
<tr>
<td>29</td>
<td>62.3</td>
</tr>
<tr>
<td>30</td>
<td>40.1</td>
</tr>
<tr>
<td>Energy and material industries</td>
<td>31.9</td>
</tr>
<tr>
<td>Labor-intensive industries</td>
<td>32.4</td>
</tr>
<tr>
<td>Machinery industries</td>
<td>18.1</td>
</tr>
<tr>
<td>Total</td>
<td>26.1</td>
</tr>
<tr>
<td>Industry</td>
<td>National income to DVA ratio (%)</td>
</tr>
<tr>
<td>----------</td>
<td>---------------------------------</td>
</tr>
<tr>
<td>1</td>
<td>94.8</td>
</tr>
<tr>
<td>2</td>
<td>85.3</td>
</tr>
<tr>
<td>3</td>
<td>96.9</td>
</tr>
<tr>
<td>4</td>
<td>93.6</td>
</tr>
<tr>
<td>5</td>
<td>89.8</td>
</tr>
<tr>
<td>6</td>
<td>90.6</td>
</tr>
<tr>
<td>7</td>
<td>90.0</td>
</tr>
<tr>
<td>8</td>
<td>89.5</td>
</tr>
<tr>
<td>9</td>
<td>87.9</td>
</tr>
<tr>
<td>10</td>
<td>86.4</td>
</tr>
<tr>
<td>11</td>
<td>91.0</td>
</tr>
<tr>
<td>12</td>
<td>84.6</td>
</tr>
<tr>
<td>13</td>
<td>90.3</td>
</tr>
<tr>
<td>14</td>
<td>90.6</td>
</tr>
<tr>
<td>15</td>
<td>84.3</td>
</tr>
<tr>
<td>16</td>
<td>86.1</td>
</tr>
<tr>
<td>17</td>
<td>89.7</td>
</tr>
<tr>
<td>18</td>
<td>84.7</td>
</tr>
<tr>
<td>19</td>
<td>73.8</td>
</tr>
<tr>
<td>20</td>
<td>80.7</td>
</tr>
<tr>
<td>21</td>
<td>90.8</td>
</tr>
<tr>
<td>22</td>
<td>85.4</td>
</tr>
<tr>
<td>23</td>
<td>95.8</td>
</tr>
<tr>
<td>24</td>
<td>96.3</td>
</tr>
<tr>
<td>25</td>
<td>96.7</td>
</tr>
<tr>
<td>26</td>
<td>85.5</td>
</tr>
<tr>
<td>27</td>
<td>91.9</td>
</tr>
<tr>
<td>28</td>
<td>96.2</td>
</tr>
<tr>
<td>29</td>
<td>96.1</td>
</tr>
<tr>
<td>30</td>
<td>95.2</td>
</tr>
<tr>
<td>Energy and material industries</td>
<td>90.1</td>
</tr>
<tr>
<td>Labor-intensive industries</td>
<td>89.6</td>
</tr>
<tr>
<td>Machinery industries</td>
<td>79.6</td>
</tr>
<tr>
<td>Total</td>
<td>85.3</td>
</tr>
</tbody>
</table>

Note: P=processing exports; N=ordinary exports; T=total exports.
Appendix 3.5
Re-estimating the domestic coefficient matrix and exports to consider round-tripped trade

Denote $m_r$ as the vector with all round-tripped imports for each of the subindustries, and $m_{ri}$ as the vector with round-tripped imports for intermediate use. These round-tripped imports lead to overestimations of China’s imports. A round-tripped imported intermediate matrix can be calculated as $Z_r^M = Z^M (\hat{\mathbf{m}})^{-1} \hat{\mathbf{m}}_{ri}$, where $\mathbf{m} = Z^M u$ and $Z^M$ is directly taken from the tripartite input-output table (see Figure 3.1). As previously mentioned, $Z_r^M$ should be part of the domestic intermediate inputs matrix, since they are produced by either DEs or FIEs and used in China. Accordingly, we split $Z_r^M$ into two parts based on a proportionality assumption. The former is formulated as $Z_r^D = Z^D \odot (Z^D + Z^N) \odot Z_r^M$, and the latter is obtained by residues, i.e., $Z_r^N = Z_r^M - Z_r^D$, where $Z^D = (Z^{DD} \ Z^{DP} \ Z^{DN})$, $Z^N = (Z^{ND} \ Z^{NP} \ Z^{NN})$, $\odot$ and $\odot$ indicate cell-by-cell (Hadamard) multiplication and cell-by-cell division respectively. Thus, after reclassification of the round-tripped imports, the true domestic coefficient matrix is $A + A_r$, with $A_r = \begin{pmatrix} Z_r^D \\ 0 \\ Z_r^N \end{pmatrix} \hat{x}^{-1}$.

The round-tripped exports are calculated by subtracting 10% from the round-tripped imports, i.e. as $0.9m_r$, given the difference between fob (in which exports are given) and cif prices (in which imports are expressed). We then adopt a proportionality assumption to split the round-tripped exports into exports of two regimes: round-tripped processing exports, and round-tripped ordinary exports. They are given by $e_r^p = e^p \odot (e^p + e^N) \odot 0.9m_r$ and $e_r^N = 0.9m_r - e_r^p$, respectively. The true export vector is $e - e_r$, with $e_r = \begin{pmatrix} e_r^p \\ e_r^N \end{pmatrix}$. 
Appendix 3.6

Decomposition on the national income share

In Section 3.5, Equation 3.8 gives the equation used to split the total change in the national income share in exports over time into parts attributable to changes in specific determinants. The results of such a structural decomposition analysis can be affected considerably by the weights used, in particular when changes over longer periods of time are considered (Dietzenbacher and Los, 1998). The weighting approach used in Section 3.5 is in line with the widely adopted recommendations of the Dietzenbacher and Los paper.

We use subscript 0 to indicate the variables in the initial year, and 1 for that in final year. We use the symbol Δ to denote the change in a variable between those two years, e.g. Δn = n_1 − n_0. The basic decomposition then reads as

\[
\Delta n = (d'_1 \odot w'_1)(I - A_1)^{-1}(f_1 \odot q_1) - (d'_0 \odot w'_0)(I - A_0)^{-1}(f_0 \odot q_0)
\]

\[
= (\Delta d' \odot w'_1)(I - A_1)^{-1}(f_1 \odot q_1)
\]

\[
+ (d'_0 \odot \Delta w')(I - A_1)^{-1}(f_1 \odot q_1)
\]

\[
+ (d'_0 \odot w'_0)[(I - A_1)^{-1} - (I - A_0)^{-1}](f_1 \odot q_1)
\]

\[
+ (d'_0 \odot w'_0)(I - A_0)^{-1}\Delta f (\odot q_1)
\]

\[
+ (d'_0 \odot w'_0)(I - A_0)^{-1}(f_0 \odot \Delta q)
\]

(A3.6.1a) (A3.6.1b) (A3.6.1c) (A3.6.1d) (A3.6.1e)

The mirror image is given by

\[
\Delta n = (d'_1 \odot w'_1)(I - A_1)^{-1}(f_1 \odot q_1) - (d'_0 \odot w'_0)(I - A_0)^{-1}(f_0 \odot q_0)
\]

\[
= (\Delta d' \odot w'_0)(I - A_0)^{-1}(f_0 \odot q_0)
\]

\[
+ (d'_1 \odot \Delta w')(I - A_0)^{-1}(f_0 \odot q_0)
\]

\[
+ (d'_1 \odot w'_1)[(I - A_1)^{-1} - (I - A_0)^{-1}](f_0 \odot q_0)
\]

\[
+ (d'_1 \odot w'_1)(I - A_1)^{-1}\Delta f (\odot q_0)
\]

\[
+ (d'_1 \odot w'_1)(I - A_1)^{-1}(f_1 \odot \Delta q)
\]

(A3.6.2a) (A3.6.2b) (A3.6.2c) (A3.6.2d) (A3.6.2e)

In line with Dietzenbacher and Los (1998), the reported contributions of the
changes in a determinant are computed by taking the arithmetic averages of two corresponding expressions in A3.6.1 and A3.6.2. To compute the contribution of changes in the domestic intermediate inputs requirements matrix $\mathbf{A}$, the sum of Equations A3.6.1c and A3.6.2c was divided by two.
Appendix 3.7

Descriptive Statistics about Input Usage and Exports

Table A3.7.1 Aggregate input coefficient (in %) in 2002-2012

<table>
<thead>
<tr>
<th></th>
<th>2002</th>
<th></th>
<th>2007</th>
<th></th>
<th>2012</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>D</td>
<td>P</td>
<td>N</td>
<td>Ag</td>
<td>D</td>
<td>P</td>
</tr>
<tr>
<td>Domestic intermediate coefficient</td>
<td>55.8 16.8 58.5 54.3 62.3 24.1 59.2 59.5 60.2 28.4 65.5 60.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Import coefficient</td>
<td>1.9 66.6 16.3 6.8 3.1 58.5 13.7 8.3 3.6 55.1 7.4 6.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value added coefficient</td>
<td>42.3 16.6 25.1 38.9 34.7 17.4 27.1 32.2 36.2 16.5 27.1 33.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NIVA ratio</td>
<td>99.5 78.3 80.5 97.4 99.4 64.4 74.2 94.7 98.9 87.3 73.8 94.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital income share</td>
<td>37.0 38.7 40.3 37.3 43.4 50.2 46.9 44.2 36.0 36.2 41.8 37.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: D=domestic production, P=processing exports, N=ordinary exports and others, Ag=aggregate. Source: Authors’ calculations based on the tripartite IO tables for 2002, 2007 and 2012.

Table A3.7.2 Export share for typical industry groups (in %) in 2002-2012

<table>
<thead>
<tr>
<th></th>
<th>2002</th>
<th></th>
<th>2007</th>
<th></th>
<th>2012</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P</td>
<td>N</td>
<td>Ag</td>
<td>P</td>
<td>N</td>
<td>Ag</td>
</tr>
<tr>
<td>Energy and Materials</td>
<td>0.4 2.1 2.5 0.5 1.2 1.7 0.4 0.4 0.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor-intensive industries</td>
<td>8.4 14.4 22.8 4.6 14.2 18.8 3.2 13.3 16.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Machinery</td>
<td>25.2 8.6 33.8 31.6 12.2 43.8 28.9 14.2 43.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Services</td>
<td>5.9 15.6 21.5 2.3 11.1 13.4 0 18.4 18.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Above aggregate</td>
<td>78.6 81 117.9 89.2 85.6 121.9 68.7 88.1 115.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: D=domestic production, P=processing exports, N=ordinary exports and others, Ag=aggregate. Source: Authors’ calculations based on the tripartite IO tables for 2002, 2007 and 2012.
CHAPTER 4

Processing Trade in Chinese Interregional Input-Output Tables: Construction and Application

4.1 Introduction

The deepening of international production fragmentation led to a boom in the trade of intermediate goods. As a consequence, imports and exports data did no longer reflect accurately what was going on in the world and were supplemented with the so-called “global value chain” (GVC) perspective (Los et al., 2015a; Johnson, 2014, 2018). To arrive at GVC results, however, global intercountry input-output (IO) tables are necessary. Their construction was at the heart of several large research projects (see Tukker and Dietzenbacher, 2013, for an overview). Given China’s role in global trade patterns, the country has been widely examined (Chen et al., 2012; Duan et al., 2012; Koopman et al., 2012; Los et al., 2012; Kee and Tang, 2016; Aichele and Heiland, 2018). The question, however, is whether a thorough analysis can be done at the country level. China is an enormous country with a huge population, and it faces serious regional inequalities in terms of physical and geographical conditions, infrastructure, globalization involvement, and economic growth. In particular, pronounced differences exist between the coastal provinces and the inland provinces. The coastal provinces participate more actively in the globalization process and grow much faster (Meng et al., 2017). This chapter therefore examines how the globalization effects propagate inside China and impact regional economies.

Existing studies find that China’s interior regions are increasingly involved in globalization by providing intermediates to the export production in coastal regions (see Feng et al., 2013; Meng et al., 2013, 2017; Pei et al., 2017). However, a defect

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1 For example, Pei et al. (2017) demonstrate that interior regions usually occupy upstream activities (such as providing natural resources and raw materials) while coastal regions carry out downstream activities and export the final products. From an environmental perspective, previous studies have emphasized that developed countries have outsourced emissions to China through international trade (Weber et al., 2008). Feng et al. (2013) further document that large parts of these emissions are transferred from China’s coastal regions to interior regions through upstream value chain activities.
of the earlier studies is that they ignore a typical feature of China’s foreign trade, i.e. the prevalence of processing trade. Processing trade in China refers to the three-step business activity of (i) importing all (or part of) the raw and auxiliary materials, components and parts, accessories and packaging materials from enterprises abroad, after which (ii) these goods are processed and assembled, before (iii) the finished products are re-exported (Yang et al., 2015). Processing trade in China developed over time by leaps and bounds and shows an extremely uneven distribution over the domestic regions. According to China’s Customs statistics, processing exports comprised about half of the gross exports since the early 1990s (and this share declined to 34.1% in 2016) and they were concentrated in coastal regions. The left panel of Table 4.1 shows the shares of regional processing exports in the national totals. In 2012, for example, processing exports in East Coast and South Coast constituted 75.2% of China’s total processing exports. In contrast, the inland provinces were only responsible for less than 15% of China’s processing exports. Moreover, processing trade played very different roles in different regions. The right panel of Table 4.1 gives the share of a region’s processing exports in its total exports. It shows that processing exports in South Coast, the major exporter of China, accounted for 48.2% of its total exports in 2012. In the inland region Northwest, this proportion was only 7.8%. Over time, the shares of processing exports have decreased for all regions except the Central Regions and Southwest from 2002 to 2012.

China’s policy that imported materials for processing trade were exempted from taxes, led to the heavy reliance of processing exports on imported inputs (Yang et al., 2015). Consequently, processing exports generated only limited domestic activities, when compared to other production. At the national level, it has been shown in the literature that failing to separate production for processing exports from other production biases the results. For example, the contribution of China’s exports to

1 Ma and Van Assche (2016) analyze the possible factors that affect the location choice of China’s export processing plants.
2 Northeast includes Heilongjiang, Jilin, and Liaoning; Northern Municipalities includes Beijing and Tianjin; North Coast includes Hebei and Shandong; East Coast includes Shanghai, Jiangsu, and Zhejiang; South Coast includes Guangdong, Fujian, and Hainan; Central Regions includes Shanxi, Henan, Hubei, Hunan, Anhui, and Jiangxi; Northwest includes Inner Mongolia, Shanxi, Ningxia, Gansu, and Xinjiang; Southwest includes Sichuan, Chongqing, Yunnan, Guizhou, Guangxi, Qinghai, and Tibet. See also Appendix 4.2 for a map.
3 Notice that Liaoning, Tianjin and Guangxi, which are coastal provinces, are respectively included in Northeast, Northern Municipalities and Southwest. Therefore, the share of processing exports in inland provinces is smaller than the sum of the shares in Northeast, Northern Municipalities, Central Regions, and Southwest.
economic growth is inflated (Pei et al., 2012), the damage of international trade to China’s environment is overestimated (Dietzenbacher et al., 2012; Su et al., 2013), and China’s vertical specialization is underestimated (Yang et al., 2015). We expect that also regional studies that use data which fail to separate processing exports will lead to misleading conclusions. However, in order to be able to check we need accurate interregional input-output (IO) tables that differentiate the production of processing exports from other production.

### Table 4.1 Distribution of processing exports across regions, 2002 - 2012

<table>
<thead>
<tr>
<th>Region</th>
<th>Distribution of processing exports (%)</th>
<th>Share of processing exports (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northeast</td>
<td>4.1</td>
<td>2.9</td>
</tr>
<tr>
<td>Northern Municipalities</td>
<td>6.2</td>
<td>5.6</td>
</tr>
<tr>
<td>North Coast</td>
<td>6.0</td>
<td>6.8</td>
</tr>
<tr>
<td>East Coast</td>
<td>24.5</td>
<td>34.4</td>
</tr>
<tr>
<td>South Coast</td>
<td>56.6</td>
<td>40.8</td>
</tr>
<tr>
<td>Central Regions</td>
<td>1.1</td>
<td>4.7</td>
</tr>
<tr>
<td>Northwest</td>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td>Southwest</td>
<td>1.0</td>
<td>4.7</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Because exports in the coastal regions are mainly processing exports, which have limited backward linkages (in terms of economics or the environment) toward inland regions, biased results are expected (Fu, 2004). This raises a series of questions. What are the “true” intra-regional and interregional linkages in China, given the prevalence of processing exports? To what extent does one region’s involvement in globalization influence economic growth in other regions? Moreover, because of China’s increasing labor costs and the country’s policy with respect to processing trade, the share of processing exports in total exports has declined in recent years. Also, processing

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4 For instance, Pei et al. (2012) analyzed the contribution of changes in exports to China’s value added change between 2002 and 2007. It was found to be 32% higher when the ordinary IO tables were used than when the tables capturing processing trade were used. Amiti and Freund (2010) found a significant skill upgrade in China's total exports between 1992 and 2005, but they found no evidence of skill upgrading when processing exports were excluded from total exports. See also Dean et al. (2011), Johnson and Noguera (2012), Koopman et al. (2012), Upward et al. (2013), Dai et al. (2016).

5 In 2006, the Ministry of Commerce announced that processing trade was prohibited or restricted for seven categories of goods. These categories currently account for about 15% of all commodities in HS 10 digit codes. HKTDC (2007) deduced that changes in China's processing trade policy have reduced the processing trade of
exports show a shift from coastal regions to inland destinations. To what extent will these changes affect intra-regional and interregional linkages as well as regional growth? Answering these questions has a large societal relevance. Answering these questions requires the appropriate interregional IO tables, which need to be constructed first.

So far, due to its extraordinary feature, processing trade has already aroused extensive attention at the national level. Using various methods, Chen et al. (2001), Koopman et al. (2012), Su et al. (2013), Ma et al. (2015) have separated production of processing exports from other production in Chinese national IO tables. Chen et al. (2019) and OECD-ICIO tables have distinguished China’s production of processing exports in international IO tables. However, to the best of our knowledge, no one has constructed interregional tables.

This chapter constructs an interregional IO table with separated processing exports (IRIOP table). We describe explicitly how information from a wide range of data sources has been harmonized, reconciled and used to arrive at this new IO table.

The rest of the chapter is structured as follows. Firstly, Section 4.2 illustrates the framework of the IRIOP table. Section 4.3 overviews the available raw data for the table construction and describes the construction methodology. Based on the new tables, Section 4.4 reexamines the domestic parts of global value chains in which China’s exports are involved, demonstrating the necessity of differentiating processing exports at the regional level. Finally, Section 4.5 concludes.

4.2 Framework of the IRIOP table

We start with a description on the IRIOP table. It is a product by product IO table for eight regions and 17 product categories. Its general structure is shown in Figure 3.1, which depicts a 2-region case to keep the exposition simple. The unique feature of this table is that the production of each region is divided into two types: the production of

products with low value-added, high pollution intensity, and high energy and resource consumption. In 2016, the State Council of China published a document (No. 4 (2016)) to issue several opinions to promote the innovative development of processing trade.

processing exports and ordinary production. Processing exports includes two types of export regimes: ‘Processing & Assembly’ (P&A) exports and ‘Processing with Imported Materials’ (PIM) exports. Ordinary production then incorporates all production for the domestic market and the production of ‘ordinary’ exports (i.e. any exports but processing exports).

Before introducing the entities in Table 4.2, we first clarify some notational principles regarding the use of indices. The subscript indices $i, j$, and $k$ represent sectors, the subscript indices $r, s, l$, and $w$ represent regions, and the superscript indices $O, P$, and $M$ represent the different types of production. The data in the IROP table are expressed in monetary units and valued in current basic prices.

<table>
<thead>
<tr>
<th>Table 4.2 Schematic outline of the IROP table (2-region case)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intermediate use</strong></td>
</tr>
<tr>
<td><strong>Region $r$</strong></td>
</tr>
<tr>
<td>$P$</td>
</tr>
<tr>
<td>$Z_{rr}^{OP}$</td>
</tr>
<tr>
<td>$P$</td>
</tr>
<tr>
<td>$Z_{sr}^{OP}$</td>
</tr>
<tr>
<td><strong>IMP</strong></td>
</tr>
<tr>
<td><strong>VA</strong></td>
</tr>
<tr>
<td>$TOT$</td>
</tr>
</tbody>
</table>

Notes: $P =$ production of processing exports; $O =$ other (or ordinary) production; $DFC =$ domestic final consumption; $FCF =$ fixed capital formation; $INV =$ inventory changes; $EXP =$ exports; $TOT =$ gross sector outputs or total imports; $IMP =$ imports; $VA =$ value added. The cells in the IROP table are divided into five parts to ease the presentation of the construction steps. The cells in grey represent step 1; the cells in yellow step 2; the cells in blue step 3; the cells in orange step 4; and the cells in green step 5.

---

7 P&A trade and PIM trade differ in terms of ownership and payment for the imported materials. Under P&A trade, materials and components are supplied by a foreign company and processed by a Chinese enterprise on a consignment basis. Ownership of raw materials and components remains with the foreign company. The Chinese enterprise (i) does not pay for the imported materials, and (ii) receives a processing fee. After processing and assembly, the finished products are owned by the foreign company which distributes them further. In contrast, under PIM trade, a Chinese enterprise purchases the raw materials and components. It therefore makes foreign currency payments and becomes the owner of the imported commodities. After processing and assembly, the Chinese enterprise exports the finished products to foreign customers.

8 Bold-faced lower-case letters are used to indicate vectors, bold-faced capital letters indicate matrices, italic lower-case letters indicate scalars (including elements of a vector or matrix). Vectors are columns by definition, row vectors are obtained by transposition, denoted by a prime (e.g. $x'$). Diagonal matrices are denoted by a circumflex (e.g. $\bar{x}$).
The variables in the IRIOP table are as follows: the matrix $Z_{rs}^{OP}$ (with typical element $z_{rsij}^{OP}$) gives the intermediate deliveries from ordinary production in region $r$ to processing exports production in region $s$; the matrix $Z_{s}^{MO}$ (with typical element $z_{sij}^{MO}$) gives the imports used as intermediate inputs for ordinary production in region $s$; the (row) vector $(v_{s}^{p})'$ (with typical element $v_{sij}^{p}$) gives the value added in each sector for the production of processing exports in region $s$; the vector $x_{s}^{O}$ (with typical element $x_{sij}^{O}$) gives the sectoral outputs of ordinary production in region $s$; the vectors $c_{rs}^{O}$ ($c_{rst}^{O}$) and $f_{rs}^{O}$ ($f_{rst}^{O}$) are respectively the sectoral deliveries of ordinary products from region $r$ for final consumption and fixed capital formation in region $s$; the vector $q_{r}^{O}$ ($q_{rl}^{O}$) gives the sectoral inventory changes of ordinary products in region $r$; the vectors $c_{s}^{M}$ ($c_{st}^{M}$) and $f_{s}^{M}$ ($f_{st}^{M}$) respectively give the sectoral imports used as final consumption and fixed capital formation in region $s$; the vectors $e_{r}^{p}$ ($e_{rl}^{p}$) and $e_{r}^{O}$ ($e_{rl}^{O}$) are respectively sectoral processing exports and ordinary exports by region $r$; the vector $m$ gives the sectoral total imports by all regions. Note that re-exports are zero.

### 4.3 Construction of the IRIOP table

In the ideal case, data for all the variables in the IRIOP table are obtained through a series of comprehensive surveys. However, conducting such surveys is extremely time-consuming and expensive. Therefore we have developed a semi-survey method, using a combination of survey data, proportionality assumptions, and applying a RAS procedure. The following subsections describe the construction process and pay attention to issues like harmonization and reconciliation of data.

#### 4.3.1 Overview of available information

The availability of consistent and reliable data is often regarded as a major barrier to construct a new IO table (Peters et al., 2011). For the IRIOP table, we have primarily used four data sources. These are: the national IO tables capturing processing trade (NIOP tables, also known as the national bipartite IO tables); the standard interregional
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IO tables (IRIO tables); international trade statistics from China’s Customs; and the Regional Economic Accounts (REA).

The NIOP table separates the production of processing exports from ordinary production in the national IO table (see Table A4.1.1 in Appendix 4.1). Aggregating the IRIOP table over the regions yields the NIOP table. The NIOP tables that we have used are compiled jointly by the Chinese Academy of Sciences (CAS) and the National Bureau of Statistics (NBS). These tables are available for 2002, 2007, and 2012 and were constructed by using a combination of survey data and mathematical methods (see Chen et al., 2001; Chen et al., 2012). They include the same 42 sectors as the official national IO tables.

The IRIOP tables are derived from the national IO tables and provide all inter- and intra-regional deliveries in a country. A 2-region version is outlined in Table A4.1.2 in Appendix 4.1. Aggregating the IRIOP table over the two types of productions (i.e., processing exports production and ordinary production) gives the IRIOP table. The IRIOP tables used in this chapter are compiled by the State Information Center (SIC) and the NBS (Zhang and Qi, 2012). The tables are available for 2002, 2007, and 2012, cover eight regions and 17 sectors (see Appendix 4.2 for the definition of the regions and Appendix 4.3 for the sector classification). Provinces are grouped into the same region not only because of geographical proximity, but also because they share a similar macroeconomic environment and show a similar development performance. This division of regions thus captures several spatial characteristics.

The third data that we have used are the international trade statistics from China’s Customs. For each province, they provide detailed data on exports and imports based on the origins and destinations of the deliveries of goods. The imports of a province

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9 There also exists another NIOP table. It is constructed for 2007 by Koopman et al. (2012) using a quadratic optimization procedure. However, we have used the tables from the CAS and the NBS because they are semi-official, publicly accessible and cover more years.
10 It needs to be mentioned that the original CAS and NBS NIOP tables are not ‘bipartite’, but ‘tripartite’. Other production was split into two parts: production of domestic enterprises to satisfy domestic demand, and a combination of the production of non-processing exports and the production of foreign invested enterprises to satisfy domestic demand. Due to data limitations, however, this split of other production cannot be made at the regional level.
11 Also other institutes (e.g. the Development Research Centre of the State Council of China) have constructed Chinese IRIOP tables, using different compilation methods and different classifications of provinces into regions. We have used the SIC-NBS tables because they are semi-official and publicly accessible, and because they adhere to division of regions that is most common in China.
12 In China’s Customs statistics, two types of provincial trade data are available. One type is based on the source or destination of a delivery, the other type is according to the location of trading companies. Usually, the two types of
thus give the value of the foreign commodities that are consumed or used in this province. The exports of a province indicate the delivery abroad of commodities for which the production, or the final assembly, or the original dispatch occurred in this province (NBS, 2017). The data are not only by commodity (at 8-digit level under the Harmonized Commodity Description and Coding System, i.e. HS for short), but also by trade regime (e.g., P&A trade, PIM trade, and ordinary trade) and by firm type (e.g., foreign-invested enterprises and domestic enterprises). The HS 8-digit data are further aggregated using the NBS concordance table. This yields the trade data classified by IO sector. These data are essential for us to determine the output, exports, imports and intermediate deliveries in the IRIOP tables. We will come back to this in Section 3.3.

The last data source we have used are the REAs published annually by the NBS. They provide the value added for several broad industries (including agriculture, manufacturing, construction, trade and transport, and other service sectors) at the province level. Moreover, the provincial totals for final consumption, fixed capital formation, and inventory changes are also taken from the REAs.

4.3.2 Inconsistency issues and some underlying principles

4.3.2.1 Inconsistencies

The use of different data sources implies conflicts between the sources. For example, ideally, aggregating the NIOP table over the two types of production and aggregating the IRIIO table over the regions should give the national IO table. However, this is not the case and all variables (except value added) show clear discrepancies. This is not surprising because the NIOP and the IRIIO tables are based on different data sources. The NIOP tables are based on the official national IO tables and the IRIIO tables are
largely based on the provincial IO tables. In the rest of this subsection, we will summarize the main inconsistency issues in the data sources.

First, P&A imports are treated differently in the NIOP tables from that in the IRIO tables for 2007 and 2012. Recall that P&A imports are materials that are owned by foreign companies and that are supplied to Chinese enterprises to produce P&A exports. This production involves processing and assembly activities for which the Chinese enterprises receive a processing fee. The national IO tables and the IRIO tables record just these processing fees and not the P&A imports and exports themselves. The NIOP tables, however, aim at reflecting the underlying technology of the processing sector. All imports (including P&A imports) used to produce processing exports are therefore recorded as intermediate inputs. As a result, imports, exports, and outputs are all larger in the NIOP tables than in the IRIO and the national IO tables. If we subtract the P&A imports from the corresponding items in the NIOP table, it is basically consistent with the official national IO table.\footnote{This inconsistency issue does not exist for 2002. That year, P&A imports were included both in the national IO table and the IRIO table.}

Second, the value of trade differs considerably at the regional level between the IRIO table and China’s Customs’ statistics. Part of the explanation is that P&A imports are included in both the imports and the exports in China Customs’ statistics, but not in the imports and exports in the IRIO tables. However, after deducting the P&A imports from Customs’ statistics, considerable gaps still remain between the two sources. In the NIOP tables, on the other hand, is merchandise trade basically consistent with China’s Customs statistics and with the official national IO tables (provided we correct for the different treatment of P&A imports).

Third, discrepancies exist also between IO tables and the REAs. For example, in 2007, Chinese GDP in the NIOP table is 3.5\% less than the total value added (i.e. summed over the 31 provinces) in the REAs. This is not surprising given the huge gaps reported by Holz (2004). Also, at the regional level are sources not consistent. For example, value added in South Coast is 5.7\% less in the IRIO table than in the REAs.\footnote{According to Zhang and Qi (2012), the value added in the IRIO table is obtained by adjusting the value added in provincial IO tables to the official national IO tables.}
4.3.2.2 Underlying principles and choices

The inconsistencies discussed above imply that choices and adjustments need to be made before the actual construction of the IRIOP table takes place. In this subsection, we will describe the choices we have made and what the underlying principles were.

First, reliable and accurate trade statistics have the highest priority in connection to the separation of processing exports production from ordinary production, which is the distinguishing feature of the IRIOP table. This implies that the NIOP table (rather than the IRIO table) has become our preferred data source. The NIOP tables are basically consistent with China’s Customs’ statistics (while the IRIO tables are not) and trade statistics from China’s Customs are believed to be the most authoritative and reliable. This is because China’s Customs is the only official institute to monitor international trade and is responsible for the trade statistics following strict regulations.

To construct the IRIOP table, we use the NIOP table as a benchmark and then distribute the two types of production over the different regions. This means that if we aggregate the IRIOP table over the regions we will get the NIOP table. The distribution is obtained from the IRIO tables, which reflect the input linkages between the regions. Another advantage of our approach to take the NIOP table as the benchmark is that all imported materials for processing exports (including P&A imports) are recorded as intermediate inputs in the IRIOP tables. The tables thus provide a full picture of the input structure of processing exports production.

Second, we give the REAs the next highest priority because they are officially published and more authoritative than other data sources. This means that, for example, data on regional value added, final consumption, and fixed capital formation are taken from the REAs, not from the IRIO tables (which also include these variables). Note that the data from the REAs should first be rescaled, however, to match with the NIOP table (which we have taken as a benchmark).

Third, in order to nest the IRIO tables into the NIOP tables, the sector classification should match. The NIOP tables have 42 sectors and the IRIO tables have

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17 An alternative way would have been to take the IRIO table as a benchmark and then split each region’s production into processing exports production and other production.
17 sectors. One way would be to disaggregate certain IRIO sectors, because more sector detail generates more accurate results (as argued by Su et al., 2010). However, making this split of sectors will require costly efforts to obtain additional data and, meanwhile, may lead to more biased results if these additional data are insufficiently accurate. Therefore we have chosen the other option, which is to aggregate the NIOP tables in line with the IRIO sector classification. See Appendices 4.2 and 4.3 for the details on regions and sectors.

4.3.3 The construction methodology

To construct the IRIOP tables, the variables in Table 4.2 need to be estimated. The estimation in Step 1 includes exports, domestic inventory changes, and outputs, Step 2 covers the imported final consumption and fixed capital formation, Step 3 deals with the value added, Step 4 estimates the intermediate use of imports (i.e. the import matrices), and Step 5 yields the intermediate input use, the final consumption, and the fixed capital formation, all for domestically produced goods and services. The estimation in Steps 3, 4, and 5 is somewhat convoluted. However, the basic idea of the estimation is that initial estimates for each variable are obtained first, after which the RAS method is performed to make the table balanced and consistent with the official statistics. In the rest of this subsection we will sketch the main construction steps, leaving the details for Appendix 4.4.

4.3.3.1 Step 1: exports, inventory changes, and outputs

This step estimates the exports (vectors $e_r^p$ and $e_r^o$ in the case of country $r$), inventory changes ($q_r^o$), and outputs ($x_r^p$ and $x_r^o$) in IRIOP tables.

Exports. For manufacturing sectors, region-sector data for processing exports and for ordinary exports are obtained by aggregating data from China’s Customs’ statistics.

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18 The RAS method is commonly used to bi-proportionally scale a matrix of unbalanced preliminary estimates of an unknown real matrix to prescribed row and column sums (Stone and Brown, 1962; Bacharach, 1970; Lenzen et al., 2009; Miller and Blair, 2009).
These region-sector data are then scaled to match the export data in the NIOP tables. Processing exports of services mainly refers to the commercial margins or to other services related to the processing exports of manufacturing goods. The processing exports of services at the regional level are estimated by distributing the processing exports of services in the NIOP table over the regions, using the regional distribution of the processing exports in manufacturing. Ordinary exports of services at the regional level are obtained by distributing the ordinary exports of services from the NIOP tables over the regions by the regional distribution of sector-specific services exports in the IRIO tables.

*Domestic inventory changes.* It should be noted that a region’s inventory changes are the inventory changes in the whole of China regarding products delivered by that particular region. A two-step procedure is adopted to estimate the elements $q_{r_i}^O$ of the vector $\mathbf{q}_r^O$. First, the regional totals of the inventory changes for region $r$ are taken from the REAs and distributed over the sectors using shares based on the sector-specific inventory changes for region $r$ from the IRIO table (i.e. $\check{\mathbf{q}}_r^O$, where a tilde indicates that the variable is from an IRIO table). This yields the initial estimate of $q_{r_i}^O$. Next, these initial estimates are rescaled such that the aggregation over the regions equals the inventory changes in the NIOP table (i.e. $\bar{\mathbf{q}}^O$, where an overbar indicates that the variable is from a NIOP table).

*Outputs.* By definition, the output of processing exports production is just the exports themselves (i.e. $\mathbf{x}_r^P = \mathbf{e}_r^P$). To estimate the regional output of ordinary production ($\mathbf{x}_r^O$), we first estimate the domestic sales of regional ordinary production ($\mathbf{d}_r^O = \mathbf{x}_r^O - \mathbf{q}_r^O - \mathbf{e}_r^O$). At the national level, the domestic sales are obtained from subtracting the ordinary exports and inventory changes from the output of ordinary production in the NIOP tables, i.e. $\check{\mathbf{d}}^O = \check{\mathbf{x}}^O - \check{\mathbf{q}}^O - \check{\mathbf{e}}^O$. Next these domestic sales are distributed over the regions of origin, using the regional distribution of domestic sales in the IRIO table, i.e. $\check{\mathbf{d}}_r = \check{\mathbf{x}}_r - \check{\mathbf{q}}_r - \check{\mathbf{e}}_r$. This then yields the estimate for $\mathbf{d}_r^O$, after which the regional outputs in the IRIO table are given by $\mathbf{x}_r^O = \mathbf{d}_r^O + \mathbf{q}_r^O + \mathbf{e}_r^O$. 
4.3.3.2 Step 2: imported final demands

This step estimates the vectors of imported final consumption ($c^M_t$), imported fixed capital formation ($f^M_t$), and imported inventory changes ($q^M_t$). We distinguish between imports that are only used for producing processing exports (which we call processing imports) and imports for other purposes (which we call non-processing imports). We also distinguish between merchandise goods (sectors 1-15) and services (sectors 16 and 17). By definition, only the non-processing imports can be used as final demand. Therefore, for merchandise goods, the revised BEC (‘broad economic categories’) method proposed by Dietzenbacher et al. (2013) is adopted to allocate the region-commodity-specific non-processing imports from China’s Customs statistics to three use categories: ‘final consumption’, ‘fixed capital formation’, and ‘intermediates’.\footnote{A major advantage of this revised BEC method is that it allows a good to go into more than one category.}

We then aggregate the data into the 17 IO sectors and scale them to match with the imported final demands from the NIOP table. We thus obtain the regional imports used for consumption ($c^M_{rt}$) and for fixed capital formation ($f^M_{rt}$). In addition, we also obtain the total imports that are used as intermediate inputs in ordinary production ($\sum_j z^M_{rij}$ in the IRIOP table).

Processing imports are, by definition, exclusively used as intermediate input in the production of processing exports. We aggregate the region-commodity-specific processing imports from China’s customs statistics into the 17 IO sectors and scale them to match the processing imports from the NIOP table. For merchandise goods, this yields the region-commodity-specific processing imports in the IRIOP table (i.e. the totals $\sum_j z^M_{rij}$). For services, we distribute the sector-level total imports data from the NIOP table over the regions using the allocation of merchandise imports. The imported inventory changes ($q^M_t$) are directly obtained from the NIOP table.
4.3.3.3 Step 3: value added

The values added for sector \( j \) in region \( s \) are obtained by using the RAS approach. The initial estimates follow from the value added ratios from the NIOP tables (i.e. \( \tilde{v}_j^P / \tilde{x}_j^P \) and \( \tilde{v}_j^O / \tilde{x}_j^O \)). These are combined with region-sector outputs from step 1 (i.e. \( x_{sj}^P \) and \( x_{sj}^O \)). The column constraints follow directly from the NIOP table, i.e. \( \sum_s v_{sj}^P = \tilde{v}_j^P \) and \( \sum_s v_{sj}^O = \tilde{v}_j^O \). For the row constraints, we have used the REAs. They provide the value added at the regional level (not distinguishing between \( P \) and \( O \)), but only for five broad sectors. One of these broad sectors is manufacturing, which covers the input-output sectors 2 – 14. Its total value added is \( \tilde{v}_{s,manufacuring} \), which is split into values added at IO sector level. For this, we use the region-sector-specific value added from the IRIO table (\( \hat{v}_{sj} \)). We thus arrive at the values added \( \hat{v}_{sj} \) for all 17 IO sectors. This would give us the national value added for industry \( j \) as \( \hat{v}_j^P + \hat{v}_j^O \) (using the NIOP table), but also as \( \sum_s \hat{v}_{sj} \) (using REA data). Given the inconsistency between the REAs and the NIOP tables, and given our preference for NIOP data, we split \( \hat{v}_j^P + \hat{v}_j^O \) over the regions using \( \hat{v}_{sj} \). This gives the row constraints \( v_{sj}^P + v_{sj}^O = (\hat{v}_j^P + \hat{v}_j^O)(\hat{v}_{sj}/ \sum_r \hat{v}_{rj}) \). Finally, the RAS procedure is applied, using the initial estimates and the set of given row and column sums. Subsequently, also the value added components (i.e. compensation of labor, fixed asset depreciation, net production tax, and operating surplus) are estimated for all industries, for all regions, and for both types of production (production of processing exports and ordinary production).

4.3.3.4 Step 4: estimating the import matrices

We use the RAS approach again and initial values for import matrices are assigned by using information from the NIOP tables. We assume that for the same production type (e.g., processing exports \( P \)), the input structure of imported intermediates is the same in all regions and is identical to the national structure. The import levels, however, vary across regions. The initial import matrices in the IRIOP table are given by \( z_{stij}^{MP} \) =
\[ z_{ij}^{MP} \left[ (x_{sj}^{p} - v_{sj}^{p})/(\bar{x}_{j}^{p} - \bar{v}_{j}^{p}) \right], \] where \( x_{sj}^{p} \) and \( v_{sj}^{p} \) are from the IRIOP table and have been estimated at an earlier stage and \( z_{ij}^{MP} \) is from the NIOP table.

Further there are three constraints that should be satisfied by \( z_{siij}^{MP} \) and \( z_{siij}^{MO} \). First, aggregating \( z_{siij}^{MP} \) and \( z_{siij}^{MO} \) over the regions should yield the corresponding import matrix in the NIOP table. That is, \( \sum_s z_{siij}^{MP} = z_{ij}^{MP} \) in case of production of processing exports. Second, aggregating \( z_{siij}^{MP} \) and \( z_{siij}^{MO} \) over the destination sectors (e.g. \( \sum_j z_{siij}^{MP} \)) yields the total imports of product \( i \) by region \( s \) for intermediate use. These totals were obtained in step 2 above. Third, for each region-sector the sum of imported inputs cannot be larger than the total amount of inputs that is required. In other words, the domestic intermediate inputs cannot be negative. The RAS procedure then results in estimates for \( z_{siij}^{MP} \) and \( z_{siij}^{MO} \).

4.3.3.5 Step 5: estimating the domestic intermediate deliveries and final demands

In the last step, we estimate the matrices with domestic intermediate deliveries (\( Z_{rsij}^{OO} \) with elements \( z_{rsij}^{OO} \) and \( Z_{rsij}^{OP} \) with elements \( z_{rsij}^{OP} \)) and the domestic final demand vectors (\( c_{rsi}^{O} \) with elements \( c_{rsi}^{O} \) and \( f_{rsi}^{O} \) with elements \( f_{rsi}^{O} \)). To this end, we adopt a hierarchical estimation method. It includes three parts, each of which uses the RAS procedure.

In part 5.1, we estimate the total intermediates and the total final demands of each product \( i \), provided by each origin region \( r \). The total is taken by summing over the destination regions. The estimation is done by splitting the total region-sector-specific domestic sales that we obtained in Step 1 (i.e. \( d_{rl}^{O} \)) into the three use categories: total intermediate use (\( y_{rl}^{O} \)), total final consumption (\( c_{rl}^{O} \)), and total fixed capital formation (\( ft_{rl}^{O} \)). To start the RAS procedure, initial values are assigned by splitting the sector-level national intermediate use (or national final consumption, or national fixed capital formation) from the NIOP tables among origin regions using information from the IRIO tables. Meanwhile, \( y_{rl}^{O} \), \( c_{rl}^{O} \), \( ft_{rl}^{O} \) are subject to two constraints. First, aggregating \( y_{rl}^{O} \), \( c_{rl}^{O} \), and \( ft_{rl}^{O} \) across origin regions should exactly yield the
corresponding elements at national level in the NIOP table. Second, the sum of $y_{ri}^O$, $ct_{ri}^O$, and $ft_{ri}^O$ must equal $d_{ri}^O$ for any $r$ and $i$.

In part 5.2, we estimate the domestic final demands ($c_{rsti}^O$, $f_{rsti}^O$) by using RAS again. The initial values for $c_{rsti}^O$ and $f_{rsti}^O$ are obtained from the IRIO tables. Meanwhile, the $c_{rsti}^O$ and $f_{rsti}^O$ are subject to two constraints. First, aggregating $c_{rsti}^O$ and $f_{rsti}^O$ over the destination regions $s$ gives the totals that were estimated previously in part 5.1 (i.e. $ct_{ri}^O$ and $ft_{ri}^O$). Second, aggregating $c_{rsti}^O$ ($f_{rsti}^O$) over the origin regions and adding the imported final consumption $c_{sti}^M$ (imported fixed capital formation $f_{sti}^M$) must yield the total consumption (fixed capital formation) consumed by each region, which is obtained by adapting NIOP data with information from the REAs.

In part 5.3, we estimate the domestic intermediate deliveries ($z_{rsij}^{OP}$ and $z_{rsij}^{OO}$). To this end, we first allocate the intermediate deliveries from the NIOP table over the destination regions (that is, we first estimate $zt_{sij}^{OP} = \sum_r z_{rsij}^{OP}$ and $zt_{sij}^{OO} = \sum_r z_{rsij}^{OO}$). Then, we further allocate these estimates over the origin regions.

From previous steps, the IRIO tables contain estimates for the total intermediate inputs used by each region $s$ and sector $j$. That is, $x_{sj}^P - \sum_i z_{si}^M - v_{sj}^P$ and $x_{sj}^O - \sum_i z_{si}^MO - v_{sj}^O$. These are further split over sectors of origin using the input structure in the IRIO tables. This yields the initial values for $zt_{sij}^{OP}$ and $zt_{sij}^{OO}$. Further, $zt_{sij}^{OP}$ and $zt_{sij}^{OO}$ are subject to two constraints. First, aggregating $zt_{sij}^{OP}$ ($zt_{sij}^{OO}$) over regions should give the national intermediates deliveries in the NIOP tables. Second, aggregating $zt_{sij}^{OP}$ ($zt_{sij}^{OO}$) over the origin sectors should equal to $x_{sj}^P - \sum_i z_{si}^M - v_{sj}^P$ (or $x_{sj}^O - \sum_i z_{si}^MO - v_{sj}^O$). Based on the initial values and constraints, the solution for $zt_{sij}^{OP}$ and $zt_{sij}^{OO}$ is obtained from the RAS procedure.

Then we estimate $z_{rsij}^{OP}$ and $z_{rsij}^{OO}$ by allocating $zt_{sij}^{OP}$ and $zt_{sij}^{OO}$ over the origin regions. For the initial values we use the IRIO tables for this allocation. Meanwhile, $z_{rsij}^{OP}$ and $z_{rsij}^{OO}$ are subject to two constraints. First, aggregating $z_{rsij}^{OP}$ and $z_{rsij}^{OO}$ over destination regions $s$ and destination sectors $j$ should yield the total intermediates supplied by each region-sector $y_{ri}^O$ (obtained in part 5.1). Second, aggregating $z_{rsij}^{OP}$ ($z_{rsij}^{OO}$) over origin regions should yield the sector-level intermediates consumed
by each region-sector $zt_{sij}^{OP}$ ($zt_{sij}^{00}$). Finally, the RAS procedure results in the estimate of the domestic intermediate deliveries matrix.

The outcome of conducting all the procedures in this section are the IRIOP tables for 2002, 2007, and 2012. They include 17 sectors, cover 8 regions and distinguish in each region between production of processing exports and ordinary production. The constraints we imposed during the construction ensure that the IRIOP tables are balanced, are perfectly in line with the NIOP tables, and are maximally consistent with the information in the official statistics and the IRIO tables.

### 4.4 Separating processing exports from ordinary production matters

When analyzing phenomena such as the exports of domestic value added, disregarding processing trade leads to serious estimation biases. At the national level, this has been well documented in the literature (Chen et al., 2012; Dietzenbacher et al., 2012; Koopman et al., 2012; Pei et al., 2012). In this section we study whether—and to what extent—this is also the case at the regional level. To this end, we compare the results based on the IRIOP tables with the results based on IRIO tables (which do not separate production of processing exports from ordinary production). For our calculations, we aggregate the IRIOP tables by taking the production of processing exports and ordinary production together (for each region and each sector). The format of this aggregated IRIOP table is exactly the same as the format of the published IRIO tables (see Table A4.1.2 in Appendix 4.1).\(^{20}\) Then we compare the results obtained with the IRIOP tables with the results obtained with the aggregated IRIOP tables.

Given China’s high involvement in globalization and given the serious regional inequality, the question how globalization has affected regions within China has attracted ample attention. A general conclusion is that China’s interior regions are also

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\(^{20}\) An alternative is to compare the results based on the IRIOP tables with the results based on the IRIO tables that have been published by the State Information Center (SIC). The SIC tables were the IRIO tables that have been used in the construction of the IRIOP tables. However, because our IRIOP tables are consistent with the NIOP tables and because the NIOP tables and the SIC IRIO tables are not consistent with each other (as mentioned in Section 4.3.2), inconsistencies also exist between the aggregated IRIOP tables and the published SIC IRIO tables. Appendix 4.5 lists the average differences. These differences are actually a mix of differences caused by disregarding processing trade and differences due to inconsistencies.
deeply involved in the globalization by providing intermediates to the export production in coastal regions (Meng et al., 2017; Pei, et al., 2017). However, the existing studies ignore the prevalence of processing trade. We argue that they overestimate the role of trade (i) for economic growth in the coastal regions and (ii) for regional inequality. Neglecting processing trade yields these overestimation, because the production of processing exports is mainly concentrated in coastal regions and because this production relies heavily on imported materials. To check this hypothesis, we investigate the role of processing trade when measuring the contribution of exports to China’s regional economic growth.

### 4.4.1 Methodology

We start with a description of the methodology in the case of the aggregated IRIOP tables and for simplicity (but without loss of generality) we assume that China consists of two regions ($r$ and $s$) only. Let $Z_{rs}$ indicate the flows of intermediate deliveries from region $r$ to region $s$, $x_s$ the vector of sectoral outputs in region $s$, $v_s$ the vector of sectoral values added in region $s$, and $e_s$ the vector of sectoral exports by region $s$. The matrix $A_{rs} = Z_{rs}(c_s)^{-1}$ gives the amounts of intermediate inputs provided by $r$ that are directly used per unit of production in $s$, with $c_s$ the diagonal matrix of $x_s$. At the national level, we have

$$A = \begin{pmatrix} A_{rr} & A_{rs} \\ A_{sr} & A_{ss} \end{pmatrix} \quad \text{and} \quad L = (I - A)^{-1} = \begin{pmatrix} L_{rr} & L_{rs} \\ L_{sr} & L_{ss} \end{pmatrix}$$

The elements of the matrix $L_{rs}$, for example, give the amounts of production that are necessary in region $r$ to satisfy one unit of final demand (e.g. domestic final consumption, domestic fixed capital formation, exports) for products from region $s$. Define $\mu' = v' (c_s)^{-1}$ as the row vector with value added coefficients in region $s$. Using input-output techniques (see Miller and Blair, 2009), the total value added of region $r$ that is embodied in the exports of region $s$ is calculated as:
\[ t_{rs}^{IRIOP} = \mu_s' L_{rs} e_s \] (4.1)

where the superscript IRIOPA is used to indicate that this is for the aggregated IRIOP tables with the production of processing exports and ordinary production aggregated together for each region.

The methodology is very much the same in case of the full IRIOP tables. The key difference is that the size of the matrices and vectors is doubled, because we now have two types of production. The relevant matrices and vectors are

\[
Z = \begin{pmatrix} Z_{OP} & Z_{OO} & Z_{OP} & Z_{OO} \\ Z_{OP} & Z_{OO} & Z_{OP} & Z_{OO} \\ Z_{OP} & Z_{OO} & Z_{OP} & Z_{OO} \end{pmatrix}, \quad x_r = \begin{pmatrix} x_r^p \\ x_r^o \end{pmatrix}, \quad e_s = \begin{pmatrix} e_s^p \\ e_s^o \end{pmatrix}, \quad v_r = \begin{pmatrix} v_r^p \\ v_r^o \end{pmatrix}
\]

The coefficients then become

\[
A = \begin{pmatrix} A_{OP} & A_{OO} & A_{OP} & A_{OO} \\ A_{OP} & A_{OO} & A_{OP} & A_{OO} \end{pmatrix}, \quad L = (I - A)^{-1} \begin{pmatrix} I & 0 & 0 & 0 \\ L_{OP} & L_{OO} & L_{OP} & L_{OO} \\ L_{OP} & L_{OO} & L_{OP} & L_{OO} \end{pmatrix}, \quad \mu_s = \begin{pmatrix} \mu_s^p \\ \mu_s^o \end{pmatrix} = \begin{pmatrix} (x_s^p)^{-1} v_s^p \\ (x_s^o)^{-1} v_s^o \end{pmatrix}
\]

The total value added of region \( r \) that is embodied in the exports of region \( s \) is now calculated as:

\[
t_{rs}^{IRIOP} = ((\mu_r^p)' (\mu_r^o)') \begin{pmatrix} L_{OP} & L_{OO} \\ L_{OP} & L_{OO} \end{pmatrix} \begin{pmatrix} e_s^p \\ e_s^o \end{pmatrix} = (\mu_r^o)' L_{rs} e_s^o + (\mu_r^o)' L_{rs} e_s^o
\]

(4.2)

where the first item on the right-hand side gives the value added of region \( r \) embodied in region \( s \)'s processing exports and the second term gives the embodiment in region \( s \)'s ordinary exports. Note that if \( r = s \), we have \( t_{rr}^{IRIOP} = (\mu_r^p)' e_r^p + (\mu_r^o)' e_r^o + (\mu_r^o)' L_{rr} e_r^o \).
4.4.2 Empirical results

Value added in region \( r \) induced by exports of region \( s \) is measured with Equations 4.1 and 4.2. We summarize our results by looking at the aggregate level, which yields two perspectives. On the one hand, the national value added generated by the exports of region \( s \) (\( \sum_r t_{rs}^{1RIOP} \) with the IRIOP tables and \( \sum_r t_{rs}^{1RIOPA} \) with the aggregated IRIOP tables). This reflects the domestic part of the value chains to which the export production in region \( s \) contributes. On the other hand, the value added generated in region \( r \) by national exports (\( \sum_s t_{rs}^{1RIOP} \) and \( \sum_s t_{rs}^{1RIOPA} \)). This reflects region \( r \) benefits from China’s participation in globalization.

4.4.2.1 Value chain activities by regions in the production of exports

We calculate the national value added generated by “an average 1000 rmb” of exports in region \( s \). That is, the exports—\( e_s \) in (4.1) and \( e_s^p + e_s^q \) in (4.2)—are rescaled such that the elements sum to 1000 rmb and their shares remain the same. The results are given in Table 4.3. For example, we calculate that 1000 rmb of (extra) exports in Northeast in 2002 would have led to 710 rmb of (extra) value added at the national level (i.e. GDP). This is the answer—given in the top panel of Table 4.3—if the calculation is based on the IRIOP table. That is, if we distinguish between the production of processing exports and ordinary production. These tables were not available and have been developed for this chapter. To mimic the standard calculation, we have used the aggregated version of the IRIOP table. In that case, we find that 1000 rmb of (extra) exports would have generated 857 rmb of (extra) GDP. This is the answer given in the middle panel of Table 4.3. Neglecting processing trade thus implies that the GDP in 1000 rmb of exports by Northeast is overestimated by (\( 857 – 710 = \)) 147 rmb, which is 20.8%. This is the bias given in the bottom panel of Table 4.3. Several observations follow from Table 4.3.

First, as expected, calculations with ordinary IRIO tables (which neglect the special role of processing trade) overestimate the contribution of regional exports to
GDP. To show the effect of separating processing exports from ordinary production, the calculations with ordinary IRIO tables are mimicked by using the aggregated IRIOP tables. The largest bias is found for South Coast in 2002 (32.2%).

Table 4.3 National value added embodied in 1000 rmb of regional exports: a comparison between using the IRIOP table and the aggregated IRIOP table

<table>
<thead>
<tr>
<th></th>
<th>NE</th>
<th>NM</th>
<th>NC</th>
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<th>CR</th>
<th>NW</th>
<th>SW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original IRIOP table (rmb)</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>2002</td>
<td>710</td>
<td>627</td>
<td>691</td>
<td>654</td>
<td>466</td>
<td>874</td>
<td>872</td>
<td>865</td>
</tr>
<tr>
<td>2007</td>
<td>708</td>
<td>675</td>
<td>718</td>
<td>575</td>
<td>497</td>
<td>814</td>
<td>887</td>
<td>803</td>
</tr>
<tr>
<td>2012</td>
<td>717</td>
<td>592</td>
<td>741</td>
<td>677</td>
<td>580</td>
<td>751</td>
<td>861</td>
<td>747</td>
</tr>
<tr>
<td>Aggregated IRIOP table (rmb)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2002</td>
<td>857</td>
<td>711</td>
<td>866</td>
<td>759</td>
<td>615</td>
<td>924</td>
<td>901</td>
<td>923</td>
</tr>
<tr>
<td>2007</td>
<td>804</td>
<td>697</td>
<td>820</td>
<td>631</td>
<td>597</td>
<td>879</td>
<td>884</td>
<td>870</td>
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<td>758</td>
<td>596</td>
<td>828</td>
<td>733</td>
<td>672</td>
<td>875</td>
<td>880</td>
<td>858</td>
</tr>
<tr>
<td>Bias (%)</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>2002</td>
<td>20.8</td>
<td>13.3</td>
<td>25.3</td>
<td>16.0</td>
<td>32.2</td>
<td>5.7</td>
<td>3.4</td>
<td>6.7</td>
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<tr>
<td>2007</td>
<td>13.6</td>
<td>3.3</td>
<td>14.2</td>
<td>9.7</td>
<td>20.3</td>
<td>8.0</td>
<td>-0.3</td>
<td>8.3</td>
</tr>
<tr>
<td>2012</td>
<td>5.7</td>
<td>0.8</td>
<td>11.7</td>
<td>8.3</td>
<td>15.8</td>
<td>16.4</td>
<td>2.3</td>
<td>14.9</td>
</tr>
</tbody>
</table>

Notes: Bias = 100\% (IRIOPA – IRIOP)/IRIOP, where IRIOP is the result with the IRIOP table and IRIOPA is the result with the aggregated IRIOP table.

This widespread overestimation is not surprising. The value added (VA) coefficients for the production of processing exports are much smaller than for ordinary production. The IRIOPA results are obtained by using average VA coefficients. Because the amount of ordinary production is much larger than the amount of production of processing exports, these average VA coefficients are similar to (but a bit smaller than) the VA coefficient for ordinary production before aggregation. When calculating the GDP in processing exports, the (small) VA coefficients for the production of processing exports are now replaced by much larger average VA.\textsuperscript{21} This also implies that the overestimation is expected to be larger if the share of processing exports in regional exports is larger.

\textsuperscript{21} Note that Northwest is the exception to the widespread overestimation. It shows a small underestimation in 2007. It appears that exports of Northwest include much non-processing exports. The VA coefficients for other production (which includes non-processing exports) are for the IRIOPA results replaced by the somewhat smaller average VA coefficients. Underestimation is then the probable consequence.
Second, the degree of the bias differs across regions and it seems closely related to the share of processing exports in each region’s exports. To check this, Figure 4.1 plots the bias for each region versus the corresponding shares of processing exports in the three years. It is observed that a higher share of processing exports is usually accompanied with a more serious bias. Two typical cases are South Coast and North West. The former usually has a high share of processing exports (65.9% in 2002) and ignoring the role of processing trade therefore leads to a large overestimation (32.2% in 2002) of the GDP content of its exports. In contrast, Northwest has small shares of processing exports (13.9% in 2002) and shows only a small bias of 3.4% in 2002. This clearly indicates the necessity to distinguish processing trade at the regional level. Moreover, the more a region depends on processing trade the larger is this necessity.

**Figure 4.1 The bias versus the share of processing exports**

![Graph showing the bias versus the share of processing exports](image)

**Notes**: The labels indicate the region and year, e.g. “SC02” indicates the values of South Coast in 2002. The dashed line gives the regression line, \( \text{Bias} = (\text{IRIOP} - \text{IRIOP}) / \text{IRIOP} \), with \( t \)-values = 5.27 and \( R^2 = 0.56 \).

Third, the bias generated by using the aggregated IRIOP tables generally decreased over time for coastal regions (NC, EC, SC) and increased for central and
western regions (CR, NW, SW). These changes are closely related to the changes in the shares of processing exports. These shares declined for most of the coastal regions but increased for central and western regions. Given the fact that the share of China’s processing exports continuously declined since 2004, it is expected that the bias generated by using ordinary IRIOP tables will also decline. A consequence is that for countries with only little processing trade, using ordinary (regional) input-output tables—i.e. tables that do not separate ordinary production from the production of processing exports—is expected to lead to correct empirical results.

4.4.2.2 The regional benefits of globalization

In this section, we calculate how much value added is created in each region due to the entire national exports. This is also termed regional value added exports. The results are shown in Table 4.4. For example, we find that the national exports generated 117 billion rmb of value added in Northeast in 2002 (see top panel). This is the outcome obtained with the IRIOP table. If the aggregated IRIOP table is used though (to mimic the use of ordinary IRIO tables), we find 142 billion rmb (see middle panel). This is an overestimation of 21.3% (see bottom panel).

**Table 4.4. Regional value added generated by national exports: a comparison between using the IRIOP table and the aggregated IRIOP table**

<table>
<thead>
<tr>
<th></th>
<th>NE</th>
<th>NM</th>
<th>NC</th>
<th>EC</th>
<th>SC</th>
<th>CR</th>
<th>NW</th>
<th>SW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>2002</td>
<td>117</td>
<td>141</td>
<td>194</td>
<td>579</td>
<td>540</td>
<td>142</td>
<td>52</td>
</tr>
<tr>
<td>IRIOP table</td>
<td>2007</td>
<td>363</td>
<td>457</td>
<td>753</td>
<td>1922</td>
<td>1327</td>
<td>672</td>
<td>344</td>
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<td>(billion rmb)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregated</td>
<td>2002</td>
<td>142</td>
<td>161</td>
<td>238</td>
<td>675</td>
<td>683</td>
<td>165</td>
<td>59</td>
</tr>
<tr>
<td>IRIOP table</td>
<td>2007</td>
<td>415</td>
<td>481</td>
<td>850</td>
<td>2094</td>
<td>1513</td>
<td>768</td>
<td>379</td>
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<tr>
<td>(billion rmb)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bias (%)</td>
<td>2002</td>
<td>21.3</td>
<td>14.9</td>
<td>22.5</td>
<td>16.7</td>
<td>26.3</td>
<td>16.6</td>
<td>13.2</td>
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<tr>
<td></td>
<td>2007</td>
<td>14.2</td>
<td>5.3</td>
<td>12.9</td>
<td>9.0</td>
<td>14.0</td>
<td>14.3</td>
<td>10.3</td>
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<tr>
<td></td>
<td>2012</td>
<td>8.9</td>
<td>4.7</td>
<td>11.6</td>
<td>7.3</td>
<td>12.1</td>
<td>15.6</td>
<td>12.2</td>
</tr>
</tbody>
</table>

Notes: Bias = 100(IRIOPA – IRIOP)/IRIOP, where IRIOP is the result with the IRIOP table and IRIOPA the result with the aggregated IRIOP table.
It follows from Table 4.4 that the income that each region generates from exports (reflecting the benefits of globalization) is seriously overestimated when ordinary IRIO tables are used. The overestimation for inland regions is slightly higher than it is for coastal regions. The consequence is that the effect of exports on regional inequality is likely to be underestimated when ordinary IRIO tables are used. IRIO tables report that exports generate more value added in coastal regions than in inland regions but IRIO tables overstate the true (i.e. IRIO) answer. The bias is larger for inland regions than for coastal regions. This implies that the true gap between the effects for coastal and inland regions is larger than the gap reported when using IRIO tables. Over time, the overestimations have become smaller because the share of processing exports decreased.

We further decompose the value added exports of each region into two parts: value added induced by the region’s own exports (i.e. the self-effect) and value added induced by the exports from all the other regions (i.e. the spillover effect). Table 4.5 presents the results. For example, using the IRIO table for 2002 we found in Table 4.4 that China’s exports generated 117 billion rmb of value added in the Northeast. 95 billion rmb was due to the exports of NE itself. The remaining 22 billion rmb was the spillover effect (see the top panel of Table 4.5), which indicates NE’s value added due to the exports by other regions. Using the aggregated IRIO table we found a spillover effect of 28 billion rmb (see the middle panel of Table 4.5). The overestimation in Table 4.4 for NE’s value added due to all exports is 25 billion rmb. The overestimation in Table 4.5 for NE’s value added due to other regions’ exports is 5 billion rmb, which is 21.6% (see the bottom panel) of the total overestimation.

The contributions to the bias as reported in Table 4.5 shows large differences between the coastal and the inland regions. For the coastal regions, the bias in their value added exports is largely caused by the self-effect (i.e. the bias in their value added due to their own exports). This holds in particular for South Coast and East Coast, to a lesser extent for North Coast. For South Coast, for example, 98.7% of the overestimation generated by using the aggregated IRIO table in 2012, is sourced from the overestimation of the value added generated by its own exports. The coastal regions have much exports and a high share of processing exports. This leads to a large bias in
the region’s value added due to their own exports. In contrast, for inland regions, the bias originates primarily from the spillover effect. For Northwest, for example, 93.6% of the overestimation is sourced from the overestimation of its value added generated by exports of other regions. In inland regions like Northwest a large part of the value added generated by exports, is generated by exports in other regions.\(^{22}\) It turns out that also a large part of the overestimation of the value added generated by exports is due to the overestimation of the value added generated by exports in other regions. The results suggest that the effect of globalization in coastal regions for the value added in inland regions is significantly overestimated by ordinary IRIO tables. This finding is consistent with the conclusion of Brun et al. (2002), who demonstrate that the linkage between Chinese regions via exports is only limited. To some extent, this also explains the failure of China’s “ladder-step strategy” to boost the economies in western areas with spillovers from the opening up of the coastal regions.\(^{23}\)

Table 4.5 Regional value added from spillover effects of other regions’ exports: a comparison between using the IRIOP table and the aggregated IRIOP table.

<table>
<thead>
<tr>
<th></th>
<th>NE</th>
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<th>EC</th>
<th>SC</th>
<th>CR</th>
<th>NW</th>
<th>SW</th>
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<tr>
<td>Original IRIOP</td>
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<td></td>
</tr>
<tr>
<td>table (billion rmb)</td>
<td>2002</td>
<td>22</td>
<td>21</td>
<td>61</td>
<td>46</td>
<td>25</td>
<td>65</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>135</td>
<td>59</td>
<td>260</td>
<td>163</td>
<td>115</td>
<td>412</td>
<td>169</td>
</tr>
<tr>
<td></td>
<td>2012</td>
<td>151</td>
<td>135</td>
<td>261</td>
<td>176</td>
<td>122</td>
<td>578</td>
<td>310</td>
</tr>
<tr>
<td>Aggregated IRIOP</td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>table (billion rmb)</td>
<td>2002</td>
<td>28</td>
<td>26</td>
<td>72</td>
<td>59</td>
<td>26</td>
<td>84</td>
<td>27</td>
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<td></td>
<td>2007</td>
<td>156</td>
<td>70</td>
<td>292</td>
<td>181</td>
<td>115</td>
<td>488</td>
<td>202</td>
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<tr>
<td></td>
<td>2012</td>
<td>175</td>
<td>156</td>
<td>297</td>
<td>208</td>
<td>125</td>
<td>676</td>
<td>366</td>
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<td>Contribution to</td>
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<td></td>
</tr>
<tr>
<td>the bias (%)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>2002</td>
<td>21.6</td>
<td>23.5</td>
<td>24.9</td>
<td>13.6</td>
<td>0.6</td>
<td>78.8</td>
<td>77.9</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>39.7</td>
<td>42.6</td>
<td>32.8</td>
<td>10.7</td>
<td>-0.2</td>
<td>79.2</td>
<td>95.0</td>
</tr>
<tr>
<td></td>
<td>2012</td>
<td>45.1</td>
<td>79.7</td>
<td>26.6</td>
<td>17.3</td>
<td>1.3</td>
<td>63.8</td>
<td>93.6</td>
</tr>
</tbody>
</table>

Notes: Contribution to the bias = \(100(\text{IRIOPA5} - \text{IRIOP5})/\text{IRIOPA4-IRIOP4}\), where IRIOP4 (IRIOP5) is the result with the IRIOP table reported in Table 4.4 (5) and IRIOPA4 (IRIOPA5) the result with the aggregated IRIOP table reported in Table 4.4 (5).

\(^{22}\) Using the information from Tables 4.4 and 4.5, of the value added in Northwest in 2012 that was due to exports, 73.2% was due to exports in other regions. For South Coast this was only 4.9%.

\(^{23}\) The ladder-step strategy was launched in China by Deng Xiaoping. Higher priorities were given to the coastal areas because of their location close to the seashore and because of their overseas connections. The development of coastal region was expected to gradually spillover to inland areas (Wei and Hao, 2010).
4.5 Conclusions

Processing trade is an important characteristic of the Chinese economy that is unevenly distributed across domestic regions. A good analysis at the regional level requires adequate data. In this chapter we therefore constructed a new interregional input-output table for China, which explicitly distinguishes the production of processing exports from ordinary production. The new tables contain 17 sectors, include eight regions, and were constructed for 2002, 2007, and 2012. After describing the available data, we detailed how the information from the different data sources was harmonized and reconciled. Then we explained the construction procedure step by step. The compilation method that we have used is not only applicable to China. It may also be adopted for countries like Mexico, with much processing trade that is unevenly distributed across regions.

We expected that failing to separate processing exports will lead to misleading conclusions, also at the regional level. As an illustration of the use of the new table, we investigated whether the separation of production of processing exports from ordinary production mattered when studying the contribution of exports to regional value added. To this end, we compared the empirical results derived from the new tables with the results derived from an aggregated version of the new tables. The aggregation combined the two types of production again in order to mimic the results as would have been derived from ordinary interregional input-output tables (i.e. without singling out processing trade). We found that the contribution of regional exports to China’s GDP is significantly overestimated if processing trade is not properly included in the models. For example, a bias of 32.2% is observed in case of South Coast’s exports.

Another result was with respect to the interregional income spillovers of exports by coastal regions. The prevailing opinion is that they generate a considerable amount of value added in inland regions. We found that this effect is seriously overestimated. To simulate the economic growth in interior regions, direct involvement in exports—instead of indirect involvement through the exports of the coastal regions—is preferred.

Next to providing more accurate empirical results, the IRIOP tables have other advantages. That is, the tables can answer questions that cannot be answered by using the ordinary IRIO tables. For example, how is the value added generated by processing
exports distributed over regions and how much does processing trade contribute to regional growth, regional inequality, as well as the regional environment changes?
Appendix

Appendix 4.1

Available data for the construction of the IRIOP table

| Table A4.1.1 Schematic outline of the national bipartite input-output (NIOP) table |
|-----------------------------------|---------------------------------|-----------------|----------------|-----------------|
|                                   | Intermediate use | Final use      | TOT            |
|                                   | P                | O              | DFC            | FCF          | INV            | EXP            |
| P                                 | 0                | 0              | 0              | 0            | 0              | 0              |
| O                                 | \( \tilde{Z}^{OP} \) | \( \tilde{Z}^{OO} \) | \( \tilde{c}^O \) | \( \tilde{f}^O \) | \( \tilde{q}^O \) | \( \tilde{e}^O \) |
| IMP                               | \( \tilde{Z}^{MP} \) | \( \tilde{Z}^{MO} \) | \( \tilde{e}^M \) | \( \tilde{f}^M \) | \( \tilde{q}^M \) | 0              |
| VA                                | \((\tilde{v}^P)'\) | \((\tilde{v}^O)'\) | \((\tilde{x}^P)'\) | \((\tilde{x}^O)'\) |
| TOT                               | \((\tilde{x}^P)'\) | \((\tilde{x}^O)'\) | \(\tilde{m}_i\) |

Notes: \( P \) = production of processing exports; \( O \) = other (or ordinary) production; \( DFC \) = domestic final consumption; \( FCF \) = fixed capital formation; \( INV \) = inventory changes; \( EXP \) = exports; \( TOT \) = gross sector outputs or total imports; \( IMP \) = imports; \( VA \) = value added.

The variables in the NIOP table are noted with an overbar. Also, we will use ‘ordinary products’ for the goods and services made by ordinary production. \( \tilde{Z}^{OP} \) (as typical element of the matrix \( Z^{OP} \)) gives the intermediate deliveries of ordinary product \( i \) used to produce processing exports in industry \( j \); \( \tilde{Z}^{OO} \) gives the intermediate deliveries of ordinary product \( i \) used for ordinary production in industry \( j \); \( \tilde{Z}^{MP} \) gives the intermediate deliveries of imported product \( i \) used to produce processing exports in industry \( j \); \( \tilde{Z}^{MO} \) gives the intermediate deliveries of imported product \( i \) used for the ordinary production in industry \( j \); \( \tilde{v}^P_j \) is the value added in industry \( j \)'s processing exports production; \( \tilde{v}^O_j \) is the value added of industry \( j \)'s ordinary production; \( \tilde{x}^O_j \) is the gross output of industry \( j \)'s ordinary production; \( \tilde{c}^O_i \) is the value of ordinary product \( i \) used as final consumption; \( \tilde{f}^O_i \) is the value of ordinary product \( i \) used as fixed capital formation; \( \tilde{q}^O_i \) gives the inventory changes of ordinary product \( i \); \( \tilde{e}^M_i \) is the value of imported product \( i \) used as final consumption; \( \tilde{f}^M_i \) is the value of imported product \( i \) used as fixed capital formation; \( \tilde{q}^M_i \) gives the inventory changes of imported product \( i \); \( \tilde{e}^P_i \) is the processing exports of product \( i \), which makes up the total output (\( \tilde{x}^P_i \)) of this sector; \( \tilde{e}^O_i \) is the ordinary exports of product \( i \); and \( \tilde{m}_i \) gives the total imports of product \( i \).
Table A4.1.2 Schematic outline of the interregional input-output (IRIO) table with two regions

<table>
<thead>
<tr>
<th>Region r</th>
<th>Region s</th>
<th>Intermediate use</th>
<th>Final use</th>
<th>TOT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Region r</td>
<td>Region s</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>DFC</td>
<td>FCF</td>
<td>DFC</td>
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<td>Regions</td>
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<tr>
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</tr>
</tbody>
</table>

\[
\begin{align*}
\mathbf{Z}_{rs} & = \mathbf{Z}_r^M \quad \mathbf{Z}_{rs}^M \\
\check{c}_{rs} & = \check{c}_r^M \quad \check{c}_{rs}^M \\
\check{f}_{rs} & = \check{f}_r^M \quad \check{f}_{rs}^M \\
\check{q}_{rs} & = \check{q}_r^M \quad \check{e}_r \\
\check{q}_{rs}^M & = \check{e}_s \\
0 & = \check{m}
\end{align*}
\]

Notes: DFC = domestic final consumption; FCF = fixed capital formation; INV = inventory changes; EXP = exports; TOT = gross sector outputs or total imports; IMP = imports; VA = value added.

The variables in the IRIO table are noted with a tilde. The variables that are used in the construction of the IRIO table are: \( \check{z}_{rsi} \) (as typical element of the matrix \( \check{Z}_{rs} \)), which gives the intermediate deliveries of product \( i \) from region \( r \) to industry \( j \) in region \( s \); \( \check{v}_{sj} \), which gives the value added of industry \( j \) in region \( s \); \( \check{c}_{rsi} \), which gives the value of product \( i \) from region \( r \) used as final consumption in region \( s \); \( \check{f}_{rsi} \), which gives the value of product \( i \) from region \( r \) used as fixed capital formation in region \( s \); \( \check{q}_{ri} \), which gives the inventory changes in all regions of product \( i \) produced in region \( r \); \( \check{c}_{si}^M \), which gives the value of the import of product \( i \) used as final consumption in region \( s \); and \( \check{f}_{si}^M \), which gives the value of the import of product \( i \) used as fixed capital formation in region \( s \).
Appendix 4.2

Classification of China’s eight regions

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Eight Regions</th>
<th>Provinces</th>
<th>Macro-regions</th>
</tr>
</thead>
<tbody>
<tr>
<td>NE</td>
<td>North East</td>
<td>Heilongjiang, Jilin, Liaoning</td>
<td>Inland</td>
</tr>
<tr>
<td>NM</td>
<td>North Municipality</td>
<td>Beijing, Tianjin</td>
<td>Coastal</td>
</tr>
<tr>
<td>NC</td>
<td>North Coast</td>
<td>Hebei, Shandong</td>
<td>Coastal</td>
</tr>
<tr>
<td>EC</td>
<td>East Coast</td>
<td>Jiangsu, Shanghai, Zhejiang</td>
<td>Coastal</td>
</tr>
<tr>
<td>SC</td>
<td>South Coast</td>
<td>Fujian, Hainan, Guangdong</td>
<td>Coastal</td>
</tr>
<tr>
<td>CR</td>
<td>Central Region</td>
<td>Anhui, Jiangxi, Henan, Hubei, Hunan, Shanxi</td>
<td>Inland</td>
</tr>
<tr>
<td>NW</td>
<td>North West</td>
<td>Gansu, Inner Mongolia, Ningxia, Xinjiang, Shaanxi</td>
<td>Inland</td>
</tr>
<tr>
<td>SW</td>
<td>South West</td>
<td>Chongqing, Guizhou, Guangxi, Qinghai, Sichuan, Tibet, Yunnan</td>
<td>Inland</td>
</tr>
</tbody>
</table>

Notes: We focus on mainland China and exclude Chinese Taiwan, Hong Kong, and Macao. The Coastal areas include Liaoning, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Hainan, and Guangxi.
## Appendix 4.3

### The correspondence of industry classification

The table below gives the correspondence of the 5-sector classification in the Regional Economic Accounts (REAs), the 17-sector classification of the IRIO table, and the 42-sector classification used by the NBS.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>1 Agriculture</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2 Mining</td>
<td>2-5</td>
<td>2-5</td>
</tr>
<tr>
<td></td>
<td>3 Food products</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>4 Textile and wearing apparel</td>
<td>7, 8</td>
<td>7, 8</td>
</tr>
<tr>
<td></td>
<td>5 Wooden products</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>6 Paper and printing</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>7 Chemical products</td>
<td>11, 12</td>
<td>11, 12</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>8 Non-metallic mineral products</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>9 Metal products</td>
<td>14, 15</td>
<td>14, 15</td>
</tr>
<tr>
<td></td>
<td>10 Machinery</td>
<td>16</td>
<td>16, 17</td>
</tr>
<tr>
<td></td>
<td>11 Transport equipment</td>
<td>17</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>12 Electronic products</td>
<td>18, 19</td>
<td>19, 20</td>
</tr>
<tr>
<td></td>
<td>13 Other manufacturing products</td>
<td>20-22</td>
<td>21-24</td>
</tr>
<tr>
<td></td>
<td>14 Electricity, gas and water supply</td>
<td>23-25</td>
<td>25-27</td>
</tr>
<tr>
<td>Construction</td>
<td>15 Construction</td>
<td>26</td>
<td>28</td>
</tr>
<tr>
<td>Trade and transport</td>
<td>16 Trade and transport</td>
<td>27, 30</td>
<td>29, 30</td>
</tr>
<tr>
<td>Other services</td>
<td>17 Other services</td>
<td>28, 29, 31-42</td>
<td>31-42</td>
</tr>
</tbody>
</table>

Notes: Further details of the 42 IO industries are given in NBS (2009, 2016).
Appendix 4.4

The construction of the IRIOP table

In this appendix, we describe the construction procedure of the IRIOP tables in detail. Recall that the procedure is in 5 steps, where each step estimates a set of variables. Data from different data sources are used. To indicate the source from which the data are taken, we use an overbar (e.g. \( \bar{x} \)) to indicate variables from the NIOP tables, a tilde (e.g. \( \tilde{x} \)) for variables from the IRIO tables, and a diaeresis (i.e. two dots, e.g. \( \ddot{x} \)) for variables from the REAs and China’s Customs statistics. We also distinguish between merchandise goods produced by industries 1 – 15 and services produced by industries 16 and 17.

A4.4.1 Variables in Step 1

We start the construction with determining the vectors for the exports (\( \mathbf{e}_p^t \) and \( \mathbf{e}_o^t \)), the outputs (\( \mathbf{x}_p^t \) and \( \mathbf{x}_o^t \)), and the domestic inventory changes (\( \mathbf{q}_p^t \)) in the IRIOP tables. These variables are used in later steps to determine the other variables.

(1) Exports

First, for mechanize goods, the data for processing exports (\( \mathbf{\bar{e}}_{ri}^t \)) and ordinary exports (\( \mathbf{\tilde{e}}_{ri}^t \)) for each region are obtained by aggregating the China’s Customs statistics. These data are scaled to match the export data in the NIOP table (i.e. \( \mathbf{e}_p^t \) and \( \mathbf{e}_o^t \)), which we take as our benchmark table. This yields for \( i = 1, \ldots, 15 \)

\[
\mathbf{e}_{ri}^t = \frac{\mathbf{\bar{e}}_{ri}^t}{\sum \mathbf{e}_{ri}^t} \mathbf{\bar{e}}_{ri}^t \quad \text{and} \quad \mathbf{e}_{ri}^t = \frac{\mathbf{\tilde{e}}_{ri}^t}{\sum \mathbf{e}_{ri}^t} \mathbf{\tilde{e}}_{ri}^t \quad (A4.4.1)
\]

For the processing exports of services, data limitations imply that the distribution of the processing exports of merchandise goods is adopted to distribute the processing services exports from the NIOP tables over the eight regions. It needs to be noted that
processing trade is principally only for merchandize trade. However, in the IO tables, processing exports are also non-zero for services. This refers to the commercial margins or the other services used for the processing exports of merchandize goods. We therefore assume that the regional distribution of processing exports is the same for merchandize goods and services. For \( i = 16, 17 \), we have

\[
e_{ri}^{p} = \frac{\sum_{j=1}^{15} e_{rj}^{p}}{\sum_{i} \sum_{j=1}^{15} e_{sj}^{p}} e_{i}^{p}
\]  

(A4.4.2)

For ordinary services exports, the only information that is available at the regional level is in the IRIO tables (i.e. \( \tilde{e}_{ri} \)). Adapting (A4.4.1) according to data availability, we distribute the ordinary exports of services from the NIOP tables over the regions as follows. For \( i = 16, 17 \), we have

\[
e_{ri}^{o} = \frac{\tilde{e}_{ri}}{\sum_{i} \tilde{e}_{si}} e_{i}^{o}
\]  

(A4.4.3)

(2) Domestic inventory changes

Data on domestic inventory changes exist at different levels. The IRIO tables show the sectoral inventory changes provided by each region \( (\bar{q}_{si}) \). The REAs give the total inventory changes in products delivered by each region \( (\bar{q}_{s}) \). The NIOP tables provide the national inventory changes at sector level \( (\bar{q}_{i}) \). It should be noted that a region’s inventory changes are the inventory changes in the whole of China regarding products delivered by that particular region.

Based on the principle that data from the NIOP tables have the highest priority, followed by data from the REAs and then the IRIO tables, a two-step procedure is developed to estimate the domestic region-industry-specific inventory changes in the IRIO tables \( (\bar{q}_{ri}^{O}) \). The first step ensures that \( \bar{q}_{ri}^{O} \) is in line with the REAs and the second step makes it consistent with the NIOP tables.

We distribute the regional totals of the domestic inventory changes from the REAs \( (\bar{q}_{r}) \) over the sectors, using \( \bar{q}_{ri} \) from the IRIO tables. This yields the initial estimate of \( \bar{q}_{ri}^{O} \). However, because inventory changes can be both positive and negative, applying the proportionality method straightforwardly may ‘blow up’ the numbers and cause
sizable swings. To avoid such swings, the proportionality method has been adapted following Dietzenbacher et al. (2013).

\[
q^O_{ri} = \bar{q}_{ri} + \frac{|\bar{q}_{ri}|}{\sum_j|\bar{q}_{rj}|} (\bar{q}_r - \sum_j \bar{q}_{rj}),
\]

(A 4.4.4)

where \(\bar{q}^O_{ri}\) gives the initial estimate (indicated by a double overbar) of the inventory changes of good \(i\) produced in region \(r\). To make the estimates in the IRIOP table consistent with the NIOP table, we distribute the \(\bar{q}_i\) from the NIOP table over the regions using the initial estimates (i.e. \(\bar{q}^O_{ri}\)). This yields

\[
q^O_{ri} = \bar{q}^O_{ri} + \frac{|\bar{q}^O_{ri}|}{\sum_{s} |\bar{q}^O_{sri}|} (\bar{q}_i - \sum_s \bar{q}^O_{sri}).
\]

(A4.4.5)

(3) Outputs

By definition, the output of processing exports production is just the exports themselves (i.e. \(x^P_r = e^P_r\)). To estimate the regional output of ordinary production (\(x^O_r\)), we can follow two routes. This is because in any IO table the output of an industry always equals the sum of the inputs in that industry. Estimating the outputs can thus be approached by looking at the columns or by looking at the rows. Because we have already estimates for the exports and the domestic inventory changes, we have chosen to use the row-wise approach.

We first estimate the domestic sales of regional ordinary production (\(d^O_{ri} = x^O_{ri} - q^O_{ri} - e^O_{ri}\)). At the national level, the domestic sales are obtained from subtracting the ordinary exports and inventory changes from the output of ordinary production in the NIOP tables, i.e. \(d^O_t = \bar{x}^O_t - \bar{q}^O_t - \bar{e}^O_t\). Next, these domestic sales are distributed over the regions of origin, using the regional distribution of domestic sales in the IRIO table, i.e. \(\hat{d}_{ri} = \bar{x}_{ri} - \bar{q}_{ri} - \bar{e}_{ri}\). This yields

\[
d^O_{ri} = \frac{\hat{d}_{ri}}{\sum_s \hat{d}_{si} \bar{q}^O_i} = \frac{(\bar{x}^O_{ri} - \bar{q}^O_{ri} - \bar{e}^O_{ri})}{\sum_{s}(\bar{x}^O_{sri} - \bar{q}^O_{sri} - \bar{e}^O_{sri})} (\bar{x}^O_i - \bar{q}^O_i - \bar{e}^O_i)
\]

(A4.4.6)

Then the output is given by \(x^O_{ri} = d^O_{ri} + q^O_{ri} + e^O_{ri}\). 

A4.4.2 Variables in Step 2

This part focuses on estimating the imported final demands in the IRIOP tables. Included are: imported consumption \( (c^M_{ri}) \), imported fixed capital formation \( (f^M_{ri}) \), and imported inventory changes \( (q^M_{li}) \). In addition, we obtain estimates for the total imported intermediates for processing exports production and ordinary production in each region. These totals are not shown in the IRIOP table (Table 4.2 in the main text), but are necessary for the estimation of other variables.

Comparing Table 4.2 in the main text and Table A4.1.1 in Appendix 4.1, we see that the total imports \( (m_i) \) and the inventory change of imports \( (q^M_{li}) \) in the IRIOP tables can be directly obtained from the NIOP tables. That is, \( m_i = \bar{m}_i \) and \( q^M_{li} = q^M_{li} \).

Next, we estimate \( c^M_{ri} \) and \( f^M_{ri} \). Imports are used either for producing processing exports only or for other purposes. We shall term them processing imports and non-processing imports. The non-processing imports are used as intermediate inputs for ordinary production and as final demands. We first focus on the non-processing imports and follow three steps.

1. **Non-processing imports**

First, the regional non-processing imports of merchandise goods are at a very detailed commodity level given in China’s Customs statistics. Using the revised BEC (‘broad economic categories’) method proposed by Dietzenbacher et al. (2013), the regional ordinary import of each commodity is split into three categories. These are ‘intermediate inputs’, ‘final consumption’, and ‘fixed capital formation’, based on a refinement of the well-known BEC codes.\(^{24}\) The resulting region-commodity-specific imports for the three categories are aggregated over the commodities so as to arrive at the 15 IO sectors producing merchandise goods. These are the initial estimates for the imports used as final consumption \( (\bar{c}^M_{ri}) \), as fixed capital formation \( (\bar{f}^M_{ri}) \), and as intermediate inputs of ordinary products \( (\bar{z}^{MO}_{ri*}, \text{ with } \bar{z}^{MO}_{ri*} \equiv \sum_j \bar{z}^{MO}_{rij}) \).

Second, we assume that the imports of each region can only be used either as final

\(^{24}\) A major advantage of this revised BEC method is that it allows that a good is used by more than one category.
demand or intermediate use in the own region, i.e. no re-exports to other regions. This assumption is reasonable since the imports from China’s Customs statistics are calculated using the principle of destination. Therefore, the vectors obtained in first step are matched to the NIOP table. This yields for the estimates in the IRIOP table, for \( i = 1, \ldots, 15 \)

\[
\begin{align*}
C_{ri}^M &= \frac{z_{ri}^M}{\sum_k f_{sji}} \cdot f_{ri}^M = \frac{z_{ri}^M}{\sum_k f_{sji}} \cdot \bar{f}_{ri}^M, \quad Z_{ri}^{MO} = \frac{z_{ri}^{MO}}{\sum_k z_{sji}^{MO}} \left( \sum_j z_{ij}^{MO} \right) \\
\end{align*}
\tag{A4.4.7}
\]

The variable \( z_{ri}^{MO} \) gives the total value of imports \( i \) used as intermediate input in ordinary production in region \( r \). It will be used in Section A4.4.4 to estimate the import matrix for ordinary production \( (Z_r^{MO}) \).

Third, for the non-processing imports of services, we assume – due to data limitations – that their regional allocation is (for each category) identical with the regional allocation of imports of merchandise goods. For \( i = 16, 17 \), we have

\[
\begin{align*}
C_{ri}^M &= \frac{\sum_{j=1}^{15} c_{sji}^{M}}{\sum_k \sum_{j=1}^{15} c_{sji}^{M}} \cdot \bar{c}_{ri}^M, \quad \bar{f}_{ri}^M = \frac{\sum_{j=1}^{15} f_{sji}^{M}}{\sum_k \sum_{j=1}^{15} f_{sji}^{M}} \cdot \bar{f}_{ri}^{M}, \quad Z_{ri}^{MO} = \frac{\sum_{j=1}^{15} z_{ri}^{MO}}{\sum_k \sum_{j=1}^{15} z_{sji}^{MO}} \left( \sum_j z_{ij}^{MO} \right) \\
\end{align*}
\tag{A4.4.8}
\]

(2) Processing imports

The estimation of total processing imports of product \( i \) for intermediate use (i.e. \( z_{ri}^{MP} \)) is not necessary in this step. However, because it is very similar to the estimation of the total \( Z_{ri}^{MO} \) for ordinary imports in Equation A4.4.7, we do it at this stage. The totals in \( z_{ri}^{MP} \) are crucial in determining later the import matrix of processing imports (i.e. matrix \( Z_r^{MP} \) with elements \( z_{rij}^{MP} \)).

According to the regulations of China’s Customs, all processing imports should be used exclusively in the production of processing exports.\(^{25}\) We further assume that the processing imports of each region are only used within this region.

For merchandise goods, we first obtain the region-commodity-specific processing imports \( (z_{ri}^{MP}) \) by aggregating data from China’s customs statistics. Then, we scale

\(^{25}\) Due to the tax-exemption policy for processing imports, processing exporters use almost only processing imports in producing their processing exports.
these totals to match them with the national processing imports in the NIOP table (i.e. $\sum_j \bar{z}_{ij}^{MP}$). This yields the region-commodity-specific processing imports in the IRIOP table, for $i = 1, \ldots, 15$

$$z_{ri}^{MP} = \frac{\bar{z}_{ri}^{MP}}{\sum_s s_x^{MP}} \left( \sum_j \bar{z}_{ij}^{MP} \right)$$ (A4.4.9)

Due to data limitations, we assume that the allocation of processing imports across regions is the same for services as it is for merchandise goods. For $i = 16, 17$, we have

$$z_{ri}^{MP} = \frac{\sum_{j=1}^{15} z_{ri}^{MP}}{\sum_s \sum_{j=1}^{15} s_x^{MP}} \left( \sum_j \bar{z}_{ij}^{MP} \right)$$ (A4.4.10)

**A4.4.3 Variables in Step 3**

In this step, we estimate the vectors with values added. Different from steps 1 and 2, the value added vectors cannot be obtained directly from existing data sources. Therefore, a more complicated procedure is followed. The general idea is that (i) initial values are assigned to the values added based on a combination of official statistics and some reasonable assumptions, (ii) row and column constraints are determined from official data, and (iii) the RAS procedure is applied on the initial values to ensure a balanced IO table that satisfies the constraints.

(1) **Initial estimates for the values added**

For industry $j$ in region $s$, we need to estimate $v_{sj}^P$ and $v_{sj}^O$. For the initial estimates ($v_{0sj}^P$ and $v_{0sj}^O$), we take the value added ratios from the NIOP table (i.e. $\bar{v}_j^P/\bar{x}_j^P$ and $\bar{v}_j^O/\bar{x}_j^O$), assume that they apply to each region, and multiply them with the output of industry $j$ in region $s$ (which was obtained in step 1). That is,

$$v_{0sj}^P = \frac{\bar{v}_j^P}{\bar{x}_j^P} x_{sj}^P \text{ and } v_{0sj}^O = \frac{\bar{v}_j^O}{\bar{x}_j^O} x_{sj}^O$$ (A4.4.11)
(2) Constraints and the RAS procedure

The NIOP table—which is our preferred data source—provides information on the national values added \( \tilde{v}_j^P \) and \( \tilde{v}_j^O \). Requiring that our regional estimates \( v_{sj}^P \) and \( v_{sj}^O \) are consistent with the NIOP table yields the column constraints

\[
\sum_s v_{sj}^P = \tilde{v}_j^P \quad \text{and} \quad \sum_s v_{sj}^O = \tilde{v}_j^O \quad \text{(A4.4.12)}
\]

The REAs provide the value added at the regional level (not distinguishing between \( P \) and \( O \)), but only for the broad sector classification (see Appendix 4.3). For agriculture \( (j = 1) \), construction \( (j = 15) \), trade and transport \( (j = 16) \), and other services \( (j = 17) \), we thus have \( \tilde{v}_{sj} \). The broad sector manufacturing covers the input-output sectors \( 2 \) – \( 14 \) and its total value added is \( \tilde{v}_{s,manufacuring} \). To split the broad sector value added into value added at IO sector level, we use the region-sector-specific value added from the IRIO table \( (\tilde{v}_{sj}) \). That is, for \( j = 2, \ldots, 14 \), \( \tilde{v}_{sj} = \frac{\tilde{v}_{sj}}{\sum_{j=2}^{14} \tilde{v}_{sj}} \tilde{v}_{s,manufacuring} \).

In principle, the national value added for industry \( j \) can be obtained as \( \tilde{v}_j^P + \tilde{v}_j^O \) (using the NIOP table), but also as \( \sum_s \tilde{v}_{sj} \) (using REA data). Given the inconsistency between the REAs and the NIOP tables, and given our preference for NIOP data, we split \( \tilde{v}_j^P + \tilde{v}_j^O \) over the regions using \( \tilde{v}_{sj} \). This gives the row constraints.

\[
v_{sj}^P + v_{sj}^O = \frac{\tilde{v}_{sj}}{\sum_r \tilde{v}_{rj}} (\tilde{v}_j^P + \tilde{v}_j^O) \quad \text{(A4.4.13)}
\]

Next, the RAS procedure is applied to the initial estimates in Equation A4.4.11, taking the column sums in Equation A4.4.12 and the row sums in A4.4.13 into account. This yields the information as sketched in Table A4.4.1.
Table A4.4.1. RAS data for the value added of industry $j$ in the IRIOP table

<table>
<thead>
<tr>
<th>Region $r$</th>
<th>Production of processing exports</th>
<th>Ordinary production</th>
<th>Row sums</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$v_{sj}^p$</td>
<td>$v_{sj}^o$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$v_{sj}^d$</td>
<td>$v_{sj}^t$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$v_{sj}^p$</td>
<td>$v_{sj}^o$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$v_{sj}^d$</td>
<td>$v_{sj}^t$</td>
<td></td>
</tr>
</tbody>
</table>

Column sums $\bar{v}_j^p$ $\bar{v}_j^o$

(3) Estimates of value added components

Value added in input-output tables includes four components: compensation of labor (index $c$), fixed asset depreciation ($d$), net production tax ($t$), and operating surplus ($q$). For industry $j$ in region $s$ in the IRIOP tables, we thus need to estimate $v_{sj}^{cp}$, $v_{sj}^{dp}$, $v_{sj}^{tp}$, and $v_{sj}^{qp}$ for the production of processing exports, and $v_{sj}^{co}$, $v_{sj}^{do}$, $v_{sj}^{to}$, and $v_{sj}^{qo}$ for ordinary production.

Before we describe the estimation procedure, we indicate the availability of data. First, the NIOP table provides the value added items at the national level. That is, $\bar{v}_j^{cp}$, $\bar{v}_j^{dp}$, $\bar{v}_j^{tp}$, and $\bar{v}_j^{qp}$ for the production of processing exports, and $\bar{v}_j^{co}$, $\bar{v}_j^{do}$, $\bar{v}_j^{to}$, and $\bar{v}_j^{qo}$ for ordinary production. These data are used for the national controls of the estimation. Second, the IRIO table provides the value added items at the level of sector-regions ($\bar{v}_{sj}^{cp}$, $\bar{v}_{sj}^{dp}$, $\bar{v}_{sj}^{tp}$, and $\bar{v}_{sj}^{qp}$) but not making a distinction between type of production ($P$ or $O$). These data are used for determining the initial estimates. Thirdly, the REA provides the totals of each value added item across industries for each region ($\bar{v}_s^{cp}$, $\bar{v}_s^{dp}$, $\bar{v}_s^{tp}$, and $\bar{v}_s^{qp}$).

The initial estimates split the region-sector-specific value added in the IRIO table (i.e., $v_{sj}^{dp}$ and $v_{sj}^{qo}$) into the four components. This is done with proportions from the IRIO table. For example, the initial estimate for $v_{sj}^{cp}$ is given by

$$v_{0sj}^{cp} = v_{sj}^{p} \frac{v_{sj}^{cp}}{v_{sj}^{dp}}$$  \hspace{1cm} (A4.4.14)
where \( \hat{v}_{sj} = \hat{v}_{sj}^c + \hat{v}_{sj}^d + \hat{v}_{sj}^l + \hat{v}_{sj}^q \). Initial estimates for the other seven variables

\( (v_{0s}^{dp}, v_{0s}^{tp}, v_{0s}^{qp}, v_{0s}^{dp}, v_{0s}^{dq}, v_{0s}^{qo}) \) are obtained in the same way.

There are three types of constraints for the value added components. First, regional aggregation of the IRIOP variables must yield the national values from the NIOP table. For example,

\[
\sum_s v_{sj}^{cP} = \hat{v}_j^{cP} \quad (A4.4.15)
\]

Second, the four components must sum to the estimates for the value added (i.e. \( v_{sj}^{P} \) and \( v_{sj}^{O} \)) as obtained in Section A4.4.3.(2). That is,

\[
v_{sj}^{cP} + v_{sj}^{dp} + v_{sj}^{tp} + v_{sj}^{qP} = v_{sj}^{P} \quad \text{and} \quad v_{sj}^{cO} + v_{sj}^{dq} + v_{sj}^{tO} + v_{sj}^{qO} = v_{sj}^{O} \quad (A4.4.16)
\]

Finally, the regional totals of the value added items are equal to the NIOP totals that have been regionally adapted using the REA data. The procedure is similar to A4.4.13 and for the compensation of labor it yields

\[
\sum_j (v_{sj}^{cP} + v_{sj}^{cO}) = \frac{\bar{v}_s}{\sum_r \bar{v}_r} \sum_j (\hat{v}_j^{cP} + \hat{v}_j^{cO}) \quad (A4.4.17)
\]

Finding a solution that satisfies constraints A4.4.15 – A4.4.17 cannot be done with the standard bi-proportional method. Instead, we use a multi-proportional method that is based on the ideas underlying TRAS (Gilchrist and St Louis, 1999). This yields a nested RAS method. That is, a RAS procedure that is nested into another bi-proportional adjustment procedure. Consider Table A4.4.2, for the value added items involved in regional production of processing exports by industry \( j \). We have a similar table for the ordinary production. This means that we have a three-dimensional estimation problem. Equation A4.4.15 gives the row sums (summing over the eight regions), Equation A4.4.16 gives the column sums (summing over the four value added categories), and Equation A4.4.17 gives the “layer” sums (summing over the two types of production, \( P \) and \( O \)).

First, RAS-using the initial estimates—given A4.4.15 and A4.4.16 as
constraints—gives the first round estimates $v_{1s_j}^{cp}$ and $v_{1s_j}^{co}$. Next these first round estimates are adapted in order to make them satisfy constraint A4.4.17, which yields the second round estimates.

$$v_{2s_j}^{cp} = v_{1s_j}^{cp} \frac{\bar{v}_s}{\sum_r \bar{v}_r \sum_f (v_{1f_j}^{cp} + v_{1f_j}^{co})} \text{ and } v_{2s_j}^{co} = v_{1s_j}^{co} \frac{\bar{v}_s}{\sum_r \bar{v}_r \sum_f (v_{1f_j}^{cp} + v_{1f_j}^{co})}$$ (A4.4.18)

Probably, the estimates $v_{2s_j}^{cp}$ and $v_{2s_j}^{co}$ violate constraints A4.4.15 and A4.4.16, after which the RAS procedure is applied again. This yields $v_{3s_j}^{cp}$ and $v_{3s_j}^{co}$, which are adapted again so as to match constraint A4.4.17. This is done similar to A4.4.18 and gives $v_{4s_j}^{cp}$ and $v_{4s_j}^{co}$. This process is repeated until convergence is reached, implying that the estimates satisfy all three constraints.

**Table A4.4.2 RAS data for the value added items of industry $j$’s production of processing exports in the IROP table**

<table>
<thead>
<tr>
<th></th>
<th>...</th>
<th>Region $r$</th>
<th>Region $s$</th>
<th>...</th>
<th>Row sums</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor compensation</td>
<td>...</td>
<td>$v_{rj}^{cp}$</td>
<td>$v_{sj}^{cp}$</td>
<td>...</td>
<td>$\bar{v}_j^{cp}$</td>
</tr>
<tr>
<td>Fixed asset depreciation</td>
<td>...</td>
<td>$v_{rj}^{dp}$</td>
<td>$v_{sj}^{dp}$</td>
<td>...</td>
<td>$\bar{v}_j^{dp}$</td>
</tr>
<tr>
<td>Net production tax</td>
<td>...</td>
<td>$v_{rj}^{tp}$</td>
<td>$v_{sj}^{tp}$</td>
<td>...</td>
<td>$\bar{v}_j^{tp}$</td>
</tr>
<tr>
<td>Operating surplus</td>
<td>...</td>
<td>$v_{rj}^{op}$</td>
<td>$v_{sj}^{op}$</td>
<td>...</td>
<td>$\bar{v}_j^{op}$</td>
</tr>
<tr>
<td><strong>Column sums</strong></td>
<td>...</td>
<td>$v_{rj}^{p}$</td>
<td>$v_{sj}^{p}$</td>
<td>...</td>
<td>$\bar{v}_j^{p}$</td>
</tr>
</tbody>
</table>

**A4.4.4 Variables in Step 4**

After the estimation in previous steps of the output ($x_{s_j}^{p}$) and the value added ($v_{s_j}^{p}$), the total amount of intermediate input use can be obtained as the residual $(x_{s_j}^{p} - v_{s_j}^{p} = \sum_r \sum_i z_{rsi_j}^{op} + \sum_i z_{sij}^{MO})$. In this sub-section, we estimate the import matrices ($z_{sij}^{MP}$ in the case of production of processing exports and $z_{sij}^{MO}$ in the case of ordinary production).
(1) The constraints

The elements of the import matrices in the IRIOP table \((z_{sij}^{MP} \text{ and } z_{sij}^{MO})\) are subject to several constraints. This is to ensure that the IRIOP table is balanced and consistent with the NIOP table and the trade statistics.

First, the IRIOP table should be in line with the bipartite table. We thus have:

\[
\sum_s z_{sij}^{MP} = \bar{z}_{ij}^{MP} \quad \text{and} \quad \sum_s z_{sij}^{MO} = \bar{z}_{ij}^{MO} \quad \text{(A4.4.19)}
\]

Next, the IRIOP table should accord with the trade statistics. Recall that in Section A4.4.2 we have estimated the variables \(z_{sij}^{MP}\) and \(z_{sij}^{MO}\). They give the total value of imports \(i\) used as intermediate input in production of processing exports \((P)\) or in ordinary production \((O)\) in region \(s\). It gives the totals over all destination sectors. Hence,

\[
\sum_j z_{sij}^{MP} = z_{sij}^{MP} \quad \text{and} \quad \sum_j z_{sij}^{MO} = z_{sij}^{MO} \quad \text{(A4.4.20)}
\]

Finally, the sum of imported inputs cannot be larger than the total amount of inputs that is required. In other words, the domestic intermediate inputs cannot be negative. This yields

\[
\sum_i z_{sij}^{MP} \leq x_{sj}^{P} - v_{sj}^{P} \quad \text{and} \quad \sum_i z_{sij}^{MO} \leq x_{sj}^{O} - v_{sj}^{O} \quad \text{(A4.4.21)}
\]

These inequalities can also be written as \(\sum_r \sum_i z_{rsj}^{OP} \geq 0\) and \(\sum_r \sum_i z_{r sj}^{OO} \geq 0\).

(2) The estimation of the import matrices

To estimate \(z_{sij}^{MP}\) and \(z_{sij}^{MO}\), we apply the RAS procedure. Consider the imports of product \(i\), then the problem is depicted in Table A4.4.3. Note that the link to the NIOP table (also in Section A4.4.2) implies that \(\sum_j z_{sij}^{MP} = \sum_s z_{sij}^{MP}\), so that the sum of the column sums equals the sum of the row sums.
Table A4.4.3 RAS data for the imports of product $i$ for production of processing exports

<table>
<thead>
<tr>
<th></th>
<th>...</th>
<th>Sector $j$</th>
<th>Sector $k$</th>
<th>...</th>
<th>Row sums</th>
</tr>
</thead>
<tbody>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Region $r$</td>
<td>...</td>
<td>$z_{r_{ij}}^{MP}$</td>
<td>$z_{r_{ik}}^{MP}$</td>
<td>...</td>
<td>$z_{r_{i*}}^{MP}$</td>
</tr>
<tr>
<td>Region $s$</td>
<td>...</td>
<td>$z_{s_{ij}}^{MP}$</td>
<td>$z_{s_{ik}}^{MP}$</td>
<td>...</td>
<td>$z_{s_{i*}}^{MP}$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Column sums</td>
<td>...</td>
<td>$z_{i_{j}}^{MP}$</td>
<td>$z_{i_{k}}^{MP}$</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

To assign initial values, we can use the structure of imported inputs either from the NIOP table (i.e. Table A4.2.1) or from the IRIO table (i.e. Table A4.2.2). The IRIO table only provides the total imports by each sector and region without information on whether they are used for production of processing exports ($P$) or ordinary production ($O$). Moreover, recall that the trade data in IRIO tables—which are crucial to the import matrices—are not consistent with other data sources. We have therefore chosen to use the information in the NIOP table to assign initial values for the import matrices in the IRIO table.

We assume that for the same production type (e.g., processing exports), the input structure of imported intermediates is the same in all regions and is identical to the national structure. The import levels, however, vary across regions. The initial import matrices in the IRIO table are given by

$$z_{0_{stij}}^{MP} = \frac{z_{ij}^{MP} x_{stij}^{P} - v_{stij}^{P}}{x_{stij}^{P} - \bar{v}_{st}^{P}} \quad (A4.4.22)$$

where $x_{stij}^{P}$ and $v_{stij}^{P}$ are from the IRIO table and have been estimated at an earlier stage.

Next, we apply the RAS procedure (with the constraints as depicted in Table A4.3.3) and this yields the first-round estimate of the import matrix ($z_{1_{stij}}^{MP}$). For every $i, j$ and $s$, we check whether $z_{1_{stij}}^{MP}$ satisfies the constraint A4.4.21. If A4.4.21 holds for all $i, j$ and $s$, we are done and have $z_{stij}^{MP} = z_{1_{stij}}^{MP}$. If Equation A4.4.21 is not satisfied
by all \(i, j\) and \(s\), we define second-round estimates. For combinations \(i, j\) and \(s\) that do satisfy \(A4.4.21\) we define \(z_{2_{stij}}^{MP} = z_{1_{stij}}^{MP}\) for the second-round estimate. Otherwise, for combinations \(i, j\) and \(s\) for which \(\sum I_{z1_{stij}}^{MT} > x_{sj}^{T} - v_{sj}^{T}\), we adjust the first-round estimate and obtain the second-round estimate as follows:

\[
z_{2_{stij}}^{MP} = z_{1_{stij}}^{MP} \frac{x_{sj}^{P} - v_{sj}^{P}}{\sum I_{z1_{stij}}^{MP}}
\]  

(A4.4.23)

Next, the RAS procedure is applied to the second-round estimates (\(z_{2_{stij}}^{MP}\)), which yields third-round estimates (\(z_{3_{stij}}^{MP}\)). If they satisfy constraint \(A4.4.21\), we are done. If not, another round of estimates is needed. This process continues until condition \(A4.4.21\) is satisfied for all \(i, j\) and \(s\).

A4.4.5 Variables in Step 5

In the last step, we estimate the matrices with domestic intermediate deliveries (\(Z_{PS}^{DO}\) with elements \(z_{rslj}^{DO}\) and \(Z_{rsl}^{DP}\) with elements \(z_{rslj}^{DP}\)) and the domestic final demand vectors (\(c_{rs}^{O}\) with elements \(c_{rsl}^{O}\) and \(f_{rs}^{O}\) with elements \(f_{rsl}^{O}\)). To this end, we adopt a hierarchical estimation method. It includes three steps, each of which uses the RAS procedure. First, the total regional domestic sales (\(d_{sl}^{O}\))—which were obtained in Equation A4.4.6 in Section A4.4.1—are split into total intermediate use, total final consumption, and total fixed capital formation. Second, the domestic final demands are determined by applying the RAS procedure. Finally, RAS is also used to estimate the domestic intermediate deliveries (\(z_{rslj}^{OP}, z_{rslj}^{OO}\)).

(1) Total intermediates and total final demands

In this sub-section, we allocate the total region-sector-specific domestic sales into the three use categories: intermediates use, final consumption, and fixed capital formation. Let \(y_{rli}^{O}\), \(c_{rli}^{O}\) and \(f_{rli}^{O}\) denote the total value of ordinary production by
sector \( i \) in region \( r \) that is used for intermediate use, for final consumption and for fixed
capital formation. That is,

\[
y^{O}_{ri} = \sum_{s} \Sigma_{j}(z^{OP}_{rsij} + z^{O0}_{rsij}), \quad ct^{O}_{ri} = \sum_{s} f^{r}_{rsi}, \quad ft^{O}_{ri} = \sum_{s} f^{r}_{rsi} \quad (A4.4.24)
\]

For the IRIOP table we have

\[
y^{O}_{ri} + ct^{O}_{ri} + ft^{O}_{ri} = d^{O}_{ri} \quad (A4.4.25)
\]

where \( d^{O}_{ri} \) has been determined earlier in Equation A4.4.6 and where \( y^{O}_{ri} \), \( ct^{O}_{ri} \) and
\( ft^{O}_{ri} \) are the unknown variables to be estimated in this sub-section.

One of our principles was that the IRIOP table should match with the NIOP table.
Aggregating \( y^{O}_{ri} \), \( ct^{O}_{ri} \), and \( ft^{O}_{ri} \) over the regions should therefore yield the
 corresponding totals at the national level as given in the NIOP table. We thus have

\[
\Sigma_{r} y^{O}_{ri} = \Sigma_{j}(\bar{z}^{O0}_{ij} + \bar{z}^{O0}_{ij}), \quad \Sigma_{r} c^{O}_{ri} = \bar{c}^{O}_{i}, \quad \Sigma_{r} f^{O}_{ri} = \bar{f}^{O}_{i} \quad (A4.4.26)
\]

Equations A4.4.25 and A4.4.26 provide the constraints that must be satisfied by
the IRIOP table. This is illustrated in Table A4.4.4. The uncolored cells are the variables
to be estimated (\( y^{O}_{ri} \), \( ct^{O}_{ri} \), and \( ft^{O}_{ri} \)), and the last column and the last row respectively
provide the row sums and column sums that are given. Using Equation A4.4.6, we can
prove that the sum of row sums equals the sum of column sums. Therefore, the RAS
procedure can be used for estimation.
Table A4.4.4 RAS data for total use of ordinary production by industry \( i \) as domestic intermediates and as domestic final demands

<table>
<thead>
<tr>
<th></th>
<th>Total domestic intermediates</th>
<th>Total domestic final consumption</th>
<th>Total domestic fixed capital formation</th>
<th>Row sums</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ldots )</td>
<td>( \ldots )</td>
<td>( \ldots )</td>
<td>( \ldots )</td>
<td>( \ldots )</td>
</tr>
<tr>
<td>Region ( r )</td>
<td>( y_{rl}^o )</td>
<td>( ct_{rl}^o )</td>
<td>( ft_{rl}^o )</td>
<td>( d_{rl}^o )</td>
</tr>
<tr>
<td>Region ( s )</td>
<td>( y_{sl}^o )</td>
<td>( ct_{sl}^o )</td>
<td>( ft_{sl}^o )</td>
<td>( d_{sl}^o )</td>
</tr>
<tr>
<td>( \ldots )</td>
<td>( \ldots )</td>
<td>( \ldots )</td>
<td>( \ldots )</td>
<td>( \ldots )</td>
</tr>
<tr>
<td>Column sums</td>
<td>( \sum_j (z_{ij}^{op} + z_{ij}^{00}) )</td>
<td>( \bar{c}_l^o )</td>
<td>( \bar{f}_l^o )</td>
<td>( \bar{f}_l^o )</td>
</tr>
</tbody>
</table>

The initial values for the RAS procedure are obtained by distributing the given column sums over the regions of origin. The distribution is based on the regional shares from the IRIO tables. That is,

\[
y_0^{00}_{rl} = \left[ \sum_j (z_{ij}^{op} + z_{ij}^{00}) \right] \frac{\sum_s \sum_j z_{rsij}}{\sum_r \sum_s \sum_j z_{rsij}}, \quad ct_0^{00}_{rl} = \bar{c}_l^o \frac{\sum_s c_{rsi}}{\sum_r \sum_s c_{rsi}}, \quad ft_0^{00}_{rl} = \bar{f}_l^o \frac{\sum_s f_{rsi}}{\sum_r \sum_s f_{rsi}}
\]

(A4.4.27)

(2) Domestic final demands

In last sub-section, we obtained the total domestic final use of products provided by industry \( i \) in region \( r \) (\( ct_{rl}^o \) and \( ft_{rl}^o \)). In this sub-section, we will split these totals according to region of destination. That is, we estimate \( c_{rsi}^o \) and \( f_{rsi}^o \), using the RAS procedure again.

The final consumption (\( c_{rsi}^o \)) and the fixed capital formation (\( f_{rsi}^o \)) in the IRIOP table are each subject to two constraints. Their row sums (summing over the destination regions \( s \)) and their column sums (summing over the origin regions \( r \)) are given. First, the row sums are given in Equation A4.4.24, i.e. \( \sum_s c_{rsi}^o = ct_{rl}^o \) and \( \sum_s f_{rsi}^o = ft_{rl}^o \). Second, for the column sums we start from the NIOP table, which gives the national total of final use of product \( i \) (i.e. \( \bar{c}_l^o + \bar{c}_l^M \) for final consumption and \( \bar{f}_l^o + \bar{f}_l^M \) for fixed capital formation). These totals are split over the regions in which the final use takes place (i.e. destination regions), using information from the REAs (i.e. \( \bar{c}_s \) and \( \bar{f}_s \)). This yields
\[ \sum_r c_{rsl}^O + c_{sli}^M = \frac{\bar{c}_s}{\sum_s \bar{c}_s} (c_{l}^O + c_{l}^M), \quad \sum_r f_{rsl}^O + f_{sli}^M = \frac{\bar{f}_s}{\sum_s \bar{f}_s} (f_{l}^O + f_{l}^M) \quad (A4.4.28) \]

from which the columns sums can be obtained (subtracting \(c_{sli}^M\) on both sides and the same for \(f_{sli}^M\)). The constraints for the RAS procedure are depicted by the shaded ells in Tables A4.4.5 and A4.4.6. Note that \(r\) and \(w\) indicate origin regions and \(s\) and \(l\) destination regions.

### Table A4.4.5 RAS data for final consumption in region \(s\) of product \(i\) produced in region \(r\).

<table>
<thead>
<tr>
<th>Region sums</th>
<th>Region (s)</th>
<th>Region (l)</th>
<th>Row sums</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
</tr>
<tr>
<td>Region (r)</td>
<td>(c_{rsl}^O)</td>
<td>(c_{rli}^O)</td>
<td>(c_{t_{rl}}^O)</td>
</tr>
<tr>
<td>Region (w)</td>
<td>(c_{wsl}^O)</td>
<td>(c_{wli}^O)</td>
<td>(c_{t_{wl}}^O)</td>
</tr>
<tr>
<td>(\ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
</tr>
<tr>
<td>Column sums</td>
<td>(\frac{\bar{c}<em>s}{\sum_s \bar{c}<em>s} (c</em>{l}^O + c</em>{l}^M) - c_{sli}^M)</td>
<td>(\frac{\bar{c}<em>l}{\sum_s \bar{c}<em>s} (c</em>{l}^O + c</em>{l}^M) - c_{l}^l)</td>
<td>(\ldots)</td>
</tr>
</tbody>
</table>

### Table A4.4.6 RAS data for fixed capital formation in region \(s\) of product \(i\) produced in region \(r\).

<table>
<thead>
<tr>
<th>Region sums</th>
<th>Region (s)</th>
<th>Region (l)</th>
<th>Row sums</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
</tr>
<tr>
<td>Region (r)</td>
<td>(f_{rsl}^O)</td>
<td>(f_{rli}^O)</td>
<td>(f_{t_{rl}}^O)</td>
</tr>
<tr>
<td>Region (w)</td>
<td>(f_{wsl}^O)</td>
<td>(f_{wli}^O)</td>
<td>(f_{t_{wl}}^O)</td>
</tr>
<tr>
<td>(\ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
</tr>
<tr>
<td>Column sums</td>
<td>(\frac{\bar{f}<em>s}{\sum_s \bar{f}<em>s} (f</em>{l}^O + f</em>{l}^M) - f_{sli}^M)</td>
<td>(\frac{\bar{f}<em>l}{\sum_s \bar{f}<em>s} (f</em>{l}^O + f</em>{l}^M) - f_{l}^l)</td>
<td>(\ldots)</td>
</tr>
</tbody>
</table>

Next, we have to assign initial values to the domestic final demands. Because production of processing exports does not deliver domestically, the final use in the IRIOP table that we need to estimate is other (or ordinary) production. Therefore, the deliveries of product \(i\) from region \(r\) to region \(s\) for final consumption (or fixed capital
formation) in the IRIOP table are just the deliveries from region \( r \) to region \( s \) that are listed in the IRIO table. We thus take the domestic final demands in the IRIO table as the initial values for domestic final demands in the IRIOP table. That is:

\[
c_0^{0s} = \tilde{c}_{rsi}, \quad f_0^{0s} = \tilde{f}_{rsi}
\]  

(A4.4.29)

(3) Domestic intermediate deliveries

In this sub-section, we estimate the domestic intermediate deliveries in the IRIOP table \( z_{rjs}^{0p} \) and \( z_{rjs}^{0o} \). This is the key part of the IRIOP table and reflects the interdependence amongst regions and sectors. The estimation takes place in two steps, starting from the NIOP table \( \bar{z}_{rjs}^{0p} \) and \( \bar{z}_{rjs}^{0o} \). First, the national deliveries are split according to destination regions. Second, the results of the first step are split according to origin regions.

(a) Allocation of the intermediate deliveries over the regions of destination

In this first step, we estimate

\[
z_{rjs}^{0p} \equiv \sum_r z_{rjs}^{0p}, \quad z_{rjs}^{0o} \equiv \sum_r z_{rjs}^{0o}
\]  

(A4.4.30)

For the RAS procedure, we will use two constraints. Summing over the (destination) regions \( s \) should give us the national total from the IOP table. That is,

\[
\sum_s z_{rjs}^{0p} = \bar{z}_{rjs}^{0p}, \quad \sum_s z_{rjs}^{0o} = \bar{z}_{rjs}^{0o}
\]  

(A4.4.31)

The other constraint is based on the column sums of the IRIOP table. The sum (taken over origin sectors and origin regions) of the intermediate deliveries is given by \( \sum_i \sum_r z_{rjs}^{0p} = \sum_i z_{rjs}^{0p} \). This equals the output of sector \( j \) in region \( s \) minus the total imported inputs and the value added \( (x_{sj}^P - \sum_i z_{rjs}^{M0} - v_{sj}^P) \). The second constraint thus becomes

\[
\sum_i z_{rjs}^{0p} = x_{sj}^P - \sum_i z_{rjs}^{M0} - v_{sj}^P, \quad \sum_i z_{rjs}^{0o} = x_{sj}^O - \sum_i z_{rjs}^{M0} - v_{sj}^O
\]  

(A4.4.32)
The RAS procedure and its constraints is illustrated in Table A4.4.7. The shaded cells give the row sums—from Equation A4.4.31—and the columns sums—from Equation A4.4.32. Note that the row sums are taken directly from the NIOP table and the column sums can be calculated from IRIOP variables that have been estimated in an earlier stage. Also, it can be shown that 
\[ \sum_i z_{ij}^{OP} = \sum_i \sum_s z_{stij}^{OP} = \sum_s (x_{sj}^P - \sum_i z_{stij}^{MP} - v_{sj}^P), \]
implying that the sum of row sums equals the sum of column sums.

**Table A4.4.7 RAS data for domestic intermediate inputs to produce sector j’s processing exports.**

<table>
<thead>
<tr>
<th></th>
<th>...</th>
<th>Region s</th>
<th>Region l</th>
<th>...</th>
<th>Row sums</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product i</td>
<td>...</td>
<td>...</td>
<td>$z_{tij}^{OP}$</td>
<td>...</td>
<td>$\tilde{z}_{ij}^{OP}$</td>
</tr>
<tr>
<td>Product k</td>
<td>...</td>
<td>...</td>
<td>$z_{skj}$</td>
<td>...</td>
<td>$\tilde{z}_{kj}^{OP}$</td>
</tr>
<tr>
<td>Column sums</td>
<td>...</td>
<td>$x_{sj}^P - \sum_l z_{stij}^{MP} - v_{sj}^P$</td>
<td>$x_{lj}^P - \sum_l z_{ltlj}^{MP} - v_{lj}^P$</td>
<td>...</td>
<td></td>
</tr>
</tbody>
</table>

To start the RAS procedure, an initial value should be assigned to $z_{tij}^{OP}$ and $z_{tij}^{OO}$. We could take the national input structure in the NIOP table as the starting point. In that case, we would distribute $\tilde{z}_{ij}^{OP}$ and $\tilde{z}_{ij}^{OO}$ over the destination regions. Alternatively, we could take the regional input structures of sector j from the IRIOP table as the starting point. In that case, we would distribute sector j’s totals $x_{sj}^P - \sum_i z_{stij}^{MP} - v_{sj}^P$ over the different region-specific inputs. We have chosen for the latter option. This is because Chinese regions differ considerably in terms of endowments and production technologies.\(^{26}\) Therefore, we think that it matters more to have detailed information of the regional intermediate input structure than to have separate structures for types of production (i.e. $P$ or $O$, as in the former option). We thus estimate the initial value

\[^{26}\text{To illustrate this point, production in China’s North East (where agriculture is well-developed) tends to use more agricultural products than production in other regions, according to the 2007 IRIOP table. In contrast, production in Northern Municipalities (where China’s cultural, commercial and political center is located and which has thriving service industries) depends more on services than production elsewhere. For example, one unit of food products used 0.41 units of agricultural products and 0.04 units of services in the North East, and 0.17 units of agricultural products and 0.11 units of services the Northern Municipalities.}\]
by using the IRIO tables. That is:

\[
zt_{0_{si}} = (x_{si} - \sum z_{sij}^{MP} - p_{sij}) \frac{\sum z_{rsij}^{MP}}{\Sigma \sum z_{rsij}^{MP}}, \quad zt_{0_{si}} = (x_{si} - \sum z_{sij}^{MO} - p_{sij}) \frac{\sum z_{rsij}^{MO}}{\Sigma \sum z_{rsij}^{MO}}
\]

(A4.4.33)

The RAS procedure then yields \( z_{r_{si}}^{OP} \) and \( z_{r_{si}}^{OO} \).

(b) Allocation of the intermediate deliveries over the regions of origin

In previous step, we obtained the intermediate inputs that are used by the different regions (i.e. \( z_{r_{si}}^{OP} \) and \( z_{r_{si}}^{OO} \)). In this sub-section, we will separate these intermediates according to the region where they originate. This will yield the domestic intermediate inputs in the IRIO table (i.e. \( z_{rsij}^{OP} \) and \( z_{rsij}^{OO} \)).

There are two constraints again for the RAS procedure in this step. From Equation A4.4.24 we have \( \sum s \sum j (z_{rsij}^{OP} + z_{rsij}^{OO}) = y_{ri}^{O} \). Note that \( y_{ri}^{O} \) was estimated earlier (in sub-section A4.4.5.1) and is therefore given in this sub-section. The other constraint follows from Equation A4.4.30 and yields \( \sum r z_{rsij}^{OP} = zt_{si}^{OP} \) and \( \sum r z_{rsij}^{OO} = zt_{si}^{OO} \), which we have estimated in the previous step (a). The case is illustrated by Table A4.4.8 for the input of good \( i \) from ordinary production. For the shaded cells, it follows from Equations A4.4.26 and A4.4.31 that the sum of row sums equals the sum of column sums. This implies that we can apply the RAS procedure.

<table>
<thead>
<tr>
<th>Table A4.4.8 RAS data for the input of good ( i ) from ordinary production.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing exports ( z_{rsij}^{OP} ) ( z_{rsij}^{OO} ) ( y_{ri}^{O} )</td>
</tr>
<tr>
<td>Processing exports production of industry ( j ) in region ( s )</td>
</tr>
<tr>
<td>( \ldots )</td>
</tr>
<tr>
<td>Region ( r )</td>
</tr>
<tr>
<td>Region ( w )</td>
</tr>
<tr>
<td>Column sums</td>
</tr>
</tbody>
</table>

Our last step is to assign initial values to the domestic intermediate inputs. We
take $z_{t_{ij}}^{op}$ and $z_{t_{ij}}^{oo}$ that were obtained in the previous step (a) and distribute it over regions of origin. For this we use the origin shares of the intermediates in the IRIO table, because it is the only data source that includes these proportions. The initial value of the domestic intermediate deliveries are as follows:

$$z_{0_{r_{ij}}}^{op} = z_{t_{ij}}^{op} \frac{\tilde{z}_{r_{ij}}}{\sum_r \tilde{z}_{r_{ij}}}, \quad z_{0_{r_{ij}}}^{oo} = z_{t_{ij}}^{oo} \frac{\tilde{z}_{r_{ij}}}{\sum_r \tilde{z}_{r_{ij}}}$$  \hspace{1cm} (A4.4.34)
Appendix 4.5

Differences between variables in the aggregated IRIOP table and the IRIO table published by the State Information Center, 2007

<table>
<thead>
<tr>
<th></th>
<th>NE</th>
<th>NM</th>
<th>NC</th>
<th>EC</th>
<th>SC</th>
<th>CR</th>
<th>NW</th>
<th>SW</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value Added (%)</td>
<td>-1.3</td>
<td>-0.6</td>
<td>0.4</td>
<td>-0.6</td>
<td>2.1</td>
<td>-0.9</td>
<td>-5.5</td>
<td>4.6</td>
<td>0.0</td>
</tr>
<tr>
<td>Output (%)</td>
<td>0.3</td>
<td>3.0</td>
<td>-0.1</td>
<td>0.0</td>
<td>5.5</td>
<td>-0.6</td>
<td>-1.7</td>
<td>-0.3</td>
<td>0.8</td>
</tr>
<tr>
<td>Final Consumption (%)</td>
<td>-1.7</td>
<td>-20.3</td>
<td>2.8</td>
<td>-1.0</td>
<td>0.5</td>
<td>7.4</td>
<td>-5.8</td>
<td>6.7</td>
<td>-0.1</td>
</tr>
<tr>
<td>Capital Formation (%)</td>
<td>5.1</td>
<td>-0.6</td>
<td>-1.0</td>
<td>-11.3</td>
<td>-13.2</td>
<td>20.3</td>
<td>9.3</td>
<td>9.9</td>
<td>0.3</td>
</tr>
<tr>
<td>Exports (%)</td>
<td>12.6</td>
<td>31.4</td>
<td>24.3</td>
<td>11.9</td>
<td>50.8</td>
<td>30.5</td>
<td>-18.7</td>
<td>14.4</td>
<td>24.6</td>
</tr>
<tr>
<td>Value added ratio</td>
<td>-0.6</td>
<td>-1.1</td>
<td>0.1</td>
<td>-0.2</td>
<td>-1.0</td>
<td>-0.1</td>
<td>-1.5</td>
<td>1.9</td>
<td>-0.3</td>
</tr>
</tbody>
</table>

Notes: Final consumption and capital formation indicate the delivery by each region of goods and services that are used for domestic final consumption and capital formation. The value added ratio is the aggregate value added divided by the total output. The differences (in value added, output, final consumption, capital formation, and exports) are measured as a percentage of value in the SIC IRIO table. The differences in the value added ratio are absolute (IRIOP table outcome minus SIC IRIO table outcome).
CHAPTER 5

China’s Rise as An Export Giant and Regional Inequality: A Value Chain Analysis

5.1 Introduction

In recent years, two of the most salient phenomena in the global economy have been a rapid increase in global interconnectedness and a significant rise in income inequality (Antràs et al., 2017). Decreases in trade and communications costs have allowed firms to split production processes into geographically distinct activities. Consequently, national and regional economies have specialized in those particular stages of production in which they have a comparative advantage. So-called global value chains (GVCs) emerged. By now, several studies have quantified characteristics of GVCs and the roles countries play in these (e.g., Johnson and Nogueria, 2012; Koopman et al., 2014; Los et al., 2015a; Timmer et al., 2014). These studies generally found substantial changes in the extent to which countries contributed to GVCs. In a different strand of literature, authors also have studied the impact of globalization on income distribution within countries (Feenstra and Hanson, 1996; Marchand, 2012; Wan et al., 2007), reflecting the long-standing interest in income inequality among economists and policymakers. By combining value chains and inequality considerations, this chapter investigates the effect of globalization on regional labor income inequality in China from a value chain perspective. In this respect, China is an interesting case, given its emergence as the “World’s Factory” (massively attracting production activities in GVCs after its accession to the World Trade Organization in 2001) and its high levels of regional income inequality.

China’s economic integration with the world has been accompanied by growing regional inequality, with coastal regions developing much faster than inland regions (Kanbur and Zhang, 2005; Tsui, 2007). Exports have always been regarded as an important contributor to inequality; however, after decades of increases, China’s regional inequality in terms of gross domestic product (GDP) per capita has decreased
recently (Li and Gibson, 2013; Xie and Zhou, 2014). The ratio of GDP per capita of the wealthiest province and the poorest province decreased from 8.5 in 2000 to 4.5 in 2018.\(^1\) It seems that China has entered an era of convergence in regional development. This development raises the question of how exports have affected regional inequality in the era of decreasing inequality. Several—somewhat older—studies have focused on this issue and found a significant positive relationship between globalization and regional inequality in China (Fujita and Hu, 2001; Kanbur and Zhang, 2005; Li and Wei, 2010; Wan et al., 2007; Zhang and Zhang, 2003). However, they ignored the indirect income effects of exports on inland regions, which provide materials and components to the production of the exports in the coastal regions.

The recent convergence in regional development also questions how different types of exports have contributed to China’s regional inequality. There are two prevalent types in China: processing exports and ordinary exports, each of which comprised about half of the country’s total exports until a few years ago.\(^2\) These two types of export products use substantially different input mixes; processing exports require far more imported intermediate inputs than ordinary exports, and ordinary exports have stronger domestic backward linkages (Pei et al., 2012). Accordingly, processing exports tend to generate considerably less domestic value added than the same amount of ordinary exports (Chen et al., 2012; Koopman et al., 2012; Pei et al., 2012). The two types of exports thus likely exert different impacts on China’s regional growth and income disparities.

Against this background, this chapter aims to quantify the contributions of different export types to China’s regional inequality by taking “indirect income effects” into full consideration. To this end, we introduce a new framework to disentangle the major forces that shape China’s regional inequality. We quantify the contributions of both processing exports and ordinary exports to regional inequality and examine temporal changes using a value chain perspective.\(^3\) This perspective implies an

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\(^1\) These provincial gross regional product (GRP) per capita levels were reported by the Chinese National Bureau of Statistics (NBS) and are expressed in current prices. In 2000, Beijing and Guizhou were the wealthiest province and the poorest province, respectively. Beijing and Gansu ranked as such in 2018.

\(^2\) Processing trade refers to the business activities of importing all or some materials abroad, and then re-exporting the finished products after processing or assembly in China. Since the 1990s, processing exports have comprised about half of China’s total exports, but this share has decreased steadily in recent years, to 33.5% in 2017.

\(^3\) This chapter is related to the literature on value chains and Chinese regions, which relies on interregional input–output (IRIO) tables. Pei et al. (2017), for example, investigated interregional income effects across regions and
Chapter 5

accounting approach, rather than a (regression) approach that would try to identify causal relationships between income inequality and underlying factors. Our value chain approach considers the Chinese (domestic) parts of GVCs. The value of a particular final product (consumer products or capital goods) used in China or a particular exported product (either an intermediate input used by sectors abroad or a final product) equals the sum of the costs of imported products required in the Chinese stages of production and value added contributed by sectors in each of the Chinese regions. Consequently, the sum of these contributions by a region to domestic parts of all GVCs constitutes its gross regional product (GRP). We use Shorrocks’s (1982) decomposition method to quantify the contributions to regional inequality of value chain activities for domestically used final products and for exported products, respectively. Our use of recently developed interregional input-output tables for China, which explicitly distinguish between production of processing exports and that of ordinary exports in each region (the so-called IRIOP tables, see Duan et al., 2019, and Table 4.2) allows for a rich analysis of the impact of China’s exports dependence (and changes therein) on regional inequality.

The remainder of this chapter is structured as follows: In Section 5.2, we summarize the nature of China’s regional inequality to motivate the subsequent empirical exercise. In Section 5.3, we introduce the framework that decomposes overall regional inequality into the contributions of activities in the three types of value chains that we consider. In Section 5.4, we discuss the data. Section 5.5 presents our empirical results, and Section 5.6 concludes.

5.2 China’s regional income inequality

This section contains a brief descriptive overview of China’s regional income, the distribution of export activities and the changes in China’s regional income inequality.

observe an upstream role of interior regions in the production of China’s exports, providing natural resources and raw materials to support more downstream production activities in coastal regions. Meng et al. (2013) used similar data to trace the value added by each region for regional final production. Meng et al. (2017) linked regional value added to entire GVCs by embedding Chinese IRIO tables into inter-country input-output tables. These studies do not link regional inequality to exports (the main focus of this chapter) and do not differentiate between processing exports and ordinary exports.
China’s rise as an export giant and regional inequality: a value chain analysis

It provides some first insights into China’s regional economic development.

5.2.1 China’s regional income and export activities

Table 5.1 documents descriptive statistics on exports and per capita income by region for 2002 and 2012. For each of these years, the first two columns depict regional labor income per capita and GRP per capita (LPC and GPC), while the third and fourth columns list regional processing exports and ordinary exports per capita (PPC and OPC) for the eight regions. The regional exports, the labor income, and GRP data come from the IRIOP tables (Duan et al., 2019). The population data are from NBS (2003, 2013) and include only those persons actually living in each region, taking interregional labor migration into consideration.

Table 5.1 Regional labor incomes and distribution of exports (in 1,000RMB per capita, in current prices)

<table>
<thead>
<tr>
<th>Region</th>
<th>LPC (1)</th>
<th>GPC (2)</th>
<th>PPC (3)</th>
<th>OPC (4)</th>
<th>LPC (5)</th>
<th>GPC (6)</th>
<th>PPC (7)</th>
<th>OPC (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NE</td>
<td>5.3</td>
<td>10.8</td>
<td>0.6</td>
<td>0.9</td>
<td>19.8</td>
<td>42.7</td>
<td>2.6</td>
<td>5.0</td>
</tr>
<tr>
<td>NM</td>
<td>10.8</td>
<td>26.6</td>
<td>3.8</td>
<td>6.3</td>
<td>42.2</td>
<td>85.0</td>
<td>7.6</td>
<td>19.8</td>
</tr>
<tr>
<td>NC</td>
<td>5.0</td>
<td>10.4</td>
<td>0.6</td>
<td>0.8</td>
<td>19.4</td>
<td>41.6</td>
<td>2.6</td>
<td>5.4</td>
</tr>
<tr>
<td>EC</td>
<td>7.5</td>
<td>18.0</td>
<td>2.5</td>
<td>4.4</td>
<td>29.4</td>
<td>64.5</td>
<td>12.1</td>
<td>18.1</td>
</tr>
<tr>
<td>SC</td>
<td>7.9</td>
<td>15.5</td>
<td>7.1</td>
<td>3.7</td>
<td>25.3</td>
<td>48.4</td>
<td>14.5</td>
<td>14.2</td>
</tr>
<tr>
<td>CR</td>
<td>3.3</td>
<td>6.4</td>
<td>0.0</td>
<td>0.2</td>
<td>15.5</td>
<td>30.0</td>
<td>0.6</td>
<td>1.3</td>
</tr>
<tr>
<td>NW</td>
<td>3.3</td>
<td>6.7</td>
<td>0.1</td>
<td>0.4</td>
<td>17.4</td>
<td>36.4</td>
<td>0.2</td>
<td>2.3</td>
</tr>
<tr>
<td>SW</td>
<td>2.9</td>
<td>5.3</td>
<td>0.1</td>
<td>0.2</td>
<td>13.7</td>
<td>25.8</td>
<td>0.4</td>
<td>1.6</td>
</tr>
<tr>
<td>National</td>
<td>4.6</td>
<td>9.6</td>
<td>1.2</td>
<td>1.3</td>
<td>19.9</td>
<td>39.8</td>
<td>4.0</td>
<td>6.2</td>
</tr>
</tbody>
</table>

Notes: Authors’ calculations based on the IRIOP tables (Duan et al., 2019). LPC = labor income per capita, GPC = GRP per capita, PPC=Processing exports per capita, OPC=Ordinary exports per capita. NE=North East; NM=North Municipality; NC=North Coast; EC=East Coast; SC=South Coast; CR=Central Region; NW=North West; SW=South West.

Table 5.1 shows a large heterogeneity in income per capita across regions. The North Municipality, which includes the national capital Beijing, is the wealthiest region.

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4 The eight regions analyzed here are those that can be analyzed by means of the IRIOP tables. See Appendix 4.2 for the regional classifications.
in terms of per capita labor income (LPC), whereas the South West is the poorest. In both 2002 and 2012, LPC in the wealthiest region was more than three times as high as that of the poorest region. More generally speaking, GDP per capita (GPC) and LPC are much larger in the coastal regions (i.e., North Municipality, North Coast, East Coast, and South Coast) than in the inland regions (i.e., North East, Central Region, North West, and South West).

The processing exports and ordinary exports per capita also reveal sizable regional inequalities, especially for processing exports; exports were more concentrated in North Municipality, the East Coast, and South Coast. In contrast, exports from the inland regions were extremely low; in 2012 for example, processing export per capita in North West was 200 RMB, only 5% of the national average.

From 2002 to 2012, labor income per capita grew quickly in all regions, with the national average increasing from 4.6 thousand RMB to 19.9 thousand RMB, at a nominal annual growth rate of 15.8%. This increase was quite rapid for a large country like China; in contrast, the growth rate of the U.S. was only 2.4% during this period.\(^5\) The growth rates varied across China’s regions, however, ranging from a high of 18.1% in the North West to a low of 12.3% in the South Coast. In general, the inland regions show higher growth rates than the coastal regions, suggesting a decline in regional income inequality. Further, more rapid export growth in the inland regions suggests an important role of exports in this declining income inequality. We further investigate the changes in China’s regional income inequality over time in a more formal way in the next sub-section.

### 5.2.2 China’s regional income inequality

#### 5.2.2.1 Regional inequality measures

The existing literature uses various mathematical measures to quantify inequality. Bourguignon (1979) and Shorrocks (1982) agreed on a set of simple principles that

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\(^5\) The growth rate for the U.S. is calculated by using data from the World Input-Output Database (Timmer et al., 2015), which provides the labor compensation for around 40 countries over the period 2000-2014. Population data of the U.S. come from the World Development Indicators. The U.S. growth rate is also in nominal terms.
define a sound inequality index. The Theil (1967) index follows these principles; it is one of the most popular measures because of its attractive decomposition property. This index measures the entropic distance between the actual distribution of income over regions and the state in which every region would have the same per capita income. A high (low) value represents a large (small) deviation from an equal distribution, which indicates a high (low) degree of inequality. Therefore, to measure regional inequality, we resort to a population-weighted version of the Theil index, expressed mathematically as:

\[ I = \sum_r p_r \frac{v_r}{y} \ln \left( \frac{v_r}{y} \right) = \sum_r \frac{v_r}{p_r v} \ln \left( \frac{v_r}{p_r v} \right), \]  

(5.1)

where \( p_r \) indicates the population share of region \( r \) in the national total; \( y_r \) and \( v_r \) indicates the income per capita and total income in region \( r \), respectively; and \( \bar{y} \) is the national average of the income per capita, calculated as \( \bar{y} = \sum_r p_r y_r \). \( v \) is the national income.

We classify the regions into two larger geographic entities, which we call “macro-regions”: the coastal macro-region and the inland macro-region. We then decompose the overall regional inequality into the contributions of inequality between regions within the coastal macro-region (\( I_c \)), inequality between regions within the inland macro-region (\( I_i \)), and the inequality between the two macro-regions (\( I_b \)) (See Appendix 4.2 for the classification of regions into macro-regions):

\[ I = \sum_{r \in c} \frac{v_r}{v} \ln \left( \frac{v_r}{p_r v} \right) + \sum_{r \in i} \frac{v_r}{v} \ln \left( \frac{v_r}{p_r v} \right) \]

\[ = \frac{v_c}{v} \sum_{r \in c} \frac{v_r}{v} \ln \left( \frac{v_r}{p_r v} \right) + \frac{v_i}{v} \sum_{r \in i} \frac{v_r}{v} \ln \left( \frac{v_r}{p_r v} \right) \]

\[ = \frac{v_c}{v} I_c + \frac{v_i}{v} I_i + \frac{v_c}{v} \ln \left( \frac{v_c}{p_c v} \right) + \frac{v_i}{v} \ln \left( \frac{v_i}{p_i v} \right) = \frac{v_c}{v} I_c + \frac{v_i}{v} I_i + I_b; \]  

(5.2)

where \( c \) denotes the coastal macro-region and \( i \) the inland macro-region; \( v_c \) and \( v_i \) are total income in the two macro-regions; \( p_{cr} \) and \( p_{ir} \) are the population share of a

---

6 We focus on regional income variation and do not consider income inequality between persons or households within regions.
region $r$ in the macro-region it is part of; finally, $p_c$ and $p_l$ are the population shares of the two macro-regions in total population, respectively. Then, $v_c I_c/vI$, $v_l I_l/vI$, and $I_b/I$ provide the contributions of $I_c$, $I_l$, and $I_b$ to overall regional inequality, respectively.

To measure the level of regional inequality, ideally regional household income should be used. Existing studies (Li and Gibson, 2013; Zhang and Zhang, 2003; Zhang and Zou, 2012) used the GRP (Gross Regional Product, the sum of value added levels over industries) per capita as a measure. This approximation suffers from a major drawback. The location at which value is added is not necessarily identical to the location to which the generated income eventually accrues. Value added includes both labor income and capital income. Sizable investment flows across regions frequently lead to parts of capital income of one region accruing as income to firms with headquarters in other regions or countries (Timmer et al., 2014, 2019; Ma et al., 2015). Duan et al. (2012) demonstrate that in 2007, about 40% of Chinese capital income induced by processing exports was actually generated by foreign-owned activities (see also Duan et al., 2018).

Since the aim of this chapter is to link regional income inequality to the production of exported products and the intermediate inputs required for these, considering household income would only have been possible if we would have had information about interregional and international flows of capital income. This information is not available. Hence, we use regional labor income inequality as an approximation of regional household income inequality. Labor income is defined as employment compensation as reported in the National Accounts and is a component of value added; it refers to the total of various forms of payment to employees for the productive activities they engage in, including all wages, bonuses, subsidies, and allowances in cash or in kind. The empirical consequences of exclusively looking at labor income are most probably limited in this context. Labor income is the main source of household income in Chinese regions. In 2007, about 69% of urban household income consisted

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7 Household income includes four components by income source: wages and salaries, net business income, income from properties, and income from transfers.

8 Capital income is defined as a residual measure, by subtracting labor income from gross value added.

9 Employment compensation also includes medical expenses, transport subsidies, social insurance, and housing funds paid by employers.
of wages and salaries (NBS, 2008). For rural households, about 92% of income came from wages, salaries and household operations; such rural household operations consisted mainly of agriculture production, for which 95% of value added was counted as labor income (NBS, 2008). Accordingly, regional labor income constitutes very large parts of regional household income and is most likely a good proxy for it when considering regional income inequality.

5.2.2.2 The temporal changes of China’s regional income inequality

Based on the regional labor income data from NBS (various years), Figure 5.1 depicts China’s overall labor income inequality across the eight regions and its three components shown in Equation 5.2 from 2000 to 2016: (income weighted) inequality within the coastal macro-region \((v_c I_c/v)\), (income weighted) inequality within the inland macro-region \((v_i I_i/v)\), and inequality between the coastal macro-region and the inland macro-region \((I_b)\).

Figure 5.1 indicates that labor income inequality across regions measured with a Theil index amounted to 0.032 in 2016. Inequality between the two macro-regions is the major source of China’s regional inequality, explaining about 80% of China’s total regional inequality in that year.

China’s regional inequality increased rapidly from 2000 to 2003, remained steady until 2006, and then started to decrease. This result is consistent with recent studies that demonstrate declining regional inequality in terms of GRP per capita (Li and Gibson, 2013). Inequality between the coastal and inland macro-regions shows a similar trend and has been the major source of China’s overall decreasing regional inequality from 2006 to 2016. About 72% of this total decrease was due to decreases in the declining inequality between the two macro-regions.\(^{10}\) The importance of the inland regions in exporting (as documented in Table 5.1) grew, while regional inequality declined. This leads us to our main research question: To what extent did changes in export levels and mixes contribute to the reduction of China’s regional

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\(^{10}\) This share was calculated according to Equation 5.2. We divided changes in inequality between the two macro-regions by the change in overall regional inequality.
inequality?

**Figure 5.1 China’s regional inequality from 2000 to 2016, measured by Theil indexes**

![Graph showing regional inequality from 2000 to 2016](image)

Notes: Author’s calculation based on the labor income and population data from NBS (various years). The labor income levels have been deflated to 2002 Beijing prices using the method of Brandt and Holz (2006) (Section 5.4 explicitly describes the deflation procedure).

### 5.3 Methodology

In this section, we propose a new framework to account for the contribution of exports to regional inequality. Our methodology includes two parts. First, we decompose regional income into the contribution of each final product, using value chain analysis. Second, by regarding each final product as a source of labor income, we further decompose overall regional inequality into the contributions of each final product, using Shorrocks’s (1982) decomposition method.

#### 5.3.1 Tracing value chains

We begin by estimating regional labor income generated in Chinese parts of value chains for final products. For some of these final products, the last stage of production
takes place in China itself, whereas Chinese exports of intermediate products are
directly or indirectly used for the production of final products abroad.

We follow a decomposition technique originally introduced by Leontief (1936)
and popularized in multi-country settings by Johnson and Noguera (2012), Timmer et
al. (2014), and Los et al. (2015a), among others. We start by modeling the Chinese
economy as an input–output structure, according to the idea that the production of final
products requires primary inputs (labor and capital) and intermediate inputs, the
production of which in turn also requires primary and intermediate inputs. By
accounting for all intermediate inputs in each stage of production, Leontief (1936)
provided a mathematical model in which the value of any particular final product can
be decomposed into the values of all labor and capital employed in any stage of
production. Accordingly, the input–output model can be used to measure how each
final product contributes to the factor income of any given region. We apply Timmer
et al.’s (2014) approach to a case in which the input-output table does not contain data
for the global economy split into countries, but for the Chinese economy split into
regions.

5.3.1.1 Illustrative example: Labor income for textiles production in East Coast

To demonstrate our methodology, we start by discussing the value chain activities in
China to produce the ordinary exports of the textiles sector in the East Coast region.
We aim to calculate not only labor income in the final production stage in East Coast,
but also labor income in more upstream activities in other regions. The data used are
those contained in the IRIOP tables, which will be described in the next section,
alongside a formal discussion of the methodology. In 2002, every RMB of ordinary
textiles exports from East Coast generated 0.366 RMB of domestic (i.e., Chinese) labor
income (see Table 5.2). Labor income in East Coast itself accounted for as much as 84%
of this 0.366 RMB. This East Coast labor income included income earned by workers
in the textiles sector, but also in East Coast sectors that indirectly contribute to local
textile production.
Table 5.2 Labor income shares in the domestic stages of the production of ordinary exports of East Coast textiles (% of exports)

<table>
<thead>
<tr>
<th>Year</th>
<th>DLI</th>
<th>NE</th>
<th>NM</th>
<th>NC</th>
<th>EC</th>
<th>SC</th>
<th>CR</th>
<th>NW</th>
<th>SW</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>36.6</td>
<td>0.2</td>
<td>0.3</td>
<td>1.2</td>
<td>30.6</td>
<td>0.9</td>
<td>2.5</td>
<td>0.5</td>
<td>0.4</td>
</tr>
<tr>
<td>2012</td>
<td>42.9</td>
<td>0.7</td>
<td>0.4</td>
<td>1.3</td>
<td>33.2</td>
<td>0.8</td>
<td>4.5</td>
<td>1.4</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Notes: Authors’ calculations with the IRIOP tables for 2002 and 2012 (Duan et al., 2019). DLI = Domestic labor income. The remaining share of value added (e.g. 63.4% in 2002) consists of capital income or taxes in China and the costs of imports. Since the IRIOP tables do not provide information on the global production structure, we have to assume that imports into China do not embody Chinese labor income.

The Chinese labor compensation share in an RMB of ordinary textiles exports grew from 0.366 RMB in 2002 to 0.429 RMB in 2012. The labor income share contributed by inland regions grew faster than the share of East Coast and other coastal regions. For example, the labor income in the Central Region amounted to 2.5% of the value of the exports considered in 2002, increasing to 4.5% in 2012.

However, this specific value chain may be not representative of the income generation due to exports at the macroeconomic level. In the next section, we use our accounting framework to analyze labor income patterns for all product groups from all regions taken together.

5.3.1.2 Analyzing the Chinese part of GVCs

In this sub-section, we will explicitly describe the methodology to quantify the role of exports in the generation of regional income. An IRIOP table is a special interregional input-output table that divides a national economy into several regional sectors and each regional sector into two production types: production of processing exports and other production (including the production of ordinary exports). Appendix 5.1 outlines the schematic framework of the IRIOP table for a two-region case.

In this system, output in each sector in each region is produced using local production factors and intermediate inputs, which can be sourced from local markets, other domestic regions, or foreign countries. Output can satisfy final demands, be used as intermediate inputs in various regions, or be sold to other countries. In an economy
with \( m \) regions and \( n \) sectors, the product market clearing condition can be written as:

\[
x_{(i,r)} = \sum_{s=1}^{m} \sum_{j=1}^{n} z_{(i,r)(j,s)} + \sum_{s=1}^{m} d_{(i,r)(s)} + e_{(i,r)},
\]

(5.3)

where \( x_{(i,r)} \) is the output in sector \( i \) of region \( r \) and \( z_{(i,r)(j,s)} \) is the value of product \( i \) in region \( r \) used as intermediate input by sector \( j \) in region \( s \). Furthermore, \( d_{(i,r)(s)} \) indicates the value of products \( i \) provided by region \( r \) and used for final use of region \( s \), and \( e_{(i,r)} \) is the value of product \( i \) provided by region \( r \) and sold to foreign countries. When we refer to a final product provided by region \( r \), we refer to the product for which the final production stage is located in region \( r \) (the ‘region-of-completion’, in the terminology of Los et al. [2015a]).

This market-clearing condition can also be expressed using matrix algebra. We use a two-region case as an example (i.e., \( m = 2 \)) in which the national economy is divided into region \( r \) and region \( s \). We use superscript \( P \) to denote the processing export variables and the superscript \( O \) to denote ordinary production variables. The \( n \)-dimension vectors \( \mathbf{x}^p_r \) and \( \mathbf{x}^o_r \) indicate the sectoral output levels for production of processing exports subsectors and ordinary production subsectors, respectively, in region \( r \); \( \mathbf{e}^p_r \) and \( \mathbf{e}^o_r \) indicate the sectoral values of processing exports and ordinary exports provided by region \( r \); \( \mathbf{d}^p_r \) and \( \mathbf{d}^o_r \) indicate the amounts of domestically sold final products provided by region \( r \). \( \mathbf{d}^p_r \) is a vector consisting of zeros, because processing exports can by definition not be sold to domestic users. The \( n \times n \) dimension matrix \( \mathbf{Z}^{op}_{rs} \) describes the intermediate deliveries of ordinary production subsectors from region \( r \) used as intermediate input by processing exports subsectors in region \( s \), and \( \mathbf{Z}^{oo}_{rs} \) indicates the intermediate deliveries of ordinary production subsectors from region \( r \) used as intermediate input for ordinary production subsectors in region \( s \). The product market-clearing conditions in Equation 5.3 can then be written as:

\[
x = \mathbf{Z} \mathbf{u} + \mathbf{d} + \mathbf{e}^p + \mathbf{e}^o,
\]

(5.4)
where \( \mathbf{x} = \begin{pmatrix} x_r^p \\ x_r^o \\ x_s^p \\ x_s^o \end{pmatrix} \); \( \mathbf{Z} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \); \( \mathbf{d} = \begin{pmatrix} d_r^0 \\ 0 \\ 0 \\ d_s^0 \end{pmatrix} \); the two types of exports are denoted by \( \mathbf{e}^p = \begin{pmatrix} e_r^p \\ 0 \\ e_s^p \\ 0 \end{pmatrix} \) and \( \mathbf{e}^o = \begin{pmatrix} e_r^o \\ 0 \\ e_s^o \\ 0 \end{pmatrix} \); and \( \mathbf{u} \) is the summation column vector with all elements equal to 1.

We define the matrix with domestic input coefficients with dimensions \((2mn \times 2mn)\) as \( \mathbf{A} = \mathbf{Z}(\hat{\mathbf{x}})^{-1} \), where a hat indicates a diagonal matrix with elements of a vector on the diagonal. \( \mathbf{A} \) describes the direct input requirements of all intermediate goods across sectors and regions per RMB of region-sector-specific output. Equation 5.4 can then be rewritten as:

\[
\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{d} + \mathbf{e}^p + \mathbf{e}^o. \tag{5.5}
\]

Solving this Equation for \( \mathbf{x} \), we arrive at the fundamental input–output identity:

\[
\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}(\mathbf{d} + \mathbf{e}^p + \mathbf{e}^o), \tag{5.6}
\]

where \( \mathbf{I} \) is an \((2mn \times 2mn)\) identity matrix with ones on the diagonal and zeros elsewhere. \((\mathbf{I} - \mathbf{A})^{-1} \) is the well-known Leontief inverse, which represents the region-subsector–specific output levels required per RMB of region-subsector–specific final demand.

To link final products to labor income, we define \( l_{(i,r)} \) as the labor income earned in sector \( i \) in region \( r \). We define \( w_{(i,r)} = l_{(i,r)}/x_{(i,r)} \) as the labor income directly required to produce an RMB of output in this particular sector and region. We create two column vectors, \( \mathbf{w}_r^p \) and \( \mathbf{w}_r^o \), given that the IRIOP table distinguishes two types of production. We derive the labor incomes generated in region \( r \) and region \( s \) directly and indirectly required for a final product vector \( \mathbf{f} \) by post-multiplying the matrix \( \mathbf{W} \) with the gross outputs needed for the production of this final demand:
\[ l = W(I - A)^{-1}f, \quad (5.7) \]

where \( W = \begin{pmatrix} w_r^p & w_r^o \\ 0 & w_s^p & w_s^o \end{pmatrix} \). Primes indicate transpositions of a vector or matrix. When \( f \) represents all final products in the system, that is, \( f = d + e^p + e^o \), the \( m \) elements in \( l \) indicate the total labor incomes in each region.

We obtain regional labor income generated in activities in value chains for each region-subsector–specific final product by diagonalizing the final demand vector in Equation 5.7. That is:

\[ L = W(I - A)^{-1} \hat{f} = W(I - A)^{-1}(\hat{e}^p + \hat{e}^o + \hat{d}) = W(I - A)^{-1} \hat{e}^p + W(I - A)^{-1} \hat{e}^o + W(I - A)^{-1} \hat{d} = L^p + L^o + L^D. \quad (5.8) \]

The element \( l_{r(1,s)} \) in the \( m \times 2mn \) dimension matrix \( L \) indicates the labor income in region \( r \) generated by final demand for the product of the first subsector \( 1 \) in region \( s \). Similarly, \( L^o \), \( L^p \), and \( L^D \), indicate the regional labor incomes implied processing exports demand, ordinary exports demand, and domestic final demand for the outputs of every region-sector, respectively. Equation 5.8 thus allows us to decompose the total labor income of each region into the amount induced by processing exports, ordinary exports, and domestic final demand. In what follows, we refer to the sum of \( L^p \) and \( L^o \) as “labor income from exports”.

### 5.3.2 Decomposing regional inequality by source

In this subsection, we aim to decompose overall regional inequality into the contributions of each type of final product, using Shorrocks’s (1982) decomposition.

One of the well-known methods of decomposing inequality by income source is the Shapley decomposition, which evaluates how overall inequality would change if income from one source were eliminated (or replaced by its mean, to evaluate the marginal effect of this source) (Shapley, 1953; Shorrocks, 1999). However, as Sastre and Trannoy (2002) indicate, the Shapley decomposition has an important problematic
Chapter 5

feature: The contribution it assigns to any income source depends on the level of disaggregation, such that it is sensitive to the ways in which other sources are clustered. Shorrocks (1982) offers a unified approach to quantify the proportional contribution of income sources to overall inequality, which has been widely used (see, e.g., Chi, 2012; Tsui, 1998). Shorrocks proves that this decomposition solution is unique in meeting a number of desirable decomposition principles, including symmetry, independence, and consistency.\(^{11}\) According to Shorrocks (1982), the Theil index (Equation 5.1) can be modified to calculate the absolute contribution of income source \(k\) to the overall inequality as:

\[
con^k = \sum_r p_r \frac{y_r^k}{\bar{y}} \ln \left( \frac{y_r}{\bar{y}} \right) = \left( \frac{\bar{y}_r^k}{\bar{y}} \right) \left[ \sum_r p_r \frac{y_r^k}{\bar{y}_r^k} \ln \left( \frac{y_r}{\bar{y}} \right) \right] = \phi^k I(y^k, y),
\]

where \(y_r^k\) is the amount of the income per capita in region \(r\) received from income source \(k\), \(p_r\) stands for the share of \(r\) in the national population, and \(\bar{y}_r^k\) indicates the mean of the \(k\)th type of income per capita. Equation 5.9 indicates that two elements determine the absolute contribution of income source \(k\) to overall inequality: the share of labor income from source \(k\) in total labor income (\(\phi^k = \bar{y}_r^k / \bar{y}\)) and the inequality implied by the distribution of labor income from source \(k\) itself (\(I[y^k, y]\)). \(I(y^k, y) = \sum_r p_r (y_r^k / \bar{y}_r^k) \ln(y_r / \bar{y})\) represents a “pseudo-Theil” index that captures the inequality regarding the \(k\)th income source. The difference between \(I(y^k, y)\) and the regular Theil index for the \(k\)th income source is in the second factor between parentheses \((y_r / \bar{y})\). It represents the ratio of income per capita in region \(r\) to the national average in the pseudo-Theil index, but the ratio of the \(k\)th type of income per capita in region \(r\) to its national average \((y_r^k / \bar{y}_r^k)\) in the Theil index.

We derive the contribution share of \(k\)th income source to overall inequality by dividing its absolute contribution by the overall inequality:

\(^{11}\) Symmetry and independence properties ensure that the contribution of any income component to overall inequality is not affected by the way the components are numbered or named, or how many types of components are distinguished. The consistency property ensures that the sum of effects of all income sources yields the overall inequality (Paul, 2004). Shorrocks’s decomposition also meets two other conditions: (1) the contribution of an income source to aggregate inequality is 0 if every household receives the same income from that source and (2) if overall inequality is divided into two income sources for which the distribution of one source is a permutation of the distribution of the other, they contribute equally to total inequality.
\[ cons^k = con^k / I, \]  

(5.10)

where \( I \) is the overall inequality, as shown in Equation 5.1. Observe that the shares add up to one (i.e. \( \sum_k con^k = I \)), because \( \sum_k y_r^k = y_r \).

We split labor income into three income sources: labor income from processing exports (indicated by superscript \( P \)), labor income from ordinary exports (\( O \)), and labor income from domestic final demands (\( D \)) as given by Equation 5.8.

By using the decomposition method illustrated above, we calculate the contribution of each final product to overall inequality adopting an accounting perspective. If we compute the inequality attributed to exports, we implicitly assume that the workers involved in the associated activities would in the absence of these exports not be employed in other activities. We believe this assumption is reasonable for China, given its initially massive rural surplus labor force (Carter et al., 1996; Chu et al., 2000), which was at least partly absorbed when it became a massive exporter of manufactured products (Los et al., 2015b). Another assumption is that wage rates paid to workers producing for domestic final demand have responded uniformly across regions to the increasing export-driven labor demand. Such general equilibrium effects might well have been different across regions, but are not considered in our analysis. We think that the export boom has actually had stronger positive effects on wage growth in the coastal regions than elsewhere in China (Han et al., 2012; Fan, 2019). If so, our results would provide a lower bound on the regional inequality effects of China’s growing exports.

5.4 Data

To calculate regional income inequality, data on regional labor income and regional population are needed. We draw measures of regional labor income from Chinese interregional input-output tables that distinguish processing trade (IRIOP tables) as constructed by Duan et al. (2019) (see the previous Chapter). Appendix 5.1 presents the outline of IRIOP tables. These tables include value added (which is split into labor and capital income), exports, and interregional and intraregional production linkages.
between sectors. To date, we have constructed IRIOP tables for 2002, 2007, and 2012. The tables contain data for 17 sectors and cover eight regions (North East, North Municipality, North Coast, East Coast, South Coast, Central Region, North West, and South West; see Appendix 4.2 for the region classification and Appendix 4.3 for the sector classification).

The variables in the IRIOP tables are expressed in current local prices. Product prices may differ significantly across time and space, which implies spatial and temporal differences in costs of living. This affects economic outcomes in general and inequality in particular. For this reason, after computing the related region labor income levels based on the IRIOP tables, we convert these into levels expressed in Beijing 2002 prices by using spatial price deflators from Brandt and Holz (2006). These authors combine a meticulous analysis of household expenditures and prices at the province level for the year 1990 with annual provincial consumer price indices (CPIs) to provide a reliable estimation of spatial price deflators at the provincial level for 1984 to 2004. We extend their 2004 price deflator to 2012 by chaining the annual provincial CPIs. We then deflate all provincial price levels in 2002, 2007, and 2012 by taking the 2002 Beijing price as the benchmark, such that the 2002 Beijing price equals 1. Finally, we aggregate the provincial deflators to the regional level by using provincial consumption as weights and obtain the price deflators for the eight regions.\footnote{Both provincial CPI and consumption data have been taken from the NBS official website (http://www.stats.gov.cn/english/Statisticaldata/AnnualData/).}

5.5 Empirical results

In this section, we apply our framework to China to determine how each type of final product, and exports in particular, contributed to regional inequality. To provide a comprehensive picture, we begin quantifying labor income earned in the Chinese parts of value chains. Next, we analyze the effect of exports on regional income. Finally, we address in detail the contributions of exports to regional inequality.
5.5.1 Labor income earned in value chains

Equation 5.8 allows us to investigate the distribution of labor income along value chains over regions and examine their dynamics from 2002 to 2012. We distinguish 408 final products (17 products × 8 regions of completion × 3 final product categories).\(^\text{13}\) We follow Los et al. (2015a) by aggregating the elements of each column of \(L\) into three parts, local labor income (LLI), inland labor income (ILI) and coastal labor income (CLI).\(^\text{14}\) For the processing exports by sector \(j\) in region \(r\), for example, we define (i) LLI as \(l_{(r)(j,r)}^p\), indicating the labor income earned in the region of completion; Here, \(l_{(t)(j,r)}^p\) is the element of \(L^p\) in Equation 5.8 that indicates the labor income in region \(t\) generated by processing exports of sector \(j\) in region \(r\). (ii) ILI as \(\sum_{t\in \text{inland}; t\neq r} l_{(t)(j,r)}^p\), showing the labor income earned in inland regions other than the region of completion; and (iii) CLI as \(\sum_{t\in \text{coast}; t\neq r} l_{(t)(j,r)}^p\), i.e. labor income earned in coastal regions, but excluding the region of completion. The sum of LLI, ILI, and CLI yields the total domestic labor income (DLI) in each value chain. For each value chain, we divide the four labor income measures by the value of the product sold to Chinese final users and foreign users, which yields three shares: the local labor income share (LLS), the inland labor income share (ILS) and the coastal labor income share (CLS). Furthermore, we define the domestic labor income share (DLS) as the sum of LLS, ILS and CLS.

Table 5.3 presents the average results for the three final product categories. For each category, the results are the final demand-weighted averages of the shares of each value chain in this group (17×8 = 136 value chains for each group). The bottom row for each year shows the weighted averages of shares in all 408 value chains.

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\(^{13}\) The three final product categories are processing exports, ordinary exports, and domestic final demands. For some value chains, the values are all 0, because there is no final output for some sectors, such as processing exports of agriculture.

\(^{14}\) The results in this subsection are based on labor income shares obtained from Equation 5.8 and have not been corrected for differences in price levels across regions and over time (see Section 5.4), since this subsection does not deal with income inequality.
Table 5.3 Labor income shares of final products, by type (in %)

<table>
<thead>
<tr>
<th></th>
<th>LLS</th>
<th>ILS</th>
<th>CLS</th>
<th>DLS</th>
<th>Local Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing exports</td>
<td>11.7</td>
<td>1.0</td>
<td>0.9</td>
<td>13.6</td>
<td>86.0</td>
</tr>
<tr>
<td>Ordinary exports</td>
<td>31.6</td>
<td>3.3</td>
<td>3.2</td>
<td>38.1</td>
<td>82.9</td>
</tr>
<tr>
<td>Domestic demand</td>
<td>35.9</td>
<td>4.2</td>
<td>5.1</td>
<td>45.2</td>
<td>79.4</td>
</tr>
<tr>
<td>Average</td>
<td>32.9</td>
<td>3.8</td>
<td>4.4</td>
<td>41.1</td>
<td>80.0</td>
</tr>
<tr>
<td>Processing exports</td>
<td>10.2</td>
<td>1.5</td>
<td>1.0</td>
<td>12.6</td>
<td>81.0</td>
</tr>
<tr>
<td>Ordinary exports</td>
<td>23.0</td>
<td>4.6</td>
<td>3.2</td>
<td>30.8</td>
<td>74.7</td>
</tr>
<tr>
<td>Domestic demand</td>
<td>25.2</td>
<td>5.9</td>
<td>5.7</td>
<td>36.8</td>
<td>68.5</td>
</tr>
<tr>
<td>Average</td>
<td>22.7</td>
<td>5.1</td>
<td>4.6</td>
<td>32.4</td>
<td>70.1</td>
</tr>
<tr>
<td>Processing exports</td>
<td>15.1</td>
<td>2.2</td>
<td>1.2</td>
<td>18.5</td>
<td>81.6</td>
</tr>
<tr>
<td>Ordinary exports</td>
<td>29.9</td>
<td>5.1</td>
<td>2.9</td>
<td>37.9</td>
<td>78.9</td>
</tr>
<tr>
<td>Domestic demand</td>
<td>31.7</td>
<td>6.6</td>
<td>6.0</td>
<td>44.3</td>
<td>71.6</td>
</tr>
<tr>
<td>Average</td>
<td>30.0</td>
<td>6.0</td>
<td>5.1</td>
<td>41.1</td>
<td>73.0</td>
</tr>
</tbody>
</table>

Notes: Authors’ calculations based on the IRIOP tables (Duan et al., 2019). Local Share = (LLS/DLS)*100, DLS = LLS + ILS + CLS.

We report three important findings. First, while China is characterized by increasing geographical fragmentation, the largest part of domestic labor income embodied in final products is still earned in the region of completion. To see this, we define the local share as (LLS)/(DLS). A high local share indicates that a large share of domestic labor income in value chains was earned in the region of completion. Table 5.3 presents the local shares of the three final product categories. In 2012, the average local share for all value chains was 73%. This suggests that the final production stage tends to require lots of labor input from the local market, and that firms often prefer to purchase materials from the local market, for example to minimize transport costs.

Second, income distributions along the value chains of the three types of final products appear to be considerably different, as expected: An RMB of processing exports generates far lower domestic labor income than the same amount of ordinary exports or domestic demand. Most materials for processing export production are imported from foreign countries, so processing exports tend to show high international
China’s rise as an export giant and regional inequality: a value chain analysis

fragmentation (Yang et al., 2015). We also find lower degrees of domestic fragmentation for processing exports than for ordinary exports. In 2012, the local shares for processing exports and ordinary exports were 81.6% and 78.9%, respectively. In other words, one RMB of extra domestic labor income due to processing exports would have implied 0.184 RMB of labor income to other regions. For ordinary exports, the corresponding figure is 0.211 RMB. This finding indicates less domestic fragmentation in processing export production.

Third, the decreasing local shares (over 2002-2012) indicate increasing domestic fragmentation of production processes, for all three final product types. This has not been a steady process, however: after 2007, substantial parts of the decrease in local shares before 2007 were undone, again for all three types of final products. This is most probably because of China’s increased capabilities to produce high-quality intermediate inputs domestically, which improved the LLS and also the local share from 2007 to 2012. ILS and CLS, however increased in both periods. ILS grew more rapidly than CLS, indicating that increased regional fragmentation of Chinese parts of GVCs benefited inland regions more than coastal regions, which might be relevant for the dynamics of regional inequality.

5.5.2 Importance of exports to labor income

Improving household income is one of the most important objectives of the Chinese government. Therefore, an interesting question is how the contributions of exports to regional income compare to the contributions of final demands by domestic users. In this section, we address this issue from a value chain perspective and decompose regional labor income into three sources: labor income earned in value chains for processing exports (LPE), labor income earned in activities required for the production of ordinary exports (LOE), and labor income earned in the production of output sold to domestic final users (LFD). We use Equation 5.8 for this. Our calculations are based on the IRIOP tables, and the results are further deflated into the

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15 China’s policy of granting firms duty exemptions on imported materials for processing exports also induces that firms prefer to purchase imported inputs for producing processing exports.
2002 Beijing price using the regional price deflators constructed in Section 2.2.

Columns 1–9 in Table 5.4 present the share of each income source in regional labor income. The first figure in Column 1, for example, indicates that in 2002, 1.9% of the North East’s labor income was generated by its direct or indirect participation in the production of China’s processing exports. The bottom row gives the results for the national economy, using regional labor income levels as weights. As shown in Equation 5.9, these shares ($\phi^k$) are important to the absolute contribution of each income source to the overall regional inequality.

A first, not very surprising, observation from Table 5.4 is that exports contribute much more to the labor incomes of coastal regions than of inland regions. In 2002, the share of labor income due to exports ranged from a high of 27.2% (11.1% + 16.1%) in South Coast to a low of 5.6% (1.0% + 4.6%) in South West. Within the coastal regions and the inland regions, the contribution of exports to labor income also varies greatly. It was 27.2% for South Coast but only 11.3% for North Coast in 2002. In particular, the contribution of processing exports to labor income was up to 11.1% for South Coast, but less than 4% for other coastal regions.

### Table 5.4 Shares of regional labor income induced by three types of final demand (%)

<table>
<thead>
<tr>
<th></th>
<th>2002</th>
<th></th>
<th></th>
<th>2007</th>
<th></th>
<th></th>
<th>2012</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>LPE</td>
<td>LOE</td>
<td>LFD</td>
<td>LPE</td>
<td>LOE</td>
<td>LFD</td>
<td>LPE</td>
<td>LOE</td>
</tr>
<tr>
<td>NE</td>
<td>1.9</td>
<td>8.0</td>
<td>90.1</td>
<td></td>
<td>2.8</td>
<td>12.8</td>
<td>84.4</td>
<td></td>
<td>2.4</td>
</tr>
<tr>
<td>NM</td>
<td>3.7</td>
<td>17.2</td>
<td>79.1</td>
<td></td>
<td>5.4</td>
<td>25.7</td>
<td>69.0</td>
<td></td>
<td>3.0</td>
</tr>
<tr>
<td>NC</td>
<td>2.1</td>
<td>9.2</td>
<td>88.7</td>
<td></td>
<td>2.9</td>
<td>14.8</td>
<td>82.3</td>
<td></td>
<td>2.7</td>
</tr>
<tr>
<td>EC</td>
<td>3.9</td>
<td>17.9</td>
<td>78.2</td>
<td></td>
<td>10.3</td>
<td>24.7</td>
<td>65.0</td>
<td></td>
<td>6.9</td>
</tr>
<tr>
<td>SC</td>
<td>11.1</td>
<td>16.1</td>
<td>72.8</td>
<td></td>
<td>13.6</td>
<td>20.6</td>
<td>65.8</td>
<td></td>
<td>9.5</td>
</tr>
<tr>
<td>CR</td>
<td>0.8</td>
<td>5.2</td>
<td>94.0</td>
<td></td>
<td>2.0</td>
<td>10.2</td>
<td>87.7</td>
<td></td>
<td>1.7</td>
</tr>
<tr>
<td>NW</td>
<td>0.8</td>
<td>6.0</td>
<td>93.2</td>
<td></td>
<td>1.7</td>
<td>14.4</td>
<td>83.9</td>
<td></td>
<td>1.3</td>
</tr>
<tr>
<td>SW</td>
<td>1.0</td>
<td>4.6</td>
<td>94.4</td>
<td></td>
<td>1.4</td>
<td>8.4</td>
<td>90.2</td>
<td></td>
<td>0.8</td>
</tr>
<tr>
<td>Average</td>
<td>3.5</td>
<td>10.5</td>
<td>86.0</td>
<td></td>
<td>5.6</td>
<td>16.2</td>
<td>78.3</td>
<td></td>
<td>3.9</td>
</tr>
</tbody>
</table>

Notes: Authors’ calculations based on the IRIOP tables (Duan et al., 2019). LPE = labor income from processing exports, LOE = labor income from ordinary exports, LFD = labor income from domestic final demand.

A second observation is that labor income was mainly generated by domestic
demand rather than exports. This might be less in line with the idea that China became the "Factory of the World", but is less unexpected if the size of the domestic economy is considered. Even in 2007, when they were most important, exports generated less than 22% of national labor income. Although the scale of processing exports was almost equal to that of ordinary exports (see Table 5.1), its contribution to income was only one-third the contribution of ordinary exports. This reflects the fact that processing exports are much more based on foreign than on domestic intermediate inputs, which implies that indirect effects in upstream sectors are relatively modest.

Although the contribution of exports to labor income varies strongly across regions, our third observation from Table 5.4 is that all regions experienced a similar pattern over time. That is, exports made increasing contributions to regional labor income from 2002 to 2007, but their share decreased after the global financial crisis. Before the financial crisis, both processing exports and ordinary exports played increasing roles in generating regional labor income, with sharply rising shares of LPE and LOE. In this regard, the East Coast region stood out, with its share of labor income due to exports dramatically increasing by 13.2 percentage points from 2002 to 2007 and then remarkably declining by 10.9 percentage points from 2007 to 2012.

Figure 5.2 displays the sectoral exports that contributed most to regional labor income in each of the regions considered. Together, they explained 62.4% of national labor income exports in 2012. Two groups of products—Textile (sector 4) and Mechanical and electrical products (sectors 10, 11, and 12)—accounted for 53.6% of total Chinese exports and 48.4% of the national labor income involved. These national shares hide some regional variation. The exports of the two sectors mentioned accounted for as much as 61.4% of labor income due to exports from the East Coast region and for 50.9% from the Central Region. A notable exception is North Municipality, where about half of labor income due to exports was generated by service exports. This is mainly due to the higher service export share in North Municipality’s total exports, which was 13.7% for Trade and Transport (sector 16) and 24.8% for Other Services (sector 17). For a comparison, their export shares were only 9.6% and 3.4% in East Coast’s total exports.
Figure 5.2 Regional labor income due to exports in 2012, by most important sectors (% total regional labor income due to exports = 100)

Notes: Authors' calculations based on the IRIOPT tables (Duan et al., 2019). Mechanical and electrical products is the aggregate of sectors 10, 11, and 12.

5.5.3 Contribution of exports to regional inequality

5.5.3.1 Decomposition of inequality by income source

In this section, we apply Equations 5.9 and 5.10 to decompose overall regional inequality into the contributions of each type of final product. Table 5.5 presents the results. Included are the Theil indexes (which indicate regional income inequality per type of final product and for all three types together), the contributions of the three types of final product to total inequality, expressed in levels and in shares in 2002, 2007, and 2012.

Of the three income sources, the Theil index of LPE is astonishingly high: 0.694 in 2002, more than twice that of LOE and 26 times higher than that of LFD. Put differently, across regions, labor income along the value chains for processing exports was more unequally distributed than along the value chains of ordinary exports and domestic final demand. This is largely a result of the features of exports and processing exports in particular. Processing exports tend to generate labor income in the region in which the processing sector is located (and hardly anywhere else in China), since most inputs are imported. The Theil index for processing exports decreased over time, which
indicates a convergence of labor income across regions, probably as a consequence of the government's policy to increasingly locate processing exports activities in the Central Region. Increasing domestic fragmentation (sourcing inputs from other regions rather than from abroad) may also have been an important contributor, enabling regions beyond the region of completion to benefit more from final product production.

**Table 5.5 Contribution of types of final products to regional income inequality**

<table>
<thead>
<tr>
<th></th>
<th>LPE</th>
<th>LOE</th>
<th>LFD</th>
<th>TOT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theil index</td>
<td>0.694</td>
<td>0.327</td>
<td>0.026</td>
<td>0.046</td>
</tr>
<tr>
<td>2002</td>
<td>0.008</td>
<td>0.019</td>
<td>0.020</td>
<td></td>
</tr>
<tr>
<td>Contribution to total</td>
<td>16.9%</td>
<td>41.0%</td>
<td>42.1%</td>
<td></td>
</tr>
<tr>
<td>Share in total</td>
<td>0.555</td>
<td>0.220</td>
<td>0.025</td>
<td>0.048</td>
</tr>
<tr>
<td>Theil index</td>
<td>0.011</td>
<td>0.023</td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>2007</td>
<td>0.011</td>
<td>0.023</td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>Contribution to total</td>
<td>23.1%</td>
<td>47.3%</td>
<td>29.6%</td>
<td></td>
</tr>
<tr>
<td>Share in total</td>
<td>0.456</td>
<td>0.214</td>
<td>0.016</td>
<td>0.029</td>
</tr>
<tr>
<td>Theil index</td>
<td>0.006</td>
<td>0.014</td>
<td>0.009</td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td>0.006</td>
<td>0.014</td>
<td>0.009</td>
<td></td>
</tr>
<tr>
<td>Contribution to total</td>
<td>19.9 %</td>
<td>46.7%</td>
<td>33.4%</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Authors’ calculations based on the IRIOP tables (Duan et al., 2019). LPE = labor income from processing exports, LOE = labor income from ordinary exports, LFD = labor income from domestic final demand, and TOT= total regional labor income.

Foreign demand proves to be the dominant contributor to China’s regional inequality. In 2012, processing exports together with ordinary exports explained 66.6% of overall regional inequality; ordinary exports alone explained 46.7%. The contribution of processing exports is relatively small, though LPE shows much larger inequality than other income sources. Table 5.4 shows that processing exports generated only a small share of total labor income, resulting in a limited contribution to regional inequality. These results resonate with early studies that identify globalization as the main contributor to Chinese regional inequality (Kanbur and Zhang, 2005; Zhang and Zhang, 2003). We will provide a deeper analysis of the drivers of change in inequality in the next subsection, but first pay some attention to the role of value chains for exports by specific sectors.

Table 5.6 lists the regional labor income inequality generated by exports by sectors and their contributions to overall inequality. The sum of their contribution
shares equal the total contribution shares of processing exports and ordinary exports in 2012 listed in Table 5.5 (i.e. 66.6%). Labor incomes generated by exports of Other services, Construction, Other manufacturing, and Paper & printing were the most unequally distributed among regions, with Theil indexes greater than 0.4. However, as the second column reveals, the sectors that contributed most to China’s overall inequality, are the five sector groups included in Figure 5.2, which generated the largest part of regional labor income induced by exports. Hence, these sectoral exports have large weights in the determination of total inequality: in 2012, their exports caused 60.2% of China’s regional income inequality.16

| Table 5.6 Contribution of sectoral exports to regional income inequality caused by all exports, 2012 |
|-------------------------------------------------|---------------------------------|---------------------------------|
| Sectors                                        | Theil index | Contribution share (%) | Sectors                        | Theil index | Contribution share (%) |
| Agriculture                                    | 0.233       | 0.2                  | Machinery                      | 0.305       | 5.5                  |
| Mining                                         | 0.285       | 0.5                  | Transport equipment            | 0.290       | 3.1                  |
| Food                                           | 0.203       | 1.0                  | Electronic products            | 0.380       | 15.5                 |
| Textile                                        | 0.273       | 10.1                 | Other manufacturing            | 0.492       | 0.9                  |
| Wood                                           | 0.205       | 1.4                  | Electricity, gas and water     | 0.243       | 0.0                  |
| Paper & printing                               | 0.477       | 1.8                  | Construction                   | 0.506       | 0.3                  |
| Chemistry                                      | 0.143       | 2.9                  | Trade and transport            | 0.380       | 11.3                 |
| Nonmetallic minerals                           | 0.092       | 0.4                  | Other services                 | 0.888       | 9.4                  |
| Metal products                                 | 0.108       | 2.4                  | Sum                            | 0.029       | 66.6                 |

Notes: Authors’ calculations based on the IRIOP tables (Duan et al., 2019).

5.5.3.2 Counterfactual analysis

Over time, China’s regional inequality increased slightly from 2002 to 2007 and then sharply declined from 2007 to 2012. During this period, the contribution of exports to
total inequality increased from 57.9% to 70.4%, and then decreased to 66.6% in 2012 (see the sums of LPE and LOE in Table 5.5). To determine how exports affected the changes in regional inequality over time, we conducted several counterfactual analyses. We sought to identify the effect of change in one particular factor, by comparing real inequality with inequality in the counterfactual situation of no change in this factor at all. If the counterfactual inequality was lower than the actual level, actual change in this factor accelerated the inequality, and vice versa.

To show the determinants of regional labor income clearly, we rewrite Equation 5.8 in more detailed terms. We denote \( t^p = u'e^p \) as the scale of processing exports and \( e^p = e^p / t^p \) as the region-sector composition of processing exports, that is, the shares of region–sector–specific processing exports in the national total for processing exports. Similarly, we denote \( t^o = u'e^o \) and \( e^o = e^o / t^o \), indicating the scale and composition of ordinary exports, respectively:

\[
I = W(I - A)^{-1} t^p e^p + W(I - A)^{-1} t^o e^o + W(I - A)^{-1} d. \tag{5.11}
\]

The right hand side of Equation 5.11 provides the potential determinants of the regional income and shows how final products affect regional inequality through the value chains.

The determinants include the scale and composition of processing exports \((t^p, e^p)\), the configuration of the value chains for processing exports \((A_{ik}^{op}\) and \(w_k^p)\), the scale and composition of ordinary exports \((t^o, e^o)\), the value chain configurations for ordinary production \((A_{ik}^{oo}\) and \(w_k^o)\), and domestic final demand \((t^d\) and \(e^d\) combined).\(^{17}\) We analyzed seven counterfactual situations, for both 2007 and 2012. We recalculated Equation 5.11 by assuming that only one of the seven factors did not change (we assume that the values for 2002 still applied in 2007, and those for 2007 in 2012), while allowing the other six factors to change to their 2007 and 2012 values, respectively.\(^{18}\) Table 5.7 presents the counterfactual results for regional income

\(^{17}\) Note that changes in the value chain configuration can relate to (1) the substitution of production in the sector itself by purchased inputs (or the reverse), (2) substitution of inputs from a region (or foreign countries) by inputs from a different region, and (3) substitution of inputs from one industry by inputs from a different industry.

\(^{18}\) It is worth noting that this is not a full structural decomposition analysis. As a mirror case, we might look at regional inequality in a situation in which only one factor takes its value in 2007 while all other factors take their values in 2002, then compare this measure of inequality with actual inequality in 2002.
inequality between the eight regions. Taking the effect of processing export scale as an example, Table 5.7 shows that if the scale of processing exports had maintained its 2002 level while everything else had taken the 2007 values, regional inequality in 2007 would have markedly decreased to 0.042, compared with the actual level of 0.048. This implies that the change in scale of processing exports increased the regional inequality from 2002 to 2007.

Table 5.7 Counterfactual levels of regional inequality in 2007 and 2012

<table>
<thead>
<tr>
<th></th>
<th>Processing exports</th>
<th>Ordinary exports</th>
<th>Domestic demand</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Scale (1)</td>
<td>Compositional (2)</td>
<td>Chain configuration (3)</td>
</tr>
<tr>
<td>2007</td>
<td>0.048</td>
<td>0.042</td>
<td>0.048</td>
</tr>
<tr>
<td>2012</td>
<td>0.029</td>
<td>0.028</td>
<td>0.029</td>
</tr>
</tbody>
</table>

Notes: Authors’ calculation based on IRIOP tables (Duan et al., 2019). The row “2007” presents the counterfactual results for 2007, while the row “2012” lists the counterfactual results for 2012, assuming that only the actual changes indicated by the column headings would not have taken place.

From 2002 to 2007, China’s regional inequality slightly increased from 0.046 to 0.048 but then sharply decreased to 0.029 in 2012 (see also the last column in Table 5.5). From 2002 to 2007, changes in scales of processing exports and ordinary exports and the value chain configuration of processing exports increased inequality, whereas domestic final demands, the value chain configuration of ordinary production, and the composition of ordinary exports reduced inequality. However, from 2007 to 2012, processing exports had a negligible effect; the change in domestic final demands mainly drove the decrease. This result was already apparent in Table 5.5. At the same time, the change in scales and value chain configurations of ordinary exports caused more inequality.

This analysis reveals three additional findings. Table 5.7 shows that the actual changes of processing and ordinary export volumes were the main culprits of increasing inequality from 2002 to 2007. The IRIOP tables show that both processing and ordinary exports tripled, whereas domestic final demand merely doubled. Since the labor incomes earned in the value chains of exports were extremely unequally distributed over regions, the export growth significantly increased regional inequality.
from 2002 to 2007. In contrast, export growth led to only slightly more inequality from 2007 to 2012 since it grew by only 35.0% while domestic final demand increased by against 112%.\textsuperscript{19} This finding shows that China’s recent policy of stimulating domestic demand and dampening foreign demand has been helpful in decreasing regional inequality.

Second, changes in the value chains for ordinary exports from 2002 to 2007 significantly reduced regional inequality. If these would have remained as in 2002, regional inequality in 2007 would have sharply increased to 0.065, instead of attaining its actual value of 0.048. This is mainly the result of inland regions getting more involved in value chains for ordinary exports by coastal regions. In 2002, for ordinary export production on the coasts, about 7.6% of intermediate inputs were provided by the inland regions; this share rapidly increased to 11.1% in 2007.\textsuperscript{20} This progress reduced the income gap between the coastal and inland regions, narrowing overall regional inequality. This suggests that China’s regional policy of promoting the inland regions to more actively participate in GVCs has effectively decreased China’s regional inequality.\textsuperscript{21}

The third interesting finding is that the change in export compositions exerted a minor effect on regional inequality, even though export compositions underwent obvious changes in both commodity structure and geographic distribution. For example, Chinese exports shifted from labor-intensive products to the output of high-tech sectors. According to the IRIOP tables, in 2002, about 17.8% of the exports were Textile (sector 4) and 29.0% were Mechanical and electrical products (sectors 10, 11, 12); in 2012, these shares were 11.8% and 41.8%, respectively. With regard to geographic distribution of exports (see Table 5.1), a considerable share of exports had shifted from South Coast to East Coast and North Coast. However, most of these shifts happened between coastal regions and made little difference to the overall income gaps between the coastal and inland regions, which account for most of the overall inequality.

It is worth noting that we investigated the effect of globalization on regional

\textsuperscript{19} The growth rates are in nominal terms, and are calculated based on the IRIOP tables.
\textsuperscript{20} This calculation is based on the IRIOP tables.
\textsuperscript{21} The Chinese government launched different policies to encourage the processing sectors to move from advanced coastal regions to inland regions. For example, by extending the Economic and Technological Development Zones from the coastline to inland regions. It is important to note explicitly that our analysis cannot say anything about the role these policies have played, but the outcomes are in line with the objectives of these.
income inequality from a value chain perspective, according to the assumption of Leontief production technologies. In other words, we attributed the effects of changing exports bundles on the labor income distribution over regions, assuming that relative prices (including wage rates) would have remained unchanged and would therefore not cause further substitution effects. We believe that considering the effects of globalization on inequality from the perspective of production networks is a useful exploration. We leave a full, comprehensive analysis of globalization and inequality, by nesting the production network into a general equilibrium framework to further research.

5.6 Conclusions

Using newly developed IRIO tables for China, we explored the contributions of both processing exports and ordinary exports to regional inequality. This novel data set, which separates the production of processing exports from other production (which includes production of ordinary exports), allowed us to distinguish the Chinese part of value chains of these two types of exports and identify their different effects on regional inequality.

This research contributes both methodologically and empirically. With regard to methodology, we proposed a new accounting framework to explore the contribution of exports to regional inequality from a value chain perspective. This framework fully accounts for a region’s indirect exports, which arise through the provision of materials, components and services to export production activities in other regions. This allows for a more comprehensive analysis of the contribution of exports to regional inequality. Empirically, we find that exports explained about 70% of China’s regional income inequality in the period 2002-2012. Processing exports contributed little, although the value chain activities were very unequally distributed over regions. They generated only little labor income in China itself (3-6% of the total, due to its reliance on imported inputs), however, which implies that its consequences for income inequality remained limited. Rather, it is ordinary exports that predominantly contributed to China’s regional inequality. These accounted for 10-16% of Chinese labor income and the
regional labor income distribution within their value chains is much more regionally clustered than in value chains for domestically sold consumption and investment products.

The substantial decline of regional inequality in the period 2002-2012 has not been due to changes in exporting activity. Even though value chains for processing exports and for ordinary exports have become distributed more equitably among regions, but in particular the growth in ordinary exports still had inequality-increasing effects. The increasing levels of domestic final demand and the changing value chain configurations of ordinary production—which have become more domestically fragmented, with inland regions increasingly involved—have been the main reasons for declining regional inequality. In this regard, the outcomes are in line with China’s recent policy of stimulating domestic demand to decrease regional inequality.
CHAPTER 6
Summary and Conclusions

6.1 Introduction

The research in this thesis focused on the role of exports in the Chinese economy. Three of the most typical characteristics of China’s exports were: the large scale of processing exports; the important role of Foreign Invested Enterprises (FIEs) in exports; and the seriously unbalanced distribution of export activities across different domestic regions. Each of these characteristics was expected to generate a substantial income effect. First, because the production of processing exports depended largely on imported materials, China’s exports were expected to induce relatively little domestic value added (DVA). Second, because a large part of the DVA earned by FIEs was foreign-owned, China’s exports were expected to contribute even less to national income (NI) than to GDP. Third, exports are generally beneficial for a region’s development. However, because China’s exports were unevenly distributed, they were expected to increase regional income inequality. Taking these three typical characteristics of China’s exports into account, this thesis thoroughly investigated the income effects of exports in China from a value chain perspective.

In doing so, the thesis attempted to contribute both methodologically and empirically. In particular, it offered new insights into several empirical questions about the income effects of China’s exports. It investigated the role of exports on national income growth (Chapter 3) and regional income inequality (Chapter 5), and the role of structural changes on income effect of exports (Chapter 2). Chapter 4 developed and constructed new interregional input-output (IO) tables for China. At the regional level, they explicitly distinguish the production of processing exports from ordinary production. The new IO tables were used to address the roles of processing exports and ordinary exports to regional economic growth. Not taking processing trade into full account at the regional level seriously biased the results.

Section 6.2 summarizes the main findings. Section 6.3 clarifies the limitations of
this thesis and provides some ideas for future research.

6.2 Summary of the main findings

An important characteristic of China’s exports was its strong dependence on assembly and processing activities. By fully taking this feature into account, Chapter 2 estimated China’s annual Vertical Specialization (VS) shares from 2000 to 2012 based on special IO tables that explicitly distinguish processing export production from other production, at the national level. The VS share measures the average import content per dollar of exports. China’s VS share increased from 2000 to 2004, after which it continuously decreased. To explore why it declined, Chapter 2 introduced a new structural decomposition approach. The decomposition allowed us to quantify how much different production types and substitution among different inputs contributed to the VS share change. We decomposed the declines in China’s VS share between 2002 and 2007 and between 2007 and 2012 into the effects of 14 components.

Chapter 2 found that the substitution of imported intermediates with domestically produced intermediates was the main driver for China’s declining VS share. This substitution effect was observed for: the production of processing exports; the production of ordinary exports; and the production of FIEs to meet domestic demand. These findings suggested an upgrade of China’s role in the global production network. The results implied that improving the quality and competitiveness of domestic intermediates may be an efficient way to upgrade a country’s role in the network of global value chains (GVCs). One option to achieve this might be to direct more research and development and foreign direct investments (FDI) flows to high-technology industries.

Another interesting finding was that the export structure increased China’s VS share in the period 2002 to 2007 but decreased it from 2007 to 2012. Processing exports were highly dependent on imports and their share in total exports declined in both periods. Because of this strong import dependence, one would therefore have expected that the decreases in the shares of processing exports would have decreased the VS share, which would have been an indication of China no longer being the ‘world’s
factory’. But, this was not what happened in the period 2002-2007. Because the effect of the changes in the commodity composition of the exports overpowered the effect of declining processing export shares, the VS share increased substantially. In the first period, China changed to exporting more capital-intensive products, which had higher VS shares. This indicates that adjusting the commodity composition of the exports may be an effective way to move up the position in global production networks.

The second typical characteristic of China’s exports was the high involvement of FIEs. The value added of these firms contains profits, which the FIEs can repatriate. In that case, an increase in DVA would not directly enhance the living standards in China. The decreasing VS share found in Chapter 2 suggested that the domestic value-added (DVA) in a unit of exports had increased over time. However, how had the national income (NI) embodied in a unit of exports changed? Chapter 3 investigated the extent to which China’s exporting activities contributed to its Gross National Income (GNI), which is a better indicator for the average living standards than DVA. On the basis of ownership, the value added was decomposed into two parts: national income and foreign income.

Chapter 3 demonstrated that the NI content in exports differed substantially from the DVA content in exports. From 2002 to 2007, DVA embodied in a unit of exports showed a clear rise, but the NI embodied in a unit of exports only increased a little. These results seriously question the traditional perception that a higher DVA share in exports indicates more gains from globalization.

Also the dynamics of national income and DVA showed different patterns before and after the 2008 financial crisis. The DVA in exports considerably increased in both periods. From 2002 to 2007, however, this increase only led to a small increase in the NI in exports, whilst the increase of DVA in exports from 2007 to 2012 translated into considerably larger increase in the NI in exports. Further structural decompositions indicated that changes in the share of capital income in value added was the main reason for these different patterns. The capital income share showed a remarkable increase before the crisis but a substantial drop thereafter. Because the foreign-owned income was mainly sourced from capital income, an increasing capital income share (before the crisis) declined the ratio of the NI content of the exports to the DVA content of the exports, and a decreasing share (after the crisis) raised the ratio.
The third typical feature of China’s exports was the seriously unequal distribution of both processing exports and ordinary exports across domestic regions. To sketch a more accurate picture of regional involvement in trade and globalization, it was important to distinguish the two types of production also at the regional level. To this end, Chapter 4 constructed new interregional input-output (IRIO) tables for China, which explicitly distinguished the production of processing exports from other production. The new tables were named IRIOP tables (with P to indicate the distinction of processing exports). They contain 17 sectors, include eight regions, and were constructed for 2002, 2007, and 2012. For their construction, different data sources were used, such as the existing IO tables for China, international trade statistics, and the Regional Economic Accounts (REA). We solved the main inconsistencies between the data sources by adapting the data from one source so as to match the data from another data source that was felt to be more reliable. After that the tables were constructed block by block using a semi-survey method, based on a combination of survey data, proportionality assumptions, and RAS procedures. Chapter 4 detailed how the information from the different data sources were harmonized and reconciled and how the tables were constructed step by step.

As an illustration of the use of the new IRIOP tables, we investigated whether the separation of production of processing exports from ordinary production mattered for studying the contribution of exports to regional value added. Both the regional value added effect of national exports and the national value added effect of regional exports were found to be significantly overestimated if processing exports were not properly included in the models. Moreover, the effect of exports by the coastal regions on income of the inland regions was also seriously overestimated. All these findings indicate that separating processing exports at the regional level matters.

Based on the new IRIOP tables, Chapter 5 quantified the contributions of both processing exports and ordinary exports to the labor income inequality across China’s eight regions from a value chain perspective.1 To this end, we proposed a value chain–based accounting framework. The framework fully accounted for a region’s indirect exports, which arose through the provision of materials, components and services to

1 Following the IRIOP tables, China mainland was divided into eight regions: North East; North Municipality; North Coast; East Coast; South Coast; Central Region; North West; and South West.
export production activities in other regions.

The chapter started with a description of Chinese temporal changes in regional inequality. We observed a significant income inequality across regions in terms of labor income per capita, which increased rapidly from 2000 to 2003, remained steady until 2006, and then decreased continuously, suggesting regional income convergence in recent years.

Empirically, it was found that exports explained about 70% of China’s regional labor income inequality in 2012. In other words, without the labor income generated by exports, China’s regional labor income inequality would have been only 30% of the actual inequality level in 2012. Processing exports contributed little, despite the unequal distribution of their value chains over the regions. Rather, ordinary exports were found as the main contributor to China’s regional inequality. Looking at the changes in the period 2002-2012, the substantial decline of regional inequality was not due to changes in exporting activity. Even though value chains for processing exports and for ordinary exports became distributed more evenly among regions, the growth in exports still had inequality-increasing effects. The main reasons for the declining regional inequality were: the increased levels of domestic final demands; and the changed value chain configurations of ordinary production—which became more domestically fragmented, with the inland regions increasingly involved. In this regard, China’s recent policy of stimulating domestic demand would effectively decrease China’s regional inequality.

6.3 Limitations and further research

This thesis documented that the three typical characteristics of China’s of exports should be fully taken into account when analyzing the role of exports for a country’s economic growth. In the end, we would like to discuss some limitations of this thesis, which are—at the same time—indications for future work built upon this research.

Chapter 2 explored the dynamics of China’s VS share and what were the determinants of the dynamics. For this, single country IO tables were used. We investigated the dependence of China’s export production on foreign value added and
assumed that all imports were produced by foreign production factors. However, this is not true since imports could be produced with materials produced in China. One direction for future research could be to use the international IO tables to clearly separate the Chinese DVA from the foreign value added in the exports (see Koopman et al., 2014). A non-trivial extension would be to decompose the changes in this "new VS share". Besides, the analysis in chapter 2 is at the national level, which implies that what happens within a country (that is, at the regional level) is not covered. Therefore, another direction for future research could be to use the IRIOP tables constructed in Chapter 4 to investigate the heterogeneity of the VS shares in regional exports, their changes over time and the determinants of these changes. These investigations will provide significant policy implications for China’s further upgrading in global production networks and for China’s regional development.

Chapter 3 provided new perspectives on the benefits of international trade by focusing on the implications of trade for national income. A single country IO table was adopted to calculate the NI content in exports. It was assumed that all imports that were used as intermediate inputs in China were produced abroad only with foreign-owned capital. This assumption is not realistic given the large amounts of outward FDI from China. To relax this assumption, an international IO model could be adopted. The value added vector in each country should in that case be explicitly divided into the income accruing to China and the income accruing to other countries. Such a framework can not only provide more accurate results on NI embodied in exports, but can also be used to quantify China’s trade balance for “trade in national income” (i.e., Chinese NI embodied in foreign countries’ final demand minus the foreign income embodied in Chinese final demand). Recently, Bohn (2019) conducted this kind of analysis. He deconstructed the GDP of each country in WIOD into bilateral transfers of primary incomes. This resulted in a GDP-GNI matrix, which indicates the share of country i’s GDP that is part of country j’s GNI. However, the analysis in Bohn (2019) is at country level and does not give the value added to income relationships between countries at the industry level. Since the large heterogeneity of the FDI ownerships across industries, a national level approach may lead to biased results and further analysis at industry level might make sense.

Chapter 3 used an open IO model and therefore ignored the income multiplier
effect of exports. That is, the NI induced by exports will further induce extra household consumption or investments. This additional household consumption will induce another round of increases in the gross outputs of industries, in labor income, and in household consumption, and so forth. To address this concern, a semi-closed IO model could be used, in which the household consumption is endogenized via the income-consumption relationship between households and industries.

Due to data limits, the construction of the IRIOP tables in Chapter 4 was based on many assumptions. For example, to assign the initial value for the import matrix, it was assumed (both for producing processing exports and for other production) that the input structure of imported intermediates was for each region the same and identical to the national structure. Also, it was assumed that the imports by a region could only be used (for final demand or for intermediate use) in the own region, i.e. no re-exports to other regions. These assumptions can be further relaxed if additional information is available.

Moreover, Chapter 4 only investigated the effect of globalization on Chinese regional growth as an illustration of the use of IRIOP tables. However, the tables could be of particular interest to answer questions that cannot be answered by using the traditional IRIO tables. For example, how much did processing exports and ordinary exports contribute to China’s regional employment and the changes therein? How did China’s regional VS share change and what were the determinants of these changes?

Chapter 5 calculated the contribution of each final product to the overall regional inequality, adopting an accounting perspective. The method has some limitations, however. First, when inequality is attributed to exports, it is implicitly assumed that the regional labor incomes that are induced by Chinese exports would not have been earned in the absence of these exports. Also, it is assumed that wage rates have responded uniformly across regions to the increase in export-driven labor demand. Further, we ignored the migration of labor across regions that was caused by the exports. We would expect that booming exports: (i) have larger positive effects on the wage growth in coastal regions than in inland regions; and (ii) have a positive effect on the migration from the inland regions to the coastal regions. Such general equilibrium effects would influence regional inequality by impacting both total regional income and labor allocation.

Second, similar to Chapter 2, we ignored the income multiplier effects of exports.
To solve these limitations, a spatial general equilibrium model could be helpful (Redding, 2016). For example, one might start from Tomb and Zhu (2019), who built a spatial general equilibrium model of China’s interregional and international trade, and who allowed for migration across regions and sectors. They quantified the effect of China’s trade liberalization and declining migration costs on regional GDP. However, they only included two sectors: agriculture and non-agriculture, and did not separate the production of processing exports from other production. Using a combination of Tomb and Zhu (2019) and Chapter 5 of this thesis, one could investigate the effect of processing exports and ordinary exports on China’s regional inequality and take export commodity compositions, migration and income multiplier effect into full consideration.

Due to data limitations, the IO tables could only be developed for a small number of years. The analysis in this thesis focused therefore only on the periods from 2002 to 2007 and from 2007 to 2012. However, the conclusions may provide some implications also for China’s development in more recent years. First, the processing export share in China’s mechanized exports decreased continuously after 2012. At the same time, the so-called high-tech machinery industries, which have relatively high VS shares, experienced declining export shares in recent years. Also, China’s product quality increased in recent years (Henn et al., 2017; Gnidenko, 2018), which makes the substitution of (some) imported inputs for domestically produced inputs quite likely. All three aspects suggest that the findings in Chapter 2 may also apply to China in more recent years, that is, China’s VS share is decreasing and China is upgrading its role in the global production networks. Second, from the Chinese national IO tables in 2015, it follows that the share of capital income in value added declined from 2012 to 2015 (as it did from 2007 to 2012). At the same time, the export shares of FIEs dropped in recent years. Combining with the findings in Chapter 3, these two aspects imply that NI per RMB of exports is very likely to increase after 2012. Third, the Chinese government encouraged the transfer of processing and manufacturing industries from the eastern coastal regions to the inland regions in recent years. As a result, both processing exports and ordinary exports became distributed more evenly across
regions.\footnote{This observation is based on trade data from China’s Customs, which provides China’s firm-level trade statistics (see Brandt et al. (2017) for details). We aggregate the trade statistics to province level and obtain the provincial processing exports and ordinary exports.} Therefore, it is expected that the income induced by exports increased more rapidly in inland regions than in coastal regions, and the value chain of exports is distributed more evenly among regions. Meanwhile, the share of domestic final demand in China’s total final products is keeping increasing in recent years. All these factors are expected to decrease China’s regional income inequality after 2012.

Last but not least, the framework developed in this thesis is not only applicable to China but also to other countries with similar export characteristics. For example, the framework constructed in Chapter 3 can be used for countries with much inward FDI, such as India, Brazil, and Mexico. It would help in investigating the gains of a country from participating global production networks. The compilation method of the IRIOP table that was developed in Chapter 4 could be adopted for countries like Mexico, for which processing trade is prevalent and unevenly distributed across domestic regions.
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**Samenvatting**

Het onderzoek in dit proefschrift richt zich op de rol van exporten in de Chinese economie. De drie meest typerende kenmerken van Chinese exporten zijn: de grote omvang van exporten die samenhangen met door de overheid gestimuleerde verwerking en assemblage van onder gunstige voorwaarden geïmporteerde materialen en onderdelen (de zogenaamde *processing exports*); de belangrijke rol van ondernemingen gefinancierd met buitenlands kapitaal (*foreign invested enterprises, FIE’s*); en de zeer onevenwichtige verdeling van exportactiviteiten over de verschillende binnenlandse regio’s. Voorafgaand aan het onderzoek werd verwacht dat elk van deze kenmerken substantiële gevolgen voor de omvang en verdeling van inkomsten zou hebben. Ten eerste werd verwacht dat de Chinese exporten relatief weinig binnenlandse toegevoegde waarde zouden opleveren, omdat voor de productie van *processing exports* rotconduels geïmporteerde grondstoffen en halffabricaten worden gebruikt. Ten tweede werd verwacht dat Chinese exporten nog minder zouden bijdragen aan het nationaal inkomen dan aan het bruto binnenlands product, omdat een groot deel van de door FIE’s gegenereerde toegevoegde waarde in buitenlandse handen valt. Ten derde zijn exporten over het algemeen gunstig voor de ontwikkeling van een regio. Maar omdat de exporten van China ongelijk zijn verdeeld, werd verwacht dat dit de regionale inkomensongelijkheid zou vergroten. Met het oog op deze drie typerende kenmerken van de Chinese exporten is in dit proefschrift uitvoerig onderzoek gedaan naar de inkomenseffecten van de Chinese exporten, vanuit een waardeketensperspectief.

Dit proefschrift levert een bijdrage op zowel methodologisch als empirisch vlak. Het biedt met name nieuwe inzichten met betrekking tot een aantal empirische vragen over de inkomenseffecten van Chinese exporten. Er is onderzoek gedaan naar de rol die exporten spelen bij de groei van het nationaal inkomen (hoofdstuk 3) en bij regionale inkomensongelijkheid (hoofdstuk 5), en naar de invloed van structurele veranderingen op het inkomenseffect van exporten (hoofdstuk 2). In hoofdstuk 4 zijn nieuwe interregionale input-output tabellen (IO tabellen) voor China geconstrueerd. Hierin wordt op regionaal niveau expliciet onderscheid gemaakt tussen de *processing exports* productie en gewone productie. De nieuwe IO tabellen zijn gebruikt om de
invloed van processing exports en van gewone exporten op de regionale economische groei te onderzoeken. Er is gebleken dat de resultaten ernstig worden vertekend als er geen rekening wordt gehouden met processing exports activiteiten op regionaal niveau.


In hoofdstuk 2 is vastgesteld dat de substitutie van geïmporteerde halffabricaten door in het binnenland geproduceerde halffabricaten de belangrijkste oorzaak is van de dalende verticale specialisatie in China. Dit substitutie-effect is waargenomen bij de processing exports productie, de productie voor gewone exporten en de productie van FIE’s om aan de binnenlandse vraag te voldoen. Deze bevindingen suggereren dat de rol van China binnen de mondiale productieketens is vergroot. De resultaten impliceren dat het verbeteren van de kwaliteit en de concurrentiepositie van binnenlandse halffabricaten een efficiënte manier kan zijn om de rol van een land in het netwerk van mondiale waardeketens te vergroten. Dit zou onder andere bereikt kunnen worden door meer onderzoek en ontwikkeling op het gebied van hoogtechnologische industrieën, en meer directe buitenlandse investeringen hierin.

Een andere interessante bevinding is dat de exportstructuur de mate van verticale specialisatie in China in de periode van 2002 tot 2007 heeft vergroot, maar van 2007 tot 2012 heeft verkleind. De processing exports waren per definitie sterk afhankelijk van importen en namen (als aandeel van de totale exporten) in beide perioden af.
Vanwege deze sterke importafhankelijkheid zou men daarom verwachten dat de afname van het aandeel processing exports de verticale specialisatie zou verkleinen, wat erop zou wijzen dat China niet langer de ‘fabriek van de wereld’ is. Maar dat bleek niet te gelden voor de periode 2002-2007. Omdat het effect van de veranderingen in de samenstelling van de exporten groter was dan het effect van het afnemende aandeel processing exports, nam de verticale specialisatie aanzienlijk toe. In de eerste periode stapte China over op de export van meer kapitaalintensieve producten, die een grotere mate van verticale specialisatie hadden. Dit wijst erop dat het aanpassen van de samenstelling van de exporten een effectieve manier kan zijn om de positie in mondiaal productieketens te verbeteren.

Het tweede typerende kenmerk van de Chinese exporten is de grote betrokkenheid van ondernemingen gefinancierd met buitenlands kapitaal (FIE’s). De toegevoegde waarde van deze bedrijven omvat winsten, die de FIE’s kunnen repatriëren. In dat geval zal een toename van de binnenlandse toegevoegde waarde de levensstandaard in China niet direct verbeteren. De afnemende verticale specialisatie die in hoofdstuk 2 is gevonden suggereert dat de binnenlandse toegevoegde waarde per RMB exportwaarde in de loop der tijd is toegenomen. Maar hoe is het nationaal inkomen per geëxporteerde RMB veranderd? In hoofdstuk 3 is onderzocht in hoeverre de exportactiviteiten van China hebben bijgedragen aan het bruto nationaal inkomen, dat een betere indicator is voor de gemiddelde levensstandaard dan de binnenlandse toegevoegde waarde. Op basis van eigendomsdata werd de toegevoegde waarde opgesplitst in twee delen: nationaal inkomen en buitenlands inkomen.

In hoofdstuk 3 is aangetoond dat het nationaal inkomen per RMB exporten substantieel verschilde van de binnenlandse toegevoegde waarde in die RMB. Van 2002 tot 2007 is de binnenlandse toegevoegde waarde per RMB exporten duidelijk gestegen, maar het ermee samenhangende nationaal inkomen nam slechts licht toe. Deze resultaten zetten serieuze vraagtekens bij de traditionele perceptie dat een hogere binnenlandse toegevoegde waarde in exporten wijst op meer welvaartswinst door globalisering.

Ook de dynamiek tussen het nationaal inkomen en de binnenlandse toegevoegde waarde vertoonde verschillende patronen voor en na de financiële crisis van 2008. De binnenlandse toegevoegde waarde per RMB exportwaarde is in beide perioden
aanzienlijk gestegen. Maar van 2002 tot 2007 leidde deze stijging slechts tot een kleine stijging van het nationaal inkomen in een geëxporteerde RMB, terwijl de stijging van de binnenlandse toegevoegde waarde in een RMB exporten van 2007 tot 2012 zich vertaalde in een aanzienlijk grotere stijging van het aandeel nationaal inkomen in exporten. Verdere structurele decompositions gaven aan dat de verandering in het aandeel kapitaalinkomen in de toegevoegde waarde de belangrijkste oorzaak was voor dit verschil in patronen. Het aandeel kapitaalinkomen vertoonde vóór de crisis een opmerkelijke stijging, maar daarna een aanzienlijke daling. Omdat het inkomen van ondernemingen in buitenlandse handen voornamelijk bestond uit kapitaalinkomen, zorgde een toenemend aandeel kapitaalinkomen (vóór de crisis) voor een daling van het nationaal inkomen per geëxporteerde RMB ten opzichte van de ermee verband houdende binnenlandse toegevoegde waarde, en een afnemend aandeel kapitaalinkomen (na de crisis) zorgde voor een stijging.

Het derde typerende kenmerk van de Chinese exporten is de zeer ongelijke verdeling van de productie van zowel de processing exports als de gewone exporten over de binnenlandse regio’s. Om een nauwkeuriger beeld te schetsen van de regionale betrokkenheid bij handel en globalisering, is het belangrijk om ook op regionaal niveau onderscheid te maken tussen de twee soorten productie. Daartoe zijn in hoofdstuk 4 nieuwe interregionale input-output tabellen (IRIO tabellen) voor China geconstrueerd, waarin expliciet onderscheid wordt gemaakt tussen de productie voor processing exports en andere productie. De nieuwe tabellen kregen de naam IRIOP tabellen (met P om de apart onderscheiden processing exports aan te duiden). Deze tabellen bestaan uit 17 sectoren en acht regio’s en zijn geconstrueerd voor 2002, 2007 en 2012. Bij de constructie zijn verschillende gegevensbronnen gebruikt, zoals de bestaande IO tabellen voor China, internationale handelsstatistieken en de regionale economische rekeningen. We hebben de belangrijkste inconsistenties tussen de gegevensbronnen opgelost door de gegevens van de ene bron aan te passen aan de gegevens van een andere bron die als betrouwbaarder werd beschouwd. Daarna zijn de tabellen blok voor blok opgebouwd volgens een methode die gebruik maakt van een combinatie van enquêtegegevens, proportionaliteitsveronderstellingen en RAS-procedures voor het updaten van matrices. In hoofdstuk 4 is beschreven hoe de informatie uit de verschillende gegevensbronnen op elkaar is afgestemd en hoe de tabellen stap voor
stap zijn opgebouwd.

Om het gebruik van de nieuwe IRIOP tabellen te illustreren, hebben we onderzocht of het scheiden van de processing exports productie en de gewone productie van belang was om de bijdrage van de export aan de regionale toegevoegde waarde te kunnen bestuderen. Zowel het effect van nationale exporten op de regionale toegevoegde waarde als het effect van regionale exporten op de nationale toegevoegde waarde bleek significant te worden overschat wanneer de processing exports niet apart in de modellen werden meegenomen. Bovendien werd ook het effect van de export door de kustregio’s op het inkomen van de regio’s in het binnenland zwaar overschat. Al deze bevindingen wijzen op het belang om de processing exports ook op regionaal niveau expliciet te onderscheiden.

Op basis van de nieuwe IRIOP tabellen is in hoofdstuk 5 gekwantificeerd in hoeverre de processing exports en de gewone exporten bijdragen aan de ongelijkheid in arbeidsinkomen in de acht regio’s van China, vanuit een waardeketenperspectief.\footnote{In navolging van de IRIOP tabellen is het vasteland van China in acht regio's verdeeld: Noord-Oost, Noordelijke Municipaliteit, Noordkust, Oostkust, Zuidkust, Centrale Regio, Noord-West en Zuid-West.} In dit perspectief is rekening gehouden met de indirecte exporten van een regio die ontstaan door de levering van grondstoffen, onderdelen en diensten aan de produceanten van exporten in andere regio’s.

Het hoofdstuk begint met een beschrijving van veranderingen in regionale ongelijkheid in China. We constateerden een aanzienlijke inkomensongelijkheid tussen de regio’s in termen van arbeidsinkomen per hoofd van de bevolking, die snel steg van 2000 tot 2003, stabiel bleef tot 2006 en vervolgens aanhoudend afnam, wat duidt op regionale inkomensconvergentie in de afgelopen jaren.

Er is empirisch vastgesteld dat de exporten in 2012 ongeveer 70% van de regionale ongelijkheid op het gebied van arbeidsinkomen in China verklaarden. Met andere woorden, zonder het arbeidsinkomen dat door de exporten werd gegenereerd, zou de regionale ongelijkheid in arbeidsinkomen in China slechts 30% van het feitelijke ongelijkheidsniveau van 2012 hebben beslagen. De processing exports speelden hierin nauwelijks een rol, ondanks de ongelijke verdeling van hun waardeketens over de regio’s. De gewone exporten bleken de belangrijkste oorzaak van de regionale ongelijkheid in China. Kijkend naar de veranderingen in de periode
2002-2012 was de substantiële afname van de regionale ongelijkheid niet het gevolg van veranderingen in de exportactiviteit. Hoewel waardeketens voor de processing exports en voor de gewone exporten gelijkmatiger over de regio’s werden verdeeld, had de groei van de exporten toch ongelijkhedsverhogende effecten. De belangrijkste redenen voor de afnemende regionale ongelijkheid waren de toegenomen binnenlandse finale vraag en de veranderde waardeketenconfiguraties van de gewone productie. Deze waardeketens raakten meer gefragmenteerd, met een toenemende betrokkenheid van de regio’s in het binnenland. In dat opzicht zou het recente Chinese beleid om de binnenlandse vraag te stimuleren de regionale ongelijkheid in China effectief kunnen verminderen.