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Economic and environmental upgrading in an era of globalized and fragmented value chains

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**Economic and environmental upgrading in an era of
globalized and fragmented value chains**

Kailan Tian

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university of
 groningen

Economic and Environmental Upgrading in an Era of Globalized and Fragmented Value Chains

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 10 February 2022 at 14.30 hours

by

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The world is still witnessing the restriction triggered by the COVID-19 pandemic. We've come a long way from where we began. Dear friends, let us talk about it when I see you offline again! Stay healthy!

Kailan Tian
December 2, 2021
Beijing, China

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Chapter 1

Introduction

1.1 Background and objective

The nature of production and international trade has substantially changed in the past decades. Firms which used to conduct all the intermediate steps necessary to produce a final product relocated parts of their production processes to cheaper locations abroad. This was enabled by the fast progress in information and communication technology and the reductions in the trade costs (Baldwin, 2006; 2016). This international fragmentation boosted trade in intermediate goods and services as well as cross-border investments. Globalization—defined as worldwide interdependence through trade in goods, services, and assets as well as the flow of people and information—has consequently accelerated remarkably. This huge increase in globalization was termed as the ‘the second wave of global unbundling’ by Baldwin (2006). Different from an earlier wave of globalization, this wave was characterized by increased international fragmentation.

The acceleration of globalization, which started in the mid-1980s, encountered an abrupt pause due to the great recession in the late 2000s. A recovery started around 2012, but in a more moderate way (Zhu and Jiang, 2019). In recent years, nationalistic sentiments have been rekindled in some countries, fuelling a rhetoric that blames foreigners for the economic woes faced by the domestic residents of these countries (Antràs, 2020). The resulting trade protectionism initiated by the United States against its major trading partners and the withdrawal of the United Kingdom from the European Union (EU) further challenged the development of globalization. The outbreak of COVID-19 exacerbated this challenge (Duan and Jiang, 2021), because it resulted in a sharp decline in international trade and cross-border investments in 2020. All this led to the current de-globalization trend in which economic agents increasingly sever their international economic links and reshore economic activities toward their domestic economies in the post COVID-19 era. A number of leading economists (e.g. Antràs, 2020;

Baldwin and Freeman, 2020; Miroudot, 2020; Seric and Winkler, 2020) have warned for the risks of such a trend.

What is currently certain is that globalization faces unprecedented uncertainties. No matter how much we would have liked to incorporate the recent years in our analyses, a lack of data availability prevents us from so doing. The studies in this thesis are at the country-industry level and rely on global multi-regional input-output tables which are not yet available for the most recent years. Therefore, the analyses in this thesis were conducted mainly for the period from the mid-1990s to the mid-2010s. This was an era that was mostly characterized by globalization, although occasional years witnessed decreasing globalization. Nevertheless, this thesis provides methodologies and measurements that are also relevant for studying the restructuring of value chains when the world witnesses a trend of de-globalization (see, e.g. Duan and Jiang, 2021; Hu et al., 2021; Zhu and Jiang, 2019).

One of the most significant evolutions in globalization since the mid-1980s has been the emergence of global (or regional) value chains (GVCs). In the past, products were mostly, if not entirely, produced by industries at home using domestic production factors. The final products were then traded among countries. Due to the advances in transport and telecommunication technology and the reductions in the trade costs, the production of a final product has been unbundled into activities that can be conducted in different countries (Antràs and de Gortari, 2020; Baldwin, 2006; 2016). Value chains are created by the full sequence of production activities (from design, through fabrication, marketing, and distribution, to support for the final consumer). In the past, this sequence used to take place within a single country (or region). Nowadays, value chains are more fragmented and the production of products is sliced up into tasks which can be conducted in multiple regions and countries.

Slicing up value chains across regions and countries has a myriad of implications for economies, societies and the environment. In this thesis, we focus on the implications for economic and environmental upgrading. As GVCs have become a defining feature of the world economy, it is crucial to explore answers to the following questions. What is economic upgrading? How have GVCs changed the concept of economic upgrading? How can upgrading be measured quantitatively? How and to what extent do GVCs affect

economic upgrading of countries in different development stages? How and to what extent does inter-regional trade impact a country's (or region's) environmental upgrading? Answering these questions and finding ways to upgrade production in a country provides relevant information for policymaking and for designing targeted tools.

Numerous studies have pointed out the positive effects of GVCs on economic development and upgrading. First, GVCs enable firms, especially in developing economies, to concentrate in a specific production activity, instead of building a full production process. This opportunity potentially yields fine-grained specialization and thereby generates more efficiency and stimulates exporting. Thailand's successful automotive policies are often cited to illustrate this view (e.g. Baldwin, 2016). In the early 2000s, Thailand abolished its local content requirements and combined high-technology inputs from advanced countries with its domestic low-cost labor to produce cars. Many global manufacturers therefore started production sites in Thailand, which indeed became a large car exporter. This suggests a successful development through GVCs. Second, GVCs may lead to employment opportunities. Large numbers of jobs have been created in developing countries from GVC participation. Examples include iPhone assembly in China, auto part production in Thailand and Mexico, and Nike shoes production in Vietnam. Third, it is argued that transactions within GVCs require deeper cooperation than pure market-based transactions via traditional international trade. As a result, GVCs allow for faster technology transfers and spillovers (Pietrobelli and Rabellotti, 2011).

However, the gains from GVCs can vary considerably depending on which production activities a country operates. On the one hand, developed countries tend to conduct high-end pre- and post-fabrication activities which create relatively much value-added. Examples of such activities include product design, software development, product management, marketing, and after-sales services. Developed countries may worry about the hollowing out of their economies as manufacturing jobs are offshored to low-technology and low-wage countries. They may also worry that their comparative advantages will be undermined as GVCs facilitate technology shifts to developing countries. Developing countries, on the other hand, tend to engage in low-end production activities (such as manufacturing and assembly) which generate relatively little value-added. Therefore, they may increasingly worry that their economies become locked

in at the bottom of the so-called “smile curve” of a GVC¹. What is worse, when wages (and thus labor costs) in a developing country increase, multinationals may decide to combine their technology with cheaper labor elsewhere. The implication may be that little production will be left in this country (Baldwin, 2014; 2016).

Despite the attention in the literature to GVCs and to economic upgrading, there seems to be a lack of quantitative evidence on the relationship between the two. In particular, when taking into account that countries may be at different development levels. This thesis analyzes such relationships by providing systematic and country-industry level evidence. However, before we can even start our empirical analyses of the interaction between GVCs and economic upgrading, we need to tackle another issue first. That is, our conclusion from the literature was that economic upgrading has not been clearly defined or measured well by appropriate quantitative indicators. We therefore begin in Chapter 2 with systematically reviewing the concepts of economic upgrading. It turns out that various perspectives on upgrading have been brought forward. In a factor analysis we then identify three quantitative measures for economic upgrading. Chapter 3 adopts these measures to examine the relationships between GVC participation and upgrading. Chapters 4 and 5 choose China as the object of study. Chapter 4 focuses on China’s economic upgrading in the GVC framework, and Chapter 5 analyzes China’s regional upgrading in environmental performance considering a domestic framework with inter-regional trade.

The studies in this thesis rely on (the measurement of) GVCs, instead of on gross exports (for which data are readily available). This is because the globalized production has boosted a rapid rise in trade in intermediate products (including materials, parts and components), which has obscured the links between domestic value added and exports. Bilateral trade data record the gross value of products as they cross borders between countries. In the past, common practice was to treat gross trade data as if it is the same as data on the value added embodied in the trade. This was tolerable because vertical specialization in trade (i.e. the use of imports to produce exports, see Hummels et al., 2001)

¹ The smile curve depicts how value added varies across the different stages of bringing a product on to the market. The concept was first proposed to describe the observation that in the computer industry, both ends of the value chain—conception and marketing—command higher value added to the product than the middle part of the value chain. If this phenomenon is presented in a graph with a Y-axis for value-added and an X-axis for value chain (stage of production), the resulting curve appears in the shape of a smile.

was limited in most countries. In other words, gross exports consisted almost entirely of domestic value added. However, in the era of GVCs, vertical specialization across countries has been a defining feature of the world economy, and intermediate inputs cross borders many times as they pass through value chains. This means that gross trade data include substantial double-counting, and gross export statistics overstate the amount of domestic value added in exports. Thus, gross trade statistics do not tell us how much of the value of an exported product is created domestically by the exporting country and how much is created by other countries (see, e.g. Johnson and Noguera, 2012; Johnson, 2014; Koopman et al., 2014; Timmer et al., 2015).

As a result, a new perspective on trade has been developed with corresponding measures. A general consensus among economists, international organizations and many countries is that “trade in value added” provides a better measure to evaluate the benefits of a country’s participation in international trade. Value added exports (i.e. the amount of domestic value added embodied in the expenditures for final products in any foreign country, Johnson and Noguera, 2012; 2017), value added in trade (Stehrer, 2012), the decomposition of exports (Koopman et al., 2014; Los et al., 2016), trade in income (Bohn, 2019; Bohn et al., 2021; Duan et al., 2021), the relative positioning of industries and countries in GVCs (Alfaro et al., 2019; Antràs et al., 2012; Antràs and Chor, 2018), the extent of GVC participation (Wang et al., 2017), and other relevant GVC accounting issues have been well discussed and studied. The creation of global input-output (IO) tables, such as the World Input-Output Database (WIOD, see Dietzenbacher et al., 2013; Timmer et al., 2015), OECD Trade in Value Added database (OECD-WTO, 2012), and others (see the overview in Tukker and Dietzenbacher, 2013) was instrumental in enabling the application of the methodologies above to trace the value that each country created along GVCs. These GVC accounting frameworks and input-output databases provide the methodological basis and data for this thesis.

1.2 Global value chains and economic upgrading

Economic upgrading, which is often also referred to as “industrial upgrading” or just “upgrading”, is a term that frequently pops up in newspapers and the popular press. While the literature in industrial economics and international trade has generated a rich

vocabulary that describes economic upgrading (including structural transformation, productivity improvement, and technology transfer), it is not defined unambiguously. It has been understood for a long time as a horizontal process in which the core economic activities shift from agriculture to manufacturing and to services (see, e.g. Lewis, 1954). The shifts were measured by the changes in the shares of value added and of employment. However, with the rise of GVCs, the definition has incorporated the notion that products are produced through a combination of specific activities within a value chain, each generating a portion of the product's overall value. This has given rise to the term “moving up the value chain”, whereby firms upgrade by engaging in an activity within the value chain that extracts a larger share of the overall value of the product.

A lack of unambiguous definition of industrial upgrading affects its measurement. A proper quantification of upgrading is crucial for relevant policy discussions on economic upgrading. Previous studies have used various measures such as changes in value-added shares and in labor productivity levels. However, these measures usually reflect certain aspects of upgrading but do not capture the full multidimensional concept of upgrading. Also, the measures do not take international production fragmentation into account.

To address these challenges, Chapter 2 starts from systematically reviewing the literature and identifying eight indicators for upgrading. We adjust four indicators that are based on gross exports and now use value-added exports, while we keep the conventional definitions for the other four indicators because many value chains are still intranational rather than global. In this way, we take into account not only the canonical features of economic upgrading but also its new interpretation from the GVC perspective. Subsequently, we employ exploratory factor analysis (EFA) on the set of indicators, trying to reduce the information contained in the eight indicators into a single variable called ‘factor’. Just like Spearman (1904) proposed to use the single conceptualized factor—human intelligence—to measure the performance on all kinds of mental tests, we expected to explore an underlying single general factor that entered into performance on all the eight upgrading indicators. However, we find that economic upgrading cannot be fully captured by a single factor. Trying to find such a single factor would then be like searching for the holy grail. Instead, we draw from the EFA three quantitative dimensions of upgrading: process upgrading, product upgrading, and skill upgrading.

Process upgrading typically refers to an increase in the efficiency of production through innovations in the production process or by using new technologies. Product upgrading refers to gaining more value from GVC production, which is related to the effects of making better and more sophisticated products. Skill upgrading refers to increasing skill intensity of employment and exports. Each of these dimensions can be linked to (but are different from) several concepts of upgrading identified by Humphrey and Schmitz (2000, 2002). These include functional upgrading (i.e. performing more sophisticated business functions or more skill-intensive activities within the same value chain) and intersectoral upgrading (i.e. pursuing more value by entering new product value chains).

We stress that the quantification of upgrading should take into account its different dimensions. It is well known by policy makers that they should focus on strengthening competitiveness and upgrading in order to gain more value-added. But what is more meaningful is that they need to decide which type of economic upgrading (process, product, or skill) they want to pursue. In Chapter 2, we therefore propose the quantification of all three different types of upgrading.

Once we know what economic upgrading is and how it can be measured, the next issue is how GVC participation affects economic upgrading. It is commonly accepted that GVCs have fueled economic growth, which is perhaps best characterized by China's successful export-driven growth after the country opened up in 2001. However, an unresolved issue is whether and to what extent GVC participation benefits economic upgrading in developing and in developed countries. Two dominant views can be distinguished from existing theoretical models. One view emphasizes that GVCs mainly benefit upgrading in developed countries. This is because GVCs enable these countries to offshore parts of low value-added tasks and upgrade by specializing in high value-added tasks (e.g. Baldwin and Robert-Nicoud, 2014; Mankiw and Swagel, 2006). A consequence for developing countries, however, is that GVCs may lock them into mostly low value-added activities. Foreign investors and trade partners do not actively pursue (and sometimes even resist) to transfer technology to developing economies (e.g., Gereffi et al., 2005; UNCTAD, 2013). The other view stresses that GVCs provide more opportunities for developing countries to upgrade. This can be achieved by initially performing low-skilled

activities and then climbing up the value chain through learning-by-doing (e.g. Amendolagine et al., 2019; Pietrobelli and Rabellotti, 2011; Taglioni and Winkler, 2016; Torres Mazzi et al., 2021).

Chapter 3 provides a country-industry level empirical analysis to indicate which of the two views is corroborated by the data. We estimate panel data regression models using the three quantitative measures of economic upgrading from Chapter 2 as the dependent (or response) variables. We measure two types of GVC participation from the backward and forward links as the independent (or explanatory) variables. The backward GVC linkage measures to what extent a country imports intermediate inputs to produce its products, while the forward GVC linkage measures the extent to which a country supply intermediates to other countries for further production. We employ input-output tables from WIOD and the associated Socio-Economic Accounts to calculate the variables for 1360 country-industry pairs (40 countries with 34 industries) for the period 1995-2009. The results show that the effect of backward GVC participation (i.e. where a country depends on foreign inputs) on process upgrading is larger in developing countries than in developed countries. The finding suggests that this import dependence provides more upgrading opportunities for developing countries through the import of sophisticated inputs, which stimulate knowledge spillovers. Forward GVC participation (i.e. where a country depends on other countries for the sale of its exports) has a positive impact on process upgrading for developed countries only, not for developing countries. For developed countries, forward GVC participation normally means that they offshore parts of their low value-added tasks and specialize in high value-added tasks. This process helps to lower labor costs, which has a positive effect on productivity improvement. For developing countries, however, forward participation in GVCs usually means that they supply raw materials and (cheap) labor and specialize in low value-added tasks. This process typically provides only few learning opportunities to improve the productivity in developing countries. Next to process upgrading, we also examine in Chapter 3 the effects of GVC participation on product upgrading and skill upgrading in developing and in developed countries.

In Chapter 4, we focus on China as the largest developing nation and study the impacts that geographic shifts in international sourcing have on its GDP. Next to the rapid

growth in the trade of intermediate products, the geographic shift in international sourcing was another feature of the GVC era. The industrial revolution originally placed the center of global production and trade in the United Kingdom, after which it moved to Western Europe, the United States, Japan, and then to Asia's Four Tigers (Jiang and Green, 2017; Lehmann, 2012). After that, mainland China timely caught the wave of GVCs. After its entry into the World Trade Organization (WTO) in 2001, it began carrying out part of the global production processes and developed into the "World's Factory". As a result, China's economy witnessed rapid growth in the past decades. However, the growth rate of Chinese GDP slid down to a medium level in recent years, and the level of China's GDP per capita is still lower than the world average although it steadily increased in the past decades. Consequently, exploring possible strategies to further increase GDP per capita remains an important challenge for China.

Therefore, in Chapter 4, we firstly quantify how past geographic shifts in international sourcing (i.e., changes in the world trade structure) have contributed to China's GDP gains. We subsequently propose a nonlinear optimization approach to explore which shifts in international sourcing would increase China's GDP per capita the most. The optimization model is built on a global input-output (IO) framework that takes linkages between industries into full account. Not only those within a country but also those between industries in different countries (which may be located in different regions of the world). In the model, the objective is to maximize China's GDP per capita relative to the world average level and given some practical constraints. In each country, we keep the production technology and the demand for final products constant (which implies that the world GDP remains unchanged), but international sourcing is variable. To narrow the income gap between China and developed countries most, our optimization results suggest two potential directions for future policies. These are import substitution at home and export promotion (leading to substitution abroad).

These two potential strategies require China to upgrade its economic activities and products. In the past decades, China mainly contributed processing and assembly activities to the global production chains (especially in the chains of technology-intensive products). Such activities relied heavily on cheap domestic labor and on imports of intermediate inputs from developed countries. Given the fact that China's wages per capita doubled in

the last decade, the country is losing its comparative advantage in simple assembly activities. To make up for this loss, China has to move to activities with a middle and high value-added content (i.e. skill upgrading). To persuade domestic (import substitution) and foreign (export promotion) producers to buy more Chinese intermediate products, China has to improve its productivity (process upgrading). Promoting domestic and foreign consumers to buy more Chinese final products requires China to produce more products with higher quality (product upgrading).

We extend our analyses by considering the situation where other countries also optimize their value-added gains using similar strategies. The results show that the optimized value-added share of a country is very close to the original value as given in the world IO table. This means that the current structure looks more or less optimal. As a consequence, this suggests that for improving a country's value-added share investments in new technology are likely to be more successful rather than non-cooperative policies (e.g. begging the neighbour).

1.3 Production fragmentation and environmental upgrading

Production fragmentation across regions or countries was followed by wide-ranging and sometimes unforeseen implications for economies, societies and the environment. Global production networks have not only fundamentally transformed the way products are produced, exchanged and consumed, they have also changed the location and scale of environmental and social impacts. When the fragments of production take place in more than one location, associated impacts become more complicated. We illustrate this with an example. China imports iron ore from Australia and processes it into steel, which is then exported to Germany for the production of cars that are destined for consumers in the United States. Employment generated, value created, energy used, and pollution emitted by mining in Australia and manufacturing in China and Germany then becomes 'embodied' in the final cars purchased by U.S. consumers. The large increase in such spatial fragmentation and the separation of production and consumption has led to a large body of literature. Namely with a focus on accounting the environmental and social impacts as embodied in trade, both of intermediate and of final products (see, e.g. Duan and Jiang, 2017; Duan and Yan, 2019; Tian et al., 2022; Xu and Dietzenbacher, 2014; Zhang et al.,

2017, 2020a, 2020b).

Currently, the production-based accounting (PBA) system is in practice widely adopted to assign responsibilities for global environmental problems to individual countries. PBA measures the amount of e.g. greenhouse gas (GHG) emitted by producers and households within a country, but it ignores the emissions embodied in international trade. In the example above, part of Australia's (and China's and Germany's) emissions are embodied in producing German cars for U.S. consumer. The consumption-based accounting (CBA) method takes this into account. It determines the amount of global emissions embodied in a country's consumption of final products. CBA includes the emissions that are emitted in a foreign country (e.g. the mining industry in Australia) but which are embodied in the final products (e.g. German cars) that are consumed at home (e.g. the U.S. households). CBA redistributes the emissions from PBA. Several researchers (see, e.g. Dietzenbacher et al., 2020; Domingos et al., 2016; Kander et al., 2015; 2016) proposed further refinements in CBA for assigning the responsibilities for global emissions.

In Chapter 5, we analyze environmental upgrading (or downgrading) in China's domestic regions, both from the production-based and the consumption-based perspective. We define environmental upgrading as lowering the carbon intensity per unit of value-added. Producers in a region can upgrade the region's emission performance in two different ways. First, by reducing their own emission content in the production. Second, by importing inputs from regions that produce these inputs more emission-intensively than the home region does. Production fragmentation across regions also enables a region to transfer "dirty" production activities to other regions. This results in inter-regional spillovers of emissions. This second way follows the idea underlying the so-called pollution haven hypothesis, albeit at a regional level. This hypothesis argues that polluting industries may relocate their production from a region (or country) with more stringent environmental policies to a region with less stringent policies (see, e.g. Duan and Jiang, 2021; López et al., 2019; Meng et al., 2018). This leads to emission leakages where regions with less stringent policies emit for regions with more stringent policies. Given that China is a vast country with considerable regional disparities and given that environmental pressures are exercised at the regional level, pollution havens are likely to

exist in China. In Chapter 5 we analyze how and to what extent changes in inter-regional trade and in inter-regional spillovers contributed to changes in China's regional environmental upgrading.

To identify the determinants of the changes in China's regional emission intensities, we conduct a multiplicative structural decomposition analysis (SDA). The SDA is based on the environmentally extended multi-regional input-output model and explicitly captures both production-side and demand-side effects (Miller and Blair, 2009). Our decomposition uses several standard drivers of the changes in regional emission intensities. These include changes in the emissions per unit of output in each industry, changes in the intermediate input structure, and changes in the demands for final products. Next to these standard drivers, we also include changes in inter-regional trade and changes in inter-regional spillovers. Changing inter-regional trade is found to have increased the emission intensity significantly in China's western and central regions. This suggests that more "dirty" production was shifted from coastal to inland regions. In 2021, China pledged that it would achieve carbon neutrality before 2060. Commitments are in China made by the central government whilst local (regional) governments are the direct executive bodies in charge of the emission reductions. Our analyses in Chapter 5 provide clear policy recommendations for China's central and regional governments to achieve the national target of carbon neutrality.

In summary, this thesis consists of four main chapters. Chapters 2, 3, and 4 focus on economic upgrading in the framework of GVCs. Chapter 5 zooms in on China's regional environmental upgrading considering regional value chains. All chapters are conducted from the perspective of (globally or regionally) fragmented value chains. Chapter 6 summarizes the main findings and suggests future research directions.

Chapter 2

Measuring industrial upgrading: applying factor analysis in a global value chain framework¹

2.1 Introduction

Industrial upgrading, which is also often referred to as ‘economic upgrading’ or just ‘upgrading’, is a term that frequently pops up in governmental reports, in documents on economic policy and in mass media. It is not very well defined though, and different users seem to differ slightly in their interpretations of what “upgrading” is. According to the Oxford English Dictionary, upgrading means to “[r]aise (something) to a higher standard, in particular improve (equipment or machinery) by adding or replacing components.”

A key challenge for workers, firms, industries and even countries is thus to enlarge the benefits (irrespective of the definition) of participating in production activities. A product or service follows several stages of production from its conception to end-use (i.e. from design, through fabrication, marketing, and distribution, to support for the final consumer). This full range of activities is called a value chain. In the past, most value chains took place within a single country (or even region). Nowadays, value chains cross borders and they have become ‘global’. The activities are carried out in global networks of inter-connected firms (Gereffi and Fernandez-Stark, 2016). It should be emphasized that there has been an enormous increase in international production fragmentation due to advances in information technology and telecommunications over the last two decades (Baldwin and Robert-Nicoud, 2014). That is, the production is sliced up (i.e. fragmented) in ever smaller pieces (or tasks) that are carried out by a foreign firm.

A proper discussion of the policy aspects of industrial upgrading requires its quantification. That is the aim of this chapter, i.e. to measure upgrading at the industry and

¹ This chapter is co-authored with Erik Dietzenbacher and Richard Jong-A-Pin and was originally published at *Economic Systems Research*, Vol. 31, No.4, 642-664 (i.e. Tian et al., 2019).

country level. As indicated above, there are two difficulties involved. On the one hand, there is no single definition of upgrading that is widely accepted as *the* definition. On the other hand, the measurement framework should take into account that production now occurs in global value chains (GVCs).

To address these challenges, we propose the following method. First, we (systematically) review the literature and identify eight indicators for upgrading. Four indicators are based on gross exports (such as export growth and the share of a country or industry in all exports). But we know that gross exports provide a biased picture of the benefits of trade when a large amount of international production fragmentation is present (Johnson and Noguera, 2012; Johnson, 2014; Koopman et al., 2014). Therefore, we argue in favor of the GVC perspective and replace the export-based indicators by similar, new indicators based on value added exports.

Second, we employ exploratory factor analysis (EFA) on the set of indicators to investigate the multidimensionality of industrial upgrading.² This is because (as we shall show in the literature review) the indicators suggest that industrial upgrading is a multidimensional phenomenon that cannot be captured by a single measure. For example, Kaplinsky and Readman (2001) and Humphrey and Schmitz (2002) identify four distinct types of upgrading: process, product, functional, and intersectoral upgrading, suggesting that several dimensions may be important. This typology has also been followed by Giuliani et al. (2005) who focus on twelve clusters in Latin America or by Evgeniev and Gereffi's (2008) study of the textiles and apparel sector in Turkey and Bulgaria. Both studies clearly suggest that upgrading has more dimensions. Using one indicator (or even several indicators) to measure upgrading would ignore certain aspects of industrial upgrading and perhaps duplicate others.

EFA is frequently used to extract information common to many indicators and reduce that information into a lower number of unobserved variables called "factors." Our indicators are calculated from the World Input-Output Database. Previewing the results from the EFA, we label the main factors as three quantitative dimensions of industrial

² Factor analysis is a statistical technique and its applications distinguish two categories. An exploratory factor analysis (EFA) explores the data and reports "what the data tell us". A confirmatory factor analysis checks whether earlier findings or a theory can be confirmed. This chapter only uses EFA, so that EFA and factor analysis will be used interchangeably.

upgrading: process upgrading, product upgrading, and skill upgrading. Each of these dimensions corresponds to a concept of upgrading identified by Kaplinsky and Readman (2001) and Humphrey and Schmitz (2002). Using these dimensions, we compare and analyze the upgrading levels of different countries and industries. Results at both the country level and the country-industry level show that process, product and skill upgrading moderately correlate, but they indeed reflect different dimensions of industrial upgrading. It confirms the multidimensionality of industrial upgrading and our proposal that upgrading should be measured in a systematic way.

2.2 The measurement of upgrading

In this section, we introduce our framework for measuring industrial upgrading in a global value chain (GVC) perspective. Section 2.2.1 starts with a brief sketch of what has been done in the past on upgrading and indicates differences of them with our work (i.e. the GVC perspective and the split of labor use according to skill types). Section 2.2.2 is a more formal and mathematical exposition that leads to the upgrading indicators to be applied to the factor analysis in Section 2.3.

2.2.1 Background and overview of the literature

Upgrading was initially defined as the ability to make better products, to make them more efficiently, or to move more into skilled activities (Porter, 1990). It is important to understand the factors that facilitate improvements in products and processes. If these factors arise from the activities of a firm, the original concept of upgrading is helpful. But, as Kaplinsky and Readman (2001) and Humphrey and Schmitz (2002) point out, this concept is restricted to the level of the firm and fails to capture upgrading processes across sectors. Also within sectors, upgrading processes that involve groups of interlinked firms in GVCs (due to the rise in international fragmentation) cannot be captured. Therefore, the interpretation of upgrading was widened by Kaplinsky and Readman (2001) and Humphrey and Schmitz (2002) who identified four distinct types of upgrading. These were process upgrading, product upgrading, functional upgrading, and intersectoral upgrading. Gereffi (2005) and Gibbon and Ponte (2005) attempted to catch these four types of upgrading in a single, more generic concept of upgrading. Upgrading is a move: to higher value added activities in production; to the use of improved technology,

knowledge and skills; and to increased benefits from participation in GVCs.

The four types of upgrading proposed by Kaplinsky and Readman (2001) and Humphrey and Schmitz (2002) were identified by them in a conceptual framework without quantitative measures. However, each of the four types of upgrading suggests its own indicators. Process upgrading refers to an increase in the efficiency of production processes. For example, the substitution of labor for capital (which happens when automation takes place) may yield a greater level of productivity. Indicators for process upgrading that have been proposed are labor productivity growth (see, e.g. Taglioni and Winkler, 2016), capital compensation growth (Milberg and Winkler, 2011) and capital intensity growth (Barrientos et al., 2011).

Product upgrading occurs where new products are introduced or when certain existing products are enhanced faster than are competing products. It entails moving into more sophisticated products within an existing value chain. Indicators that have been proposed for product upgrading are export growth and growth of the export share. Kaplinsky and Readman (2005) suggest the combination of the export share growth with the growth in the export unit value (reflecting the average price of the exported products). Higher prices for the exported products despite constant (or increasing) export shares suggests that products have upgraded (see also Amighini, 2006). Li and Song (2011) provide further motivation for the use of the export share and the export unit value by arguing that product quality is the linchpin. Differences in product quality are globally evaluated by consumers and reflected in their preferences (and the shares) and consequently product prices. Higher quality products have higher prices than do low quality products (Aiginger, 1997). A price increase thus reflects an upgrade of the quality of the product or service if the share is stable or rising

Functional upgrading involves performing more sophisticated business functions or more skill-intensive activities. A typical example of functional upgrading is a move from simple assembly to full-package production or to developing an own product design. This is reflected by increasing shares of skill-intensive activities and the use of high-skilled workers. Two proposed indicators for functional upgrading are the increase in the skill intensity of the sector's employment and the increase in the skill intensity of the exports (Milberg and Winkler, 2011; Barrientos et al., 2011).

The fourth type of upgrading is intersectoral upgrading. It is the shift to a more technologically advanced production chain. This involves disintegrating processes into other industries and/or other value chains. Intersectoral upgrading is related to changing the production mix towards producing goods and services with a higher value added. The production (and employment and exports) of a country gradually shifts across sectors, from agriculture and natural resource extraction to light industries like textile, and subsequently towards more modern manufacturing and the services sectors (see, e.g. Lewis, 1954, for a discussion of structural change). So far, there is no unambiguous indicator to measure intersectoral upgrading. But some researchers (e.g. Lin and Yu, 2012) use the sectoral composition of gross domestic product (GDP) and the sectoral composition of exports to study intersectoral upgrading at country level.³

In conclusion, we extract from the literature the following eight indicators of upgrading: labor productivity growth; capital compensation growth; capital intensity growth; export growth; export share growth; growth of export unit value; growth of the skill intensity of employment; and growth of high-skilled labor exports. A list of these indicators and their sources is provided in Table A2.1 of Annex 2.

Four out of the eight indicators suggested in the literature are based on gross exports. Increased international production fragmentation has led to an enormous growth in the trade in intermediate products and to countries specializing in small parts of value chains. This was made possible by rapidly falling communication and transport costs over the past two decades implying that various stages of production can be performed in other regions and countries. In the past, a country performed the whole production process of a product and exported the product to compete with other countries in the global market. The value that the exporting country received was the price of the exported product, and it reflected the gains or benefits for that country. Due to globalization, today's products and services are made in global production networks or GVCs, rather than in a specific country (Timmer et al., 2013, 2015). A country imports raw materials and intermediate goods, adds

³ In the EFA, later in the chapter, we do not include the sectoral composition of GDP or exports as an indicator though. We think a country's sectoral change is captured by other indicators that we do include. For example, a country's change in its sectoral composition of exports is reflected in its change in the unit value added exports (i.e. value added exports per dollar of gross exports). Because they add little or no additional information, we avoid using similar indicators for the sake of orthogonality, i.e., they would overweight a factor. Nevertheless, we do consider the effects of a change in the share of exports between natural resource and non-resource intensive sectors and run a robustness check of country-specific results in Section 4.3.

one or more layers of value, and sells the resulting product to a foreign producer who adds the next layer(s). This corresponds to Baldwin's (2006) 'second unbundling', where the location of the production of intermediate inputs differs from the location of making the final product. In today's situation, the price of an exported product is no longer the value that the exporting country receives for the product. Consequently, the value of gross exports (as recorded by customs data and reported in official trade statistics) goes to all the countries involved in the production stages and not only to the final exporter. To capture this new situation, we suggest new indicators of industrial upgrading. We suggest that they use the domestic value added of a country that is embodied in all foreign final demands (also known as value added exports), rather than the value of gross exports.

Concerns about the gap between the value of gross exports and the value added exports have been expressed. Case studies of the Apple iPad and iPhone (Kraemer et al., 2011) reveal that the value added generated in China (which exports the final Apple products) is only 1.8% of their export value for China. Because Apple continues to keep its pre- and post-fabrication activities (such as product design, software development, product management, and marketing) in the USA, the USA remains the main beneficiary in value added terms. Other case studies of the iPod and laptops (Dedrick et al., 2010) and the Nokia smartphone (Ali-Yrkkö et al., 2011) confirm that these pre- and post-fabrication activities generate much value added (Baldwin and Evenett, 2012). China's benefits from participating in Apple's GVCs are thus much smaller than the huge gross export values from China suggest. This is because China is involved only in the assembly part of the GVCs, which generates little value added. Koopman et al. (2012) and Chen et al. (2018) focus on the role of assembly activities in producing export products. Their results show that the value added in exports related to assembly activities is much lower than the value added in other exports and is far lower than otherwise suggested by the gross export values (see Johnson and Noguera, 2012, for similar findings for a larger set of countries). This gap between the value of gross exports and the value added exports is well recognized. The OECD and the WTO have launched their 'Made in the World' initiative and proposed 'trade in value added'. This alternative approach for the measurement of world trade provides a better answer to certain questions (see OECD-WTO, 2012).

When measuring industrial upgrading, however, to our knowledge, only a few recent

studies have adopted value added based indicators from a GVC perspective.⁴ In this chapter, we adjust conventional indicators and replace the value of gross exports by the value added exports (i.e. the value added created in one country to satisfy – directly and indirectly – final demand in another country, see Johnson and Noguera, 2012). For example, the growth of the export share is replaced by the growth of the share in value added exports. In the same way are export growth and export unit value growth adjusted. With regard to the other four indicators that are not based on gross exports (i.e. labor productivity growth, capital compensation growth, capital intensity growth and growth of the skill intensity of employment), we keep their conventional definitions. The detailed definitions for the eight indicators are provided in the following subsection (and in Table A2.1 of Annex 2).

A second feature of our study is that we split labor according to skill types. High-, medium- and low-skilled labor is determined by educational attainment of the workers. We focus in particular on high-skilled labor. The reason is that high-skilled workers are supposed to be more able than medium- and low-skilled workers to make better products and/or to make them more efficiently. High-skilled workers also often specialize in higher value added activities such as R&D, design and marketing activities, whereas lower-skilled workers are often production or service workers who create less value. A rising share of high-skilled labor thus indicates that an industry has experienced upgrading. The growth in the share of high-skilled labor is a proxy for the increased skill intensity of employment. For example, growth of the skill intensity of exports is measured by the growth in the high-skilled labor embodied in foreign final demand.

2.2.2 Indicators of industrial upgrading

Our starting-point is the world multi-regional IO table in Table 2.1 with n countries and m sectors (or industries) in each country.⁵ The $m \times m$ matrix $\mathbf{Z}^{sr}$ gives the intermediate deliveries from country s to country r . Its typical element z_{ij}^{sr} gives the

⁴ A few recent studies started to adopt the GVC perspective when using the measure of economic upgrading. For instance, Taglioni and Winkler (2016) and Ahmad and Primi (2017) adopted the growth of domestic value added in gross exports as the measure of economic upgrading. Rather than using such a single measure, in this chapter, we point out that industrial upgrading can be a multifaceted phenomenon that cannot be characterized well by a single measure.

⁵ 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). Subscripts indicate industries and superscripts indicate countries. Vectors are columns by definition, row vectors are obtained by transposition, denoted by a prime (e.g. $\mathbf{x}'$). Diagonal matrices are denoted by a circumflex (e.g. $\hat{\mathbf{x}}$).

value of goods and services shipped from sector i in country s for intermediate use by sector j in country r . The value of goods and services shipped from sector i in country s to country r for final use (household consumption, private investments, and government expenditures) is given by f_i^{sr} , the typical element of the vector $\mathbf{f}^{sr}$. The value of the output by sector i in country s is given by y_i^s , the typical element of the vector $\mathbf{y}^s$. The accounting identity (or product market clearing condition) is

$$y_i^s = \sum_j \sum_r z_{ij}^{sr} + \sum_r f_i^{sr}. \quad (2.1)$$

Table 2.1 The world multi-regional input-output table

	Intermediate use					Final use					Gross outputs
	in 1	...	in r	...	in n	in 1	...	in r	...	in n	
Country 1	$\mathbf{Z}^{11}$	...	$\mathbf{Z}^{1r}$	...	$\mathbf{Z}^{1n}$	$\mathbf{f}^{11}$	...	$\mathbf{f}^{1r}$	...	$\mathbf{f}^{1n}$	$\mathbf{y}^1$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
Country r	$\mathbf{Z}^{r1}$	...	$\mathbf{Z}^{rr}$	...	$\mathbf{Z}^{rn}$	$\mathbf{f}^{r1}$	...	$\mathbf{f}^{rr}$	...	$\mathbf{f}^{rn}$	$\mathbf{y}^r$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
Country n	$\mathbf{Z}^{n1}$	...	$\mathbf{Z}^{nr}$	...	$\mathbf{Z}^{nn}$	$\mathbf{f}^{n1}$	...	$\mathbf{f}^{nr}$	...	$\mathbf{f}^{nn}$	$\mathbf{y}^n$
Value added	$(\mathbf{w}^1)'$	...	$(\mathbf{w}^r)'$	...	$(\mathbf{w}^n)'$						
Total inputs	$(\mathbf{y}^1)'$	...	$(\mathbf{y}^r)'$	...	$(\mathbf{y}^n)'$						

If we use $\mathbf{u}$ to indicate the m -element summation vector consisting entirely of ones, then the accounting identities can be written in matrix form as

$$\begin{pmatrix} \mathbf{y}^1 \\ \vdots \\ \mathbf{y}^r \\ \vdots \\ \mathbf{y}^n \end{pmatrix} = \begin{bmatrix} \mathbf{Z}^{11} & \dots & \mathbf{Z}^{1r} & \dots & \mathbf{Z}^{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{Z}^{r1} & \dots & \mathbf{Z}^{rr} & \dots & \mathbf{Z}^{rn} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{Z}^{n1} & \dots & \mathbf{Z}^{nr} & \dots & \mathbf{Z}^{nn} \end{bmatrix} \begin{pmatrix} \mathbf{u} \\ \vdots \\ \mathbf{u} \\ \vdots \\ \mathbf{u} \end{pmatrix} + \begin{pmatrix} \sum_t \mathbf{f}^{1t} \\ \vdots \\ \sum_t \mathbf{f}^{rt} \\ \vdots \\ \sum_t \mathbf{f}^{nt} \end{pmatrix}. \quad (2.2)$$

The $m \times m$ matrix $\mathbf{A}^{sr} = \mathbf{Z}^{sr}(\hat{\mathbf{y}}^r)^{-1}$ gives the input coefficients. Its typical element $a_{ij}^{sr} = z_{ij}^{sr}/y_j^r$ gives the dollars of input from sector i in country s for intermediate use by (and measured per dollar of output by) sector j in country r . This yields

$$\begin{pmatrix} \mathbf{y}^1 \\ \vdots \\ \mathbf{y}^r \\ \vdots \\ \mathbf{y}^n \end{pmatrix} = \begin{bmatrix} \mathbf{A}^{11} & \dots & \mathbf{A}^{1r} & \dots & \mathbf{A}^{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{A}^{r1} & \dots & \mathbf{A}^{rr} & \dots & \mathbf{A}^{rn} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{A}^{n1} & \dots & \mathbf{A}^{nr} & \dots & \mathbf{A}^{nn} \end{bmatrix} \begin{pmatrix} \mathbf{y}^1 \\ \vdots \\ \mathbf{y}^r \\ \vdots \\ \mathbf{y}^n \end{pmatrix} + \begin{pmatrix} \sum_t \mathbf{f}^{1t} \\ \vdots \\ \sum_t \mathbf{f}^{rt} \\ \vdots \\ \sum_t \mathbf{f}^{nt} \end{pmatrix}. \quad (2.3)$$

Let the final demands vector be split into n vectors, one for each receiving country. That is, define

$$\mathbf{f} = \begin{pmatrix} \sum_t \mathbf{f}^{1t} \\ \vdots \\ \sum_t \mathbf{f}^{rt} \\ \vdots \\ \sum_t \mathbf{f}^{nt} \end{pmatrix} = \begin{pmatrix} \mathbf{f}^{11} \\ \vdots \\ \mathbf{f}^{r1} \\ \vdots \\ \mathbf{f}^{n1} \end{pmatrix} + \dots + \begin{pmatrix} \mathbf{f}^{1n} \\ \vdots \\ \mathbf{f}^{rn} \\ \vdots \\ \mathbf{f}^{nn} \end{pmatrix} = \mathbf{f}^1 + \dots + \mathbf{f}^n.$$

Equation (2.3) can be written as $\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{f} = \mathbf{A}\mathbf{y} + (\mathbf{f}^1 + \dots + \mathbf{f}^n)$ and the solution is given by $\mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1}(\mathbf{f}^1 + \dots + \mathbf{f}^n) = \mathbf{L}(\mathbf{f}^1 + \dots + \mathbf{f}^n)$, where $\mathbf{L} \equiv (\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse. In its partitioned form this $nm \times nm$ matrix is given by

$$\mathbf{L} = \begin{bmatrix} \mathbf{L}^{11} & \dots & \mathbf{L}^{1r} & \dots & \mathbf{L}^{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{L}^{r1} & \dots & \mathbf{L}^{rr} & \dots & \mathbf{L}^{rn} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{L}^{n1} & \dots & \mathbf{L}^{nr} & \dots & \mathbf{L}^{nn} \end{bmatrix}.$$

The outputs that are necessary for (or embodied in) the final demands of any country except country s are given by $\mathbf{L}(\sum_{t \neq s} \mathbf{f}^t)$. Note that for country s the nm -element vector $\sum_{t \neq s} \mathbf{f}^t$ gives *foreign* final demands. The domestic output embodied in the foreign final demands is, for country s , given by $\sum_k \mathbf{L}^{sk} (\sum_{t \neq s} \mathbf{f}^{kt})$.

The m -element vector $(\mathbf{v}^r)' = (\mathbf{w}^r)'(\hat{\mathbf{y}}^r)^{-1}$ gives the value added coefficients in country r . Its typical element $v_j^r = w_j^r/y_j^r$ gives the value added (in dollars) generated in sector j in country r per dollar of output in this sector. The value added generated in sector i in country s that is embodied in foreign final demands (i.e. final demand outside country s) is given by the i th element of the vector

$$\mathbf{vax}^s = \sum_k \sum_{t \neq s} \hat{\mathbf{v}}^s \mathbf{L}^{sk} \mathbf{f}^{kt}. \quad (2.4)$$

This is value added of country s that ultimately ends up in a foreign final demand bundle (e.g. consumption of households abroad). This is the export by country s of its domestic value added. The value added exports of country s (vax^s) and the value added exports of sector i in country s are given by: $vax^s = \mathbf{u}' \mathbf{vax}^s$ and vax_i^s (i.e. the i th element of $\mathbf{vax}^s$).

Instead of value added, we can also take any factor input such as capital or labor. For example, let the typical element h_j^r of the m -element vector $\mathbf{h}^r$ give the amount of

high-skilled labor used in sector j in country r . Let the m -element vector $(\mathbf{l}^r)' = (\mathbf{h}^r)'(\hat{\mathbf{y}}^r)^{-1}$ give the input coefficients for high-skilled labor in country r . Its typical element $l_j^r = h_j^r/y_j^r$ gives the amount of high-skilled labor used in sector j in country r per dollar of output in this sector. The export by country s of high-skilled labor is defined as the high-skilled labor in country s that is embodied in final demands abroad (i.e. outside country s). Similar to equation (2.4), it is calculated as $\sum_k \sum_{t \neq s} \hat{\mathbf{l}}^s \mathbf{L}^{sk} \mathbf{f}^{kt}$. This sketches the GVC perspective on measuring the embodiment of factor inputs in foreign final demands.

We continue with presenting and defining the upgrading indicators that we will use in the factor analysis in the next section.

(1) *labpr*: labor productivity growth. Labor productivity is calculated as the ratio of value added to labor, i.e. the value added per unit of labor. Labor is defined as ‘all persons engaged’. This includes, next to all paid employees, also the self-employed and informal workers. Note that this indicator (and all indicators hereafter) is a growth rate. That is, $labpr = (p_t - p_{t-1})/p_{t-1}$, where p_t denotes the labor productivity of a country in year t .

(2) *capcom*: capital compensation growth. Capital is one of the three primary factors of production (i.e. natural resources, labor and capital), consisting of both tangible (like machinery and buildings) and intangible assets (like patents and copyrights). Capital compensation refers to the remuneration for the use of capital assets.

(3) *capint*: capital intensity growth. Capital intensity is calculated as the ratio of capital stock to labor. The capital stock is the value of the fixed capital that can be used as input in production of goods and services in an accounting interval. For many countries, capital stocks have been constructed on the basis of the Perpetual Inventory Method in which the capital stock in year t is estimated as the sum of the depreciated capital stock in year $t - 1$ plus real investment in year t .

(4) *vax*: growth of value added exports. The value added exports is calculated in equation (2.4).

(5) *vaxshare*: growth of the share of country s in all value added exports. The share

of country s is calculated as $vaxshare^s = vax^s / \sum_r vax^r$ at the country level and as $vaxshare_i^s = vax_i^s / \sum_r vax_i^r$ at the sector level.

(6) *vaxr*: growth of the unit value added exports. The unit value added exports is also known as the VAX-ratio (Johnson and Noguera, 2012). It is calculated as the value added exports (of a country or industry) divided by the gross exports.

(7) *hsemp*: growth of the skill intensity of employment. The skill intensity of employment is obtained as the amount of high-skilled labor (measured in working hours) as a share of total employment. The labor force in each industry distinguishes low-skilled, medium-skilled and high-skilled workers.

(8) *hse*: growth of high-skilled labor exports. It is calculated as the amount of high-skilled labor (also measured in working hours) that is directly and indirectly needed in the production for foreign final demand.

Note that among the above eight indicators we adjust the four indicators that are based on gross exports, while we keep the conventional definitions for the other four indicators. Intuitively, to make all indicators consistent with the GVC framework, we could have also adjusted the other measures (i.e. labor productivity growth *labpr*, capital compensation growth *capcom*, capital intensity growth *capint*, and growth of the skill intensity of employment *hsemp*) from the GVC perspective by connecting them to foreign final demands. However, we choose not to do this because this may cause some conceptual bias for GVC-driven upgrading. That is, if we would calculate labor productivity as the ratio of the value added embodied in foreign final demand and the amount of labor embodied in foreign final demand, then we would capture the part of labor productivity that is linked to global production networks (GPNs). However, then we would neglect the isolated domestic part. We believe that even those sectors which are relatively isolated from GPNs can significantly contribute to the country's productivity. For example, China is a huge importer (rather than exporter) of natural resources. Its resource-extracting sectors (e.g. mining and quarrying) could have weak links to foreign final demands (not in the center of GPNs like electronic equipment), but may have strong links to domestic production. The development of excavation technology can also help a lot in search and exploration of latent natural resources, i.e. boosting productivity and

upgrading. We should not neglect this kind of upgrading in our framework. Taking this remark into account, we decide to keep the conventional definitions for the indicators *labpr*, *capcom*, *capint*, and *hsemp*.

Implementing the GVC perspective outlined above and calculating the indicators at country and sector level requires a time series of global multi-regional input-output tables. The World Input-Output Database (WIOD 2013 Release, Dietzenbacher et al., 2013) contains these tables and it provides the necessary employment data for the three skill levels using the same sector classification. It also provides capital compensation and capital stock data at the same sectoral level. The data are for 40 countries and the rest of the world (RoW) using a 35-sector classification (see Table A2.2 in Annex 2 for a listing of the countries and sectors). Considering that price fluctuation might affect the results, we use world input-output tables in previous years' prices and data on capital stock, gross output and value added at constant prices to calculate corresponding indicators.

The factor analysis in the next section uses the eight upgrading indicators for the years 1996-2009. Although the published input-output data cover the period 1995-2011, data for employment by skill type are not available for 2010 and 2011. Also, no labor data are available for sector c35 (Private households with employed persons), and this sector exports little in any case. All input-output calculations include 35 sectors (with labor input coefficients for sector c35 set equal to zero), but only the indicators for the first 34 sectors are used in our factor analysis.

2.3. Latent variables and factor analysis

2.3.1 Factor analysis: theory and method

In Section 2.2, we have identified eight indicators that have been proposed in the literature to measure industrial upgrading. These indicators do not perfectly correlate (see correlation matrix in Table 2.2), and therefore, each indicator contains a different aspect of the (latent) concept of industrial upgrading. It may even be the case that industrial upgrading is a multifaceted phenomenon that cannot be characterized well by a single indicator. But we believe that there may exist a lower number of underlying variables that captures common information (about upgrading) that is contained in the eight identified indicators of upgrading. Therefore, we propose to examine the dimensionality of these

indicators using EFA.

Factor analysis finds its origin in the measurement of human intelligence in psychometrics. Spearman (1904) observed that children's performance ratings, across seemingly unrelated school subjects, were positively correlated, and reasoned that these correlations reflected the influence of an underlying general mental ability that entered into performance on all kinds of mental tests. He suggested that all mental performance could be conceptualized in terms of a single general ability factor, which was termed human intelligence.

Similar to the measurement of human intelligence, we here use the eight different indicators that proxy different aspects of upgrading to measure the underlying latent variable 'upgrading'. However, (like later human intelligence measurement studies, see, e.g. Thomson, 1916; Carroll, 1993), we allow for the possibility that upgrading may be multidimensional. Previewing our results, we find that the latent variable 'industrial upgrading' consists of three separate latent sub-variables ('process upgrading', 'product upgrading', and 'skill upgrading').

Factor analysis describes the statistical variance common among observed, correlated variables (called indicators) in terms of a potentially lower number of unobserved (i.e. latent) sub-variables called factors. For present purposes, we employ EFA to identify the variance shared by the indicators to form a latent variable (industrial upgrading in our case). EFA creates the latent variable by assuming that the observed indicators are "generated" by a linear combination of other latent variables (the factors) and an individual error term. Following Wansbeek and Meijer (2000), this linear model can be expressed as follows:

$$\mathbf{x} = \mathbf{B}\boldsymbol{\xi} + \boldsymbol{\varepsilon}, \quad (2.5)$$

where $\mathbf{x}$ is a vector containing m observed indicators (in our case the eight indicators of industrial upgrading), and $\boldsymbol{\xi}$ is a vector of latent variables (*factors*) that the indicators are supposed to measure. $\mathbf{B}$ is the matrix of parameters (*factor loadings*) with dimension $(m \times k)$ (k is the number of factors and we will illustrate how to decide on the value for k in the following paragraph, $k \leq m$); the parameters are weights applied to the indicators that reveal the latent factors. As such, a (relatively) high (in absolute value)

factor loading implies that the observed indicator contains a relatively high amount of information about the specific latent factor. ε is the random measurement error term, and its variance is called the *unique variance*. It is the part of the observed indicator that cannot be explained by the underlying factors. The predicted values of ξ are $\hat{\xi}$, and are called *factor scores* (in our case upgrading scores).

Table 2.2 Correlation matrices of the upgrading indicators

	<i>labpr</i>	<i>capcom</i>	<i>capint</i>	<i>vax</i>	<i>vaxs</i>	<i>vaxr</i>	<i>hsemp</i>	<i>hse</i>
<i>labpr</i>	1							
<i>capcom</i>	0.43	1						
<i>capint</i>	0.56	0.16	1					
<i>vax</i>	0.34	0.25	0.14	1				
<i>vaxs</i>	0.34	0.29	0.15	0.75	1			
<i>vaxr</i>	0.11	0.08	-0.07	0.11	0.23	1		
<i>hsemp</i>	0.16	0.12	0.12	0.14	0.17	-0.07	1	
<i>hse</i>	0.15	0.06	-0.09	0.21	0.18	-0.31	0.55	1
<i>labpr</i>	1							
<i>capcom</i>	0.34	1						
<i>capint</i>	0.45	0.12	1					
<i>vax</i>	0.25	0.36	0.05	1				
<i>vaxs</i>	0.23	0.35	0.04	0.72	1			
<i>vaxr</i>	0.09	0.14	-0.01	0.15	0.19	1		
<i>hsemp</i>	0.12	0.01	0.14	0.12	0.02	-0.01	1	
<i>hse</i>	0.19	0.05	-0.18	0.44	0.42	-0.06	0.59	1

Notes: The table shows pairwise correlation coefficients. The estimates are based on the data over the period of 1996-2009. The acronyms refer to: (*labpr*) labor productivity growth, (*capcom*) capital compensation growth, (*capint*) capital intensity growth, (*vax*) growth of value added exports, (*vaxs*) growth of the share in value added exports, (*vaxr*) growth of unit value added exports, (*hsemp*) growth in the share of high-skilled labor in total employment, (*hse*) growth of high-skilled labor exports. The upper panel shows correlation coefficients for the sample of countries (40 countries $\times$ 14 years = 560 observations). The lower panel is for the sample of country-industries (40 countries $\times$ 34 industries $\times$ 14 years = 19040 observations). We note that there are 35 sectors in input-output tables from WIOD. But we exclude sector c35 because many indicators for this sector have null values due to the unavailability of basic data. Outside of that, there are more null values in our empirical test. For example, there are no capital stock data for some European countries for the years 2008 and 2009. In this case, the indicator “*capint*” will have null values for these countries. In the EFA, these cases with missing values are deleted to prevent overestimation (Tabachnick and Fidell, 2007).

In factor analysis it is critical to decide on the number of factors that will represent the indicators. Theoretically, we can get as many factors as we have indicators (m). But the

point of factor analysis is to reduce the number of information sources—a small group of factors that capture the core information from the indicators. There are three ways to decide on the appropriate number of factors to retain. First, is the Kaiser criterion, which recommends that all factors with eigenvalues greater than one should be included in the model. The second, is to ‘eyeball’ the scree plot of the eigenvalues for the factors and find a point where the plot suddenly gets relatively flat—the elbow of the scree plot (Cattell, 1966). Third, a likelihood ratio test can be performed to contrast the factor model against the alternative saturated model. Not surprisingly, the scree test has been criticized being too subjective, and the likelihood ratio test is sensitive to model overfitting. So we also consult information criteria such as Akaike’s information criterion and the Schwarz criterion.

It is possible that the resulting latent factors of the standardized outcome of the model are difficult to interpret (and hence to label). This happens when indicators load substantially on more than one factor. Fortunately, the matrix of factor loadings can be multiplied by any orthonormal matrix without affecting the distribution of the indicators. This multiplication, called a ‘rotation,’ can make the factor loadings more readily interpreted when it simplifies the factor structure. We use the Oblimin rotation, which minimizes the correlation between columns of the factor loadings matrix. In doing so, every indicator resulted in a high loading on just one factor and substantially lower loadings on all other factors. Such a clear distribution of the factor loadings matrix made it possible for us to attach an economic meaning to the estimated factors.

With the factor loadings set, it become possible for us to calculate factor scores. We use the Bartlett (1937) predictor, i.e., the best linear unbiased predictor of the factor scores. They are based on a linear combination of the estimated factor loadings and the observed indicators. The factor scores, in turn, serve as our measures of the dimensions of industrial upgrading. We thus call them upgrading scores hereafter. For a technical exposition on factor loading estimation and factor scores prediction, see Wansbeek and Meijer (2000).

2.3.2 Factor analysis: results

In this section, we employ EFA to examine the dimensionality of industrial upgrading and obtain upgrading scores. We provide estimation results for two samples as we aim to

analyze the upgrading performance at both country level and country-industry level. The first analysis consists of 40 countries, and the other consists of 1360 (40 countries $\times$ 34 industries) country-industries. Both analyses are based on eight indicators for the period 1996 to 2009. The pairwise correlation matrices of the indicators are shown in Table 2.2. As can be seen from Table 2.2, the different indicators of upgrading are correlated, as they should, because they are intended to measure the same concept. However, the correlations between these indicators are not perfect (i.e., -1 or 1). As they all intend to measure the same concept, we conclude that (it is very likely that) each indicator is an imperfect measure of upgrading, and each of them may capture some aspects of upgrading.

Figure 2.1 Cattell's scree test

Notes: The left plot shows the scree test for the sample of countries and the right one for the sample of country-industries.

To extract the appropriate number of factors to be included in the analysis, we use various statistical tests. First, we look at the scree plot. The left plot in Figure 2.1 shows the scree test for the sample of countries and the right for the sample of country-industries. Following the 'elbow criterion', the left plot is not very decisive for determining the number of factors to retain. Both the third and the fourth data points show some kind of an 'elbow'. However, it can be seen from the right plot that three factors have a large eigenvalue relative to the other factors and explain a relatively large part of the variance contained in all indicators. Hence, it seems appropriate to opt for three factors. This is confirmed by the fact that in both samples three eigenvalues exceed one and by the Kaiser criterion. Next, we perform the LR test, which compares the three-factor model against a saturated model. In both samples the test rejects the null-hypothesis that the estimates of a saturated model are equal in favor of the (restricted) three-factor model. It suggests the

three-factor model is appropriate. Finally, we also consider the value of Akaike's information criterion and the Schwarz criterion. For both criteria, we find the minimal test statistic in case of a factor model with three factors. All these outcomes lead us to conclude that three factors is the most appropriate option.

The estimation results of our factor analysis are shown in Table 2.3. The estimates in this table are best interpreted as correlation coefficients (factor loadings) between the factor and the indicators. Since the unrotated factor loadings are (as explained) not so informative, we show the results after Oblimin rotation. This leads to a pattern in which the first factor has a high loading on some indicators and the other factors on the other indicators, etc. In Table 2.3, it is clear that the same indicators have high loadings on the specific factor in both samples. For example, the indicator 'labpr' has a high loading (0.86) on the second factor while it has much lower loadings on the first (0.24) and third (0.03) factor. The indicators with high loadings can be used to interpret the factors. The indicator 'labpr', therefore, can be used to interpret the second factor.

Table 2.3 Rotated factor loadings matrices and unique variance estimates

Indicator	Factors				Factors			
	Product upgrading	Process upgrading	Skill upgrading	Unique variance	Product upgrading	Process upgrading	Skill upgrading	Unique variance
<i>labpr</i>	0.24	0.86	0.03	0.21	0.28	0.82	0.06	0.23
<i>capcom</i>	0.26	0.56	0.13	0.62	0.26	0.59	-0.13	0.55
<i>capint</i>	0.01	0.81	-0.08	0.34	0.16	0.84	0.01	0.26
<i>vax</i>	0.89	0.12	0.13	0.18	0.89	0.02	0.12	0.17
<i>vaxs</i>	0.92	0.13	0.03	0.13	0.90	0.01	0.10	0.16
<i>vaxr</i>	0.32	-0.11	-0.31	0.78	0.39	0.05	-0.20	0.75
<i>hsemp</i>	0.06	0.16	0.75	0.40	0.05	0.12	0.92	0.13
<i>hse</i>	0.19	-0.14	0.87	0.18	0.23	-0.26	0.78	0.28

Notes: Factor loadings are estimated using maximum likelihood method and the method of rotation is Oblimin. The left panel shows the estimates for the sample of countries and the right panel for the sample of country-industries. Factor loadings with absolute terms larger than 0.3 are in grey.

Recalling that we concluded in Section 2.2.1 that the eight (conventional) indicators were related to the four conceptual types of industrial upgrading proposed by Kaplinsky and Readman (2001) and Humphrey and Schmitz (2002), we believe it is not difficult to label our three quantitative dimensions of upgrading. In both samples, the first factor has

high loadings for growth of value added exports, growth of the share in value added exports and growth of the unit value added exports. These three indicators all relate to gaining more value through global value chains, which is related to the effect of making better products, hence product upgrading. Better products lead to more use by producers located further downstream in the GVC. The second factor follows from the three indicators (labor productivity growth, capital compensation growth, and capital intensity growth) with high loadings. These three indicators are clearly related to improving the efficiency of production processes in terms of their factor use. We can say that this factor is the quantitative reflection of process upgrading. Therefore, instead of devising a new label, we follow previous work and label the second factor as ‘process upgrading’. Finally, the third factor has high loadings for indicators that relate to the increase of skill intensity. This factor is thus labelled ‘skill upgrading’.

It should be stressed that we label the third factor as ‘skill upgrading’ (which is also a commonly used term, see, e.g. Taglioni and Winkler, 2016) instead of sticking to ‘functional upgrading’. That is because, although ‘skill upgrading’ provides information about functional upgrading, it focuses on the skill intensity of employment only and functional upgrading is broader in its coverage. As Timmer et al. (2019) recently suggested, once occupation data at the country-industry level are available, we can use them to distinguish the functions (fabrication, R&D, marketing and management, etc.) that are carried out by a particular occupational class of workers and, further, to measure functional upgrading.

Note that we do not include the fourth conceptual type of industrial upgrading (i.e. ‘intersectoral upgrading’) that was proposed by Kaplinsky and Readman (2001) and Humphrey and Schmitz (2002). This is because both ‘skill upgrading’ and ‘product upgrading’ capture elements of intersectoral upgrading. This is the case for ‘skill upgrading’ because the growth of high-skilled labor exports adopts the GVC perspective, which accounts for intersectoral linkages. This is also the case for our GVC-based ‘product upgrading’ because both domestic and international interdependencies between sectors are already well captured by the indicators based on value added exports.

Apart from the factor loadings, Table 2.3 also reports the estimated measurement errors of the individual indicators. The variance of an indicator contains two parts, the

common variance and the unique variance. The factors account for the common variance and the latter refers to the variance contained in the individual indicators that cannot be attributed to any of the factors. In other words, the indicators with a low unique variance contain relatively little variance that cannot be attributed to the multiple dimensions of upgrading.

Table 2.4 Correlation matrices of the factor scores for the three dimensions of upgrading

	Product	Process	Skill	Product	Process	Skill
Product	1.00			1.00		
Process	0.23	1.00		0.36	1.00	
Skill	0.15	0.09	1.00	0.22	0.12	1.00

Notes: The left panel shows the correlation coefficients between the three factors of upgrading for the sample of countries and the right panel does so for the sample of country-industries.

The upgrading scores we obtained reflect different dimensions of upgrading. Table 2.4 shows the correlation matrices of the predicted upgrading scores. It can be seen that the factors moderately correlate, which implies that they indeed reflect different dimensions of upgrading. Our findings are summarized by Figure 2.2.

Figure 2.2 A three-level hierarchy for industrial upgrading

2.4. Empirical results

Since individual countries and sectors are heterogeneous with respect to their production structures, the upgrading scores of the dimensions are country- and sector-specific. For example, the upgrading level of the Chinese transport equipment industry may be different from that of the Chinese chemicals industry as well as from that of the German transport equipment industry. We first present the country-specific results, which are based on the national sample. Then we zoom in further to consider sector-specific upgrading levels in subsection 2.4.2.

2.4.1. Country-specific results

Figure 2.3 presents a color map of the country-specific upgrading scores from 1996 to 2009. Note countries are ordered by their average scores on level of product, process and skill upgrading. The following observations can be made. First, the figure shows that the importance of the three dimensions of industrial upgrading varies across countries and within countries over time. Second, there are more red grids (reflecting high scores) for product upgrading than for process and skill upgrading. This implies that most countries performed better in product upgrading than in process and skill upgrading. Third, the upgrading scores largely decreased in 2009 since the color grids tend to be darker blue. The global financial crisis turns out to have a major effect upon upgrading scores.

We say a country has experienced upgrading (downgrading) when the factor score for this country is greater (less) than zero. The number of countries that have experienced upgrading or downgrading over the period of 1996-2009 is given in Table A2.3 of Annex 2. We see that most countries have experienced upgrading in this period. In almost all years before 2009, there are more upgrading countries than downgrading countries. But in 2009, when the global financial crisis started, the opposite is the case. Since 2002, most countries have performed ever better with respect to product upgrading. China is a typical beneficiary of the prosperous global economy. In Figure 2.3 we observe that the color grids of China's product upgrading are red and orange from 2002 to 2007. The underlying data show that China's product upgrading scores remained around 20% from 2002 to 2007. These results are consistent with other findings that suggest industrial upgrading in Chinese manufacturing in the 2000s (e.g. Kee and Tang, 2016). An explanation of this

stable growth is China's accession to the World Trade Organization (WTO) and its subsequent integration into global value chains.

Figure 2.3 The colormap of the country-specific upgrading scores

According to overall average scores of the dimensions over the entire period, emerging countries such as Turkey, China and India have experienced more upgrading than have developed countries such as the USA and Japan. This supports the convergence theory that developing countries have the potential to upgrade faster than developed countries. Figure 2.3 shows that Turkey, Romania, China, Poland and India are the top five countries to experience upgrading. But the rankings in Table A2.4 of Annex 2 reflect that the top five most upgraded countries on one dimension are not necessarily among the top five on another dimension. For example, countries with the highest scores on the 'product upgrading' dimension are China, Poland, Romania, Lithuania and Russia, while on the 'process upgrading' dimension they are Turkey, Romania, Estonia, Russia and China. Again, this reinforces the view that these three dimensions moderately correlate, but indeed are different dimensions of industrial upgrading.

2.4.2. Sector-specific results

Since sectors in different countries are heterogeneous with respect to their production structures, we now zoom in on sector-specific upgrading levels in this section. Figure 2.4 presents the color map of upgrading scores by sector over the period. They are average scores in a given year and are – by sector – derived as arithmetic means of sector scores for the 40 countries in a year. For example, the product upgrading score of Electrical and optical equipment (WIOD code: c14) in 1996 (see the first column and the third row in Figure 2.4) is 9.53%. It means that for the 40 sampled countries the average product-upgrading level for sector c14 is 9.53% in 1996. In Figure 2.4, industries are ordered by the rank of their average level of upgrading scores across the period. We find that in the global value chains the sector with most upgrading is Post and telecommunications (c27); it has an average score of 6.50%. Renting (c30) and Electrical and optical equipment (c14) are consistently (and respectively) the second and third highest in upgrading scores. In contrast, Textiles and textile products (c4) and Leather, leather and footwear (c5) have the lowest.

To be more specific, we have the following findings.

- Similar to the country-specific results, the rankings based on the ‘product upgrading’ dimension differ from that based on ‘process upgrading’ and ‘skill upgrading’.
- For all three dimensions, but especially for product upgrading, service sectors generally perform better than other sectors.
- In the manufacturing sectors, technology-intensive industries like Electrical and optical equipment (c14) and Transport equipment (c15) show higher levels of upgrading. They rank in the top end no matter whether the ranking is based on ‘product upgrading’ or any other dimensions.
- Resource- and labor-intensive industries have lower levels of upgrading. These industries are (in descending order of their rankings): Mining and quarrying (c2); Wood and products of wood and cork (c6); Coke, refined petroleum and nuclear fuel (c8); Textiles and textile products (c4) and Leather, leather and footwear (c5).
- Due to the global financial crisis, the extent of international trade in intermediates

and final goods largely decreased in 2009. The crisis turns out to have a dramatic effect on industrial upgrading. The upgrading scores, especially for product upgrading, largely decreased in 2009.

Figure 2.4 The colormap of the sector-specific upgrading scores

As illustrated above, Electrical and optical equipment (c14) is the most upgraded manufacturing sector. We will compare whether this typical globalized sector has experienced more upgrading in one country than in others. If we rank the 40 countries by their arithmetic means of the three upgrading scores (depicted in Figure 2.5), over the 14 considered years, we find:

- The average score is positive for each of the 40 countries. This implies that all countries have experienced upgrading in this period. But their upgrading is different. According to the average scores, Romania and China are the top two upgraded countries in Electrical and optical equipment (c14).
- If we rank the countries by the average level of product, process and skill dimensions separately, we find that China and Romania do not perform well in process upgrading (see Table A2.5 of Annex 2). Countries like South Korea, Finland, Japan, USA and Turkey perform best.

- The upgrading scores of Electrical and optical equipment (c14) have a much wider range than country- and sector-specific results. This implies that the scores of a particular sector for a specific country can fluctuate heavily.

Our results indicate that developing countries have generally upgraded more than developed countries in technology-intensive industries like Electrical and optical equipment and Transport equipment. Yet, it should be stressed that more upgrading does not imply higher absolute levels of competitiveness in GVCs. For example, China performed significantly better than USA, Japan and European countries in upgrading, but its absolute values of labor productivity, high-skilled intensity of workers and value added exports ratio were much lower than that of these countries.

Figure 2.5 The colormap of upgrading scores for electrical and optical equipment

2.4.3. Robustness check of country-specific results

So far, our country-specific results in subsection 2.4.1 are based on a sample that includes all sectors, both natural resource and non-resource intensive sectors. However, one may argue that the growth in the domestic value added exports at the country level does not necessarily indicate successful upgrading in GVCs. For example, the growth may

be due to an increase in exports of natural resources (which typically have a large domestic value added content). In this case, a country— in particular a country that is well endowed with natural resources – may experience some upgrading if, for example, a certain excavation technology is largely improved. This kind of upgrading in GVCs, however, plays no (or just a minor) role in countries with small endowments of natural resources. The literature on upgrading focuses on improvements that can be achieved through well-chosen policies, rather than on improvements that follow from pure technological changes (which are often considered as exogenous). So, for upgrading, we are particularly concerned with international success in relatively sophisticated sectors that use complex technologies and high-skilled human resources. To check the robustness of our country-specific results, we therefore redo the analysis, but exclude the resource-intensive sectors from the data. The excluded sectors are: Agriculture, hunting, forestry and fishing (c1); Mining and quarrying (c2); Wood and products of wood and cork (c6); Coke, refined petroleum and nuclear fuel (c8); Other non-metallic mineral (c11); Basic metals and fabricated metal (c12).

After the resource-intensive sectors have been dropped, we recalculated the indicators, repeated the factor analysis and got new upgrading scores for the countries. The comparison for the country-specific results before and after dropping six resource-intensive sectors is presented in Table A2.6 of Annex 2. We observe that the upgrading scores and rankings for the countries change slightly, which suggests that the results are generally robust and consistent. The second observation is that after dropping the resource-intensive sectors, almost all countries' upgrading scores increase except for Brazil, Australia, Mexico and Canada. This is consistent with the results in subsection 2.4.2 that the six resource-intensive sectors were among the least upgrading sectors. Hence, the average upgrading scores of the non-resource sectors become larger after dropping the least upgrading sectors.

Going into further details, we find that countries with a decreasing (increasing) share of their resource-intensive sectors in the exports climb up (descend) the ranking ladder. From Table A2.6 of Annex 2 we observe that Luxembourg climbs up the most (from rank 32 to 17), and Australia falls (from 25 to 29). Looking further into the underlying data, we find that the aggregate value added export share of these six sectors in the total value

added exports is very low of Luxembourg and it declines from 11.7% in 1995 to 4.9% in 2009. In contrast, the value added export share of the six excluded sectors is much higher in Australia and it increases from 38.3% in 1995 to 49.3% in 2009. From this we draw the conclusion that the changes in the export structure matters when it comes to the upgrading level in global value chains.

2.5. Conclusion

The main purpose of this chapter is to measure the industrial upgrading level of different countries and industries in global value chains. We point out that some conventional indicators (such as changes in trade volumes and changes in shares in world exports markets) are increasingly misleading in a world that increases the fragmentation of production along GVCs. Therefore, we adjust such indicators to the GVC perspective. Using eight indicators for upgrading in an exploratory factor analysis, we examine the multidimensionality of industrial upgrading. We wind up with three quantitative dimensions of industrial upgrading: process upgrading, product upgrading, and skill upgrading. With these dimensions, we compare and analyze the upgrading levels for countries and for sectors.

We find that process, product and skill upgrading correlate somewhat, but, indeed, reflect different dimensions of industrial upgrading. Importantly, the upgrading scores of the dimensions can be derived for sectors and countries. Almost all countries appear to have experienced downgrading in 2009 due to the global financial crisis. The results also follow the convergence theory as developing countries such as Turkey, China and India seem to have experienced more upgrading than did developed countries such as USA and Japan.

In terms of sectors, service sectors and technology-intensive sectors such as Electrical and optical equipment and Transport equipment experienced higher levels of upgrading than did resource- or labor- intensive sectors. The upgrading levels of technology-intensive sectors in developing countries was generally higher than in developed countries. Of course, higher upgrading levels suggest only faster growth; they do not mean that developing countries are absolutely better off positionally than are developed countries in GVCs.

We stress that industrial upgrading should be measured systematically due to its multidimensionality. So we propose three quantitative dimensions of industrial upgrading from a GVC perspective. From a policy perspective, we obtain useful empirical insights from our measures. For instance, we observe that China's Electrical and optical equipment performed quite well in product upgrading during our studied timeframe, especially after China's accession to the WTO. That is to say, by integrating into GVCs, China not only exported more Electrical and optical equipment, but also gained more value by exporting better and more sophisticated electrical products. A good example is the success of China's mobile phone industry in moving from the production of low-end feature phones to high-end smart phones (e.g. Huawei, Xiaomi, Oppo and Vivo). We also observe that China's Electrical and optical equipment industry performed less well in process (productivity) upgrading. This is likely because China integrated into the global value chain of Electrical and optical equipment by performing simple and low value-added tasks (assembly type of activities) on a large scale. Such assembly activities are labor intensive, and China has been able to engage in GVC via its low wages. As a consequence, China's performance is low after the growth of capital compensation and capital intensity are accounted. As its labor costs have effectively increased, China has become less interested in promoting such "simple" activities. Instead, China has become engaged in policies that can help promote productivity and competitiveness in more technology-intensive activities.

Our results also provide a quantitative basis for future research. One possible direction is to empirically examine how integrating into GVCs affects industrial upgrading. There has been a wide-ranging set of conflicting discussion about whether and to what extent integration into GVCs benefits its participants (i.e., developed and developing countries). One position is that the rise of GVCs enables developed countries to offshore some low value-added tasks so they can focus upon specializing in high value-added tasks. This approach supports industrial upgrading. But this suggests that the ensuing technological transfer from developed to developing countries could shift some competitive advantages from the former to the latter. To understand the viability and degree of such concerns, we need more empirical evidence. The latter requires the use of quantitative measures of industrial upgrading such as the ones we have proposed here.

Annex 2

Table A2.1 List of indicators, sources and their definitions

Indicator	Source	Definition
Labor productivity growth	Milberg and Winkler (2011) Taglioni and Winkler (2016)	Growth of labor productivity. Labor productivity is calculated as the ratio of value added to labor.
Capital compensation growth	Milberg and Winkler (2011)	Growth of capital compensation.
Capital intensity growth	Barrientos et al. (2011)	Growth of capital intensity. Capital intensity is calculated as the ratio of capital stock to labor.
Export growth	Kaplinsky and Readman (2005) Milberg and Winkler (2011) Barrientos et al. (2011)	Growth of value added exports (adjusted from GVC perspective).
Export share growth	Kaplinsky and Readman (2005) Amighini (2006) Li and Song (2011)	Growth of the share in value added exports (adjusted from GVC perspective).
Unit value exports growth	Kaplinsky and Readman (2005) Amighini (2006) Evgeniev and Gereffi (2008) Li and Song (2011)	Growth of the unit value added exports (adjusted from GVC perspective).
Increased skill intensity of employment	Milberg and Winkler (2011) Barrientos et al. (2011)	Growth of the skill intensity of employment. The skill intensity of employment is obtained as the amount of high-skilled labor as a share of total employment.
High-skilled labor exports	Milberg and Winkler (2011) Barrientos et al. (2011)	Growth of the amount of high-skilled labor that is directly and indirectly needed in the production for foreign final demand (adjusted from GVC perspective).

Table A2.2 WIOD country acronyms and industry classification

Acronym	country	Code	Industry description
AUS	Australia	c1	Agriculture, hunting, forestry and fishing
AUT	Austria	c2	Mining and quarrying
BEL	Belgium	c3	Food, beverages and tobacco
BRA	Brazil	c4	Textiles and textile products
BGR	Bulgaria	c5	Leather, leather and footwear
CAN	Canada	c6	Wood and products of wood and cork
CHN	China	c7	Pulp, paper, printing and publishing
CYP	Cyprus	c8	Coke, refined petroleum and nuclear fuel
CZE	Czech Republic	c9	Chemicals and chemical products
DNK	Denmark	c10	Rubber and plastics
EST	Estonia	c11	Other non-metallic mineral
FIN	Finland	c12	Basic metals and fabricated metal
FRA	France	c13	Machinery, nec
DEU	Germany	c14	Electrical and optical equipment
GRC	Greece	c15	Transport equipment
HUN	Hungary	c16	Manufacturing, nec; recycling
IND	India	c17	Electricity, gas and water supply
IDN	Indonesia	c18	Construction
IRL	Ireland	c19	Sale, maintenance and repair of motor vehicles and motorcycles; Retail sale of fuel
ITA	Italy	c20	Wholesale trade and commission trade, except of motor vehicles and motorcycles
JPN	Japan	c21	Retail trade, except of motor vehicles and motorcycles; Repair of household goods
KOR	Korea	c22	Hotels and restaurants
LVA	Latvia	c23	Inland transport
LTU	Lithuania	c24	Water transport
LUX	Luxembourg	c25	Air transport
MLT	Malta	c26	Other supporting and auxiliary transport activities; Activities of travel agencies
MEX	Mexico	c27	Post and telecommunications
NLD	Netherlands	c28	Financial intermediation
POL	Poland	c29	Real estate activities
PRT	Portugal	c30	Renting of machinery & equipment and other business activities
ROU	Romania	c31	Public admin and defence; Compulsory social security
RUS	Russia	c32	Education
SVK	Slovak Republic	c33	Health and social work
SVN	Slovenia	c34	Other community, social and personal services
ESP	Spain	c35	Private households with employed persons
SWE	Sweden		
TWN	Taiwan		
TUR	Turkey		
GBR	United Kingdom		
USA	United States		

Table A2.3 The number of upgrading and downgrading countries

	product		process		skill	
	upgrading	downgrading	upgrading	downgrading	upgrading	downgrading
1996	28	12	37	3	31	9
1997	25	15	37	3	35	5
1998	31	9	37	3	32	8
1999	21	19	36	4	34	6
2000	18	22	37	3	38	2
2001	27	13	33	7	29	11
2002	37	3	33	7	30	10
2003	37	3	30	10	30	10
2004	37	3	36	4	35	5
2005	29	11	36	4	35	5
2006	36	4	35	5	37	3
2007	40	0	36	4	33	7
2008	20	6	16	10	25	1
2009	6	18	13	11	4	20

Table A2.4 Ranking most upgraded and downgraded countries

Ranking	Product upgrading	Process upgrading	Skill upgrading
1	China	Turkey	Poland
2	Poland	Romania	Turkey
3	Romania	Estonia	China
4	Lithuania	Russia	Spain
5	Russia	China	Romania
6	Hungary	India	India
7	Bulgaria	Latvia	Ireland
8	Latvia	Slovenia	Italy
9	Slovak Republic	Indonesia	Austria
10	Greece	Lithuania	Brazil
11	Ireland	South Korea	Sweden
12	Estonia	Taiwan	South Korea
13	India	Ireland	Hungary
14	Turkey	Slovak Republic	Greece
15	Czech Republic	Hungary	Portugal
16	Indonesia	United States	Netherlands
17	Brazil	Portugal	Taiwan
18	Mexico	Bulgaria	Bulgaria
19	Malta	Czech Republic	Malta
20	Spain	Finland	Slovenia
21	Australia	Sweden	France
22	Luxembourg	United Kingdom	Belgium
23	Slovenia	Brazil	Denmark
24	Austria	Australia	Germany
25	United Kingdom	Canada	Indonesia
26	Cyprus	Poland	United Kingdom
27	Germany	Netherlands	Slovak Republic
28	South Korea	Cyprus	Luxembourg
29	Portugal	Greece	Czech Republic
30	Sweden	Belgium	Australia
31	Finland	France	Japan
32	Italy	Austria	Finland
33	Canada	Germany	Canada
34	Denmark	Denmark	Lithuania
35	Netherlands	Japan	Cyprus
36	United States	Mexico	Mexico
37	France	Italy	United States
38	Belgium	Spain	Latvia
39	Taiwan	Malta	Russia
40	Japan	Luxembourg	Estonia

Notes: The countries are ranked according to their average upgrading scores over the period 1996-2009. Ranking of overall average scores (i.e. on all three components of upgrading) is reflected in Figure 2.3.

Table A2.5 Ranking most upgraded and downgraded countries for Electrical and optical equipment

Ranking	Product upgrading	Process upgrading	Skill upgrading
1	Romania	South Korea	Romania
2	China	Finland	China
3	Czech Republic	Japan	Turkey
4	Hungary	United States	Poland
5	India	Turkey	Greece
6	Slovak Republic	Lithuania	Slovak Republic
7	Poland	India	Taiwan
8	Turkey	Slovenia	Italy
9	Bulgaria	Taiwan	Czech Republic
10	Finland	Estonia	Ireland
11	Lithuania	Czech Republic	India
12	South Korea	Cyprus	Spain
13	Indonesia	Sweden	Austria
14	Latvia	Germany	Brazil
15	Estonia	Portugal	Hungary
16	Taiwan	Denmark	Slovenia
17	Ireland	Hungary	Luxembourg
18	Sweden	Latvia	Portugal
19	Slovenia	Slovak Republic	South Korea
20	Greece	Ireland	Bulgaria
21	Luxembourg	Bulgaria	Canada
22	Germany	Russia	Latvia
23	Portugal	China	Finland
24	Denmark	Malta	Sweden
25	Austria	Indonesia	France
26	United States	France	Indonesia
27	Italy	Canada	Estonia
28	Spain	Poland	Netherlands
29	Russia	Australia	Denmark
30	Brazil	Austria	Australia
31	Mexico	United Kingdom	Germany
32	France	Mexico	Belgium
33	Canada	Luxembourg	Mexico
34	Japan	Belgium	Malta
35	Australia	Italy	United Kingdom
36	Malta	Spain	Japan
37	Belgium	Romania	United States
38	United Kingdom	Brazil	Lithuania
39	Netherlands	Netherlands	Russia
40	Cyprus	Greece	Cyprus

Notes: The countries are ranked according to their average upgrading scores over the period 1996-2009. Ranking of overall average scores (i.e. on all three components of upgrading) is reflected in Figure 2.5.

Table A2.6 Comparison for country-specific results: factor scores and rankings

Country	Factor score I (%)	Ranking I	Factor score II (%)	Ranking II
Turkey	9.98	1	10.20	1
Romania	9.79	2	9.81	3
China	9.75	3	9.97	2
Poland	8.81	4	8.94	4
India	7.87	5	8.13	5
Ireland	6.87	6	7.14	7
Russia	6.66	7	6.82	9
Hungary	6.64	8	6.89	8
Lithuania	6.37	9	6.63	10
Latvia	6.12	10	6.38	11
Bulgaria	5.93	11	6.27	12
Indonesia	5.92	12	7.56	6
Estonia	5.79	13	5.93	14
Slovak Republic	5.75	14	5.88	15
Greece	5.50	15	6.01	13
Slovenia	5.37	16	5.46	16
Brazil	4.96	17	4.82	20
South Korea	4.86	18	4.93	19
Czech Republic	4.76	19	4.96	18
Spain	4.58	20	4.69	21
Austria	4.15	21	4.21	22
Portugal	3.95	22	4.05	23
Malta	3.86	23	3.89	25
Sweden	3.84	24	3.91	24
Australia	3.65	25	3.35	29
Italy	3.44	26	3.53	26
United Kingdom	3.41	27	3.48	27
Taiwan	3.36	28	3.38	28
Netherlands	3.17	29	3.23	30
Germany	2.98	30	3.05	31
Mexico	2.97	31	2.90	33
Luxembourg	2.93	32	5.00	17
Finland	2.79	33	2.91	32
Denmark	2.57	34	2.59	35
Cyprus	2.54	35	2.78	34
France	2.33	36	2.42	36
Belgium	2.31	37	2.36	37
Canada	2.30	38	2.06	39
United States	2.21	39	2.24	38
Japan	1.08	40	1.11	40

Notes: Factor score I and ranking I show the country-specific results for the aggregate sample which includes 34 industries. Factor score I shows the overall average scores of the three dimensions over the period 1996-2009, which are shown in Figure 2.3. Ranking I is the same as the ranking shown in Figure 2.3. Factor score II and ranking II show the results for the sample which drops six resource-intensive industries.

Chapter 3

Global value chain participation and its impact on industrial upgrading⁷

3.1 Introduction

The nature of production and international trade has changed in an important way during the last decades.⁸ Whereas countries (or firms) used to perform almost all tasks of the overall production process before exporting the product to other countries for consumption, advances in transport and telecommunication technology make it nowadays possible for a country to unbundle its tasks. That is, to minimize total production costs, firms perform one or few specific tasks themselves and then offshore other tasks to foreign countries for the next layer of production (Grossman and Rossi-Hansberg, 2008, 2012). Baldwin and Robert-Nicoud (2014) refer to the traditional trade pattern as ‘trade in goods’ and call the new phenomenon ‘trade in tasks’. The set of all value-adding tasks that are needed in production is called a value chain. In the ‘trade in goods’ era, most value chains took place within a single country. Nowadays, value chains have become “global” and the production is fragmented into smaller tasks that are carried out in multiple countries. With the enormous expansion of global value chains (GVCs)⁹, the relevance of GVCs has been set out in the academic literature (see, e.g., Johnson and Noguera, 2012; Koopman et al., 2014; Los et al., 2016) and new data sets on “value-added” trade (that remove the biased picture of trade benefits in traditionally measured ‘gross’ trade) emerged. One example is the OECD-WTO Trade in Value Added database (OECD-WTO, 2012).

Countries (or firms) that perform one or some tasks in the production phase of globally produced products are called GVC participants. In this chapter, we examine the effects of GVC participation on a country’s degree of industrial upgrading. Industrial

⁷ This chapter is co-authored with Erik Dietzenbacher and Richard Jong-A-Pin and is accepted by *World Economy*.

⁸ See, for example, Baldwin (2006), Grossman and Rossi-Hansberg (2008, 2012), Hummels et al., (2001), Jones and Kierzkowski (1990), Rodriguez-Clare (2010).

⁹ However, Timmer et al. (2016) observe that GVC expansion halted since 2011, and find that major reasons are the decreasing foreign demand and a shift toward service demand.

upgrading is a term that frequently pops up in governmental reports, in economic policy documents and in mass media. However, industrial upgrading is a concept with many definitions as different users seem to differ in the interpretation of the concept (see Chapter 2 or Tian et al., 2019). Irrespective of the definition, industrial upgrading has the aim to improve a country's competitive advantage and enlarge the benefits of participation in production tasks. An unresolved debate is whether and to what extent GVC participation (or integration) benefits industrial upgrading in developed and in developing countries.

Two dominant views can be distinguished. The first view states that GVCs mainly benefit developed countries' upgrading and that the opportunities for developing countries are limited. There are studies that emphasize that the rise of GVCs enables developed countries to offshore parts of low value-added tasks and specialize in high value-added tasks (e.g. Baldwin and Robert-Nicoud, 2014; Bhagwati et al., 2004; Mankiw and Swagel, 2006). This specialization decreases production costs and increases resource allocation to more sophisticated tasks (and products), both of which are good for industrial upgrading in developed countries. However, with this specialization, a concern for developing countries is that GVCs will leave them little scope for upgrading if the country's GVC participation is locked mostly in exploiting natural resources, unskilled and low-cost labor, or simple tasks (Gereffi et al., 2005; UNCTAD, 2013).

The second view states that GVC participation provides more opportunities for developing countries to upgrade (Navas-Alemán, 2011). Hira and Hira (2008), Li and Liu (2014) and Samuelson (2004), for example, stress that GVCs facilitate technological transfers from developed to developing countries and, hence, shift competitive advantage from the former to the latter. Also, GVCs offer developing countries good opportunities to integrate into global production networks without having to master all relevant knowledge and without the need to possess all resources of the overall production process of a product (Amendolagine et al., 2019; Taglioni and Winkler, 2016). It enables developing countries to enter into more modern manufacturing by initially performing simple tasks, which evolve through learning into more sophisticated tasks (see, e.g. Lin, 2011; Lin and Wang, 2012; Pietrobelli and Rabellotti, 2011).

Each of these viewpoints highlights one or more important aspects of the relationship

between GVCs and industrial upgrading. This suggests that GVCs have uncertain effects on industrial upgrading which raises the following two questions. What concerns about GVCs are justified and for which countries will GVC participation lead to better industrial development? To answer these questions, we examine these issues empirically as there has been to date, to the best of our knowledge, no such study.

The purpose of this study is twofold. The first aim is to empirically analyze the effect of GVC participation on industrial upgrading. In our analysis, we measure GVC participation from two perspectives: backward and forward. The backward links reflect the use of foreign intermediate inputs to produce the final products of a GVC (Los et al., 2015). The forward links reflect the value-added in the exported intermediate inputs. We distinguish between backward and forward GVC participation, because different studies (e.g., Havranek and Irsova, 2011; Javorcik, 2004) suggest that backward and forward links have different effects on productivity improvement.

Since different studies suggest that industrial upgrading is a multidimensional phenomenon (see Humphrey and Schmitz, 2002; Pipkin and Fuentes, 2017; Tian et al., 2019), we use three quantitative dimensions of industrial upgrading as our dependent variables as proposed by Tian et al. (2019). These measures capture process upgrading, product upgrading, and skill upgrading.

Using the world multi-regional input-output tables from the World Input-Output Database (WIOD, 2013, see Dietzenbacher et al., 2013), we calculate the GVC participation of 1360 country-industries (40 countries with 34 industries) for the period 1995-2011.¹⁰ We combine this with available data from the WIOD Socio Economic Accounts to calculate the three measures of industrial upgrading for the period of 1995-2009. We use the data to estimate a panel data regression model and find that an increase in GVC participation (no matter whether backward or forward) increases industrial upgrading in product and skill upgrading. However, we also find that backward and forward GVC participation show different effects on process upgrading.

The second aim of this chapter is to test whether a country's development stage

¹⁰ We are also aware of WIOD (2016 release) which provides input-output tables for the period 2000-2014. However, the new release does not provide the coupled Socio Economic Accounts which allow us to calculate the measures of industrial upgrading.

matters for the effects of GVC participation on industrial upgrading. We do this by distinguishing between developing countries and developed countries, and we test whether backward or forward GVC participation have stronger or weaker effects on industrial upgrading in developing countries or developed countries. Our results show that backward participation has stronger effects on industrial upgrading in developing countries, while forward participation provides higher level of upgrading effect on developed countries. Specifically, the process upgrading (productivity improvement) of developing countries relies more on backward GVC links than forward links. Comprehensively considering the effects of backward and forward GVC participation on the three dimensions of industrial upgrading, we do find that GVC integration benefits industrial upgrading for both developed and developing countries. Our results suggest that theoretical concerns that GVC integration have negative effects are not supported by the data. A nation that seeks to ban the international reorganization of production may find that such reluctance will hinder industrial upgrading. That is, attempts to resist GVC participation while other nations embrace it may be futile or even counterproductive.

The remainder of the chapter proceeds as follows. Section 3.2 discusses the theoretical channels through which GVC participation affects industrial upgrading in developed and developing countries. Section 3.3 first presents the indicators of GVC participation and the three dimensions of industrial upgrading and continues with the empirical specification. In Section 3.4 and Section 3.5 we introduce data and present econometric results. Finally, Section 3.6 concludes.

3.2 Literature review: how GVC participation affects industrial upgrading

Trade can benefit its participants through a myriad of channels including economies of scale, deepening specialization and efficient reallocation of resources. As to trade in final goods, the traditional gains-from-trade theorem based on the Heckscher-Ohlin-Vanek framework states that trade entails gains for all parties involved, and some trade is better than none. However, recent theoretical research shows that GVCs have changed the way trade is conducted, which has led to discussion about the impact of GVC participation on industrial upgrading. This literature examines typical GVCs that link low-wage countries,

the South, to technologically advanced nations with high wages, the North. The difference between the two country groups generates incentives to trade tasks, which in turn create a set of benefits and costs depending on the assumptions of the models.

There has been much discussion about the consequences of increased production fragmentation and offshoring on the North's and the South's industrial upgrading. From this discussion, two popular viewpoints can be clearly distinguished. The first states that it is the North that mainly benefits from GVC participation, while the opportunities for the South are limited. This view emphasizes both the static (cheaper intermediate inputs) and dynamic (reallocation of factors towards more efficient tasks) positive effects of GVC participation on the North. For example, Baldwin and Robert-Nicoud (2014) show how the rise of GVCs causes productivity and welfare improvement for the North. In their framework, in which trade in goods and trade in tasks both arise, both the North and the South compete for the production of either a good or a task. Since the North has lower unit labor requirements but higher wages, the rise of GVCs enables the North to combine its superior technology with low wages in the South through offshoring some of its tasks. The North can specialize in tasks which require better technology and generate higher value-added. This specialization decreases average production costs for the North and leads to an increased allocation of resources to more sophisticated tasks, causing a rise in Northern output and wages. In other words, participating in GVCs enables the North to have cheaper intermediate inputs and reallocate more domestic resources toward higher value-added tasks, both of which have positive effects on industrial upgrading. On the other hand, the South is concerned that GVCs will force the South to specialize in simple and low value-added tasks for Northern final goods production with little scope for industrial upgrading in the long run (UNCTAD, 2013).

In contrast, a different theory states that it is the South that will upgrade most when it participates in GVCs. In Li and Liu (2014)'s dynamic model, a final good is produced using a continuum of tasks under the assumption that for each task Northern unit labor requirements are equal or below the ones of the South. The rise of GVCs allows the North and the South to specialize in tasks according to their skills and comparative advantage. Over time, participation in GVCs enables the South to lower its unit labor requirements, improve its productivity and make more sophisticated products through a

learning-by-doing process, which leads the North to offshore more tasks to the South in the next period. This process will repeat itself until it reaches an ‘integrated equilibrium’, in which wages and technology are equalized. Throughout the process the South upgrades, but the North encounters downgrade pressure because its competitive advantage deteriorates when the South becomes more productive in tasks that had been performed in the North before. Rodríguez-Clare (2010) has a similar view. He embodies the Grossman and Rossi-Hansberg (2008) approach in a Ricardian model à la Eaton and Kortum (2002), and shows that increases in offshoring benefit the South but harm the North in the short run.

However, Rodríguez-Clare (2010) also shows that the North can also upgrade in the long run. He points out that technology levels are determined by research efforts and research productivity. The rise of GVCs makes it possible that the resources released by offshoring in the North lead to an increased allocation of resources to research. According to his dynamic model, the overall effects of GVC participation should be positive for the North as long as the reallocation between production and research is not too sluggish. In other words, enabled by the shift of resources toward research, the North can upgrade by doing more sophisticated tasks or creating new technologies. Baldwin and Robert-Nicoud (2014) also show that for both the North and the South upgrading is possible when there is technology diffusion. Recent empirical findings suggest that this is very likely. For instance, Piermartini and Rubínová (2014) provide evidence that GVCs are a much stronger facilitator of knowledge spillovers than final goods trade. And Benz et al. (2015) present firm-level evidence on spillovers induced by offshoring.

To summarize, the discussed works suggest different channels through which GVC participation affects industrial upgrading of its participants. The main transmission channels include increased availability and quality of inputs, technology spillovers from multinationals, learning-by-doing, gains from specialization as well as resources reallocation, and pro-competitive effects of global competition (Criscuolo and Timmis, 2017). Gereffi et al. (2005) and Gereffi and Sturgeon (2013) also stress the importance of national governance and industrial policy for industrial development in a GVC era. However, the above claims are purely theoretical and the materialization of these theoretical effects is uncertain. Therefore, empirical research is necessary for testing the

theoretical predictions.

A few recent studies attempt to quantify the effects of GVC participation on economic upgrading. Kummritz et al. (2017) use the level of domestic value added generated in a sector as the measure of economic upgrading, and quantify the effects of both backward (measured by the amount of foreign value added embodied in exports) and forward (measured by the amount of domestic value added re-exported by third countries) GVC participation on sectoral value added growth. They find that GVC integration generally increases an industry's value added, and they also highlight the importance of country-specific characteristics and policy for benefitting from trade integration. Constantinescu et al. (2019) also use the foreign value-added embodied in a country's gross exports as the measure of backward GVC linkage to investigate whether it increases productivity. They find that backward participation in GVCs is a significant driver of labor productivity in a set of 40 countries since 1995 (using WIOD 2016 release). Pahl and Timmer (2020) confirm the findings of Constantinescu et al. (2019), using a wider set of countries and including more lower-income countries for a longer time period. Yet, these studies only focus on value-added gains or labor productivity, i.e., one aspect of economic upgrading. Instead, the aim of this chapter is to fully consider the multidimensionality of industrial upgrading. Moreover, we employ improved indicators of backward and forward GVC participation, as we will present in the next section.

3.3 Methodology

3.3.1 GVC participation indicators

GVC participation indicators measure to what extent countries/industries/firms are involved in vertically fragmented production. We use indicators based on backward linkages and on forward linkages, reflecting the two different ways in which a country can participate in GVCs. The backward linkage focuses on a country's GVC participation to the extent that they import intermediates to produce products, while the forward linkage reflects that a country's GVC participation insofar they supply intermediate inputs to other countries for further production. The backward linkage is also referred to as a user's perspective and the forward linkage is referred to as a provider's perspective.

In this chapter, we adopt the decomposition framework of Wang et al. (2017) and construct forward and backward GVC participation indices by decomposing value-added and final goods in an inter-country input-output (IO) model. Our starting-point is the standard world multi-regional IO accounting framework (see Miller and Blair, 2009) in Table 2.1 with n countries and m sectors (or industries) in each country. In compact form, the static input-output system (see equation 2.3) can be rewritten as $\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{f}$ and the solution is given by

$$\mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{B}\mathbf{f}, \quad (3.1)$$

where $\mathbf{y}$ is a $nm \times 1$ vector that gives all country-sectors' gross outputs (inputs), $\mathbf{A}$ the $nm \times nm$ global input-output matrix, and $\mathbf{f}$ a $nm \times 1$ vector of final demand. $\mathbf{I}$ is an $(nm \times nm)$ identity matrix with ones on the diagonal and zeros elsewhere. $\mathbf{B} \equiv (\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse with element b_{ij}^{sr} , which gives the extra gross output of sector i in country s that is required for a one-unit increase in final demand of sector j in country r . In its partitioned form this $nm \times nm$ matrix is given by

$$\mathbf{B} = \begin{bmatrix} \mathbf{B}^{11} & \dots & \mathbf{B}^{1r} & \dots & \mathbf{B}^{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{B}^{r1} & \dots & \mathbf{B}^{rr} & \dots & \mathbf{B}^{rn} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{B}^{n1} & \dots & \mathbf{B}^{nr} & \dots & \mathbf{B}^{nn} \end{bmatrix}.$$

Using the method of Wang et al. (2017), we decompose both the intermediate input matrix and final demand vector into two parts and rewrite $\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{f}$ as

$$\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{f} = \mathbf{A}^D\mathbf{y} + \mathbf{f}^D + \mathbf{A}^F\mathbf{y} + \mathbf{f}^F, \quad (3.2)$$

$$\text{where } \mathbf{A}^D = \begin{bmatrix} \mathbf{A}^{11} & \dots & \mathbf{0} & \dots & \mathbf{0} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{0} & \dots & \mathbf{A}^{rr} & \dots & \mathbf{0} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{0} & \dots & \mathbf{0} & \dots & \mathbf{A}^{nn} \end{bmatrix} \text{ and } \mathbf{f}^D = \begin{pmatrix} \mathbf{f}^{11} \\ \vdots \\ \mathbf{f}^{rr} \\ \vdots \\ \mathbf{f}^{nn} \end{pmatrix}.$$

$\mathbf{A}^D$ is a $nm \times nm$ diagonal block matrix of domestic input coefficients with $\mathbf{0}$ standing for a matrix of $m \times m$ dimension filled with zeros. $\mathbf{A}^F$ is a $nm \times nm$

off-diagonal block matrix of imported input coefficients, and $\mathbf{A}^F = \mathbf{A} - \mathbf{A}^D$. $\mathbf{f}^D$ is a $nm \times 1$ vector of final demand for domestic final products, and $\mathbf{f}^F = \mathbf{f} - \mathbf{f}^D$ is a $nm \times 1$ vector of final demand for foreign final products, i.e., final product exports. Rearranging equation (3.2) yields

$$\mathbf{y} = (\mathbf{I} - \mathbf{A}^D)^{-1} \mathbf{f}^D + (\mathbf{I} - \mathbf{A}^D)^{-1} (\mathbf{A}^F \mathbf{y} + \mathbf{f}^F) = \mathbf{L} \mathbf{f}^D + \mathbf{L} \mathbf{f}^F + \mathbf{L} \mathbf{A}^F \mathbf{B} \mathbf{f}, \quad (3.3)$$

where $\mathbf{L} = (\mathbf{I} - \mathbf{A}^D)^{-1}$ is a $nm \times nm$ diagonal block that denotes the domestic Leontief inverse.

Let $(\mathbf{v}^s)' = (\mathbf{w}^s)'(\hat{\mathbf{y}}^s)^{-1}$ be the m -element row vector which gives the value-added coefficients in country s . Its typical element $v_j^s = w_j^s/y_j^s$ gives the value-added (in dollars) generated in sector j in country s per dollar of output in this sector. Combining this with equation (3.3), we can decompose country s ' sectoral value-added as

$$\mathbf{w}^s = \hat{\mathbf{v}}^s \mathbf{y}^s = \hat{\mathbf{v}}^s \mathbf{L}^{ss} \mathbf{f}^{ss} + \hat{\mathbf{v}}^s \mathbf{L}^{ss} \sum_{r \neq s}^n \mathbf{f}^{sr} + \hat{\mathbf{v}}^s \mathbf{L}^{ss} \sum_{r \neq s}^n \mathbf{A}^{sr} \mathbf{y}^r. \quad (3.4)$$

This decomposition equation gives the distribution of value-added created in one country-sector that is absorbed by final products in all country-sectors.¹¹ It has three terms. The first term is domestic value-added (DVA) in production of final products for domestic demand without border-crossing production activities. The second term is DVA in production of final products exports, which does not involve any border-crossing production activities either. This part of DVA crosses national borders once, but only for final consumption. The third term is DVA in production of intermediate exports. It is DVA that relates to production activities outside the source country and it denotes the source country's contribution to global production.

Decomposition equation (3.4) shows how a country-sector's value-added is used as primary input to produce goods and services, and to which country it is sold (i.e. "where does the value-added go to"). This is a so-called provider's perspective. From this

¹¹ Note that we can write $\mathbf{y}^r = \sum_u^n \mathbf{B}^{ru} (\sum_g^n \mathbf{f}^{ug})$ which implies that each country-sector is included as location of absorption.

perspective, the forward GVC participation index (**fgvc**) is the DVA embodied in the exports of intermediate products as a share of the country-sector's total value-added, namely

$$\mathbf{fgvc} = (\hat{\mathbf{w}}^s)^{-1} \hat{\mathbf{v}}^s \mathbf{L}^{ss} \sum_{r \neq s}^n \mathbf{A}^{sr} \mathbf{y}^r, \quad (3.5)$$

where the numerator is the third term in equation (3.4). Note that by combining (3.4) and (3.5) we can also write

$$\mathbf{fgvc} = \boldsymbol{\iota} - (\hat{\mathbf{w}}^s)^{-1} \hat{\mathbf{v}}^s \mathbf{L}^{ss} (\mathbf{f}^{ss} + \sum_{r \neq s}^n \mathbf{f}^{sr}) = \boldsymbol{\iota} - (\hat{\mathbf{w}}^s)^{-1} \hat{\mathbf{v}}^s \mathbf{L}^{ss} \mathbf{f}^s, \quad (3.6)$$

with $\mathbf{f}^s = \sum_u^n \mathbf{f}^{su}$.

The backward GVC participation indicator is constructed from the decomposition of final products. The value of a final product is equal to the summation of value-added contributions by all country-sectors. The traditional way (see, e.g. Los et al., 2015) of decomposing country s 's final products ($\mathbf{f}^s = \sum_u^n \mathbf{f}^{su}$) is to decompose them into two parts: value-added contributed by country s itself and value-added sourced from all foreign countries. That is $(\mathbf{f}^s)' = (\mathbf{v}^s)' \mathbf{B}^{ss} \sum_u^n \hat{\mathbf{f}}^{su} + \sum_{r \neq s}^n (\mathbf{v}^r)' \mathbf{B}^{rs} \sum_u^n \hat{\mathbf{f}}^{su}$. The backward GVC participation can now be defined as the share of foreign value-added (the second part) in the total value of this final product. That is, $[\sum_{r \neq s}^n (\mathbf{v}^r)' \mathbf{B}^{rs} \hat{\mathbf{f}}^s] (\hat{\mathbf{f}}^s)^{-1} = \sum_{r \neq s}^n (\mathbf{v}^r)' \mathbf{B}^{rs}$. However, this is not what we propose. The reason is that this measure of backward GVC participation would not include the following phenomenon. Consider a German car that is assembled in a German factory. It contains accessories that are made by workers in the Slovak Republic (and thus Slovak value-added). The production of these accessories uses steel imported from Germany and thus German value-added. In our opinion, the German value-added that is in the steel should be part of Germany's GVC participation. The traditional measure, however, excludes it because it is embodied in German final products (namely cars).

We suggest that cases like the German value-added in steel production belong to GVC participation since they involve border-crossing GVC production activities.

Therefore, we decompose country s 's final products as¹²

$$(\mathbf{f}^s)' = (\mathbf{v}^s)' \mathbf{L}^{ss} \hat{\mathbf{f}}^{ss} + (\mathbf{v}^s)' \mathbf{L}^{ss} \sum_{r \neq s}^n \hat{\mathbf{f}}^{sr} + \text{border_crossing}. \quad (3.7)$$

This decomposition gives the contribution of value-added from all source country-sectors that are embodied in country s 's sectoral final products. The first term represents final products that are produced with only domestic value-added and that are consumed domestically. It does not involve any border-crossing trade or foreign production activities. The second term refers to final products that are produced with only domestic value-added but that are consumed directly by the importing country r . This is traditional final products trade and it does not involve any foreign production activities either. The third term refers to all value-added that is embodied in country s 's final products and that includes border-crossing production activities. These are the foreign value-added in the imported inputs but also the domestic value-added that is in exported intermediate products (e.g. German steel) which return in a next stage when they are embodied in imports (Slovak accessories).

Decomposition equation (3.7) shows where a country-sector's final products come from and where the value is created. This is the so-called user's perspective. From here, the backward GVC participation index (**bgvc**) can be calculated as the share of a country-sector's final products produced with value-added that is involved in GVC activities, namely $\mathbf{bgvc} = (\text{border_crossing})(\hat{\mathbf{f}}^s)^{-1}$. Using (3.7) it follows that

$$\mathbf{bgvc} = \mathbf{I}' - (\mathbf{v}^s)' \mathbf{L}^{ss} (\hat{\mathbf{f}}^{ss} + \sum_{r \neq s}^n \hat{\mathbf{f}}^{sr}) (\hat{\mathbf{f}}^s)^{-1} = \mathbf{I}' - (\mathbf{v}^s)' \mathbf{L}^{ss}. \quad (3.8)$$

Note that the structure of equation (3.8) is exactly the same as the structure of equation (3.6).

A different (more traditional) measure of GVC participation dates back to Hummels et al. (2001), who propose vertical specialization. It refers to the imported foreign content

¹² It can be shown that the row vector $\text{border_crossing} = \sum_r^n (\mathbf{v}^r)' \mathbf{L}^{rr} \sum_{u \neq r}^n \mathbf{A}^{ur} \mathbf{B}^{rs} \sum_g^n \hat{\mathbf{f}}^{sg}$.

(both direct and indirect foreign value-added) in a country's exports. In our robustness analysis we use this measure and refer to it as VS. A second measure (to which we will refer as VS1) is also proposed by Hummels et al. (2001) and looks at vertical specialization from the export side. It is calculated as the value of a country's intermediate exports that are used as inputs into another country's production of export goods. Hummels et al. (2001) provide a mathematical definition for VS using national input-output model, but do not provide mathematical terms for VS1. Koopman et al. (2014) have provided mathematical terms for both VS and VS1 based on their decomposition of gross exports using the world multi-regional IO framework. However, Wang et al. (2017) point out that the shares in the VS and VS1 measures use gross exports as the denominator, which may cause double counting problems and bias for some industries. Therefore, in this chapter we adopt the measures defined above in (3.6) and (3.8) for the baseline analysis, and we use the VS and VS1 share to examine the robustness of our results.

3.3.2 Empirical specification

To capture the effects of GVC participation on industrial upgrading, we estimate a panel fixed effects model for industry i of country r at time t :

$$upg_{i,r,t} = \alpha + \beta_1 gvc_{i,r,t} + \alpha_{i,r} + \alpha_{i,t} + \alpha_{r,t} + \varepsilon_{i,r,t} . \quad (3.9)$$

As the dependent variable, we use (one of) the measures of industrial upgrading ($upg_{i,r,t}$) which are introduced in Chapter 2. GVC participation ($gvc_{i,r,t}$) is proxied by either forward GVC participation ($fgvc_{i,r,t}$) or backward participation ($bgvc_{i,r,t}$), which were both defined in Section 3.3.1. In the benchmark regressions, the independent variables are lagged by one period. A set of industry-country fixed effects ($\alpha_{i,r}$), industry-year fixed effects ($\alpha_{i,t}$) and country-year fixed effects ($\alpha_{r,t}$) are included. Note that we have accounted for possible country, industry and time unobserved heterogeneity by using such fixed effects, and we thus argue that omitted variables bias is not a (big) concern. The model controls for country specific effects, for instance, due to country-size differences: larger countries tend to have lower GVC participation because more intermediates are

domestically available (see, e.g., Baldwin and Lopez-Gonzalez, 2015). It also captures effects due to country-industry specific differences. For example, Russian mining and petroleum industries have higher (forward) GVC participation than other countries because of its abundant natural resources. We are also aware of that some alternative variables such as the role of national states and state capacity could be potential explanations for upgrading. However, we stress that the main goal of this chapter is to examine the relation between GVC participation and upgrading, instead of to come up with an exhaustive analysis what explains upgrading. We thus leave some other variables captured by fixed effects.

To examine whether the stage of development matters for the contribution of GVC participation to industrial upgrading, we also estimate models that include an interaction between the stage of development (d_r) and our GVC participation indicators to equation (3.9):

$$upg_{i,r,t} = \alpha + \beta_1 gvc_{i,r,t} + \beta_2 gvc_{i,r,t} * d_r + \alpha_{i,r} + \alpha_{i,t} + \alpha_{r,t} + \varepsilon_{i,r,t} . \quad (3.10)$$

We include a dummy variable d_r to distinguish between countries that are developed ($d_r = 1$) and countries that are developing ($d_r = 0$). To categorize countries, we use the classification of the World Bank based on gross national income (GNI) per capita for year 1995 (i.e., the start of the sample period). Developed countries refer to as high-income economies and developing countries refer to as low- and middle-income economies.¹³ It should be noted that we have not included d_r independently in the regression specification. This is because this variable is fully captured by the country fixed effects, which ensures that our model is properly specified. In the empirical analysis we also run regressions on developed and developing countries separately by splitting the sample. It turns out that a sample split is identical to a fully interacted model. The estimated coefficients based on the split samples tell the same story as our interaction model. We

¹³ The World Bank classifies economies into four income groups: low, lower-middle, upper-middle, and high income. However, WIOD includes only a few low-income economies (only China and India in 1995). It will sharply reduce the degrees of freedom and may cause estimation bias if we run regression using the four-group classification.

thus present the results using our interaction setting.

We would further like to stress that our results mainly show associations between GVC participation and industrial upgrading, rather than causal effects. In particular, the regression model is potentially plagued by reverse causality. High level of upgrading (e.g. high productivity improvement), for example, may be the pre-requisite for integration into GVCs. We make efforts to deal with this issue in the following empirical analysis by using lagged independent variables and an instrumental variable to do robustness tests. However, this may be insufficient to eradicate the reverse causality concern. For this reason, we refrain from stating any causal relationships.

3.4 Data source and descriptive analysis

3.4.1 Data source

We use the WIOD (2013 release) as our primary data source. WIOD covers 35 sectors for 40 countries (see Table A3.1 in Annex 3 for an overview of the countries and sectors) in the world including most of the developed countries as well as major emerging economies like Eastern European countries and the ‘BRIC’ (Brazil, Russia, India and China), which are of interest for industrial upgrading research. Estimates of the economic structure concerning the “Rest-of-World” are also provided, to ensure that the production structure of the whole world is documented. It provides multi-regional input-output tables annually from 1995 to 2011. The IO tables contain information on international trade in both intermediate inputs and final products, and the primary inputs (value-added) in the production of each country-industry, which allow us to implement the decomposition as outlined in Section 3.3.1.

We are also aware of other alternative data sources that are currently available, like the OECD-WTO Trade in Value Added (TiVA) database (OECD-WTO, 2012), the Eora database (Lenzen et al., 2013), and the Global Trade Analysis Project (GTAP, Aguiar et al., 2016). These datasets include more countries and more detailed industrial classifications

than WIOD. However, they do not have a coupled supplementary dataset that allows for all measures of industrial upgrading. Therefore, we prefer to use WIOD as our data source. In the following analysis, GVC participation indicators cover the period 1995-2011, while industrial upgrading indicators only cover the period 1996-2009 since the upgrading indicators are calculated as growth rates and data for employment by skill type are not available for 2010 and 2011. Furthermore, no labor data are available for sector 35 (Private households with employed persons). All input-output calculations include 35 sectors, but only the indicators for the first 34 sectors are used in our factor analysis and empirical estimation.

3.4.2 Forward and backward GVC participation

Figure 3.1 shows the relationship between the measures of forward and backward GVC participation. It shows 160 ($=40 \text{ regions} \times 4 \text{ aggregated sectors}$) observations at the country-sector level for the year of 2007 in subplot (a) and of 2720 ($=160 \times 17 \text{ years}$) pairs for all years 1995-2011 in subplot (b). The first observation is that forward and backward participation are positively correlated. The corresponding correlation coefficients for each year are in between 0.37 and 0.69, while the overall correlation coefficient for all 2720 pairwise observations is 0.45, with all coefficients being highly statistically significant. In the scatterplots for backward and forward GVC participation of Figure 3.1, we also distinguish between four broadly defined sector categories, i.e., Agriculture, Service, Mining and Manufacturing. It can be seen that ‘Agriculture’ and ‘Service’ have significant lower GVC participation levels than ‘Mining’ and ‘Manufacturing’. It confirms the widely held view that manufactured goods (when compared to services and agricultural products) are more globally fragmented with higher levels of international dependence.

Figure 3.1 Scatterplots of the forward and backward GVC participation

Notes: Sectors' abbreviations 'Agriculture', 'Mining', 'Manufacture' and 'Service' stand, respectively, for industry 'c1', 'c2 and c8', 'c3-c7 and c9-c16' and 'c17-c35'. We could have presented a scatterplot for 35 industries from 40 regions over the period from 1995 to 2011. However, it turns out to be much less visualizable with too many scatters for 35 sectors (it is still available upon request). For ease of visualization and interpretation, we present the scatterplot for these four aggregated categories.

Source: Authors' elaboration based on WIOD database.

Subplot (a) in Figure 3.2 presents both forward and backward participation measures for each sector. Three sector groups can be distinguished. For the first group, both the forward and backward participation ratios are greater than the average level, which indicates their active participation in GVCs as both providers and users of intermediates. These sectors include most manufacturing sectors such as Electrical and optical equipment (c14) and Chemicals and chemical products (c9). Some case studies (e.g. Apple's iPod, Dedrick et al., 2010; the Nokia smartphone, Ali-Yrkkö et al., 2011) confirm the increased international fragmentation of such electrical products. For the second group, both the forward and backward participation ratios are low, indicating a low degree of GVC participation. These sectors include Agriculture (c1) and most Service sectors (e.g. c21, c22, and c29). The forward participation ratio of the third group is significantly greater than its backward participation. Mining and quarrying (c2) is the only sector in this group,

developing countries. Balance of payments data provides some information on disaggregated trade flows in the business services industries, which corroborates what we find with the WIOD. For example, the United States and Germany outsourced especially in the computer services, business consulting, advertising, and legal services sectors (Bohn et al., 2018). On the other hand, the rising GVC participation of manufactured goods industries also enhances services' participation as services are not only directly involved in GVCs but also embodied in manufacturing trade.

Table 3.1 GVC forward and backward participation at sectoral level (%)

Sector	Forward Participation			Backward Participation		
	1995	2011	change	1995	2011	change
Agriculture	9.3	10.8	1.6	8.8	10.0	1.2
Mining	39.3	47.9	8.6	8.8	8.9	0.1
Manufacturing	19.5	25.7	6.1	18.8	26.3	7.5
Service	6.0	8.3	2.2	6.7	10.0	3.3

Notes: The four categories' correspondence with the WIOD 35-industry classification is given in the note to Figure 3.1.

Subplot (b) in Figure 3.2 presents both forward and backward participation measures for each country (region) in the sample. Similar to the sectoral analysis, these countries can be classified into three groups. For the first group, both the forward and backward participation ratios are greater than the average level. Luxembourg and Ireland are examples. For the second group, both the forward and backward participation ratios are lower than the average level. The United States and Japan fall into this group and have much lower degree of GVC participation. These results are in line with the literature (see, e.g. Baldwin and Lopez-Gonzalez, 2015) that states that larger countries tend to have lower GVC participation because more intermediates are domestically available. Russia belongs to the third group, with its forward participation ratio being significantly greater than its backward participation. This is mostly because of its large exports of natural resources such as petroleum products and mineral ores. Countries like Germany, South Korea and Canada are around the average level. Similar to the sectoral results, most countries' forward and backward participation ratios have increased over the period 1995-2011 and encountered a significant decline in 2009 (see Tables A3.2 and A3.3 in

Annex 3 for more details).

We observe that the participation ratio of the same industry in different countries is likely to be heterogeneous due to different country characteristics. Table 3.2 presents some examples. For Mining and quarrying (c2), countries like Australia, Canada and Russia, have a very large forward participation ratio but a very small backward ratio, reflecting that these countries are major exporters of natural resources because of their large endowments. Russia also shows a similar pattern in Coke and refined petroleum (c8), which reveals that Russia is also well endowed with energy resources. However, countries like Germany, Japan and the United States follow a reverse pattern regarding refined petroleum, with their backward participation ratio being very large and significantly larger than their forward ratio. They rely more on imported energy as consumers than they can provide to the world as suppliers. In Electrical and optical equipment (c14), Germany comes out as the main global supplier, with its highest forward participation ratio. Another observation is that in sector c14 advanced countries like Germany, Japan and United States tend to have a larger forward than backward participation ratio. For developing countries like China, India and Mexico the opposite holds.

Table 3.2 GVC participation measures at country-sector level (%), year 2007

	Forward Participation			Backward Participation		
	c2	c8	c14	c2	c8	c14
Australia	73.9	29.1	22.1	10.6	32.6	20.6
Canada	65.9	30.5	41.9	6.6	30.6	33.2
China	22.2	23.2	30.3	15.0	37.8	36.4
Germany	26.9	36.3	45.7	22.7	55.9	28.7
Japan	20.6	15.4	37.4	40.5	54.9	15.5
India	28.9	13.7	13.6	5.2	13.9	26.5
Mexico	45.6	11.2	45.3	4.2	7.2	57.8
Russia	73.7	31.8	14.6	4.6	5.2	13.5
United States	10.5	11.0	27.0	11.3	39.8	16.8

Notes: Sectors' abbreviations 'c2', 'c8', and 'c14' stand, respectively, for industry 'Mining and quarrying', 'Coke, refined petroleum and nuclear fuel', and 'Electrical and optical equipment'.

Table 3.3 Average levels of GVC participation and industrial upgrading

	group	forward	backward	process	product	skill
Australia	H	0.151	0.099	0.022	0.049	0.037
Austria	H	0.215	0.187	0.016	0.041	0.068
Belgium	H	0.267	0.255	0.023	0.008	0.052
Brazil	LM	0.217	0.262	0.032	0.081	0.047
Bulgaria	LM	0.078	0.070	0.019	0.071	0.038
Canada	H	0.192	0.148	0.020	0.037	0.032
China	LM	0.122	0.150	0.071	0.143	0.084
Cyprus	H	0.093	0.177	0.016	0.039	0.023
Czech	LM	0.251	0.281	0.028	0.081	0.034
Denmark	H	0.170	0.135	0.014	0.034	0.041
Estonia	LM	0.177	0.169	0.014	0.020	0.043
Finland	H	0.098	0.137	0.008	0.055	0.034
France	H	0.252	0.253	0.101	0.108	0.023
Germany	H	0.218	0.171	0.027	0.026	0.031
Greece	LM	0.109	0.115	0.016	0.010	0.044
Hungary	LM	0.145	0.124	0.026	0.037	0.039
India	LM	0.073	0.136	0.024	0.103	0.064
Indonesia	LM	0.238	0.300	0.042	0.100	0.058
Ireland	H	0.181	0.149	0.055	0.070	0.044
Italy	H	0.079	0.116	0.063	0.110	0.051
Japan	H	0.318	0.323	0.046	0.091	0.089
Korea	H	0.107	0.128	0.009	0.025	0.049
Latvia	LM	0.071	0.06	0.008	0.014	0.054
Lithuania	LM	0.180	0.19	0.057	0.045	0.061
Luxembourg	H	0.201	0.224	0.064	0.128	0.021
Malta	LM	0.460	0.354	0.015	0.052	0.020
Mexico	LM	0.196	0.204	0.081	0.102	0.018
Netherlands	H	0.118	0.14	0.015	0.081	0.023
Poland	LM	0.255	0.274	0.015	0.055	0.060
Portugal	H	0.236	0.218	0.020	0.020	0.058
Romania	LM	0.158	0.18	0.016	0.085	0.055
Russia	LM	0.112	0.163	0.037	0.031	0.051
Slovak	LM	0.146	0.194	0.093	0.112	0.057
Slovenia	LM	0.239	0.080	0.073	0.119	0.016
Spain	H	0.253	0.288	0.052	0.098	0.043
Sweden	H	0.202	0.232	0.088	0.051	0.057
Taiwan	H	0.216	0.18	0.027	0.029	0.063
Turkey	LM	0.074	0.119	0.137	0.070	0.048
UK	H	0.244	0.207	0.054	0.006	0.069
US	H	0.061	0.068	0.037	0.016	0.023

Notes: The column 'Group' shows the income classification according to World Bank in 1995. H stands for high-income economies while LM stands for low- and middle-income economies. The values in the table give the average levels. The forward and backward participation values are calculated as the average levels for the years 1995-2011, and the values for the three dimensions of industrial upgrading are derived as arithmetic means of upgrading scores for the years 1996-2009.

3.4.3 GVC participation and industrial upgrading

Before presenting the econometric results in the next section, we present in Table 3.3 the measures of (forward and backward) GVC participation and the three dimensions of industrial upgrading for each country/region. We include 21 developed countries and 19 developing countries. The values for each country/region are calculated as the arithmetic means across different years. The correlation coefficients between forward (backward) participation and process, product and skill upgrading are 0.004 (0.083), 0.050 (0.191) and 0.009 (0.173) respectively.

We also rank the country-industries by their average level of (forward and backward) GVC participation over the period 1995 to 2009. We define the top quartile of these observations as the group with ‘high participation’, and the bottom quartile as the group with ‘low participation’. In Table 3.4, we present the differences in the average upgrading level between the two groups. The group with ‘high participation’ appears to have a higher level of industrial upgrading. For process upgrading, the mean is 0.037 (0.035) for observations with low forward (backward) GVC participation, and 0.044 (0.056) for observations with high forward (backward) GVC participation in the full set of countries. In the subset of developing countries, it is 0.030 (0.037) and 0.039 (0.064), respectively. For product and skill upgrading, we observe similar results. These descriptive results suggest higher GVC participation might contribute positively to industrial upgrading.

Table 3.4 Differences in two groups: average upgrading level over 1996-2009

	Forward Participation		Backward Participation	
	Low	High	Low	High
<i>All countries</i>				
process upgrading	0.037	0.044	0.035	0.056
product upgrading	0.052	0.085	0.061	0.102
skill upgrading	0.023	0.039	0.028	0.050
<i>Developing countries</i>				
process upgrading	0.030	0.039	0.037	0.064
product upgrading	0.064	0.092	0.071	0.118
skill upgrading	0.027	0.039	0.033	0.053

Notes: ‘High GVC participation’ are all observations in the top quartile of the respective distribution of the GVC participation index. ‘Low GVC participation’ are all observations in the bottom quartile of the distribution.

Table 3.5 GVC participation and industrial upgrading

Variables	Process	Product	Skill	Process	Product	Skill
	(I) Full sample			(II) Full sample		
backward (-1)	0.0581*** (0.0088)	0.0934*** (0.0112)	0.0450*** (0.0096)	0.0593*** (0.0110)	0.1042*** (0.0136)	0.0478*** (0.0116)
backward (-1)* d_t				-0.0128* (0.0187)	-0.0125** (0.0235)	-0.0056 (0.0199)
Adjusted R ²	0.2816	0.3968	0.3670	0.2875	0.3976	0.3695
forward (-1)	-0.0380 (0.0046)	0.0967*** (0.0057)	0.0553*** (0.0051)	-0.0436 (0.0058)	0.0775*** (0.0075)	0.0476*** (0.0066)
forward (-1)* d_t				0.0562** (0.0099)	0.0240** (0.0125)	0.0223* (0.0108)
Adjusted R ²	0.2818	0.4035	0.3712	0.2820	0.4036	0.3696
Observations	16420	16420	16420	16420	16420	16420
(III) Manufacturing sectors				(IV) Technology-intensive sectors		
backward (-1)	0.0626*** (0.0261)	0.1089*** (0.0298)	0.0513*** (0.0181)	0.0715*** (0.0312)	0.1162*** (0.0356)	0.0627*** (0.0254)
backward (-1)* d_t	-0.0145** (0.0436)	-0.0132** (0.0498)	-0.0068* (0.0305)	-0.0264*** (0.0515)	-0.0346*** (0.0685)	-0.0145** (0.0532)
Adjusted R ²	0.3685	0.4830	0.6612	0.4058	0.5025	0.6832
forward (-1)	-0.0330 (0.0098)	0.0845*** (0.0113)	0.0506*** (0.0068)	-0.0245 (0.0083)	0.0926*** (0.0257)	0.0568*** (0.0086)
forward (-1)* d_t	0.0585*** (0.0158)	0.0342*** (0.0179)	0.0194* (0.0112)	0.0615*** (0.0226)	0.0385*** (0.0247)	0.0218** (0.0196)
Adjusted R ²	0.3682	0.4935	0.6645	0.4035	0.5126	0.6921
Observations	6520	6520	6520	2240	2240	2240
Country- Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cluster standard errors are reported in parentheses. Variables of GVC participation and upgrading levels are in natural logarithms. The independent variables are lagged by one period. The full sample covers 34 sectors for 40 countries over 14 years (1996-2009), while manufacturing sectors cover 13 industries (c3-c7, c9-c16) for the same country group over the same period. Technology-intensive sectors cover 4 industries (c13-c16). It should be noted that there are 35 sectors in input-output tables from WIOD. But many upgrading indicators for sector 35 have null values because of the unavailability of underlying data. We thus exclude sector 35 in our panel estimation. Except for that, there are more null values in our empirical test. For example, there are no capital stock data for some European countries in year 2008 and 2009. When running the regression, those observations with null values are excluded automatically. Therefore, the number of observations in full sample is less than 19040 (= 40 countries $\times$ 34 sectors $\times$ 14 years). d_t denotes development stage. Developed countries refer to as high-income economies and developing countries refer to as low- and middle-income economies, which are classified according to World Bank's income classification in 1995.

3.5 Econometric results

3.5.1 Does GVC participation enhance industrial upgrading?

Table 3.5 presents the results for the effects of both forward and backward GVC participation on the three dimensions of industrial upgrading. Focusing on the results for product upgrading and skill upgrading (section I of Table 3.5), we find a strong positive and significant relationship between GVC participation and industrial upgrading. Results based on the full sample show that a one percent increase in backward participation is associated with 0.093 and 0.045 percentage point higher level in product and skill upgrading, respectively. Likewise, a one percent increase in forward participation leads to similar increase in product upgrading and skill upgrading. However, for process upgrading, we find that backward participation has a significant and positive effect, while the effect of forward participation is negative and not statistically significant.

The results suggest that expanding and strengthening a country's GVC participation has positive effects on industrial upgrading, but forward participation has no effect on process upgrading. Instead of producing all inputs domestically, a country has access to better, cheaper and a wider variety of inputs through backward GVC participation, which reduces the production costs and thus improves the profits of firms that incorporate these inputs into their products. This process helps countries/firms to make better products and to make these products more efficiently, i.e. improving process and product upgrading. Forward GVC participation is to provide intermediate inputs to global buyers, which enables a country to gain more value from these products (hence product upgrading). As to skill upgrading, GVC participation makes it possible for skill-abundant countries to relocate the unskilled-intensive tasks of the production process to the relatively unskilled-abundant countries, which increases the relative demand for skilled labor in the skill-abundant country and hence enhances skill upgrading. GVCs also provide possibilities for unskilled-abundant countries to increase their skill intensity through learning by doing. For example, multinational firms (MNEs) are key players in the

materialization of GVC production. The unskilled workers employed by MNEs in unskilled-abundant countries can be improved by training and on-the-job-learning, because MNEs typically provide more training and upgrading of human capital in order to achieve better outcomes.

We further investigate several avenues to explore heterogeneities of the impacts of two types of GVC participation on industrial upgrading. We explore heterogeneities across country groups and industries. In Table 3.5, we report in section II the conditioning effect of the stage of development on the relation between GVC participation and industrial upgrading. The point estimates of backward* d_r for process and product upgrading are negative and statistically different from zero (90% confidence level for process upgrading and 95% for product upgrading). This suggests that developing countries benefit more from backward GVC participation than developed countries. We repeat the exercise by focusing on the manufacturing sectors¹⁴ (section III of Table 3.5) and technology intensive industries¹⁵ (section IV of Table 3.5). The results largely confirm the results of the full sample and the point estimates of backward* d_r become larger than those in section II. This finding points to that manufacturing sectors in developing countries are particularly benefiting from backward GVC participation. This is consistent with Rodrik's (2013) convergence theory that lagging countries can catch up with the world productivity leader in manufacturing.

An important motivation that we conduct separate analysis on manufacturing sectors is that GVC participation as measured in this study may be potentially more relevant in manufacturing. As shown in Section 3.4.2, in contrast to agriculture and the service sectors,

¹⁴ We also exclude sector c8, 'Coke, refined petroleum and nuclear fuel'. There are some reasons to do so. Firstly, like another natural resource intensive sector c2 'Mining and quarrying', the value chain of c8 provides little useful information about upgrading for countries with small endowments of natural resources. A very high forward GVC participation of this sector simply suggests that this country is well endowed with natural resources and exports a lot. A high backward GVC participation of sector c8 suggests that this country needs to import oil or other resources because they are not available domestically and this will not change. Secondly, trading raw oil is unlikely to have similar productivity dynamics as when trading intermediates in other manufacturing value chains. The economic relationship that we intend to study may thus not hold in this value chain.

¹⁵ We classify industries of machinery (c13), electrical and optical equipment (c14), transport equipment (c15), and manufacturing, nec (c16) as technology-intensive sectors.

manufacturing value chains are more fragmented, in which we thus expect stronger spillovers. To this end, we attempt to classify sectors by sophistication of used intermediates and repeat the exercise for technology-intensive sectors separately. Comparing the point estimates in section II, III, and IV of Table 3.5, we indeed find a stronger upgrading effect for the technology-intensive industries than for the general manufacturing, and the effect for manufacturing is further larger than that for all the sectors. This suggests that, if a country imports sophisticated materials and components for the next layer of local production, this may activate learning, for example, through embodied technology. In contrast, assembly of simple inputs or raw materials may generate much less learning and the upgrading potential might arise from cooperation with global buyers rather than from importing. That is why GVC participation offer less upgrading scope for the remaining industries with less sophisticated intermediate use, which are split between light manufacturing (e.g. food, textiles and wood) and resource-intensive industries (e.g. chemicals, rubber and metals).

The above analyses point to the conclusion that backward GVC participation provides more upgrading opportunities for developing countries as it enables a less developed country to import sophisticated inputs, which stimulate knowledge spillovers. In contrast, we find that forward GVC participation has higher level of upgrading effect on developed countries. The effect of forward participation on the three dimensions of industrial upgrading are significantly larger in developed countries than in developing countries, with the three coefficients of forward* d_r (in section II, III, and IV of Table 3.5) being positive and significant. More specifically, forward participation has a positive impact on product upgrading and skill upgrading for both developed and developing countries. However, its positive impact on process upgrading is observed only for developed countries, not for developing countries. A possible explanation for the different results among developed and developing countries could be their difference in forward GVC participation. For developed countries, forward integration into GVCs normally means that they can offshore parts of low value-added tasks and specialize in high

value-added tasks. This process helps to lower labor costs, which has a positive effect on productivity improvement. However, for developing countries, forward participation in GVCs tends to be supplying raw materials and (cheap) labor and specializing in low value-added tasks. This process may generate employment and value-added, but does not necessarily provide learning opportunities to improve the productivity in developing countries.

Table 3.6 Robustness tests

	Process	Product	Skill
Variables	(I) alternative measures of GVC participation		
VS	0.0563*** (0.0116)	0.1568*** (0.0213)	0.0484*** (0.0253)
VS * d_r	-0.0148** (0.0089)	-0.0457** (0.0327)	-0.0135 (0.0092)
Adjusted R ²	0.4026	0.6235	0.6587
VS1	0.0021 (0.0013)	0.0733*** (0.0108)	0.0216*** (0.0058)
VS1 * d_r	0.0358*** (0.0126)	0.0205** (0.0067)	0.0124* (0.0053)
Adjusted R ²	0.3655	0.5256	0.6339
Observations	6520	6520	6520
Fixed effects	Country-Industry, Country-Year, Industry-Year		
	(II) independent variables lagged by five years		
backward (-5)	0.0918*** (0.0365)	0.1434*** (0.0387)	0.0657*** (0.0203)
backward (-5) * d_r	-0.0272*** (0.0312)	-0.0413*** (0.0139)	-0.0126** (0.0089)
R ²	0.3982	0.5226	0.6687
forward (-5)	0.0083 (0.0026)	0.1126*** (0.0193)	0.0584*** (0.0073)
forward (-5) * d_r	0.0617*** (0.0132)	0.0481*** (0.0171)	0.0212** (0.0092)
Adjusted R ²	0.3525	0.5125	0.6829
Observations	4280	4280	4280
Fixed effects	Country-Industry, Country-Year, Industry-Year		
	(III) IV estimate		
backward (-1)	0.0782*** (0.0261)	0.0912*** (0.0254)	0.0548*** (0.0145)
Adjusted R ²	0.3778	0.4982	0.6712
Observations	6520	6520	6520
Fixed effects	Country-Industry, Country-Year, Industry-Year		

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cluster standard errors are reported in parentheses. The robustness tests are conducted on the sample of manufacturing sectors.

3.5.2 Robustness tests

The aforementioned findings suggest that GVC participation plays a role in boosting industrial upgrading. However, there are possible concerns that the results may depend on the choice of GVC participation indicator(s), and reverse causality and any omitted variables may lead to a biased estimate of coefficient. For example, a possible reverse causality concern is that a country-sector where productivity growth is high tends to have high GVC participation and economies with a comparative advantage in high-skilled labor may be more willing to participate in GVCs. We attempt to address such concerns in a series of robustness tests. As mentioned above, manufacturing sectors are the major GVC participants, we thus focus on the sample of manufacturing in the following robustness tests.

The first robustness check deals with the alternative measures of GVC participation. We rerun the regressions by replacing the present indicators with two other GVC participation measures (VS and VS1 share, introduced in Section 3.3.1). The results are shown in section I of Table 3.6. The results lead to similar conclusions to those presented above. Second, as stated in the literature review, the effects of GVC participation on industrial upgrading may materialize over a longer time period, and the effects in the short run may differ from those in the long run. Therefore, we use longer-period lagged values (i.e., a 5-year lag) to allow for a delayed response and to minimize reverse causality concerns. The results in section II of Table 3.6 show that most coefficients for lagged values are statistically significant and slightly larger than the corresponding benchmark estimates in Table 3.5. The estimates based on lagged values are largely consistent with the benchmark, but suggest larger positive effects of GVC participation on upgrading.

Third, we use an instrumental variable technique to address the possibility that reserve causality and any omitted variables are leading to a biased result. Here, we focus only on the backward participation as we failed to find a good instrument for forward participation. We adopt the instrument for backward participation from Constantinescu,

Mattoo, and Ruta (2019). The idea is based on the work of Baldwin and Lopez-Gonzalez (2015) who argue the existence of a technological asymmetry in the international production network whereby there are “headquarter economies” and “factory economies”. Firms in the headquarter economies arrange the production networks and they are the main providers of intermediates essential to exporting. Factory economies provide the labor. Specifically, Baldwin and Lopez-Gonzalez (2015) find that the distinction of headquarter-versus-factory-economy exists clearly in backward specialization, which they refer to as “import to export”. For industry i of country r at year t , we compute the instrument as the average value-added from the United States, Germany and Japan (headquarter economies) embodied in exports of industry i of three countries in the sample that are closest in income to country r . The underlying assumption is that the information and communication technology developments in these three economies and declining trade costs globally were the main drivers of GVC expansion. The instrument is positively and significantly correlated with the backward participation indicator that we proposed in Section 3.3.1. The results in section III of Table 3.6 point to a significant positive effect of backward participation on process, product and skill upgrading, which confirms our previous findings.

The fourth robustness check is to deal with the potential endogeneity (simultaneity) problem between GVC participation and product upgrading. As said, the three dimensions of industrial upgrading are a weighted linear combination of eight indicators. Particularly, the dimension ‘product upgrading’ has high weights on three of the indicators: growth of value-added exports, growth of the share in value-added exports and growth of the unit value-added exports. These three indicators are based on value-added exports, which may overlap with GVC participation measures. To address this concern, we exclude the dimension ‘product upgrading’ and focus on the other two dimensions (‘process upgrading’ and ‘skill upgrading’). Although process upgrading and skill upgrading have relatively low weights on the three indicators, we set the values of these three indicators to zero when calculating the dimensions ‘process upgrading’ and ‘skill upgrading’. We do this to

cancel the influence of these three indicators. We find that the new coefficients for process and skill upgrading are in line with the benchmark estimates (results are available upon request).

Finally, classifying countries into income categories is arbitrary. Alternatively, we use a different classification based on GDP per capita. We rerun the relevant regressions using the alternative country classification based on GDP per capita. The results are similar to the ones reported above (results are available upon request). Overall these exercises confirm the benchmark results, and it suggests that the findings are not largely dependent on the chosen classification strategy.

3.6 Conclusion

This study is one of the first attempts to empirically assess the effects of GVC participation on industrial upgrading to provide objective evidence for some theoretical debates and inform policy making. Using the WIOD that covers 40 countries at different stages of development, this chapter examines the impacts of backward and forward GVC participation on three dimensions of industrial upgrading. We find a positive effect of GVC participation on product and skill upgrading. This finding holds for both forward and backward GVC participation and across developed and developing countries. For process upgrading, the effects of forward integration and backward integration present different results. We find that the effect of backward GVC participation on industrial upgrading in developing countries is larger than that in developed countries. For forward participation, the contrary is the case. The results reveal that developed countries upgrade more through forward linkages, while developing countries (especially process upgrading) rely more on backward links than forward links. Comprehensively considering the effects of both types of GVC participation on the three dimensions of industrial upgrading, we can conclude that GVC integration benefits industrial upgrading for both developed and developing countries.

This shows that potential concerns about the negative effects of GVC integration in some countries (either developed countries or developing countries) are not supported by the data. Countries that participate in GVC production are likely to upgrade and develop new competitive advantages because of the different endowments and technologies of developed and less developed countries. We stress that industrial upgrading through GVC participation is possible, but far from automatic. As Gereffi and Sturgeon (2013) argued, the successful developments of China and Thailand through GVC participation depend on their new and GVC-supportive industrial policies. On the contrary, a nation that seeks to ban the international fragmentation and GVC participation may find that such resistance will hinder industrial upgrading.

While these findings provide convincing evidence on the beneficial effects of GVCs, further research is necessary to improve our understanding of their functioning. Optimally, we would like to analyze firm-level data to see how firms respond to new competition through GVCs and how firms within GVC networks benefit each other. Our empirical results did not provide very solid evidence for developing countries that forward GVC participation benefits their upgrading. However, one might argue that forward integration trigger international competition among suppliers leading to productivity improvements. Future firm-level analysis may capture such influence channels that our industry-level data failed to capture. In particular, multinational firms play an important role in materializing GVC production. In this case, firm-level analyses or specific case-study approaches are better suited to explore the relationship between firms' GVC participation and upgrading.

Furthermore, it is essential for theoretical research to shed further light on how GVCs affect industrial upgrading. It is central to understand which effects dominate under which conditions and which policies could help to overcome barriers to gains from GVCs. Moreover, dynamic models could explore ways to move into higher value-added tasks within global value chains, a key interest of policy makers. Such models could then again provide testable hypotheses for future empirical work.

Annex 3

Table A3.1 WIOD country acronyms and industry classification

Acronym	Country/Region	Group	Code	Industry description
AUS	Australia	H	c1	Agriculture, hunting, forestry and fishing
AUT	Austria	H	c2	Mining and quarrying
BEL	Belgium	H	c3	Food, beverages and tobacco
BRA	Brazil	LM	c4	Textiles and textile products
BGR	Bulgaria	LM	c5	Leather, leather and footwear
CAN	Canada	H	c6	Wood and products of wood and cork
CHN	China	LM	c7	Pulp, paper, printing and publishing
CYP	Cyprus	H	c8	Coke, refined petroleum and nuclear fuel
CZE	Czech Republic	LM	c9	Chemicals and chemical products
DNK	Denmark	H	c10	Rubber and plastics
EST	Estonia	LM	c11	Other non-metallic mineral
FIN	Finland	H	c12	Basic metals and fabricated metal
FRA	France	H	c13	Machinery, nec
DEU	Germany	H	c14	Electrical and optical equipment
GRC	Greece	LM	c15	Transport equipment
HUN	Hungary	LM	c16	Manufacturing, nec; recycling
IND	India	LM	c17	Electricity, gas and water supply
IDN	Indonesia	LM	c18	Construction
IRL	Ireland	H	c19	Sale, maintenance and repair of motor vehicles and motorcycles; Retail sale of fuel
ITA	Italy	H	c20	Wholesale trade and commission trade, except of motor vehicles and motorcycles
JPN	Japan	H	c21	Retail trade, except of motor vehicles and motorcycles; Repair of household goods
KOR	Korea	H	c22	Hotels and restaurants
LVA	Latvia	LM	c23	Inland transport
LTU	Lithuania	LM	c24	Water transport
LUX	Luxembourg	H	c25	Air transport
MLT	Malta	LM	c26	Other supporting and auxiliary transport activities; Activities of travel agencies
MEX	Mexico	LM	c27	Post and telecommunications
NLD	Netherlands	H	c28	Financial intermediation
POL	Poland	LM	c29	Real estate activities
PRT	Portugal	H	c30	Renting of machinery & equipment and other business activities
ROU	Romania	LM	c31	Public admin and defence; Social security
RUS	Russia	LM	c32	Education
SVK	Slovak Republic	LM	c33	Health and social work
SVN	Slovenia	LM	c34	Other community, social and personal services
ESP	Spain	H	c35	Private households with employed persons
SWE	Sweden	H		
TWN	Taiwan	H		
TUR	Turkey	LM		
GBR	United Kingdom	H		
USA	United States	H		

Notes: The column 'Group' shows the income classification according to World Bank in 1995. H stands for high-income economies while LM stands for low- and middle-income economies.

Table A3.2 GVC forward participation at country level (%)

	1995	2000	2005	2008	2009	2011	average
AUS	13.4	15.7	14.6	17.4	14.9	16.9	15.1
AUT	16.3	20.8	22.3	24.2	21.4	23.9	21.5
BEL	25.0	27.3	26.4	27.9	26.0	27.4	26.7
BGR	16.1	20.5	18.1	23.9	21.4	21.7	21.7
BRA	5.4	6.4	9.7	9.4	7.6	8.4	7.8
CAN	19.1	21.6	20.0	20.4	16.7	18.2	19.2
CHN	8.8	10.0	14.3	14.1	10.8	11.9	12.2
CYP	7.3	9.2	10.3	9.8	9.4	9.3	9.3
CZE	22.8	24.6	25.8	26.1	23.9	27.5	25.1
DEU	11.6	15.4	18.3	20.6	17.8	20.2	17.0
DNK	13.5	18.0	19.0	20.3	17.1	20.2	17.7
ESP	8.0	10.1	9.5	9.9	8.9	11.2	9.8
EST	23.1	27.2	26.2	26.0	25.5	25.9	25.2
FIN	20.6	23.5	21.7	23.1	19.6	21.4	21.8
FRA	10.6	12.2	10.9	10.8	9.7	10.9	10.9
GBR	13.7	14.2	13.9	15.8	15.1	16.3	14.5
GRC	3.5	6.9	8.4	9.3	7.7	7.8	7.3
HUN	16.9	21.4	22.4	26.1	25.6	29.3	23.8
IDN	13.5	21.2	21.3	19.6	16.5	17.9	18.1
IND	5.9	6.9	9.3	9.3	6.7	7.7	7.9
IRL	23.0	32.3	30.3	32.3	34.5	37.6	31.8
ITA	10.2	10.9	10.8	11.4	9.5	11.4	10.7
JPN	5.3	6.0	8.0	9.6	7.6	8.2	7.1
KOR	13.8	16.0	17.6	20.8	20.5	22.6	18.0
LTU	18.2	16.1	21.8	22.1	22.2	21.3	20.1
LUX	43.6	45.5	44.2	49.1	47.8	48.4	46.0
LVA	22.0	21.7	21.1	18.3	19.8	19.6	19.6
MEX	12.3	11.2	12.5	12.7	11.4	13.9	11.8
MLT	20.4	25.1	24.4	28.6	27.7	28.0	25.5
NLD	22.2	23.1	23.5	25.9	23.6	26.1	23.6
POL	12.1	12.9	16.1	17.0	16.6	18.4	15.8
PRT	9.7	10.8	10.9	12.6	11.4	11.6	11.2
ROM	11.9	14.8	15.0	15.1	14.9	15.0	14.6
RUS	19.9	31.3	27.2	23.6	21.5	24.4	23.9
SVK	27.7	25.4	26.1	26.9	23.8	24.5	25.3
SVN	17.3	19.1	21.0	22.3	19.8	21.0	20.2
SWE	19.1	21.4	22.1	23.5	22.4	23.2	21.6
TUR	4.6	5.8	6.2	9.5	9.5	9.8	7.4
TWN	17.5	20.7	26.4	28.6	27.5	29.9	24.4
USA	6.3	5.9	5.7	6.8	6.1	7.2	6.1

Table A3.3 GVC backward participation at country level (%)

	1995	2000	2005	2008	2009	2011	average
AUS	10.4	10.4	9.9	10.3	9.4	10.2	9.9
AUT	15.1	18.0	19.5	20.9	18.0	20.5	18.7
BEL	23.5	26.4	24.9	28.1	24.6	27.4	25.5
BGR	20.9	24.3	22.9	30.9	25.6	25.4	26.2
BRA	4.9	7.2	7.4	8.4	6.6	7.8	7.0
CAN	14.6	17.1	15.0	14.6	13.6	14.1	14.8
CHN	11.6	12.2	18.1	16.2	13.5	15.8	15.0
CYP	18.1	18.2	17.1	19.5	16.4	16.5	17.7
CZE	23.7	28.3	28.2	29.5	26.4	30.7	28.1
DEU	9.7	13.2	14.3	16.4	13.7	16.3	13.5
DNK	13.7	16.1	17.9	20.1	16.8	18.7	16.9
ESP	11.1	15.2	14.0	15.0	12.2	14.2	13.7
EST	28.6	29.0	27.4	25.0	21.5	21.3	25.3
FIN	14.7	17.2	17.9	19.8	16.9	19.1	17.1
FRA	9.9	12.2	11.7	12.7	10.8	12.7	11.5
GBR	12.4	12.1	12.1	13.6	12.9	14.2	12.4
GRC	11.1	15.5	13.1	16.3	13.2	13.2	13.6
HUN	22.3	33.3	28.4	32.5	29.1	33.0	30.0
IDN	13.5	17.3	17.2	16.4	13.0	15.1	14.9
IND	7.7	9.7	12.5	13.5	12.1	12.0	11.6
IRL	28.4	34.6	31.8	32.7	33.3	35.3	32.3
ITA	11.3	12.8	12.8	14.6	12.3	15.1	12.8
JPN	3.9	4.7	6.4	9.5	6.4	8.2	6.0
KOR	14.8	18.0	17.7	24.0	21.1	23.9	19.0
LTU	23.7	21.7	24.2	24.7	20.7	20.7	22.4
LUX	25.2	34.0	37.2	37.9	36.5	36.4	35.4
LVA	20.6	18.9	23.1	20.8	17.7	17.7	20.4
MEX	13.2	15.3	13.6	13.9	12.7	14.9	14.0
MLT	28.9	29.9	26.7	29.4	26.3	26.6	27.4
NLD	20.3	22.1	21.2	23.4	21.8	24.0	21.8
POL	11.0	16.7	18.1	20.3	18.1	21.3	18.0
PRT	16.3	17.4	16.4	18.1	15.1	15.4	16.3
ROM	16.4	19.5	20.9	20.1	18.5	18.3	19.4
RUS	7.7	10.2	8.7	8.3	6.2	7.9	8.0
SVK	23.4	28.2	30.0	31.2	26.4	26.4	28.8
SVN	21.5	22.5	24.5	25.7	22.0	21.7	23.2
SWE	15.6	18.1	18.1	20.4	18.2	18.8	18.0
TUR	9.3	11.8	13.2	11.9	9.5	12.4	11.9
TWN	20.0	20.0	21.1	23.9	19.2	23.0	20.7
USA	5.6	6.2	7.3	8.5	6.4	8.3	6.8

Chapter 4

Past and potential income gains in China from geographic shifts in international sourcing¹⁶

4.1 Introduction

The world has witnessed different waves of globalization. Since the mid-1980s, globalization accelerated until the Great Recession of the late 2000s brought an abrupt pause to it. A recovery started around 2012, but in a more moderate way. One of the notable signals is that the growth rate of world merchandise export value has begun to be lower than that of world GDP since 2012 (Zhu and Jiang, 2019). The trade protectionism initiated by the Trump administration against China in recent years, the withdrawal of the United Kingdom from the European Union (EU), and the outbreak of the COVID-19 pandemic have further slowed down the pace of globalization. Some economists even have spotted the beginnings of an era of de-globalization.

Two major reasons for the large increase in globalization were the advancements in information and communication technology and reductions in trade costs. They fostered international fragmentation of production. That is, the production of final products was unbundled into different activities which were increasingly carried out in multiple economies and regions (Antràs and Gortari, 2020; Baldwin and Robert-Nicoud, 2014; Johnson and Noguera, 2012; Timmer et al., 2014). The full range of activities forms a value chain and value chains became global. As a result, trade in intermediate products increased rapidly in the past decades (Koopman et al., 2014; Johnson, 2014), and international trade was also characterized by geographic shifts of sourcing regions which provide the products (OECD et al., 2014). Originally, the United Kingdom was the center of global production and international trade due to its successful industrial revolution.

¹⁶ This chapter is co-authored with Erik Dietzenbacher, Bingqian Yan and Richard Jong-A-Pin.

Then the Western Europe (and Germany in particular) emerged as an important source of global trade. The United States and Japan followed and Asia's Four Tigers (Singapore, South Korea, Chinese Hongkong and Taiwan) also developed as important factories for global products. After that, mainland China became the world's factory. Recently, there has been a trend that increasing production started to shift towards less developing regions such as some Southeast Asian and African countries (see Jiang and Green, 2017; Lehmann, 2012).

China has timely caught the wave of globalization since the 1980s by its opening-up policy, and has deepened its participation in global value chains (GVCs) after it entered into the World Trade Organization (WTO) in 2001. Furthermore, China has become an important engine of the global trade boom of the early 2000s, which positively affected its economic growth (e.g. Pei et al., 2012). Although China's GDP per capita has steadily increased in the past decades, it is still lower than the world average level. Consequently, exploring possible strategies to further increase GDP per capita has become an important challenge for China. The importance was further aggravated because the growth rate of Chinese GDP slid down to a medium level in recent years. In this paper, we quantify how the geographic shifts in international sourcing (or the evolution of world trade structure) have contributed to China's value-added gains using a global input-output (IO) accounting framework. We also explore which shifts in international sourcing would increase China's GDP per capita the most, assuming a constant world GDP per capita.

This paper adds contribution by conducting three analyses. In the first analysis, we follow Hoekstra et al. (2016) and Jiang et al. (2018) who define the geographic shift in international sourcing as changing the seller's country. That is, if an intermediate or final good is no longer purchased from one source country but from a new source country. We adopt a what-if scenario analysis approach. More specifically, we assume that the international sourcing structure in year t_1 is hypothetically replaced by the structure in t_0 . We then calculate how much GDP the t_1 -demand would have generated with the

t_0 -structure. The difference with the actual GDP in t_1 quantifies the contribution of geographic shifts in international sourcing to China's income gains.

Second, we adapt the model of Gurgul and Lach (2019) and apply a nonlinear optimization approach to investigate in which direction international sourcing should change to further increase China's GDP per capita. Our optimization model is built upon the global IO framework. In this way, it takes into account not only intranational inter-industrial linkages but also international relations among industries which locate in different regions of the globe. In our model, the objective is to maximize China's GDP per capita relative to the world average level given some practical constraints. We keep constant the production technology and the final demand in each country, but leave international sourcing variable. The optimal solution addresses the following three important questions. (a) How can GDP in one country (in our case China) be boosted most in the presence of global interdependencies; (b) in which sectors should China improve its competitiveness to enhance GDP most; and (c) which countries affect GDP in China most. Answers to these questions will be helpful for Chinese policymakers to develop strategies that aim at narrowing the income gap between China and developed countries.

Third, we analyze and discuss the scope of our model. We look at longer run where other countries also optimize their value-added gains. This leads to the case where all countries follow this optimization strategy. The results show that the value-added share of a country is very close to the original value-added share as given in the world IO table. This implies that the model is beneficial for a country only in the short run.

We organize the remainder of this paper as follows. In Section 4.2 we introduce the methodology; in Section 4.3 we describe the data; in Section 4.4 we illustrate the effects of international sourcing shifts on China's GDP per capita during the years 2005-2015 and offer the optimization results; in Section 4.5 we extend our analysis by modifying the setting of the base model. Section 4.6 summarizes our findings and provides implications.

4.2 Methodology

4.2.1 Measuring the value-added effect of geographic shifts in international sourcing

We first outline our approach to measure how geographic shifts in international sourcing contributed to China's GDP (value-added) per capita relative to the world average using the input-output (IO) accounting framework with multiple regions (see Miller and Blair, 2009). Since we focus on a global IO model, let us assume that there are n countries and m sectors (or industries) in each country (see Table 2.1). In compact form, the static global input-output system can be rewritten as $\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{F}\mathbf{u}$ and the solution is given by

$$\mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{F}\mathbf{u} = \mathbf{L}\mathbf{F}\mathbf{u}, \quad (4.1)$$

where $\mathbf{y}$ is a $nm \times 1$ vector that gives all country-sectors' gross outputs, $\mathbf{A}$ is a $nm \times nm$ block that denotes global input-output matrix. $\mathbf{F}$ is a $nm \times n$ matrix of final demand. $\mathbf{I}$ is an $(nm \times nm)$ identity matrix. $\mathbf{L} \equiv (\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse, whose element l_{ij}^{sr} gives the gross output of sector i in country s that is required for the final use of one unit from sector j in country r . $\mathbf{u}$ is the column vector of appropriate length with all elements being ones so that it can sum the elements of a matrix in a row-wise fashion.

Let $\mathbf{w}'$ denote the $1 \times nm$ row vector of value-added for each of the country-sectors, and $\mathbf{v}'$ be the corresponding vector of value-added coefficients which give the sector-wise value-added per unit of output, with $\mathbf{v}' = \mathbf{w}'(\mathbf{y})^{-1}$. Then we can trace the value-added generated along global production networks as follows:

$$\mathbf{w}'\mathbf{u} = \mathbf{v}'\mathbf{y} = \mathbf{v}'(\mathbf{I} - \mathbf{A})^{-1}\mathbf{F}\mathbf{u}. \quad (4.2)$$

The left-hand side of (4.2) gives the summation of value-added in all sectors across all countries in the world, which equals world GDP.

Adapting this equation allows us to split world GDP in various ways. For example,

we could measure the part of world GDP that is generated by the final demand of a single country. Another option is to split world GDP into the GDPs of each country. In this study, we are interested in China's GDP. This can be obtained by replacing the vector $\mathbf{v}$ in (4.2) with a vector $\mathbf{v}^{China}$, which is a vector of equal length, but in which all elements apart from those corresponding to the sectors in China are set as zeros. This yields

$$GDP^{China} = (\mathbf{v}^{China})'(\mathbf{I} - \mathbf{A})^{-1}\mathbf{F}\mathbf{u}. \quad (4.3)$$

Subsequently, we define the ratio of China's GDP per capita to the world GDP per capita (henceforth, $GDPcapratio^{China}$) using the following formula:

$$GDPcapratio^{China} = \frac{GDP^{China}/POP^{China}}{\mathbf{w}'\mathbf{u}/POP^{World}} = \frac{(\mathbf{v}^{China})'(\mathbf{I} - \mathbf{A})^{-1}\mathbf{F}\mathbf{u}}{\mathbf{v}'(\mathbf{I} - \mathbf{A})^{-1}\mathbf{F}\mathbf{u}} \cdot \frac{POP^{World}}{POP^{China}}, \quad (4.4)$$

where POP^{China} and POP^{World} denote China's population and world population, respectively.

Our next step is to measure the effect of geographic shifts in international sourcing on $GDPcapratio^{China}$. This shift affects the worldwide trade structure of intermediate inputs and of final demands. To determine the impact of geographic shifts on value-added creation, we compare the actual outcome for year $t1$ with a hypothetical outcome. This hypothetical outcome is obtained by assuming that the international sourcing structures (of intermediate inputs and final demands) of year $t0$ also applies to year $t1$. For this, we need to isolate the change in the international sourcing structures. We follow the idea of Arto and Dietzenbacher (2014), Xu and Dietzenbacher (2014), and Jiang et al. (2018), and split the intermediate input matrix $\mathbf{A}$ into two parts. That is, (a) a part ($\tilde{\mathbf{A}}$) that reflects the production technologies of different economies; and (b) a part (Φ) that reflects the international sourcing structure of the intermediate inputs. Define the $nm \times nm$ matrices $\tilde{\mathbf{A}}$ and Φ as

$$\tilde{\mathbf{A}} = \begin{bmatrix} \tilde{\mathbf{A}}^1 & \dots & \tilde{\mathbf{A}}^n \\ \vdots & \ddots & \vdots \\ \tilde{\mathbf{A}}^1 & \dots & \tilde{\mathbf{A}}^n \end{bmatrix}, \text{ and } \Phi = \begin{bmatrix} \Phi^{11} & \dots & \Phi^{1n} \\ \vdots & \ddots & \vdots \\ \Phi^{n1} & \dots & \Phi^{nn} \end{bmatrix},$$

with the $m \times m$ sub-matrix $\tilde{\mathbf{A}}^r = \sum_{s=1}^n \mathbf{A}^{sr}$ ($r = 1, \dots, n$). These technology matrices give the sector-wise total amount of inputs per unit of output irrespective of the geographic source of the inputs. The matrix with regional shares is given by $\Phi^{sr} = \mathbf{A}^{sr} / (\sum_{s=1}^n \mathbf{A}^{sr})$, with $//$ denoting cell-by-cell division. It indicates the sector-wise share sourced from region s in the total sector-wise intermediate inputs used for production in region r . This yields $\mathbf{A} = \Phi \otimes \tilde{\mathbf{A}}$, where the Hadamard product $\otimes$ indicates element-by-element multiplication.

The final demand can be split in a similar way. Define

$$\tilde{\mathbf{F}} = \begin{bmatrix} \tilde{\mathbf{f}}^1 & \dots & \tilde{\mathbf{f}}^n \\ \vdots & \ddots & \vdots \\ \tilde{\mathbf{f}}^1 & \dots & \tilde{\mathbf{f}}^n \end{bmatrix}, \text{ and } \mathbf{\Pi} = \begin{bmatrix} \boldsymbol{\pi}^{11} & \dots & \boldsymbol{\pi}^{1n} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\pi}^{n1} & \dots & \boldsymbol{\pi}^{nn} \end{bmatrix},$$

with $\tilde{\mathbf{f}}^n = \sum_{s=1}^n \mathbf{f}^{sr}$ as the vector of total final demands, and $\boldsymbol{\pi}^{sr} = \mathbf{f}^{sr} / (\sum_{s=1}^n \mathbf{f}^{sr})$ as the vector with regional final demand shares. We then have $\mathbf{F} = \mathbf{\Pi} \otimes \tilde{\mathbf{F}}$. Next, China's actual GDP per capita in the year $t1$ relative to the world average level can be calculated as:

$$\text{GDPcapratio}_{t1}^{China} = \frac{(\mathbf{v}_{t1}^{China})' (\mathbf{I} - \Phi_{t1} \otimes \tilde{\mathbf{A}}_{t1})^{-1} (\mathbf{\Pi}_{t1} \otimes \tilde{\mathbf{F}}_{t1}) \mathbf{u}}{\mathbf{v}_{t1}' (\mathbf{I} - \Phi_{t1} \otimes \tilde{\mathbf{A}}_{t1})^{-1} (\mathbf{\Pi}_{t1} \otimes \tilde{\mathbf{F}}_{t1}) \mathbf{u}} \cdot \frac{\text{POP}_{t1}^{World}}{\text{POP}_{t1}^{China}}. \quad (4.5)$$

For the hypothetical case, we assume that global final demand $\tilde{\mathbf{F}}_{t1}$, production technology $\tilde{\mathbf{A}}_{t1}$ and value-added coefficients $\mathbf{v}_{t1}$ are the same and only the international sourcing structures (Φ_{t1} and $\mathbf{\Pi}_{t1}$) are replaced by the values in year $t0$ (i.e., Φ_{t0} and $\mathbf{\Pi}_{t0}$). The GDPcapratio in this hypothetical case becomes:

$$\text{GDPcapratio}_{hypothetical}^{China} = \frac{(\mathbf{v}_{t1}^{China})' (\mathbf{I} - \Phi_{t0} \otimes \tilde{\mathbf{A}}_{t1})^{-1} (\mathbf{\Pi}_{t0} \otimes \tilde{\mathbf{F}}_{t1}) \mathbf{u}}{\mathbf{v}_{t1}' (\mathbf{I} - \Phi_{t0} \otimes \tilde{\mathbf{A}}_{t1})^{-1} (\mathbf{\Pi}_{t0} \otimes \tilde{\mathbf{F}}_{t1}) \mathbf{u}} \cdot \frac{\text{POP}_{t1}^{World}}{\text{POP}_{t1}^{China}}. \quad (4.6)$$

The difference between the two GDPcapratios is only due to the geographic shifts between $t0$ and $t1$ in international sourcing.

4.2.2 Optimizing geographic shifts in international sourcing

The second goal of this chapter is to examine how China should change the structure

of international sourcing such that the GDPcapratio for China increases the most. For this, China has two options: changing its import structure and trying to achieve changes in its export structure (for example by making exports more competitive). For Chinese GDP, it is beneficial to substitute imported inputs and final products for the same goods and services that are produced domestically. Without loss of generality, let China be country 1. Import substitution means that $\mathbf{A}^{11}$ and $\mathbf{f}^{11}$ increase whilst the import content decreases. So, $\Delta \mathbf{A}^{11} > 0$ and $\sum_{s \neq 1} \Delta \mathbf{A}^{s1} = -(\Delta \mathbf{A}^{11}) < 0$. Note that it is assumed that China's technology does not change, which implies that $\Delta \tilde{\mathbf{A}}^1 = \Delta \mathbf{A}^{11} + \sum_{s \neq 1} \Delta \mathbf{A}^{s1} = 0$. The strategy of export promotion implies that China tries to persuade foreign countries to substitute the products they buy from other countries by the same products made in China. Consequently, $\Delta \mathbf{A}^{1r} > 0$ and $\sum_{s \neq 1} \Delta \mathbf{A}^{sr} = -(\Delta \mathbf{A}^{1r}) < 0$.¹⁷

The two strategies are not entirely independent. In some cases, an economy may need to import more intermediate inputs if its exports are increased. For example, China's processing exports used to rely heavily on imported intermediate goods because China was not capable of providing the required inputs. What strategy is feasible in practice partly depends on different economies' production technologies and trade relations. Global IO tables provide explicit information about the production technologies of different economies and their trade relations. Henceforth, we employ a global IO-based nonlinear optimization approach to examine this problem. We conduct the optimization model for the short-run and keep the production technologies of each country constant while changing the trade structure.

The optimization approach is based on an analysis of some specific hypothetical modifications to the global IO model in equation (4.1). Let us denote the changes in the international sourcing matrix as $\Delta \Phi$ (for trade in intermediate products) and $\Delta \Pi$ (for final products trade). The new sourcing matrices are given by $\bar{\Phi} = \Phi + \Delta \Phi$ and $\bar{\Pi} = \Pi + \Delta \Pi$. Then, $\Delta \mathbf{A} = (\Delta \Phi) \otimes \tilde{\mathbf{A}}$ denotes the changes in the direct global input

¹⁷ The same holds for final products. For import substitution: $\Delta \mathbf{f}^{11} > 0$ and $\sum_{s \neq 1} \Delta \mathbf{f}^{s1} = -(\Delta \mathbf{f}^{11}) < 0$, and for export promotion: $\Delta \mathbf{f}^{1r} > 0$ and $\sum_{s \neq 1} \Delta \mathbf{f}^{sr} = -(\Delta \mathbf{f}^{1r}) < 0$.

coefficient matrix and $\bar{\mathbf{A}} = (\mathbf{A} + \Delta\mathbf{A})$ is the new input coefficient matrix. In the same way, we have for the final demands: $\Delta\mathbf{F} = (\Delta\Pi) \otimes \tilde{\mathbf{F}}$ as the changes and $\bar{\mathbf{F}} = (\mathbf{F} + \Delta\mathbf{F})$ as the new matrix. The new outputs are then given by $(\mathbf{y} + \Delta\mathbf{y}) = \bar{\mathbf{y}} = (\mathbf{I} - \bar{\mathbf{A}})^{-1}\bar{\mathbf{F}}\mathbf{u}$, the new world GDP by $\mathbf{v}'\bar{\mathbf{y}}$, and new GDP in China as $(\mathbf{v}^{China})'\bar{\mathbf{y}}$. The new values-added at the sectoral level can be written as $\hat{\mathbf{v}}\bar{\mathbf{y}}$. Our aim is to find matrices $\bar{\Phi}$ and $\bar{\Pi}$ that make China's new GDPcapratio as large as possible. This is to be done under certain constraints, which include basic constraints in the input-output model and some boundary conditions which are added from a practical point of view. This leads to the following nonlinear optimization problem.

The nonlinear optimization problem

Objective: Maximize

$$\text{GDPcapratio}^{China} = \frac{(\mathbf{v}^{China})'(\mathbf{I} - \bar{\Phi} \otimes \tilde{\mathbf{A}})^{-1}(\bar{\Pi} \otimes \tilde{\mathbf{F}})\mathbf{u}}{\mathbf{v}'(\mathbf{I} - \bar{\Phi} \otimes \tilde{\mathbf{A}})^{-1}(\bar{\Pi} \otimes \tilde{\mathbf{F}})\mathbf{u}} \cdot \frac{\text{POP}^{World}}{\text{POP}^{China}}$$

with respect to the elements of matrices $\bar{\Phi}$ and $\bar{\Pi}$ subject to the following constraints.

C1: The IO model: $\bar{\mathbf{y}} = (\mathbf{I} - \bar{\mathbf{A}})^{-1}\bar{\mathbf{F}}\mathbf{u}$ with $\bar{\mathbf{A}} = \bar{\Phi} \otimes \tilde{\mathbf{A}}$ and $\bar{\mathbf{F}} = \bar{\Pi} \otimes \tilde{\mathbf{F}}$

C2: The production technologies of each economy remain unchanged:

$$\sum_{s=1}^n \bar{\mathbf{A}}^{sr} = \sum_{s=1}^n \mathbf{A}^{sr} = \tilde{\mathbf{A}}^r \quad (r = 1, \dots, n).$$

C3: The final demands of each economy remain unchanged:

$$\sum_{s=1}^n \bar{\mathbf{F}}^{sr} = \sum_{s=1}^n \mathbf{f}^{sr} = \tilde{\mathbf{f}}^r \quad (r = 1, \dots, n).$$

C4: The change in the gross output is bounded for each country-sector:

$$y_i^r - b_i^{r,y-} \leq \bar{y}_i^r \leq y_i^r + b_i^{r,y+} \quad (i = 1, \dots, m; r = 1, \dots, n)$$

with $b_i^{r,y-} \geq 0$ the maximum decrease and $b_i^{r,y+} \geq 0$ the maximum increase.

C5: The change in the final demand is bounded for each country-sector:

$$f_i^{sr} - b_i^{sr,f-} \leq \bar{f}_i^{sr} \leq f_i^{sr} + b_i^{sr,f+} \quad (i = 1, \dots, m; s, r = 1, \dots, n)$$

with $b_i^{sr,f-} \geq 0$ the maximum decrease and $b_i^{sr,f+} \geq 0$ the maximum increase.

C6: The elements of the new IO matrix are nonnegative: $\bar{a}_{ij}^{sr} \geq 0$.

C7: The change in the intermediate input coefficients is bounded:

$$a_{ij}^{sr} - e_{ij}^{sr,e-} \leq \bar{a}_{ij}^{sr} \leq a_{ij}^{sr} + e_{ij}^{sr,e+} \quad (i, j = 1, \dots, m; s, r = 1, \dots, n)$$

with $e_{ij}^{sr,e-} \geq 0$ the maximum decrease and $e_{ij}^{sr,e+} \geq 0$ the maximum increase.

Constraint C1 ensures that equation (4.1) holds for the global IO model in the new situation. Constraint C2 ensures unchanged production technology in each economy-sector and constraint C3 ensures unchanged final demands in each economy. Note that constraint C2 also implies that the value-added coefficient remains unchanged in each country-sector ($\bar{v}_j^r = 1 - \sum_s \sum_i \bar{a}_{ij}^{sr} = 1 - \sum_s \sum_i a_{ij}^{sr} = v_j^r$). The reason for choosing these constraints is that we would like to find a short-term solution. Therefore, C2 is appropriate because changing the production technology normally takes time. Trade on the other hand is more flexible and may change in the short run, for example, due to adjustments of bilateral or multilateral trade policies. C2 implies a constant technology in the sense the total amount of each intermediate input of a country-sector is the same but the sourcing of the intermediate inputs may change.

Constraint C3 reflects a similar requirement for the final demands. In a similar vein, we keep the total final demand of a country unchanged. What is flexible in the model is that the final users in a country can change where they purchase the products they want to consume. C3 also implies that the world GDP remains unchanged because the summation of value-added across all sectors in all countries (i.e. world GDP) equals to the overall final demand, i.e. $\sum_{r=1}^n \sum_{j=1}^m w_j^r = \sum_{s=1}^n \sum_{r=1}^n \sum_{i=1}^m f_i^{sr}$. This, in turn, leads to the outcome that our model redistributes the world value-added in a global IO framework. Increasing China's value-added via small changes in international sourcing implies that the value-added of the remaining economies will reduce by the same value. It should be noted that we use this model to investigate the redistribution of a fixed-sized cake via changing international sourcing. We do not consider the effect that changes in the international

sourcing could alter the size of the cake, which we leave for future extension.

Constraints C4-C7 refer to general restrictions that are used to control the changes in country-sector-specific outputs and final demands and on the changes in the direct intermediate input coefficients in the IO model. Constraint C6 ensures that elements of the new intermediate input coefficient matrix ($\bar{\mathbf{A}}$) cannot become negative, which makes no sense in the input-output model.

It should be emphasized that the changes in direct intermediate input coefficients ($\Delta\mathbf{A}$) in this chapter only originate from geographic shifts in international sourcing ($\Delta\Phi$). Changes in intermediate input coefficients are in general the result of many mechanisms, including technological changes and geopolitical changes affecting trade relationships. It is difficult, however, to take all of these economic mechanisms into account in a single optimization framework (Tarancón et al., 2008). We therefore focus on changes in geographic sourcing and study the effects on value-added redistribution.

Table 4.1 Choices of the bounds for the optimization

Choice of the bounds	Description
$b_i^{r,y-} = b_i^{r,y+} = 0.05 \times y_i^r$ $b_i^{sr,f-} = b_i^{sr,f+} = 0.05 \times f_i^{sr}$	Small values are set for the country-sector boundaries on the changes in the new outputs and final demands. We choose 5% of the observed value in 2015.
$e_{ij}^{sr,e-} = e_{ij}^{sr,e+} = 2 \times sda_{ij}^{sr}$ sda_{ij}^{sr} = standard deviation of $\{sda_{ij}^{sr,2005}, \dots, sda_{ij}^{sr,2015}\}$ $i, j = 1, \dots, m$ $s, r = 1, \dots, n$	A typical two-sigma rule is assumed for the changes in direct intermediate input coefficients. That is, assuming that approximately 95% of the new coefficients lie within two standard deviations of the observed values for the year 2015. The standard deviation is calculated using historical data on changes in intermediate input coefficients in the period 2005-2015.

Table 4.1 gives our choices of the bounds in constraints C4-C7. Our choices can easily be replaced by other values, in case more or better information is available, for example, for changes in production technologies or bilateral trade relationships. A typical feature of applying optimization methods is specifying exogenous values for constraints,

which allows for researcher freedom but also some kind of arbitrariness. Because our focus is on the short-run we follow earlier research (e.g. Gurgul and Lach, 2019) and assume that all changes in our model are ‘small’. We restrict the changes in a country-sector’s output and final demand to 5%. The restriction for the change range of any IO coefficient is based on past changes of that coefficient, which is set as twice the standard deviation of values for that coefficient in the years 2005-2015. Such an approach minimizes the influence of possible supply constraints and enables us to assume that the supply problem is not a (big) concern here.

4.3 Data

We employ the inter-country input-output (ICIO) tables (2018 edition) compiled by the OECD (OECD and WTO, 2012). The database provides annual ICIO tables for the period 2005-2015. The tables contain data for 65 economies with 36 industries in each economy (see Table A4.1 in Annex 4). The tables are global because one of the 65 economies provides an estimate of the economic structure in the “Other Countries”.

The OECD ICIO tables distinguish the production of China into activities related to the production of processing exports and activities related to any other production. It is well known that the production for processing exports relies heavily on imported intermediate products but creates less value-added for China than other production (see, e.g. Chen et al., 2012; Koopman et al., 2012; Yang et al., 2015). As a result, this distinction in national, regional or global IO tables between the two types of production activities is necessary (Chen et al., 2019, 2020; Duan et al., 2021; Tian et al., 2020). Another reason why it is important is that China’s trade depends much on processing trade. Processing exports accounted for more than half of China’s total exports for the years 1996-2007. Processing trade also played an important role in facilitating the international sourcing shifts from developed countries to China.

We use the General Algebraic Modeling System (GAMS) solver to solve our non-linear constrained optimization problem introduced in Subsection 2.2. The NEOS

Server¹⁸ is adopted to conduct the computations and find a global solution. We use the full ICIO tables for our calculations but for presentation purposes we will aggregate the results and group certain countries or industries together. This chapter focuses on China's value-added gains by choosing the sourcing, within a GVC framework. We thus choose to include China's six major trading partners for the presentation of our results. These are the US, EU (28 members of the European Union, still including the United Kingdom), ASEAN (Association of Southeast Asian Nations),¹⁹ Japan, South Korea, and India. All the other economies (including the 'economy' that we termed "Other Countries") are aggregated into the Rest-of-the-World (RoW).

When presenting the results, we also aggregate the 36 industries in the OECD's ICIO tables into seven industry-groups (see Table A4.2 in Annex 4). Short value chains are often local and are observed for industries in the groups "Agriculture and mining" (C1) and "Services and construction" (C7). Other goods-producing industries are more global and more likely to form long value chains (De Backer and Miroudot, 2013). These industries are aggregated in five industry-groups: "Textiles and leather products" (C2); "Chemical products" (C3); "Electronic products and machinery" (C4); "Transport equipment" (C5); and "Remaining manufacturing" (C6).

4.4 Analysis of the results

Subsection 4.4.1 is descriptive and looks back. That is, we present how much the shifts in international sourcing have contributed to China's increase in GDP per capita in the past years. Subsection 4.4.2 presents the results obtained with the optimization model. The subsection looks at the potential gains in the sense that it sketches how China might benefit from a shift in international sourcing. It yields strategies for China to narrow the income gap with developed countries.

¹⁸ For details, please refer to <http://www.neos-server.org>.

¹⁹ In the ICIO tables by the OECD, two ASEAN countries (Laos and Myanmar) are included in the group of RoW due to data unavailability.

4.4.1 The contribution of international sourcing shifts to China's income gains

In Figure 4.1 we compare the actual ratio of China's GDP per capita relative to the world average level (i.e., $GDPcapratio_{t1}^{China}$ as measured by equation (4.5)) with three alternative scenarios (i.e., $GDPcapratio_{hypothetical}^{China}$ as measured by equation (4.6)) for the period 2005-2015.²⁰ In the alternative scenarios, the structure of both intermediates trade and final products trade is assumed to be replaced by the structure in a specific year. For example, the line indicated as "2005 structure" gives the hypothetical results for $t1 = 2005, \dots, 2015$, with $\Phi_{t0} = \Phi_{2005}$ and $\Pi_{t0} = \Pi_{2005}$. The hypothetical result coincides with the actual result in the first year (2005 in this example). The difference between the two ratios gives the effect on China's GDP per capita of the geographic shifts in international sourcing.

Figure 4.1 indicates that the ratio of China's GDP per capita to the world average level (i.e., $GDPcapratio$) would have been smaller than the observed ratio if the trade structure of a previous year had been adopted. That is, the geographic shifts in international sourcing contributed positively to China's income gains in the period 2006-2015. Our results show that in 2015 the $GDPcapratio$ would have been 0.62 (rather than the observed 0.73) if only the 2005 trade structure would have applied. In other words, the geographic shifts in international sourcing increased China's GDP per capita relative to the world average level by 0.11.

We also observe that the gains are monotonous in the sense that in each year the international sourcing pattern is better than the previous year's pattern, where better means a higher $GDPcapratio$. For example, if the trade structure of 2008 (or 2011) had been adopted, the contribution would still have been positive, but the gains in 2015 would have been smaller. The ratio in 2015 of would have been 0.66 (0.67) in case the 2008 (2011) sourcing structure had applied.

²⁰ We are aware that the 2016 edition of OECD ICIO database provides annual ICIO tables for the period 1995-2011, which enables us to do the same analysis for the period 1995-2011. However, the sector classifications in the two editions of database are not the same, implying that we cannot link the period 1995-2011 to the period 2005-2011.

It should be noted that the difference between China's GDPcapratio under the 2005 structure and the 2008 structure seems to be constant over time. However, it is not and actually increases slowly over the years.²¹

Figure 4.1 The ratios of China's GDP per capita to the world average level: the observed ratios and the ratios under three scenarios of international sourcing

Notes: The observed ratios are calculated using equation (4.5). The other ratios are calculated using equation (4.6), assuming that the actual sourcing structure is replaced by the structure in 2005, 2008, or 2011.

4.4.2 Optimization results

In Figure 4.2, we compare the share of value-added in global GDP for eight groups of

²¹ It follows from equation (4.6) that the orange line is based on Φ_{2005} and Π_{2005} which are weighted with $v'_t, \tilde{A}_t, \tilde{F}_t$, and $(POP_t^{World}/POP_t^{China})$. The grey line applies the same weights to Φ_{2008} and Π_{2008} . The weights, however, are different for each year t . The difference between the orange line and the grey line is 0.037 for 2015 (using $v'_{2015}, \tilde{A}_{2015}, \tilde{F}_{2015}$, and $POP_{2015}^{World}/POP_{2015}^{China}$), while the difference is 0.031 for 2009 (using $v'_{2009}, \tilde{A}_{2009}, \tilde{F}_{2009}$, and $POP_{2009}^{World}/POP_{2009}^{China}$).

economies in two cases. One case shows the actual (or observed) shares, and the other shows the shares after China has solved its optimization problem. The sum of all the bars in either case is 100%. The results show that by choosing an optimal sourcing structure China may increase the share of its GDP in global GDP by 2.66 percentage points. This is equivalent to an increase in China's GDPcapratio of 0.14 (from 0.73 to 0.87). At the same time, China's optimization strategy would lead to a drop in the value-added share in the remaining economies, especially the EU (1.13 percentage points) and the USA (1.10 percentage points).

Figure 4.2 The observed and optimal value-added shares in 2015

Note: The optimal shares are found after solving the nonlinear optimization problem, using the OECD ICIO table for the year 2015. Two ASEAN countries (Laos and Myanmar) are classified into the group of RoW because OECD does not provide IO tables for Laos and Myanmar.

The results presented in Figure 4.3 give the contribution by each industry as a share of China's GDP. It compares the actual (or observed) shares with the shares that would apply if China had optimized its international sourcing. The optimal value-added share of the aggregated manufacturing industries (c2-c6) is 6.50 percentage point larger than the observed share, 30.09% vs. 36.59%. The largest rise in value-added share due to optimization is reported in the case of electronic products and machinery (c4, 3.62%) and

remaining manufacturing (c6, 1.68%). On the other hand, the share of the aggregated industries in agriculture and mining (c1) and in services and construction (c7) decrease by 2.08 and 4.41 percentage points, respectively. The results suggest that China still needs to improve its earnings in manufacturing industries in order to bring China's GDP per capita closer to the global level. This finding is consistent with the conclusions in some other studies (e.g. Guo and Peng, 2021) based on development theory. It is also reflected in China's 14th-Five-Year plan which emphasizes the importance of manufacturing.

Figure 4.3 China's observed and optimal industry shares in 2015

Note: c1: Agriculture and mining; c2: Textiles and leather products; c3: Chemical products; c4: Electronic products and machinery; c5: Transport equipment; c6: Remaining manufacturing; c7: Services and construction.

Of course, the next question is how China manages to improve its earnings in the manufacturing industries. In order to explore some answers to this question, we take a closer look at the changes in the global matrices for intermediate inputs and final demands after solving the nonlinear constrained optimization problem. Table 4.2 presents the particular changes in China's domestic intermediate input coefficients. The element in row i and column j indicates the extent to which the input of domestically produced product i used for producing one unit output of industry j is changed. The lower part of Table 4.2 is

for the production of processing exports and the upper part is for all other production. So, the input of Chinese agricultural and mining products that is used per Rmb of Chinese textile and leather products has risen by 0.000180 (in case of other production). Table 4.3 presents the same changes in the foreign input coefficients. For example, the input of Chinese agricultural and mining goods (produced by other production) that is used per Rmb of the US textile and leather products has risen by 0.000012.

Our first observation is that in the optimum China uses more of its own inputs and (therefore) less imported inputs. This boosts China's production and hence its value-added gains. The increase in using domestic inputs applies both for the production of processing exports and for other production. We observe in Table 4.2 that almost all domestic intermediate input coefficients increase (i.e., none of them decreases) in the optimal sourcing structure. In other words, import substitution is considerable which holds in particular for the intra-industry inputs. The input coefficients on the main diagonal are the ones that usually show the largest increases (especially in the case of the industries 'electronic products and machinery' (c4) and 'transport equipment' (c5)). Also some off-diagonal elements (indicating inter-industry deliveries) of China's domestic input matrix show much import substitution (for example, the deliveries from China's 'remaining manufacturing' (c6) to China's 'electronic products and machinery' (c4)). These results suggest that the strategy of substituting foreign intermediate inputs by domestically provided inputs helps to increase Chinese GDPcapratio.

The results in Table 4.3 suggest that a second strategy is to foster export promotion, so that foreign countries choose China as the country to source their inputs from. This applies in particular for China's major trading partners, i.e. the US, the EU, ASEAN, Japan, India, and South Korea. Table 4.3 shows that increasing the use of China's intermediate inputs in foreign production processes works particularly well for China's 'electronic products and machinery' (c4), 'Textiles and leather products' (c2), 'Chemical products' (c3), and 'Transport equipment' (c5). A third observation from the results (in

Table A4.3 of Annex 4) is that the strategies of import substitution in China and export promotion also apply to final demands.

We emphasize that the strategy of import substitution does not imply returning to autarky. Export promotion and import substitution interact and co-exist in a Ricardian world. In the past decades, China's rapid economic growth was fueled by its "go-global" strategy and the engagement in GVCs. The idea was primarily that China would gain from carrying out part of the global production processes. This part was processing and assembly, which meant enormous amounts of imports of materials and semi-finished products and exports of finished products. Because these processing and assembly activities basically required cheap and flexible labor (which is exactly what China was able to offer), the value-added gains remained limited. The recent trend is that China's GDP per capita may further improve if China is able to produce and sell more products with a higher value-added content. This current line of thinking is supported by our optimization results. They show that China gains most from increasing the sales of domestically produced products with a relatively large value-added content per Rmb of output. In so doing, China should focus not only on the international market but also on the domestic market. This is also reflected in China's 14th-Five-Year plan which outlines the economic and social policy agenda for the period 2021-2025 and beyond. According to the plan, China should follow a dual development strategy. On the one hand is there an external focus aiming at a deeper engagement in the international arena. For instance, one of China's efforts to strengthen its links to external economies (Asian economies in particular) is that China signed the Regional Comprehensive Economic Partnership (RCEP) with Japan, South Korea, Australia, New Zealand, and the 10 members of ASEAN on 15 November 2020. On the other hand is there an internal focus emphasizing the resilience of domestic production and taking full account of the enormous size of China's domestic demand.

It should be stressed that the magnitudes of the changes in input coefficients in Tables

4.2 and 4.3 rely on the choice of the boundaries on possible changes as listed in Table 4.1. Our main goal is to examine how the coefficients should change to enlarge China's value-added most and we link the changes directly to trade. We therefore focus on the direction and relative size of the coefficient changes rather than on the absolute size. To check whether this approach is warranted, we conducted a robustness analysis. All parameter constraints were reset at half of their initial values as listed in Table 4.1. It turned out that, the absolute sizes of the coefficient changes decreased slightly, but the main findings remained unchanged.

4.5 Discussion

The model above optimized China's GDP per capita level under the assumption that other countries do not respond, which is only realistic in the short run. In the longer run, other countries will respond to the Chinese strategy by doing the same (i.e., all countries want to maximize their value-added gains). Therefore, we extended the base model of Section 4.2.2 to a multi-objective optimization model. In so doing, we expanded the model in a sequential way where step-by-step we added another country to the existing model. First, we optimized the value-added share of two economies simultaneously, assuming that the remaining countries do not respond. In the case of China and the US, for example, the value-added share would increase by 1.72 percentage points in China and by 1.18 percentage points in the US. This means that the share for the remaining economies would decrease by 2.90 percentage points. The changes in the global flows for intermediate inputs and final demands show that both China's flows of products to the US and the US flows to China would increase in the optimal situation. The result suggest that the two strategies of import substitution and export promotion apply for both the US and China.

Next, we can include another country and optimize the value-added shares for a group of three countries. This process can be continued until all countries are included. Optimizing the value-added share of all economies, leads to a full equilibrium that is very close to the starting situation (i.e., the original value-added shares). This indicates that the

situation as represented by the global IO table already reflects the optimal global equilibrium under the current international specialization. This also suggests that trying to improve the value-added share of a certain country by changing the international sourcing can only be successful in the short run. That is, as long as no other country responds by adopting the same strategy of maximizing its value-added share. The short-run gains decrease once more and more countries follow this strategy and the gains vanish if all countries use this strategy.

If a single country wants to increase its value-added share in the longer run, it has to break the current equilibrium by improving the competitiveness of its products (e.g., by improving its production technology). It then can persuade domestic (import substitution) and foreign (export promotion) buyers to buy more of its products. This, however, requires a different model. Recall that our base model is restricted by the constraint that production technology is constant in each country in the short run, because we wanted to focus on the effects of shifts in international sourcing.

In such a new model, the increase of China's value-added (in absolute terms) may be coupled to value-added increases in other countries. This is because releasing the constraint that China's production technology remains unchanged also implies that world final demand (or world GDP) is no longer fixed. In other words, even if we still look at the pieces of the cake, the size of the cake will have increased. The development of such a model is, however, beyond the scope of the present paper.

4.6 Conclusion

In this chapter, we first quantified how the geographic shifts in international sourcing have contributed to China's value-added gains. We found continuous positive contributions to China's increase in GDP per capita in the past decades. After that, we explored which shifts in international sourcing would increase China's GDP per capita the most so as to develop potential strategies for further increasing China's value-added gains.

We applied a nonlinear optimization approach in a global input-output framework which considers both intranational and international inter-industry linkages. Our optimization results suggested two potential directions for China's future policies which endeavor to narrow its income gap with developed countries. They are import substitution at home and export promotion (leading to substitution abroad).

We extended the base model by considering the situation where other countries also optimize their value-added gains. The outcomes suggested that optimizing the value-added share of a certain country by only changing the international sourcing only worked in the short run, as long as no other country had responded by employing the same strategy. More generally, our model can also be extended to work for other countries.

In a GVC era, firms can theoretically self-select where to sell their products and from which country to source their imports based on their comparative advantages (Antràs et al., 2017). These advantages are theoretically speaking a function of productivity, trade costs, and other specific variables. In reality, however, the working of the theoretical model is often hindered by bilateral and multilateral trade policies. It should be stressed that the technically optimal strategies obtained with our optimization results interact and their implementation builds upon much practical consideration. Simultaneously increasing the exports and decreasing the imports will increase China's trade surplus. In our case, China's trade surplus would increase by 2.4%, from the observed surplus of 2235 billion RMB in 2015 to a surplus of 2288 billion RMB in the optimal situation. China's trade surplus has been an international concern for some years. Several countries have suggested that China should appreciate its national currency, and China got involved in increasing bilateral trade disputes. One of the recent influential examples is the outbreak of the trade war between the US and China during Donald Trump's presidency. The US government decided to impose an extra tariff on imports from Chinas in order to hinder the expansion of the Chinese market share in the US.

Our optimization results suggest that the strategy of import substitution holds in

particular for China's technology-intensive industries. A main direction of improving China's situation is to substitute imported technological inputs by domestically produced analogues. This change is triggered by internal and by external causes. From the internal perspective, Chinese production of electronic products and transport equipment (in particular the production for processing exports) relied heavily on its domestic cheap labor and the substantial imports of intermediate inputs from developed countries. However, as data from China's National Bureau of Statistics show, China's wage per capita doubled in the last decade. The increase in China's labor cost results in China's losing comparative advantage in simple assembly activities with low value-added content. China noticed this change and launched strategic plans (e.g., the Made in China 2025 blueprint) to promote the upgrading of high-tech manufacturing, to foster Chinese brands, and to enhance service-oriented manufacturing.

From the external perspective, the rise of China's high-tech manufacturing brought pressure on some developed countries. As a result, the US increasingly imposed sanctions on Chinese technological firms (e.g., Huawei and ZTE) and prohibited US enterprises to export high-tech intermediate inputs (e.g. chips) to China. In particular the latter prohibition forced China to lower its dependence on US inputs and develop a strategic sourcing to ensure its security in global supply chains. This recent example also points at building a resilient production structure. In order to avoid that production is suddenly halted (due to a disaster or a trade war), firms might want to diversify the suppliers of their core intermediate inputs. For example, when the US banned sales of semiconductors to China, it switched to importing more semiconductors from the EU, Japan and South Korea. In the longer run it is apparent that China seeks to reduce its vulnerability to future shocks through self-development and import substitution. China is strengthening its institutional and financial support for R&D activities to resolve technological "bottlenecks". The government is creating an environment for enterprises to innovate and to cultivate talent, aiming at reducing China's reliance on core technologies controlled by foreign countries.

Table 4.2 Changes in China's dependence on domestic inputs

	Agriculture and mining	Textile and leather products	Chemical products	Electronic products and machinery	Transport equipment	Remaining manufacturing	Services and construction
Source: China's other production							
Destination: China's other production							
Agriculture and mining	0.000670	0.000180	0.000080	0.000020	0.000010	0.004070	0.010130
Textile and leather products	0.000000	0.043200	0.000190	0.000020	0.000150	0.000330	0.003370
Chemical products	0.000450	0.000520	0.016290	0.000090	0.000160	0.000250	0.004530
Electronic products and machinery	0.001910	0.000120	0.000090	0.057300	0.002080	0.000400	0.004370
Transport equipment	0.000030	0.000000	0.000000	0.000440	0.057640	0.000050	0.006530
Remaining manufacturing	0.006530	0.000000	0.003570	0.009160	0.002360	0.021270	0.032880
Services and construction	0.002700	0.004050	0.008780	0.006180	0.003460	0.011760	0.076850
Source: China's other production							
Destination: China's production for processing export							
Agriculture and mining	0.000000	0.000060	0.000030	0.000030	0.000050	0.003130	0.000000
Textile and leather products	0.000000	0.031450	0.000110	0.000050	0.000260	0.000210	0.000000
Chemical products	0.000000	0.000360	0.012530	0.000070	0.000350	0.000430	0.000000
Electronic products and machinery	0.000000	0.000050	0.000050	0.061500	0.003190	0.000220	0.000000
Transport equipment	0.000000	0.000000	0.000000	0.000360	0.048520	0.000090	0.000000
Remaining manufacturing	0.000000	0.000000	0.002760	0.008610	0.003630	0.015360	0.000000
Services and construction	0.000000	0.003510	0.004630	0.004350	0.002520	0.010630	0.000000

Notes: China's other production covers all production in China except the production of processing exports. Coefficient changes larger than 0.03 (in absolute sense) are in dark grey and changes between 0.005 and 0.03 (in absolute sense) are in light grey.

Table 4.3 Changes in foreign dependence on China's intermediate inputs from other production

	Agriculture and mining	Textile and leather products	Chemical products	Electronic products and machinery	Transport equipment	Remaining manufacturing	Services and construction
Source: China's other production							
Destination: the U.S.							
Agriculture and mining	0.000029	0.000012	0.000016	0.000020	0.000016	0.000033	0.000011
Textile and leather products	0.000005	0.002132	0.000020	0.000027	0.000115	0.000065	0.000061
Chemical products	0.000196	0.001046	0.002155	0.000120	0.000101	0.000298	0.000102
Electronic products and machinery	0.000388	0.000235	0.000322	0.003565	0.002595	0.000402	0.001184
Transport equipment	0.000037	0.000023	0.000028	0.000229	0.002063	0.000042	0.000178
Remaining manufacturing	0.000136	0.000295	0.000338	0.000876	0.000926	0.000711	0.000571
Services and construction	0.000038	0.000163	0.000095	0.000076	0.000128	0.000081	0.000255
Source: China's other production							
Destination: EU							
Agriculture and mining	0.000035	0.000010	0.000017	0.000022	0.000014	0.000033	0.000013
Textile and leather products	0.000044	0.004636	0.000071	0.000043	0.000167	0.000088	0.000135
Chemical products	0.000183	0.000268	0.001623	0.000088	0.000082	0.000187	0.000115
Electronic products and machinery	0.000189	0.000118	0.000218	0.007719	0.001993	0.000335	0.001320
Transport equipment	0.000018	0.000017	0.000022	0.000151	0.000772	0.000029	0.000108
Remaining manufacturing	0.000175	0.000213	0.000377	0.000653	0.000666	0.000729	0.000502
Services and construction	0.000120	0.000118	0.000254	0.000370	0.000220	0.000210	0.001012
Source: China's other production							
Destination: Japan							
Agriculture and mining	0.000242	0.000019	0.000026	0.000025	0.000012	0.000409	0.000112
Textile and leather products	0.000054	0.002456	0.000042	0.000041	0.000029	0.000033	0.000107
Chemical products	0.000234	0.000767	0.003173	0.000138	0.000111	0.000259	0.000180
Electronic products and machinery	0.000039	0.000062	0.000106	0.006562	0.002009	0.000262	0.001163
Transport equipment	0.000043	0.000015	0.000019	0.000099	0.001897	0.000018	0.000158
Remaining manufacturing	0.000297	0.000327	0.000722	0.000987	0.000700	0.001217	0.001243
Services and construction	0.000142	0.000122	0.000133	0.000112	0.000065	0.000121	0.000541
Source: China's other production							
Destination: ASEAN							
Agriculture and mining	0.000076	0.000028	0.000042	0.000035	0.000037	0.000316	0.000033
Textile and leather products	0.000244	0.013411	0.000461	0.000280	0.001085	0.000501	0.000944

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Chemical products	0.000247	0.000216	0.002859	0.000352	0.000306	0.000437	0.000358
Electronic products and machinery	0.000688	0.000189	0.000215	0.013445	0.003611	0.000313	0.002185
Transport equipment	0.000042	0.000022	0.000027	0.000165	0.002495	0.000027	0.000328
Remaining manufacturing	0.000459	0.000498	0.001231	0.001944	0.002290	0.001347	0.001281
Services and construction	0.000190	0.000237	0.000251	0.000289	0.000242	0.000117	0.000770
Source: China's other production							
Destination: India							
Agriculture and mining	0.000015	0.000013	0.000031	0.000050	0.000040	0.000329	0.000020
Textile and leather products	0.000030	0.002261	0.000067	0.000042	0.000050	0.000042	0.000091
Chemical products	0.000294	0.000738	0.004420	0.000224	0.000178	0.000392	0.000196
Electronic products and machinery	0.000103	0.000259	0.000200	0.005189	0.003103	0.000292	0.000581
Transport equipment	0.000028	0.000017	0.000030	0.000124	0.003263	0.000029	0.000414
Remaining manufacturing	0.000056	0.000215	0.000626	0.001963	0.001661	0.001104	0.001062
Services and construction	0.000006	0.000017	0.000011	0.000051	0.000034	0.000021	0.000065
Source: China's other production							
Destination: South Korea							
Agriculture and mining	0.000599	0.000170	0.000055	0.000069	0.000096	0.000093	0.000471
Textile and leather products	0.000060	0.001787	0.000064	0.000039	0.000025	0.000074	0.000234
Chemical products	0.000607	0.000436	0.003253	0.000516	0.000127	0.000415	0.000700
Electronic products and machinery	0.000164	0.000568	0.000282	0.008304	0.003435	0.000458	0.002539
Transport equipment	0.000106	0.000323	0.000060	0.000241	0.002874	0.000102	0.000375
Remaining manufacturing	0.001068	0.000811	0.001541	0.004047	0.004570	0.004731	0.003303
Services and construction	0.000110	0.000319	0.000351	0.000292	0.000262	0.000269	0.001738
Source: China's other production							
Destination: RoW							
Agriculture and mining	0.000213	0.000095	0.000063	0.000037	0.000075	0.000051	0.000132
Textile and leather products	0.000021	0.001214	0.000051	0.000126	0.000062	0.000036	0.000013
Chemical products	0.000755	0.000263	0.002357	0.000627	0.000075	0.000021	0.000015
Electronic products and machinery	0.000125	0.000316	0.000154	0.003920	0.000672	0.000226	0.000161
Transport equipment	0.000021	0.000056	0.000035	0.000113	0.002276	0.000073	0.000128
Remaining manufacturing	0.000273	0.000435	0.000687	0.000865	0.001257	0.003172	0.000087
Services and construction	0.000087	0.000136	0.000215	0.000223	0.000157	0.000194	0.000675

Notes: China's other production covers all production in China except the production of processing exports. Coefficient changes larger than 0.001 (in absolute sense) are in dark grey and changes between 0.0005 and 0.001 (in absolute sense) are in light grey.

Annex 4

Table A4.1 Economies in OECD ICIO tables

AUS	Australia	ARG	Argentina
AUT	Austria	BRA	Brazil
BEL	Belgium	BRN	Brunei Darussalam
CAN	Canada	BGR	Bulgaria
CHL	Chile	KHM	Cambodia
CZE	Czech Republic	CHN	China (People's Republic of)
DNK	Denmark	COL	Colombia
EST	Estonia	CRI	Costa Rica
FIN	Finland	HRV	Croatia
FRA	France	CYP	Cyprus ²
DEU	Germany	IND	India
GRC	Greece	IDN	Indonesia
HUN	Hungary	HKG	Hong Kong, China
ISL	Iceland	KAZ	Kazakhstan
IRL	Ireland	MYS	Malaysia
ISR	Israel ¹	MLT	Malta
ITA	Italy	MAR	Morocco
JPN	Japan	PER	Peru
KOR	Korea	PHL	Philippines
LVA	Latvia	ROU	Romania
LTU	Lithuania	RUS	Russian Federation
LUX	Luxembourg	SAU	Saudi Arabia
MEX	Mexico	SGP	Singapore
NLD	Netherlands	ZAF	South Africa
NZL	New Zealand	TWN	Chinese Taipei
NOR	Norway	THA	Thailand
POL	Poland	TUN	Tunisia
PRT	Portugal	VNM	Viet Nam
SVK	Slovak Republic	ROW	Rest of the World
SVN	Slovenia	CN1	China - Activities excluding export processing
ESP	Spain	CN2	China - Export processing activities
SWE	Sweden		
CHE	Switzerland		
TUR	Turkey		
GBR	United Kingdom		
USA	United States		
MX1	Mexico - Activities excluding Global Manufacturing		
MX2	Mexico - Global Manufacturing activities		

Table A4.2 List of aggregated sectors analyzed in the optimization

Aggregated sector description	Sectors in OECD-ICIO 2018 edition
c1 Agriculture and mining	D01T03 Agriculture, forestry and fishing D05T06 Mining and extraction of energy producing products D07T08 Mining and quarrying of non-energy producing products D09 Mining support service activities
c2 Textiles and leather products	D13T15 Textiles, wearing apparel, leather and related products
c3 Chemical products	D20T21 Chemicals and pharmaceutical products
c4 Electronic products and machinery	D26 Computer, electronic and optical products D27 Electrical equipment D28 Machinery and equipment n.e.c.
c5 Transport equipment	D29 Motor vehicles, trailers and semi-trailers D30 Other transport equipment
c6 Remaining manufacturing	D10T12 Food products, beverages and tobacco D16 Wood and products of wood and cork D17T18 Paper products and printing D19 Coke and refined petroleum products D22 Rubber and plastic products D23 Other non-metallic mineral products D24 Basic metals D25 Fabricated metal products D31T33 Other manufacturing; repair and installation of machinery and equipment
C7 Services and construction	D35T39 Electricity, gas, water supply, sewerage, waste and remediation services D41T43 Construction D45T47 Wholesale and retail trade; repair of motor vehicles D49T53 Transportation and storage D55T56 Accommodation and food services D58T60 Publishing, audiovisual and broadcasting activities D61 Telecommunications D62T63 IT and other information services D64T66 Financial and insurance activities D68 Real estate activities D69T82 Other business sector services D84 Public admin. and defence; compulsory social security D85 Education D86T88 Human health and social work D90T96 Arts, entertainment, recreation and other service activities D97T98 Private households with employed persons

Table A4.3 Changes in final demand of different economies for China's products (%)

	China	U.S.	EU	Japan	ASEAN	India	South Korea	RoW
Source: China's other production								
Agriculture and mining	0.62	0.29	0.46	0.28	0.57	0.41	0.34	0.73
Textile and leather products	1.75	2.46	2.36	2.01	1.29	0.13	0.52	2.81
Chemical products	1.55	2.10	2.83	2.15	3.06	1.58	2.35	3.06
Electronic products and machinery	3.82	3.35	3.22	2.71	4.35	3.05	2.28	3.55
Transport equipment	3.46	2.03	1.92	1.52	3.52	2.85	1.18	3.56
Remaining manufacturing	2.63	1.25	2.45	1.36	2.68	1.63	1.31	2.71
Services and construction	0.72	0.23	0.08	0.19	0.45	0.26	0.07	0.61
Source: China's production for processing export								
Agriculture and mining	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Textile and leather products	0.00	0.31	0.62	0.40	0.29	0.03	0.71	0.15
Chemical products	0.00	1.02	1.57	1.98	1.16	1.42	1.09	2.17
Electronic products and machinery	0.00	4.32	4.00	3.27	2.51	1.20	2.69	2.43
Transport equipment	0.00	1.93	2.31	1.78	1.21	0.74	2.36	1.32
Remaining manufacturing	0.00	2.07	1.84	1.76	1.07	0.53	1.82	0.07
Services and construction	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: China's other production covers all production in China except the production of processing exports.

Chapter 5

Upgrading or downgrading: China's regional carbon emission intensity evolution and its determinants²²

5.1 Introduction

Global warming has become one of the greatest environmental challenges that humans currently face. There is consensus amongst the world's scientists that this is mainly caused by the increase of carbon emissions emitted by anthropogenic activities (Moser, 2010). As the largest developing country and the “world's factory”, China became the world's leading emitter of carbon dioxide (CO₂) around 2006. In 2013, its emissions accounted for nearly 30% of the world's total CO₂ emissions from fossil fuels combustion (Quéré et al., 2015). As a response, China took its responsibility to mitigate CO₂ emissions. At the Paris Climate Change Conference in 2015, China committed itself to (i) have the peak of carbon emissions around 2030 (or earlier), and (ii) lower the carbon emission intensity (CO₂ emissions per unit of GDP) of its economy by 60% to 65% from the 2005 level.²³ The emission intensity (EI) captures the environmental costs (measured by CO₂ emissions in this chapter) for a country to obtain economic gains (measured by value-added) from production. An increase (decrease) in EI suggests that the country bears more (less) environmental costs for the same economic gains. Here, we call the increase (decrease) in EI environmental downgrading (upgrading).

Two specific aspects have motivated this study. First, the top-down policy process. Commitments in China are made by the central government whilst local (regional) governments are the direct executive bodies in charge of the emission reductions. At the same time, however, local governments are pushed by the central government to improve economic performance, which normally has priority over the emission reduction target.

²² This chapter is co-authored with Erik Dietzenbacher, Bingqian Yan and Yuwan Duan and was originally published at *Energy Economics*, Vol. 91 (i.e. Tian et al., 2020).

²³ These are China's intended nationally determined contributions (INDCs). Before that, China committed at the 2009 Copenhagen Climate Change Conference to reduce CO₂ emissions per unit of GDP by 40-45% towards 2020.

Both forces influence EI, but in opposite ways. Second, China is a very large country with striking regional disparities in resource endowments, production technology, energy efficiency, industrial structures, and economic development level. As a result, the EIs and their evolution over time differ across regions. For example, the EIs of Ningxia and Shanxi, which are located in the Northwestern regions, were 12 and 8 times of that in Beijing, respectively (Wang et al., 2020). According to our estimation in Section 4, the EI of the Beijing-Tianjin region decreased by 37% from 2002 to 2012, but the EI of the Northwest increased by 27% in that period.

These two aspects suggest that China needs to strengthen the regional coordination of EI reduction in order to achieve its national targets for low-carbon transformation. It is therefore important that the evaluation of the development of EIs and the quantification of the determinants (or drivers) of the changes in EIs take place at the regional level. This may help to check the effectiveness of environmental policies and to design more effective decarbonizing measures.

In this chapter, we examine China's EIs at the regional level. We first check whether regional environmental upgrading has taken place, whether EIs differ much across regions, and whether the development of regional EIs over time is similar across regions. Subsequently, we employ a multiplicative Structural Decomposition Analysis (SDA) to identify what has driven the changes in regional EIs over the period 2002-2012 and to quantify how much each driver has contributed. In the analysis, we will define EI from the demand perspective. That is, both at the national and the regional level, we consider embodied EI indicators for domestic final demands and for international exports (Su and Ang, 2017). In particular, when studying the embodied EIs in exports, we distinguish between processing exports and ordinary exports.²⁴ This is important because processing exports account for a large share of China's export and because the production of processing exports differs largely from the production of ordinary exports (Chen et al., 2012; Koopman et al., 2012; Dietzenbacher et al., 2012; Su and Thomson, 2016). We will employ the (IRIOP) tables constructed by Duan et al. (2014) and Yan et al. (2020) for the

²⁴ Processing exports follow from the business activity of importing from abroad all, or part of, the raw and auxiliary materials, parts and components, accessories, and packaging materials, and re-exporting the finished products after processing or assembly by enterprises in China. In this thesis, the processing exports include both the exports of processing with imported materials and the exports of processing and assembly.

years 2002, 2007, and 2012. These are inter-regional input-output (IRIO) tables that split the Chinese economy into 8 regions, each with 2 production types (production of processing exports and ordinary production) and 17 industry groups.

This study contributes to the literature in two ways. First, we introduce new drivers in our multiplicative SDA. Standard drivers are changes in direct emission coefficients (emissions per unit of output), changes in the intermediate input structure, and changes in the final demands. Next to these standard drivers, we also include changes in inter-regional trade and changes in inter-regional spillovers as drivers of the changes in regional EIs.

The motivation to include these new drivers is as follows. Producers in a region can upgrade the region's emission performance in two different ways. First, by reducing their own emissions content and/or increasing the value-added content (both contents per unit of output). Second, by giving up the production of certain "dirty" products at home. Instead, the production is transferred to other regions after which the "dirty" products are imported. This results in inter-regional spillovers of carbon emissions. This second way follows the idea underlying the pollution haven hypothesis, albeit at a regional level. Given that China is a vast country with remarkable regional disparities and given that environmental pressures are exercised at the regional level, pollution havens are very likely to exist in China. As a response, the Chinese government released in 2010 a regulation called "Opinions of the State Council on the Transfer of Industries to the Central and Western Regions". This report targets the undesirable emission leakages (where the Central and Western regions emit for the regions on the East Coast). To the best of our knowledge, however, no study has considered the effect of emission leakages on China's regional EI evolution (see the next section for a review of the literature). We analyze how and to what extent changes in inter-regional trade and in inter-regional spillovers changed China's regional EIs.

The second contribution of this study to the literature is that it combines two research lines that have been separate hitherto. One line of research deals with China's regional emissions and the other line deals with China's processing exports. Previous studies on China's regional emissions have largely neglected the role of processing exports. Vice versa, most studies on processing exports were only at the national level. Although the

share of processing exports in total exports declined from 55.3% in 2002 to 33.7% in 2019, it still is very substantial.²⁵ An important feature of China's processing exports is its uneven distribution over the regions, with the main concentration in coastal regions. For example, in 2012, over half of South Coast exports can be attributed to processing exports, while in the Northwest region the share is less than 10%. Over time, the share of processing exports has been decreasing for most regions, but not for every region. Some previous work (e.g. Dietzenbacher et al., 2012; Su et al., 2013; Yan et al., 2020) suggests that production for processing exports is relatively clean. Therefore, when studying China's export-related emissions it is important to distinguish between production for processing exports and other production. However, to our knowledge, few studies have quantified whether and to what extent a region's changes in processing exports contribute to the changes in its EI.

The rest of this chapter proceeds as follows. After briefly reviewing the current studies on China's regional emissions in Section 5.2, we introduce the details of our analytic approach and discuss the data in Section 5.3. Section 5.4 describes the evolution of China's regional emissions and Section 5.5 presents and analyzes the decomposition results. Finally, Section 5.6 offers conclusions and policy implications.

5.2 Literature review

Carbon emission intensity is a globally adopted indicator by policymakers and researchers to evaluate emission performance. In response to the problem of global warming, a number of countries (e.g., China, South Korea, and India) have set reduction targets in terms of EI (UNFCCC, 2015). Several studies have analyzed EIs from a regional, national and global perspective (e.g., Zhang et al., 2014; Su and Ang, 2015; Ang and Su, 2016; Su and Ang, 2017; Duan and Yan, 2019; Wang et al., 2020), and decomposition analysis has been widely used to analyze the determinants of changes in EIs. Two most

²⁵ The data are from China's National Bureau of Statistics. The reasons for this decline are twofold. On the one hand, a change in trade policy. Triggered by a very biased policy, China had a large share of processing exports in its total exports around the 2000s. After decades of rapid trade growth, the policy regarding processing trade changed in the mid-2000s. In 2006, the Ministry of Commerce selected several commodities for which processing trade became prohibited or restricted. 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). On the other hand, a change in wage policy. China's reform in 2004 of its minimum-wage policy effectively increased labor costs in China (and cheap labor was one of the major reasons to carry out processing and assembly activities in China).

frequently used decomposition methods are Index Decomposition Analysis (IDA) and Structural Decomposition Analysis (SDA). IDA uses aggregate sector information and captures direct effects mainly from a production-based perspective, and IDA can handle both quantity and intensity indicators (see, e.g. Ang, 2004 for a review of IDA). Applications of IDA to the decomposition of changes in EI include Fan et al. (2007) and Chen (2011). In contrast, SDA (which is typically based on an input-output model) is able to capture explicitly both production-side and demand-side effects (Miller and Blair, 2009). SDA studies use either an additive decomposition (see Su and Ang, 2012 for a survey of SDA studies using additive decompositions) or a multiplicative decomposition, depending on the purposes. In this chapter, we aim at identifying the drivers of changes in China's regional EI between 2002 and 2012. Because EI is determined as a ratio, we adopt a multiplicative SDA framework.

Because China is the largest emitter of global carbon emissions, a growing list of SDA studies analyzes China's emission intensity evolution. The first strand of literature covers analyses at the national level. For example, Su and Ang (2015) introduced four different models to calculate a country's aggregate EI using the input-output framework. Using the four models and multiplicative SDA, they investigated the determinants of the change in China's aggregate EI from 2007 to 2010. Later, Su and Ang (2017) showed that the aggregate EI can be expressed as a weighted summation of the EIs for final demand categories or for sectors. They further employed multiplicative SDA to analyze China's aggregate EI reduction during 2007–2012. More recently, Yan et al. (2018) applied multiplicative SDA to both the Leontief and the Ghosh model to investigate China's EI changes during 2002–2012. Su et al. (2019) combined structural path analysis with SDA to extract the important paths and driving forces of EI reduction.

The second strand of literature covers analyses of China's EI at the subnational (i.e. regional and provincial) level. This was made possible by the improvement of China's regional statistics on environmental aspects. For example, Su and Ang (2016) compared the emission performance across 30 regions in China and employed spatial-SDA to explain the EI differences between pairs of regions. Whereas a number of studies analyzed China's emissions at the regional level (e.g., Meng et al., 2013, 2017; Li et al., 2017), only Wang et al. (2020) focused on regional EI evolution. They extended the methods of Su

and Ang (2017) to a provincial setting and adopted multiplicative SDA to quantify the contribution of the drivers to the EI changes in the period 2007–2012 for China’s 30 provincial units. Next to the standard drivers that were also included in Wang et al. (2020), this study also includes other drivers (changes in inter-regional trade and in inter-regional spillovers). These additional drivers follow from extending Oosterhaven and Hoen (1998) and Xu and Dietzenbacher (2014) to an inter-regional framework. Given that China is a vast country with large regional disparities, carbon leakages between regions are present (Meng et al., 2017; Wen and Wang, 2020). Therefore, it is important to investigate how changes in inter-regional trade effect and in inter-regional spillovers contribute to changes in regional EIs.

This chapter is also closely related to studies that focus on China’s EI embodied in international trade. This EI embodied in trade is defined as the ratio of emissions embodied in trade to value-added embodied in trade. Using global multi-region input-output (GMRIO) tables, Wang et al. (2017) proposed two SDA models and quantified both the domestic and trade related effects on global and countries’ emission intensities from 2000 to 2009. Also Duan and Yan (2019) conducted an SDA of the pollution intensity of China’s value-added exports.

The aforementioned studies that were undertaken at the regional level neglected the production of processing exports. Processing trade has primarily been studied at the national level. Chen et al. (2012), Koopman et al. (2012), and Su et al. (2013) have differentiated processing exports from other production in China’s national input-output tables. They consistently concluded that processing exports rely heavily on imported intermediates. When compared to other production, producing processing exports generates less domestic activities and therefore less domestic value added. Failing to distinguish processing exports biases the intermediate input structure which may seriously affect the outcomes, e.g. on export-related emission. Examples include Dietzenbacher et al. (2012) and Su and Thomson (2016), who documented that the damage of international trade to China’s environment would be significantly overestimated if processing exports were not distinguished. More recently, Chen et al. (2019) proposed an adapted GMRIO model which splits China’s national production into production for domestic use, production of processing exports, and production of non-processing exports. Jiang et al.

(2016) revisited the global net emission transfers by applying such an adapted GMRIO table and found that the results obtained with traditional tables overestimated the net emissions from China to other countries by 15%. All the results in previous studies suggest that processing exports are relatively cleaner than ordinary exports in the sense that they have a lower embodied EI. This emphasizes the necessity to separate processing exports from ordinary exports.

At the regional level, to the best of our knowledge, only a few studies (Jiang et al., 2017; Zhang et al., 2019; Yan et al., 2020) recently distinguished processing exports in China's IRIO table. Jiang et al. (2017) employed an IRIO table that separates processing exports to study China's regional disparity of energy intensity. However, their data do not cover emissions and are only for 2007. Also Zhang et al. (2019) took processing exports into account and focused on investigating the unbalanced distribution of trade-related economic benefits and environmental costs across different regions in 2007 and 2012. Yan et al. (2020) used the new IRIOP tables to reestimate the emissions embodied in regional exports. No study so far has analyzed (the evolution of) China's regional EIs with IRIOP tables. We aim to fill this gap by applying SDA to the IRIOP tables.

5.3 Methodology and data

5.3.1 An inter-regional input-output table distinguishing processing exports

Our starting point is a unique inter-regional input-output table proposed by Duan et al. (2014), which distinguishes between the input structures of production of processing exports and ordinary production (IRIOP table). The general structure of the IRIOP table is outlined in Table 5.1. The unique feature of the IRIOP table is that domestic production of each region and each industry is divided into two types: production for processing exports and ordinary production.

China²⁶ is grouped into n regions with g sectors (or industries) in each region. In the IRIOP table, two types of production are distinguished for each industry: production of processing exports (indicated by superscript P), and ordinary production (indicated by superscript O). Ordinary production contains production of non-processing exports and

²⁶ In this thesis, China does not include Taiwan and (because of data unavailability) the special administrative regions of Hong Kong and Macao.

production for domestic use. Aggregation over the production types within each region in the IRIOP table yields the ordinary IRIO table. The $g \times g$ matrix $\mathbf{Z}_{sr}^{OP}$ (or $\mathbf{Z}_{sr}^{OO}$) denotes the sector-wise intermediate inputs produced by ordinary production in region s and used in region r for processing exports (or ordinary production). Note that processing exports are exclusively used for foreign demand, and therefore the (row) sales of processing exports (P) are zero in intermediate use and domestic final use. The value of goods and services shipped from region s to region r for domestic final use (domestic household consumption, government expenditures, gross fixed capital formation, and inventory changes) is given by the $g \times 1$ vector $\mathbf{f}_{sr}^O$. The $g \times 1$ vector $\mathbf{e}_s^P$ (or $\mathbf{e}_s^O$) gives the sector-wise processing exports (or non-processing exports) of region s . The vector $\mathbf{y}_s^P$ (or $\mathbf{y}_s^O$) represents the domestic gross output for processing exports (or ordinary production) of region s . The accounting identity (or product market clearing condition) is

$$\begin{pmatrix} \mathbf{y}_1^P \\ \mathbf{y}_1^O \\ \vdots \\ \mathbf{y}_n^P \\ \mathbf{y}_n^O \end{pmatrix} = \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 \\ \mathbf{Z}_{11}^{OP} & \mathbf{Z}_{11}^{OO} & \cdots & \mathbf{Z}_{1n}^{OP} & \mathbf{Z}_{1n}^{OO} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 \\ \mathbf{Z}_{n1}^{OP} & \mathbf{Z}_{n1}^{OO} & \cdots & \mathbf{Z}_{nn}^{OP} & \mathbf{Z}_{nn}^{OO} \end{bmatrix} \begin{pmatrix} \mathbf{u} \\ \mathbf{u} \\ \vdots \\ \mathbf{u} \\ \mathbf{u} \end{pmatrix} + \begin{pmatrix} 0 \\ \sum_t \mathbf{f}_{1t}^O \\ \vdots \\ 0 \\ \sum_t \mathbf{f}_{nt}^O \end{pmatrix} + \begin{pmatrix} \mathbf{e}_1^P \\ \mathbf{e}_1^O \\ \vdots \\ \mathbf{e}_n^P \\ \mathbf{e}_n^O \end{pmatrix}, \quad (5.1)$$

where $\mathbf{u}$ indicates the summation vector of appropriate length consisting entirely of ones.

Table 5. 1 The inter-regional input-output table distinguishing processing exports

	Intermediate use					Domestic final use			EXP	TOT
	in 1		in n							
	P	O	P	O		1	...	n		
Region 1	P	O								
	0	0	...	0	0	0	...	0	$\mathbf{e}_1^P$	$\mathbf{y}_1^P$
	$\mathbf{Z}_{11}^{OP}$	$\mathbf{Z}_{11}^{OO}$	...	$\mathbf{Z}_{1n}^{OP}$	$\mathbf{Z}_{1n}^{OO}$	$\mathbf{f}_{11}^O$	...	$\mathbf{f}_{1n}^O$	$\mathbf{e}_1^O$	$\mathbf{y}_1^O$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Region n	P	O				0	...	0	$\mathbf{e}_n^P$	$\mathbf{y}_n^P$
	$\mathbf{Z}_{n1}^{OP}$	$\mathbf{Z}_{n1}^{OO}$	...	$\mathbf{Z}_{nn}^{OP}$	$\mathbf{Z}_{nn}^{OO}$	$\mathbf{f}_{n1}^O$	...	$\mathbf{f}_{nn}^O$	$\mathbf{e}_n^O$	$\mathbf{y}_n^O$
IMP	$\mathbf{Z}_1^{MP}$	$\mathbf{Z}_1^{MO}$	...	$\mathbf{Z}_n^{MP}$	$\mathbf{Z}_n^{MO}$	$\mathbf{f}_1^M$	...	$\mathbf{f}_n^M$	0	$\mathbf{y}^M$
VA	$(\mathbf{w}_1^P)'$	$(\mathbf{w}_1^O)'$	...	$(\mathbf{w}_n^P)'$	$(\mathbf{w}_n^O)'$					
TOT	$(\mathbf{y}_1^P)'$	$(\mathbf{y}_1^O)'$	...	$(\mathbf{y}_n^P)'$	$(\mathbf{y}_n^O)'$					
Emissions	$(\boldsymbol{\rho}_1^P)'$	$(\boldsymbol{\rho}_1^O)'$	...	$(\boldsymbol{\rho}_n^P)'$	$(\boldsymbol{\rho}_n^O)'$					

Notes: P = production of processing exports; O = ordinary production, containing production of non-processing exports and production for domestic use; Domestic final use = household consumption, government expenditures, gross fixed capital formation, and changes in inventories; EXP = exports; TOT = gross sector outputs or total imports; IMP = imports; VA = value added.

Define the domestic input coefficient matrix $\mathbf{A}_{sr}^{OP} = \mathbf{Z}_{sr}^{OP} (\hat{\mathbf{y}}_r^P)^{-1}$ (or $\mathbf{A}_{sr}^{OO} = \mathbf{Z}_{sr}^{OO} (\hat{\mathbf{y}}_r^O)^{-1}$), which denotes the sector-wise intermediate inputs from ordinary production in region s and used in region r for producing one unit of output of processing exports (or ordinary production). This yields

$$\begin{pmatrix} \mathbf{y}_1^P \\ \mathbf{y}_1^O \\ \vdots \\ \mathbf{y}_n^P \\ \mathbf{y}_n^O \end{pmatrix} = \begin{bmatrix} 0 & 0 & \dots & 0 & 0 \\ \mathbf{A}_{11}^{OP} & \mathbf{A}_{11}^{OO} & \dots & \mathbf{A}_{1n}^{OP} & \mathbf{A}_{1n}^{OO} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 0 \\ \mathbf{A}_{n1}^{OP} & \mathbf{A}_{n1}^{OO} & \dots & \mathbf{A}_{nn}^{OP} & \mathbf{A}_{nn}^{OO} \end{bmatrix} \begin{pmatrix} \mathbf{y}_1^P \\ \mathbf{y}_1^O \\ \vdots \\ \mathbf{y}_n^P \\ \mathbf{y}_n^O \end{pmatrix} + \begin{pmatrix} 0 \\ \sum_t \mathbf{f}_{1t}^O \\ \vdots \\ 0 \\ \sum_t \mathbf{f}_{nt}^O \end{pmatrix} + \begin{pmatrix} \mathbf{e}_1^P \\ \mathbf{e}_1^O \\ \vdots \\ \mathbf{e}_n^P \\ \mathbf{e}_n^O \end{pmatrix}. \quad (5.2)$$

In compact form, this system can be rewritten as $\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{f} + \mathbf{e}$ and the solution is given by

$$\mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1}(\mathbf{f} + \mathbf{e}) = \mathbf{L}(\mathbf{f} + \mathbf{e}), \quad (5.3)$$

where $\mathbf{I}$ is the $2ng \times 2ng$ identity matrix, and $\mathbf{L} \equiv (\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse. In its partitioned, this matrix is given by

$$\mathbf{L} = \begin{bmatrix} \mathbf{I} & 0 & \dots & 0 & 0 \\ \mathbf{L}_{11}^{OP} & \mathbf{L}_{11}^{OO} & \dots & \mathbf{L}_{1n}^{OP} & \mathbf{L}_{1n}^{OO} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & \mathbf{I} & 0 \\ \mathbf{L}_{n1}^{OP} & \mathbf{L}_{n1}^{OO} & \dots & \mathbf{L}_{nn}^{OP} & \mathbf{L}_{nn}^{OO} \end{bmatrix}.$$

Define $\boldsymbol{\lambda}'$ as the $1 \times 2ng$ row vector of carbon emissions coefficient representing the sector-wise carbon emissions per unit of output by production type and region, with $(\boldsymbol{\lambda}_s^P)' = (\boldsymbol{\rho}_s^P)'(\hat{\mathbf{y}}_s^P)^{-1}$ and $(\boldsymbol{\lambda}_s^O)' = (\boldsymbol{\rho}_s^O)'(\hat{\mathbf{y}}_s^O)^{-1}$. Then carbon emissions generated by domestic final use and exports via domestic inter-regional and inter-industrial supply chains are given by $\boldsymbol{\rho} = \hat{\boldsymbol{\lambda}}\mathbf{L}(\mathbf{f} + \mathbf{e})$, where a hat symbol indicates a diagonal matrix with the element of a vector on the diagonal. For a specific region s , its carbon emissions can be decomposed as follows:

$$\mathbf{c}_s = \boldsymbol{\rho}_s^P + \boldsymbol{\rho}_s^O = \hat{\boldsymbol{\lambda}}_s^O \sum_k \mathbf{L}_{sk}^{OO} (\sum_t \mathbf{f}_{kt}^O) + \hat{\boldsymbol{\lambda}}_s^P \mathbf{e}_s^P + \hat{\boldsymbol{\lambda}}_s^O \sum_k \mathbf{L}_{sk}^{OP} \mathbf{e}_k^P + \hat{\boldsymbol{\lambda}}_s^O \sum_k \mathbf{L}_{sk}^{OO} \mathbf{e}_k^O, \quad (5.4)$$

where $\mathbf{c}_s$ is the $g \times 1$ vector gives sector-wise emissions generated in the g industries. This equation reflects the fact that a region's emissions ($\mathbf{c}_s$) depend on its own carbon emissions coefficient, its own and other regions' final demands, and exports (including both processing and non-processing exports) via domestic supply chains. The first term in

equation (5.4) is emissions generated by domestic final demands. The second is emissions generated in production type P to produce the own processing exports and the third term gives the emissions generated in region s when producing the inputs of type O necessary for all the processing exports. The last term is emissions generated by non-processing exports. The aggregate emissions in region s for domestic final demand and exports is given by $c_s = \mathbf{u}'\mathbf{c}_s$.

In the same way as we measured carbon emissions, we can also measure value-added generated by domestic final demand and exports in the same way. Let $\mathbf{v}'$ be the $1 \times 2ng$ vector of value-added coefficient representing sector-wise value-added per unit of output, with $(\mathbf{v}_s^P)' = (\mathbf{w}_s^P)'(\hat{\mathbf{y}}_s^P)^{-1}$ and $(\mathbf{v}_s^O)' = (\mathbf{w}_s^O)'(\hat{\mathbf{y}}_s^O)^{-1}$. Then value-added generated by domestic final demand and exports is given by $\mathbf{w} = \hat{\mathbf{v}}\mathbf{L}(\mathbf{f} + \mathbf{e})$. Similar to equation (5.4), the value-added generated in region s can be decomposed as follows:

$$\mathbf{va}_s = \mathbf{w}_s^P + \mathbf{w}_s^O = \hat{\mathbf{v}}_s^O \sum_k \mathbf{L}_{sk}^{OO} (\sum_t \mathbf{f}_{kt}^O) + \hat{\mathbf{v}}_s^P \mathbf{e}_s^P + \hat{\mathbf{v}}_s^O \sum_k \mathbf{L}_{sk}^{OP} \mathbf{e}_k^P + \hat{\mathbf{v}}_s^O \sum_k \mathbf{L}_{sk}^{OO} \mathbf{e}_k^O. \quad (5.5)$$

Aggregate value-added in region s is given by $va_s = \mathbf{u}'\mathbf{va}_s$. The aggregate emission intensity (EI) of production in region s is given by:

$$EI_s = c_s/va_s = \mathbf{u}'\mathbf{c}_s/\mathbf{u}'\mathbf{va}_s. \quad (5.6)$$

The emission intensity measures the emissions a region generates in order to obtain one unit of value-added. The numerator proxies the environmental costs in region s from its production and the denominator proxies the economic gains from its production. A larger emission intensity suggests that the region has higher environmental costs for each unit of economic gain.

In the empirical analysis, we will also analyze the regional EI for separate final demand categories (domestic consumption, investment, and international exports). It is possible to measure the EI of region s for a specific final demand category with a slight adaptation of equations (5.4) and (5.5). For example, for the EI of processing exports one only keeps the demand for processing exports in equations (5.4) and (5.5) instead of accounting for all final demand categories. In particular, we will compare the regional EIs of all exports (i.e. EI_s^e) using the IRIOP tables and using the traditional IRIO tables

without distinguishing processing exports.²⁷ Denote EI_s^{pe} and EI_s^{oe} as the emission intensity of processing exports and ordinary exports, respectively.²⁸ Then the weighted summation of EI_s^{pe} and EI_s^{oe} yields the aggregate emission intensity of exports (EI_s^e). That is,

$$\omega_s^{pe} \cdot EI_s^{pe} + \omega_s^{oe} \cdot EI_s^{oe} = EI_s^e, \quad (5.7)$$

where ω_s^{pe} denotes the value added embodied in processing exports as a share of the value added embodied in all exports (both processing and ordinary exports) and ω_s^{oe} is the share of the embodied value added by ordinary exports. Note that $\omega_s^{pe} + \omega_s^{oe} = 1$. This idea is similar to that presented by Su and Ang (2017).

5.3.2 Multiplicative structural decomposition analysis

It is clear that the value of EI_s in equation (5.6) depends on: the emission coefficients vector λ_s , with $(\lambda_s)' = ((\lambda_s^O)' (\lambda_s^P)')$; the value-added coefficients vector $\mathbf{v}_s$, with $(\mathbf{v}_s)' = ((\mathbf{v}_s^O)' (\mathbf{v}_s^P)')$; the domestic final demands vector $\sum_t \mathbf{f}_{st}^O$; the two exports vectors $\mathbf{e}_k^P$ and $\mathbf{e}_k^O$; and the Leontief inverse $\mathbf{L}$, which in its turn relies on the input matrix $\mathbf{A}$. Our SDA is based on Arto and Dietzenbacher (2014) and Xu and Dietzenbacher (2014). We follow Oosterhaven and Hoen (1998) in splitting the inter-regional domestic intermediate inputs matrix $\mathbf{A}$. We split $\mathbf{A}$ into three parts. (a) A part that gives the overall production technology ($\mathbf{T}$), reflecting the total intermediate inputs that are required per unit of output, (b) a part that gives the domestic shares ($\mathbf{S}$), reflecting the substitution effect between domestic and imported intermediate inputs, and (c) a part that gives the regional shares (Φ), which captures the structure of inter-regional trade in intermediate inputs. Define the $2ng \times 2ng$ matrices $\mathbf{T}$, $\mathbf{S}$ and Φ as

$$\mathbf{T} = \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 \\ \mathbf{T}_1^{OP} & \mathbf{T}_1^{OO} & \cdots & \mathbf{T}_n^{OP} & \mathbf{T}_n^{OO} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 \\ \mathbf{T}_1^{OP} & \mathbf{T}_1^{OO} & \cdots & \mathbf{T}_n^{OP} & \mathbf{T}_n^{OO} \end{bmatrix}, \quad \mathbf{S} = \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 \\ \mathbf{S}_1^{OP} & \mathbf{S}_1^{OO} & \cdots & \mathbf{S}_n^{OP} & \mathbf{S}_n^{OO} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 \\ \mathbf{S}_1^{OP} & \mathbf{S}_1^{OO} & \cdots & \mathbf{S}_n^{OP} & \mathbf{S}_n^{OO} \end{bmatrix}, \text{ and}$$

²⁷ The calculation of the EI of exports based on the traditional IRIO tables follows the same methodology, except for the distinction between P and O . More details about the comparison between IRIOP model and the traditional IRIO model are given in Yan et al. (2020).

²⁸ $EI_s^{pe} = \mathbf{u}'(\hat{\lambda}_s^P \mathbf{e}_s^P + \hat{\lambda}_s^O \sum_k \mathbf{L}_{sk}^{OP} \mathbf{e}_k^P) / \mathbf{u}'(\hat{\mathbf{v}}_s^P \mathbf{e}_s^P + \hat{\mathbf{v}}_s^O \sum_k \mathbf{L}_{sk}^{OP} \mathbf{e}_k^P)$ and $EI_s^{oe} = \mathbf{u}'(\hat{\lambda}_s^O \sum_k \mathbf{L}_{sk}^{OO} \mathbf{e}_k^O) / \mathbf{u}'(\hat{\mathbf{v}}_s^O \sum_k \mathbf{L}_{sk}^{OO} \mathbf{e}_k^O)$.

$$\Phi = \begin{bmatrix} 0 & 0 & \dots & 0 & 0 \\ \Phi_{11}^{OP} & \Phi_{11}^{OO} & \dots & \Phi_{1n}^{OP} & \Phi_{1n}^{OO} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 0 \\ \Phi_{n1}^{OP} & \Phi_{n1}^{OO} & \dots & \Phi_{nn}^{OP} & \Phi_{nn}^{OO} \end{bmatrix},$$

with the $g \times g$ sub-matrices $\mathbf{T}_r^{OP} = \sum_{k=1}^n \mathbf{A}_{kr}^{OP} + \mathbf{M}_r^P$ and $\mathbf{T}_r^{OO} = \sum_{k=1}^n \mathbf{A}_{kr}^{OO} + \mathbf{M}_r^O$ ($r = 1, \dots, n$). These technology matrices give the total amount of inputs per unit of output irrespective of their geographical source. Here $\mathbf{M}_r^P$ and $\mathbf{M}_r^O$ are matrices with imported input coefficients, which are derived as $\mathbf{M}_r^P = \mathbf{Z}_r^{MP}(\hat{\mathbf{y}}_r^P)^{-1}$ and $\mathbf{M}_r^O = \mathbf{Z}_r^{MO}(\hat{\mathbf{y}}_r^O)^{-1}$. The matrices with domestic shares are given by $\mathbf{S}_r^{OP} = (\sum_{k=1}^n \mathbf{A}_{kr}^{OP}) // \mathbf{T}_r^{OP}$ and $\mathbf{S}_r^{OO} = (\sum_{k=1}^n \mathbf{A}_{kr}^{OO}) // \mathbf{T}_r^{OO}$. They express the shares of all required inputs that are sourced domestically. Here $//$ denotes elementwise division. The matrices with regional shares are given by $\Phi_{kr}^{OP} = \mathbf{A}_{kr}^{OP} // (\sum_{k=1}^n \mathbf{A}_{kr}^{OP})$ and $\Phi_{kr}^{OO} = \mathbf{A}_{kr}^{OO} // (\sum_{k=1}^n \mathbf{A}_{kr}^{OO})$. This yields $\mathbf{A} = \mathbf{T} \otimes \Phi \otimes \mathbf{S}$, where the Hadamard product $\otimes$ indicates cell-by-cell multiplication.

The emission intensity of region s can now be written as a function of seven matrices and vectors (please refer to Annex 5.1 for the explicit expression). That is:

$$\text{EI}_s = f(\lambda_s, \mathbf{v}_s, \mathbf{T}, \Phi, \mathbf{S}, \mathbf{F}, \mathbf{e}). \quad (5.8)$$

To examine to what extent a region's emission intensity is affected by intra-regional factors and inter-regional spillover effects, we split $\mathbf{T}$, Φ and $\mathbf{S}$ into two parts. That is, for region r , within the region ($\mathbf{T}_{(r)}$, $\Phi_{(r)}$ and $\mathbf{S}_{(r)}$) and outside the region ($\mathbf{T}_{(-r)}$, $\Phi_{(-r)}$ and $\mathbf{S}_{(-r)}$), where $\mathbf{T}_{(r)}$ includes the columns of $\mathbf{T}$ that correspond to region r and all other columns are zero. We thus have $\mathbf{T} = \mathbf{T}_{(r)} + \mathbf{T}_{(-r)}$. By analogy, the other matrices and vectors can also be split into two parts depending on the research purpose.

The idea of an SDA is to consider the change in EI due to the change in one driver, assuming the other drivers remain unchanged. Dietzenbacher and Los (2000) explicated that this means that the drivers need to be independent, in the sense that —technically speaking— it must be possible to change one driver without having to change another driver. In the present case, this requirement is violated, because by definition we have $\mathbf{u}'\mathbf{T} + \mathbf{v}' = \mathbf{u}'$. It is thus not possible to change $\mathbf{v}$ without changing $\mathbf{T}$. The solution that we use is to consider changes in $\mathbf{v}$ and $\mathbf{T}$ together. In our tables with results, we denote this combined effect as $\mathbf{T}^*$. This indicates the effects of changes in production technology,

combining changes in inputs and values added (Su and Ang, 2017).

It has long been recognized in the literature on SDA that decompositions are not unique. To overcome this non-uniqueness problem, Dietzenbacher and Los (1998) have indicated that the average of all decompositions can be adequately approximated by the average of the two so-called polar decomposition forms. De Haan (2001) extended this result to the average of any two “mirror” decompositions. In this chapter, we use the average of the two polar forms.

The first polar form is derived by starting the decomposition with changing the first variable first, followed by changing the second variable, changing the third variable, and so forth. The second polar form is derived exactly the other way around. That is, by changing the last variable first, followed by changing the one but last variable, etcetera. The explicit expression of the two polar forms, is given in Annex 5.1. The final decomposition is obtained as the geometric average of the two polar forms.

As mentioned above, another aim of this study is to analyze how changes in processing exports affect the EIs embodied in exports. Thus, we split the exports vector $\mathbf{e}$, and define

$$\mathbf{e} = \begin{pmatrix} \mathbf{e}_1^P \\ \mathbf{e}_1^O \\ \vdots \\ \mathbf{e}_n^P \\ \mathbf{e}_n^O \end{pmatrix}, \mathbf{b} = \begin{pmatrix} \mathbf{b}^{Tot} \\ \mathbf{b}^{Tot} \\ \vdots \\ \mathbf{b}^{Tot} \\ \mathbf{b}^{Tot} \end{pmatrix}, \mathbf{h} = \begin{pmatrix} \mathbf{h}_1 \\ \mathbf{h}_1 \\ \vdots \\ \mathbf{h}_n \\ \mathbf{h}_n \end{pmatrix}, \text{ and } \mathbf{x} = \begin{pmatrix} \mathbf{x}_1^P \\ \mathbf{x}_1^O \\ \vdots \\ \mathbf{x}_n^P \\ \mathbf{x}_n^O \end{pmatrix},$$

with $\mathbf{b}^{Tot} = \sum_k^n (\mathbf{e}_k^P + \mathbf{e}_k^O)$, which gives the vector of total exports of each product, $\mathbf{h}_k = (\mathbf{e}_k^P + \mathbf{e}_k^O) // \mathbf{b}^{Tot}$, which gives the shares of exports (in total exports) by region k for each product, and $\mathbf{x}_k^P = \mathbf{e}_k^P // (\mathbf{e}_k^P + \mathbf{e}_k^O)$, which gives the shares of processing exports (in exports of region k), and $\mathbf{x}_k^O = \mathbf{e}_k^O // (\mathbf{e}_k^P + \mathbf{e}_k^O) = \mathbf{u} - \mathbf{x}_k^P$, which gives the shares of ordinary exports. We then have $\mathbf{e} = \mathbf{x} \otimes \mathbf{h} \otimes \mathbf{b}$. This implies that we can write the emission intensity embodied in exports in equation (5.7) as $EI_s^e = f(\lambda_s, \mathbf{v}_s, \mathbf{L}, \mathbf{x}, \mathbf{h}, \mathbf{b})$. Subsequently, we employ multiplicative SDA to calculate the contributions of each driver.

5.3.3 Data

Implementing the decomposition analysis outlined above requires IRIOP tables and the corresponding CO₂ emissions data by region, by industry and by production type. The

IRIOP tables for the years 2002, 2007 and 2012 were compiled by Duan et al. (2014). Their compilation of IRIOP tables was based on two types of IO tables. The first is the Chinese IRIO table compiled by China State Information Center (SIC) and the National Bureau of Statistics of China (NBS) (Zhang and Qi, 2012). The second is the tripartite national IO table compiled by the Chinese Academy of Sciences (CAS) and the NBS (Chen et al., 2012). The unique table distinguishes between the production of processing exports, of ordinary exports and other production (which is largely domestic use).

Assuming proportionality and applying a bi-proportional estimation procedure (RAS), Duan et al. (2014) nested the IRIO table within the national bipartite table and constructed the new IRIOP table.²⁹ In the process, other provincial statistics were used to ensure the IRIOP table is balanced and consistent with the official statistics. These statistics include Chinese provincial economic accounts (for data on, for example, value added, final consumption, and fixed capital formation at the sectoral level), and provincial customs statistics by trade regime (i.e. processing trade and ordinary trade) and by commodity (at the 8-digit level under the Harmonized Commodity Description and Coding System). All data are provided by NBS. Following the regional and sector classifications used in Chinese IRIO tables, China in the IRIOP table is divided into eight geographical regions: Northeast, Northern Municipalities, North Coast, East Coast, South Coast, Central region, Northwest, and Southwest. Each region distinguishes 17 industries (see Table A5.2.1 in Annex 5.2 for the region and sector classifications).

The CO₂ emissions data by region, by industry and by production type is the other necessary dataset for our calculation. They were compiled by Yan et al. (2020), who conducted three steps to estimate the data. First, they estimated the province-industry-level energy use data by adapting statistics from the China Energy Statistical Yearbooks (CESY) and the Provincial Statistical Yearbooks (PSY), considering 17 types of fossil fuels. Second, they estimated the CO₂ emissions data for 43 industries in each province, following the estimation procedure in the Intergovernmental Panel on Climate Change guidelines (IPCC, 2006; Peters et al., 2006; and Guan et al., 2012). Third, combining the method in Dietzenbacher et al. (2012) and Jiang et al. (2015), they split the

²⁹ The national bipartite table is aggregated from the national tripartite table, by taking production of ordinary exports and other production together. For a full exposition of the estimation procedure the IRIOP table, see Duan et al. (2014).

region-industry-specific emissions into the emissions by different production types (processing production and ordinary production). The estimation was based on the extent to which each production type relies on domestic intermediate inputs. This is reasonable since less domestic intermediate inputs implies less activities and thus less emissions in the production processes. The production of processing exports relies heavily on imported inputs and requires primarily domestic labor for assembly. It is therefore expected to emit less emissions than ordinary production.

We are aware of one other database that provides disaggregated IRIO tables of China. For example, provincial level IRIO tables with 30 sectors are already available (Liu et al., 2018). Although spatially more detailed than the eight regions in Yan et al. (2020), the provincial IRIO tables do not distinguish processing exports. Failing to separate processing exports biases the intermediate input structure (Chen et al., 2019), which further biases the decomposition results.

5.4 China's regional CO₂ emission intensity evolution

We start in subsection 5.4.1 with the stylized facts of regional emission intensities. Subsection 5.4.2 deals with the EIs for separate final demand categories (domestic final demands and international exports).

5.4.1 China's CO₂ emission intensity by region

China's total CO₂ emissions increased from 3595 million metric tons (Mt) in 2002 to 9092 Mt in 2012, observing a significant growth rate of 153%.³⁰ Figure 5.1 gives the EIs across the eight regions.

The first observation is that there are large regional disparities in the EI levels. The levels of Northern Municipalities (Beijing-Tianjin region) and two of the coastal regions (South Coast and East Coast) are clearly smaller than those of inland regions. In other words, the production in coastal regions is relatively clean (i.e. less emissions for the same

³⁰ The CO₂ emissions obtained in the present study is the same as those in Yan et al. (2020). They differ from those in earlier studies. For example, China's estimate of CO₂ emissions in 2007 in this chapter is 7060 Mt, whilst they are 6386 Mt in Su and Ang (2014) and 6081 Mt in Su and Ang (2017). It should be noted that such differences may be caused by, for example, using different data sources, different aggregation of industries and regions. A major difference of estimating emissions in Yan et al. (2020) is that they adopt new emission factors from Liu et al. (2015) and Shan et al. (2018). These new emission factors are updated according to the survey on China's fossil fuel quality and the production process of cement. The new factors are more accurate than the historical default values from other reports (such as IPCC).

‘earnings’). Figure 5.1 shows that Northern Municipalities had the smallest EI (1.38 tons CO₂ per 10-thousand RMB of value-added generation) in 2012. It was closely followed by South Coast and East Coast (1.44 and 1.69 tons per 10-thousand RMB, respectively). In contrast, the EI in Northwest was 5.87 tons per 10-thousand RMB. Northwest had a high carbon-intensive industrial structure, with 37% of its outputs concentrated in high-carbon manufacturing products. Northern Municipalities and the two south-eastern coastal regions had a cleaner industrial structure and were becoming more service-oriented. In addition did these regions face more rigorous environmental regulations to which they often responded by improving production technology. The results for 2002 and 2007 sketch a similar picture. Thus, the regional pattern of EIs is one of large disparities that are stable over time.

Figure 5.1 Evolution of China’s regional CO₂ emission intensity

Notes: To calculate regional emission intensity and make the figures in the three years comparable, we use provincial GDP deflator to adjust nominal GDP in 2007 and 2012 into that at constant 2002 price (base year: 2002).

The second observation is that the EIs at both the national and the regional level (except Northwest) decreased from 2002 to 2012, indicating that the carbon emission performance upgraded. That is, China and its sub-regions emitted in 2012 less CO₂ to generate the same value-added than in 2002. However, we also observe that the carbon emission performance downgraded during 2002-2007 (see Guan et al., 2014 for similar results) but upgraded more during 2007-2012. This is because we see that most regions

(except Northern Municipalities and Northeast) increased their EIs in the first period and all regions showed a decrease in the second period. The result for the period 2007-2012 is consistent with that obtained by Su and Ang (2017) and Wang et al. (2020). The efforts to upgrade carbon emission performance were successful during this period.

The third observation is that the level of upgrading differs across regions and suggests convergence of the EIs. In general, the environmental performance improvement in regions with a high EI seems a little stronger than for the regions with a low EI. For example, the decline from 2002 to 2012 of the EI in Northeast (from 3.71 to 2.64 tons per 10-thousand RMB) and Central Region (from 3.59 to 2.85 tons per 10-thousand RMB) is larger than that in the coastal regions in the Southeast. Despite this progress in EI reduction, there is still a major gap between Southeast coastal regions and inland regions (especially the Northwest). This suggests that there is room for further upgrading in carbon emission performance.

5.4.2 Regional emission intensities for separate final demand categories

The results in Subsection 5.4.1 were for the EIs at the regional level (calculated as the emissions in region s as embodied in China's final demands divided by value added in region s as embodied in China's final demands). The findings in Dietzenbacher et al. (2012), Su and Ang (2017), and Wang et al. (2020) suggest that the EIs may differ substantially when considered for the separate final demand categories. Table 5.2 presents the results of the regional and national EIs by final demand category.

The first observation for the EIs is that in almost all cases $FCF > WEX > CSP$. Different final demand categories boost the production in different industries. Investments primarily trigger the production of infrastructure and equipment (e.g., manufacturing of machinery), which are carbon-intensive industries in China with large EIs. The relatively large EIs for exports are partly due to the fact that carbon-intensive manufacturing exports account for a large proportion of China's exports. From a policy point of view, this finding suggests that decreasing regional investment- and export-related EIs will help most to decrease the overall regional EIs.

The second observation is that the EIs of processing exports are smaller than those of ordinary exports, which holds both at the regional and the national level. This is consistent

with the finding of Dietzenbacher et al. (2012) at the national level.

Table 5.2 Emission intensities for each final demand category

Region	2002						2012					
	CSP	FCF	PEX	OEX	WEX	EX	CSP	FCF	PEX	OEX	WEX	EX
Northeast	3.39	4.42	3.40	3.72	3.65	3.75	2.11	2.81	2.45	2.98	2.87	2.92
North Municip.	1.92	2.73	2.07	2.14	2.12	3.18	0.69	1.24	0.84	1.07	1.04	1.09
North Coast	2.62	4.70	3.03	3.75	3.61	3.64	2.28	3.97	3.27	3.60	3.54	3.59
East Coast	1.98	2.72	1.42	2.12	1.98	2.03	1.43	2.13	1.25	2.03	1.81	2.03
South Coast	1.44	2.08	1.28	2.02	1.72	1.89	1.37	2.26	1.05	1.82	1.60	1.81
Central Region	2.73	4.91	4.51	5.15	5.06	5.18	2.20	3.77	3.21	3.79	3.67	3.88
Northwest	3.80	5.68	5.40	6.27	6.16	6.22	4.88	7.30	6.19	6.67	6.59	6.94
Southwest	2.54	4.80	4.35	4.78	4.70	4.76	1.94	4.08	4.01	4.11	4.10	4.07
China	2.48	4.02	2.01	2.85	2.60	2.78	2.06	3.49	1.87	2.76	2.55	2.70

Notes: CSP = Consumption (by households and governments), FCF = Fixed Capital Formation, PEX = Processing Exports, OEX = Ordinary Exports. WEX = Weighted Export intensity, the EI values in this column are the weighted sums of the EIs in columns PEX and OEX, see equation (5.7). All results (except EX) are calculated using the IRIOP tables. EX = Exports, the EI values in this column are obtained by using the traditional inter-regional input-output table without distinguishing processing exports. The values are in tons CO₂ per 10000 RMB. The results for year 2007 are also available upon request.

The third observation is that for the EIs of exports, it matters whether the IRIOP tables are used or the standard IRIO tables. Following Su and Ang (2017), the EIs in the columns WEX are the weighted sums of PEX and OEX, both obtained by using the IRIOP tables. The results in the columns EX are calculated with the standard IRIO tables (which do not distinguish processing exports). We find $EX > WEX$ for all cases, except for Southwest in 2012, and a large gap for Northern Municipalities. This means that the standard IRIO model overestimates the emission intensities of the exports because it assumes that the two types of processing exports have the same production structure. Because the average production structure resembles the production structure of ordinary exports and because $OEX > PEX$, we have $EX > WEX$ (see Yang et al., 2015). Our results confirm the conclusion that failing to distinguish processing export biases the intermediate input structure, which further biases China's EIs of exports.

The fourth observation is that the findings in Subsection 5.4.1 on upgrading and downgrading also apply to separate final demand categories. Comparing 2002 and 2012, almost all EIs indicate upgrading, except for Northwest (where all EIs increased, suggesting downgrading). What is not shown in Table 5.2 is that the carbon emission performance downgraded from 2002 to 2007, which was followed by a larger upgrading from 2007 to 2012. The evolution also shows heterogeneity among regions, with some of the inland regions presenting more upgrading than the coastal regions.

5.5 Driving factors of China's regional emission intensity evolution

The previous section described China's CO₂ emission intensity evolution both by region and final demand category. However, it did not show to what extent the emission intensities were affected by various driving forces. Employing the multiplicative SDA technique outlined in Section 5.3 gives the contributions of each driver of the changes in national and regional EIs. The drivers (or determinants) are the changes in: emission coefficients (λ , emissions per unit of output); the technology (T^*); the inter-regional intermediate trade structure (Φ); the substitution effects (S); the domestic final demand structure (F); and the export structure (e). At the regional level, we also distinguish between the intra-regional effects and the inter-regional spillover effects. Table 5.3 presents our decomposition results for China and Table 5.4 for its eight regions.

To explain what is in the table, let us consider the results for 2007-2012, in which period China's EI decreased by 22.57%. If only λ had changed (and anything else would have remained the same) the EI would have decreased by 9.83%. Let us denote this as $EI(\lambda) = 0.9007$ (see Table A5.2.2 in Annex 5.2). The other effects are $EI(T^*) = 0.8745$, $EI(\Phi) = 1.0048$, $EI(S) = 0.9957$, $EI(F) = 0.9870$, and $EI(e) = 0.9955$. Note that $EI \text{ change} = 0.7743 = EI(\lambda) \times EI(T^*) \times \dots \times EI(e)$. In order to derive contributions of the drivers that add to 100%, we first take the natural logarithms: $\ln[EI \text{ change}] = \ln[EI(\lambda)] + \ln[EI(T^*)] + \dots + \ln[EI(e)]$. The contribution of the changes in λ to the change in EI (-22.57%) then amounts to $100 \times \ln[EI(\lambda)]/\ln[EI \text{ change}] = 40.9\%$. Note that changes in Φ only would have increased EI. The contribution to the change in EI is -1.9%. So, a negative contribution of a driver means that it would have driven EI to change in the opposite direction as the actual change in EI.

The first observation in Table 5.3 is that over 2002-2012 the national aggregate EI decreased by 9.30% (indicating mild upgrading) but that it hides a serious contrast. Downgrading took place in 2002-2007 (an increase of EI by 17.14%), followed by considerable upgrading in 2007-2012 (a decrease in EI by 22.57%). The same finding holds for most regions.

The second observation is that two determinants have largely driven the results. Over the entire period, emission coefficients decreased, which led to serious upgrading,

contributing 477.1% of the 9.30% decrease in EI. On the other hand, changes in production technology (T^*) led to sizeable downgrading, contributing -310.9% of the 9.30% decrease in EI. The subperiods again sketch two different pictures. In 2002-2007, we observe much upgrading due to improved emission coefficients which was more than nullified by the technology changes so that the overall result was downgrading. In 2007-2012, the upgrading due to improved emission coefficients was much less than that in the period before, but it was accompanied by technology changes that also led to upgrading. Together, they led to substantial upgrading in the second subperiod.

From an industry perspective, the upgrading due to lower carbon emission coefficients can be attributed to the improvement of energy efficiency in some energy industries such as “Petroleum refining, coking and nuclear fuel processing” and “Electricity, gas and water supply”. The energy efficiency improvement meant a significant drop in emissions per unit of output. Because advanced energy-saving and emission-reducing technologies were actively promoted, they were much more used (Zheng et al., 2019). It should be noted that the improvement in energy efficiency works primarily in an indirect way. That is, the production processes of making final products require considerable amounts of intermediate inputs from energy industries and thus affect CO₂ emissions indirectly. Improving the energy efficiency of the high energy-intensive industries contributes a lot to abating CO₂ emissions.

Change in production technology (T^*) was the other major factor that contributed most to the national and regional EIs. They had a strong downgrading effect from 2002 to 2007 and an upgrading effect from 2007 to 2012. This result indicates that China’s intermediate input structure became “dirtier” in the first subperiod and “cleaner” in the second subperiod. This finding is consistent with China’s rapid industrialization during 2002-2007, when the GDP share of the secondary industry increased rapidly from 44.5% to 47.6%. In general, the transformation to an industrial economy relies heavily on “dirty” industrial inputs. In the second period 2007-2012, the share of the secondary industry decreased slightly. Instead, the GDP share of the tertiary industry—which generally relies on relatively “clean” intermediate inputs— increased from 42.9% to 45.3%. As a result, changes in overall intermediate inputs increased the EIs during 2002-2007 and reduced them during 2007-2012.

Table 5.3 Decomposition results at national level, changes in EI (%) and contributions to the changes (as %), 2002-2012

China	EI change	λ	T^*	Φ	S	F	e
2002-2012	-9.30	477.1	-311.0	-16.8	-12.4	-26.0	-11.0
2002-2007	17.14	-228.3	276.6	7.3	10.4	24.3	9.6
2007-2012	-22.57	40.9	52.4	-1.9	1.7	5.1	1.8

Table 5.4 Decomposition results at regional level, changes in EI (%) and contributions to the changes (as %), 2002-2012

Region	EI change	λ	$T^*_{(-r)}$	$\Phi_{(r)}$	$\Phi_{(-r)}$	$S_{(r)}$	$S_{(-r)}$	$F_{(r)}$	$F_{(-r)}$	$e_{(r)}$	$e_{(-r)}$
2002-2012											
Northeast	-28.87	150.5	-21.0	-17.3	-1.1	0.7	-0.1	14.1	-7.1	-12.0	-5.2
North Municipalities	-37.26	197.9	-78.8	-14.2	-0.1	-0.2	-0.1	29.8	-17.5	-6.6	-4.9
North Coast	-13.07	508.0	-457.2	-8.7	45.6	-0.5	4.9	-0.1	105.8	15.8	-23.7
East Coast	-23.06	157.1	-87.3	-1.1	22.2	0.6	-12.6	-0.1	30.7	-0.5	-0.7
South Coast	-14.15	157.4	-57.7	-3.6	22.8	1.2	-65.2	-0.3	46.8	-2.4	7.2
Central Region	-20.78	269.5	-109.9	-5.4	-27.9	-4.9	-0.2	53.1	-46.0	-8.5	-18.9
Northwest	26.52	-59.9	87.7	4.2	40.0	7.4	4.1	0.3	-50.9	47.1	3.6
Southwest	-15.59	273.5	-170.7	-5.9	27.4	-1.4	4.8	-1.8	-51.5	-29.7	-18.3
2002-2007											
Northeast	-3.44	1375.7	-590.2	-28.3	-155.8	-3.4	-10.7	-1.4	52.2	-42.2	-63.2
North Municipalities	-4.22	1628.3	-1051.3	-42.8	-355.6	-5.4	-21.9	-1.6	36.6	-33.4	-49.3
North Coast	22.83	-266.5	396.5	5.8	-23.7	-2.1	0.6	0.5	-41.6	10.5	6.1
East Coast	6.50	-533.1	591.5	8.4	-20.4	-0.2	56.0	0.4	-10.6	14.7	-13.3
South Coast	12.96	-152.3	167.7	4.5	-20.0	-0.7	101.5	0.1	-33.4	4.9	22.3
Central Region	8.43	-554.0	480.3	26.6	18.9	4.3	1.0	2.8	-24.0	66.1	31.2
Northwest	27.29	-55.2	70.8	6.6	32.8	0.9	2.5	0.6	1.0	23.1	4.2
Southwest	12.76	-226.1	309.8	13.5	-71.3	1.2	2.0	1.3	-46.0	71.6	19.6
2007-2012											
Northeast	-26.33	10.3	44.2	1.5	-1.4	-0.9	2.1	0.0	9.8	40.7	-6.2
North Municipalities	-34.50	52.1	20.3	-1.4	20.6	0.4	2.0	0.0	29.1	-15.9	-0.4
North Coast	-29.22	47.3	50.6	-0.1	4.4	-1.4	2.3	0.2	18.2	-30.2	10.0
East Coast	-27.76	23.4	44.2	0.8	13.9	0.4	0.7	0.0	22.7	2.5	-9.2
South Coast	-24.00	19.9	42.4	0.0	3.8	0.3	8.8	-0.1	11.2	0.8	13.9
Central Region	-26.94	57.1	42.3	2.8	-15.8	-2.5	0.1	0.1	33.2	-17.1	-1.0
Northwest	-0.60	128.0	-582.1	97.6	-245.4	-250.6	-60.8	13.2	2013.4	-905.5	27.1
Southwest	-25.14	66.4	28.5	2.1	-13.6	-0.3	3.6	-0.5	24.1	-0.5	-9.3

Notes: The factors contributing to the changes in emission intensity (EI) are: λ , effect of changes in carbon emissions per unit of output; T^* , effect of changes in production technology; Φ , effect of changes in inter-regional intermediate trade structure; S , effect of changes in substitution effect between domestic and imported intermediate inputs; F , effect of changes in domestic final demand structure; e , effect of changes in export structure. Note that the sum of the separate effects equals 100.

The third observation is the sharp distinction between the Northwest (NW) and the other regions. NW locates in the remote inland area of China. It has a relatively low level of economic development but is rich in mineral resources. Natural gas from the Northwest accounts for about 58% of the national total, NW's coal reserves for nearly 30%, and the region's oil reserves for 23% (Zhou et al., 2018). Due to a continuous improvement of the transportation infrastructure in the western regions, NW has gradually transformed to a resource-based production hub. There are significant carbon transfers between NW and other regions. Our decomposition results reflect this by a clear contribution of the changes in the inter-regional trade of the other regions (i.e. 7.4% for $\Phi_{(-r)}$ in NW) and the changes in the inter-regional spillovers (i.e. 47.1% for $F_{(-r)}$ in NW). Producers in other regions buy more ‘dirtier’ intermediate inputs from NW and domestic consumers rely more on final products from NW. Data for the inter-regional intermediate flows show that 5.8% of China's high-carbon intensive intermediates were sourced from NW in 2002 and this share increased to 10.0% in 2012.

The only other region for which something similar applies is the Central Region (CR). Due to its geographic centrality and well-developed transportation infrastructure, CR plays an important role in providing intermediates for coastal regions. It is kind of a “transmission channel” through which embodied CO₂ emissions flow from inland regions to coastal regions. Our results show that changes in inter-regional intermediate trade contributed -4.9% (for all other regions the contribution of $\Phi_{(-r)}$ is negligible) to the decrease of EI in this region. The data from the IO tables show that 18.0% of China's high-carbon intensive intermediates were sourced from CR in 2002 and this share increased to 22.0% in 2012. Also changes in inter-regional spillovers had a large increasing effect on the EI of CR, the contribution of $F_{(-r)}$ was -46.0%.

In contrast to NW and CR, coastal regions are more competitive in human resources and focus more on clean industries (like machinery and electronics) and services. We find that changes in inter-regional intermediate trade ($\Phi_{(r)}$) decreased significantly the EIs of coastal regions. This supports the finding that they are “importing” “dirtier” products from inland regions, in particular from CR and NW. The coastal regions are the ones that show clear contributions of the substitution of imported for domestically produced intermediate inputs (i.e. $S_{(r)}$). Coastal regions have better access to foreign markets and use more

imported intermediates for production. The emission intensity of China's imported intermediate inputs is generally lower than that of its domestically produced intermediate inputs (Duan and Jiang, 2017). Substitution will therefore increase the emission intensity. We find that, from 2002 to 2012, substitution in South Coast contributed -65.2% to the decrease in the region's EI. In East Coast the contribution of substitution was -12.6%.

As mentioned above, another aim of this chapter is to study whether and how processing exports affect the embodied CO₂ emission intensity of exports.³¹ Table 5.5 presents the decomposition results for embodied EI of exports. The major driving forces for the export-related EI evolution are the changes in the direct emission coefficients and in the production technology. These are the same factors that also drove the changes in regional EIs (in Table 5.4). However, this SDA shows that processing exports matter for the regional EIs of exports and that its effects show regional heterogeneity. It increased the export EIs for regions with a decreased share of processing exports and, vice versa, decreased for regions with an increased share of processing exports. For example, from 2002 to 2012, the share of processing exports (**x**) in South Coast decreased from 65.9% to 50.5%. The export EI of South Coast decreased by 6.86%, and the change in the share of processing export (**x**) increased the export EI with its contribution being -63.2%. In contrast, the share of processing export in Central Region increased from 15.2% to 31.2%. This decreased the export EI of Central region and its contribution was 19.3%. These results are in line with the fact that the emission intensity of processing exports is much smaller than that of ordinary exports. Our results confirm that it is very important to differentiate between processing exports and ordinary exports when studying China's export-related questions. Also, at the regional level.

³¹ We can also analyze the effect of processing exports on regional EIs using the multiplicative SDA. However, because the share of production of processing exports in total regional production is small (less than 6%), the contribution of changes in processing exports to the changes in regional EIs is limited. We do not present the results here, they are available upon request. Instead, we focus on export-related emissions (like Dietzenbacher et al., 2012; Su et al., 2013; Yan et al., 2020) and explore the effect of changes in processing exports on the embodied EI of exports.

Table 5.5 Decomposition results of changes in China's regional EI for exports, 2002-2012

Region	Change in EI for exports	λ	T^*	Φ	S	x	h	b
2002-2012								
Northeast	-21.39	251.8	-46.1	3.1	-7.9	-8.8	-59.2	-32.9
North Municipalities	-49.01	223.6	-47.4	-42.2	-3.5	-6.2	-3.2	-21.1
North Coast	-7.55	828.6	-708.6	72.4	-19.1	-24.7	56.9	-105.5
East Coast	-0.44	8980.5	-5908.5	260.0	-1266.3	69.6	-743.0	-1292.2
South Coast	-6.86	216.7	67.9	51.3	-160.4	-63.2	35.9	-48.1
Central Region	-27.05	179.0	-73.9	-6.9	-5.9	19.3	20.2	-31.7
Northwest	16.03	-75.2	93.3	11.7	28.4	16.1	-46.2	71.7
Southwest	-13.78	303.4	-162.0	28.2	-10.2	-3.7	16.0	-71.6
China	-1.57	3154.0	-1563.4	-151.3	-251.6	-254.7	-339.5	-493.5
2002-2007								
Northeast	14.96	-335.6	183.0	49.7	16.5	19.2	96.6	70.7
North Municipalities	1.54	-4559.6	2449.0	1396.7	174.7	151.7	-554.3	1041.9
North Coast	35.72	-159.6	252.9	-35.6	4.0	9.8	-12.4	41.0
East Coast	19.55	-138.6	180.9	-0.6	31.7	-17.6	11.4	32.8
South Coast	20.63	-39.7	41.0	-14.5	70.1	5.7	29.1	8.2
Central Region	3.90	-968.5	904.3	-70.6	58.6	-52.1	-41.7	270.0
Northwest	14.16	-153.1	137.5	49.8	22.7	26.7	-71.3	87.7
Southwest	10.18	-351.1	339.5	-40.0	25.7	17.4	11.3	97.2
China	27.68	-136.8	145.6	8.7	18.3	7.9	20.5	35.9
2007-2012								
Northeast	-31.62	36.3	38.0	20.2	1.0	1.5	-2.0	5.1
North Municipalities	-49.78	117.4	8.0	-10.3	0.4	-2.7	-15.4	2.5
North Coast	-31.88	42.4	56.3	-13.5	-0.7	2.7	1.8	11.1
East Coast	-16.72	80.5	34.5	5.6	0.6	-15.5	-6.8	1.0
South Coast	-22.77	30.6	48.4	3.5	6.9	-13.2	31.0	-7.2
Central Region	-29.79	54.8	31.9	-13.8	1.1	11.6	13.5	0.9
Northwest	1.64	559.2	-265.9	-297.9	74.8	-70.2	158.1	-58.1
Southwest	-21.75	44.7	36.2	1.2	4.0	4.7	14.2	-4.9
China	-22.91	63.5	41.6	-1.0	1.8	-8.1	-1.4	3.7

Notes: The factors contributing to the changes in emission intensity (EI) are: λ , effect of changes in carbon emissions per unit of output; T^* , effect of changes in production technology; Φ , effect of changes in inter-regional intermediate trade structure; S , effect of changes in substitution effect between domestic and imported intermediate inputs; x , effect of changes in the share of processing exports in regional exports; h , effect of changes in the regional pattern of exports; and b , effect of changes in the product composition of exports. Note that the numbers give the percentage contribution of a certain factor (in the column) to the change of the EI for exports (in the row). The sum of the separate contributions in a row equals 100.

5.6 Conclusion

This chapter analyzed China's emission intensities at the regional level. The results showed that the EIs exhibit clear heterogeneities across the eight regions and across final demand categories. The EIs of coastal regions and the Beijing-Tianjin region are smaller than those of inland regions. In terms of final demand categories, the EIs of investments and exports are larger than those of consumption. The evolution of regional EIs showed that China's regional carbon emission performance experienced "downgrading" first and then "upgrading" during 2002-2012. The EI increased for most regions in the period 2002-2007 (which indicates downgrading) and decreased (indicating upgrading) in the period 2007-2012.

We employed an inter-regional input-output based multiplicative SDA to identify the drivers (or determinants) of China's regional EI changes over time. The SDA showed that changes in direct emission coefficients and in production technology were the major driving forces for the EI evolution of most regions. Changes in inter-regional intermediate trade structures and in inter-regional spillover effects exerted different influences on the regional EIs. They decreased the EIs of coastal regions but increased the EIs of inland regions. This finding suggested that the upgraded performance of coastal regions should partly be attributed to the fact that over time these regions imported more “dirtier” products from inland regions. We also distinguished processing exports in the inter-regional input-output table. The results showed that the changes in the share of processing exports had small contributions to the aggregate EIs at national and regional level, but they did matter for the embodied CO₂ EI of exports.

With respect to the reduction of China's regional EIs, our empirical findings point to some policy recommendations. First, measures should be taken to reduce the EI gap between developed coastal regions and other regions. Given that Northwest and Central Region are facing higher levels of EI, it is important to make great efforts to reduce them. Inland regions might adopt local policies (e.g., policies regarding taxes and subsidies) to encourage the upgrading of energy efficiency and production techniques. It is also important for inland regions to stimulate local producers to adopt the energy-saving and cleaner production technologies from the coastal regions.

Second, the upgrading target of inland regions should be one of sharing responsibility with developed coastal regions. Our empirical results show that the central and western regions have been emitting CO₂ for producing “dirty” products that are required by the coastal regions. Therefore, it is necessary for both the central government and local governments to co-ordinate the design and implementation of mechanisms to share the emission-reduction responsibility. For example, establishing an emissions trading system³² and implementing stricter standards for investments from coastal regions. Other potential measures include establishing a regular exchange system and strengthening the coordination between coastal and inland regions to accelerate the diffusion of cleaner

³² This could possibly be achieved by the so-called Domestic Emission Trade System (Cui et al., 2014; Guan and Hubacek, 2010). This scheme uses emission caps and trade permits to effectively link developed coastal regions with inland regions.

production technologies to inland regions.

Third, it is important to promote the use of cleaner inputs because changes in the production structure appears to a major driving force of the changes in regional EIs. In this aspect, producers could be encouraged to use cleaner, more knowledge-intensive and service-related inputs as a substitute for emission-intensive inputs. In addition, for policy making it is important to distinguish processing exports from ordinary exports at the regional level. From the perspective of emission reduction, processing exports (which are relatively clean) could be given priority in regions (e.g. Northwest and Southwest) with a low share of processing exports.

Our research can be extended in several directions. First, to work with subnational input-output tables that differentiate China's processing exports from ordinary exports, provinces had to be aggregated into regions. Provincial or city level tables, however, may provide additional insights into important emission-related topics. For example, how spillover effects change the emissions of a province or city. Second, the multiplicative SDA in this chapter could also be extended to a spatial multiplicative SDA framework that analyzes emission performance disparities across different regions. Lastly, the analysis is not limited to China. The same method can be generalized to other countries with a high share of processing exports and vast regional disparities, such as Mexico. The analysis could contribute to providing support to establish more effective emission reduction policies.

Annex 5

Annex 5.1 The decomposition of emission intensity evolution

According to the variables defined in Section 5.3, emissions intensity in region s can be rewritten as:

$$EI_s = \frac{(0' \dots \lambda_s' \dots 0')L(f+e)}{(0' \dots v_s' \dots 0')L(f+e)} = \frac{(0' \dots \lambda_s' \dots 0')(I-T \otimes \Phi \otimes S)^{-1}(Fu+e)}{(0' \dots v_s' \dots 0')(I-T \otimes \Phi \otimes S)^{-1}(Fu+e)}. \quad (B.1)$$

We use superscript t to denote the variable at time t . Then the change of EI_s from time $t-1$ to t can be decomposed as:

$$\Delta EI_s = \frac{EI_s^t}{EI_s^{t-1}} = \frac{f(\lambda_s^t, v_s^t, T^t, \Phi^t, S^t, F^t, e^t)}{f(\lambda_s^{t-1}, v_s^{t-1}, T^{t-1}, \Phi^{t-1}, S^{t-1}, F^{t-1}, e^{t-1})} \quad (B.2a)$$

$$= \frac{f(\lambda_s^t, v_s^t, T^t, \Phi^t, S^t, F^t, e^t)}{f(\lambda_s^{t-1}, v_s^t, T^t, \Phi^t, S^t, F^t, e^t)} \quad (B.2b)$$

$$\times \frac{f(\lambda_s^{t-1}, v_s^t, T^t, \Phi^t, S^t, F^t, e^t)}{f(\lambda_s^{t-1}, v_s^{t-1}, T^t, \Phi^t, S^t, F^t, e^t)} \quad (B.2c)$$

$$\times \frac{f(\lambda_s^{t-1}, v_s^{t-1}, T^{t-1}, \Phi^t, S^t, F^t, e^t)}{f(\lambda_s^{t-1}, v_s^{t-1}, T^{t-1}, \Phi^{t-1}, S^t, F^t, e^t)} \quad (B.2d)$$

$$\times \frac{f(\lambda_s^{t-1}, v_s^{t-1}, T^{t-1}, \Phi^{t-1}, S^{t-1}, F^t, e^t)}{f(\lambda_s^{t-1}, v_s^{t-1}, T^{t-1}, \Phi^{t-1}, S^{t-1}, F^{t-1}, e^t)} \quad (B.2e)$$

$$\times \frac{f(\lambda_s^{t-1}, v_s^{t-1}, T^{t-1}, \Phi^{t-1}, S^{t-1}, F^{t-1}, e^t)}{f(\lambda_s^{t-1}, v_s^{t-1}, T^{t-1}, \Phi^{t-1}, S^{t-1}, F^{t-1}, e^{t-1})} \quad (B.2f)$$

The decomposition from another polar is calculated as:

$$\Delta EI_s = \frac{EI_s^t}{EI_s^{t-1}} = \frac{f(\lambda_s^t, v_s^t, T^t, \Phi^t, S^t, F^t, e^t)}{f(\lambda_s^{t-1}, v_s^{t-1}, T^{t-1}, \Phi^{t-1}, S^{t-1}, F^{t-1}, e^{t-1})} \quad (B.3a)$$

$$= \frac{f(\lambda_s^t, v_s^{t-1}, T^{t-1}, \Phi^{t-1}, S^{t-1}, F^{t-1}, e^{t-1})}{f(\lambda_s^{t-1}, v_s^{t-1}, T^{t-1}, \Phi^{t-1}, S^{t-1}, F^{t-1}, e^{t-1})} \quad (B.3b)$$

$$\times \frac{f(\lambda_s^t, v_s^t, T^t, \Phi^{t-1}, S^{t-1}, F^{t-1}, e^{t-1})}{f(\lambda_s^t, v_s^{t-1}, T^{t-1}, \Phi^{t-1}, S^{t-1}, F^{t-1}, e^{t-1})}$$

$$\times \frac{f(\lambda_s^t, v_s^t, \mathbf{T}^t, \Phi^t, \mathbf{S}^{t-1}, \mathbf{F}^{t-1}, \mathbf{e}^{t-1})}{f(\lambda_s^t, v_s^t, \mathbf{T}^{t-1}, \Phi^{t-1}, \mathbf{S}^{t-1}, \mathbf{F}^{t-1}, \mathbf{e}^{t-1})} \quad (\text{B.3c})$$

$$\times \frac{f(\lambda_s^t, v_s^t, \mathbf{T}^t, \Phi^t, \mathbf{S}^t, \mathbf{F}^{t-1}, \mathbf{e}^{t-1})}{f(\lambda_s^t, v_s^t, \mathbf{T}^{t-1}, \Phi^{t-1}, \mathbf{S}^{t-1}, \mathbf{F}^{t-1}, \mathbf{e}^{t-1})} \quad (\text{B.3d})$$

$$\times \frac{f(\lambda_s^t, v_s^t, \mathbf{T}^t, \Phi^t, \mathbf{S}^t, \mathbf{F}^t, \mathbf{e}^{t-1})}{f(\lambda_s^t, v_s^t, \mathbf{T}^{t-1}, \Phi^{t-1}, \mathbf{S}^t, \mathbf{F}^{t-1}, \mathbf{e}^{t-1})} \quad (\text{B.3e})$$

$$\times \frac{f(\lambda_s^t, v_s^t, \mathbf{T}^t, \Phi^t, \mathbf{S}^t, \mathbf{F}^t, \mathbf{e}^t)}{f(\lambda_s^t, v_s^t, \mathbf{T}^t, \Phi^t, \mathbf{S}^t, \mathbf{F}^t, \mathbf{e}^{t-1})} \quad (\text{B.3f})$$

The final decomposition results can be derived from the geometric average of the two polar results. More specifically, the changes of EI_s in time t relative to time $t - 1$ caused by λ_s , $\mathbf{T}^*$, Φ , $\mathbf{S}$, $\mathbf{F}$, and $\mathbf{e}$ are respectively shown as:

$$\Delta \text{EI}_s(\lambda_s) = [(\text{B. 2a}) \times (\text{B. 3a})]^{1/2} \quad (\text{B.4a})$$

$$\Delta \text{EI}_s(\mathbf{T}^*) = [(\text{B. 2b}) \times (\text{B. 3b})]^{1/2} \quad (\text{B.4b})$$

$$\Delta \text{EI}_s(\Phi) = [(\text{B. 2c}) \times (\text{B. 3c})]^{1/2} \quad (\text{B.4c})$$

$$\Delta \text{EI}_s(\mathbf{S}) = [(\text{B. 2d}) \times (\text{B. 3d})]^{1/2} \quad (\text{B.4d})$$

$$\Delta \text{EI}_s(\mathbf{F}) = [(\text{B. 2f}) \times (\text{B. 3f})]^{1/2} \quad (\text{B.4e})$$

$$\Delta \text{EI}_s(\mathbf{e}) = [(\text{B. 2g}) \times (\text{B. 3g})]^{1/2} \quad (\text{B.4f})$$

By taking the natural logarithm, we achieve the percentages of contribution of each determinant.

Annex 5.2 Tables

Table A5.2.1 The classification of regions and industry groups in the IRIOP table

Region	Provinces/autonomous regions/municipalities included
Northeast (NE)	Heilongjiang, Jilin, Liaoning
Northern Municipalities (NM)	Beijing, Tianjin
North Coast (NC)	Hebei, Shandong
East Coast (EC)	Shanghai, Jiangsu, Zhejiang
South Coast (SC)	Guangdong, Fujian, Hainan
Central (CE)	Shanxi, Henan, Hubei, Hunan, Anhui, Jiangxi
Northwest (NW)	Inner Mongolia, Shanxi, Ningxia, Gansu, Xinjiang
Southwest (SW)	Sichuan, Chongqing, Yunnan, Guizhou, Guangxi, Qinghai, Tibet
Industry No.	Industry
1	Agriculture
2	Mining
3	Food products
4	Textile and wearing apparel
5	Wooden products
6	Paper and printing
7	Chemical products
8	Non-metallic mineral products
9	Metal products
10	Machinery
11	Transport equipment
12	Electronic products
13	Other manufacturing products
14	Electricity, gas and water supply
15	Construction
16	Trade and transport
17	Other services

Table A5.2.2 Decomposition results of China's regional EI changes, 2002-2012
Decomposition results at national level (corresponding to Table 5.3)

China		λ	T^*	Φ	S	F	e
EI change							
2002-2012		0.9070	0.6277	1.3546	1.0165	1.0122	1.0108
2002-2007		1.1714	0.6969	1.5491	1.0116	1.0165	1.0154
2007-2012		0.7743	0.9007	0.8745	1.0048	0.9957	0.9955

Decomposition results at regional level (corresponding to Table 5.4)											
Region	EI change	λ	$T^*_{(r)}$	$T^*_{(-r)}$	$\Phi_{(r)}$	$\Phi_{(-r)}$	$S_{(r)}$	$S_{(-r)}$	$F_{(r)}$	$F_{(-r)}$	$e_{(-r)}$
2002-2012											
Northeast	0.7113	0.5989	1.0740	1.0053	1.0607	1.0039	0.9975	1.0005	0.9530	1.0243	1.0418
North Municipalities	0.6274	0.3974	1.4441	1.0248	1.0685	1.0004	1.0009	1.0006	0.8702	1.0850	1.0314
North Coast	0.8693	0.4909	1.8970	1.0123	0.9382	1.0006	0.9932	1.0003	0.8622	1.1343	0.9781
East Coast	0.7694	0.6624	1.2573	1.0028	0.9435	0.9985	1.0336	1.0003	0.9227	1.0013	1.0216
South Coast	0.8585	0.7866	1.0920	1.0054	0.9638	0.9981	1.1046	1.0004	0.9312	1.0037	0.9890
Central Region	0.7922	0.5338	1.2918	1.0127	1.0670	1.0114	1.0004	1.0020	0.8837	1.1132	1.0199
Northwest	1.2652	0.8685	1.2291	1.0100	1.0987	1.0175	1.0098	1.0006	0.8871	1.1171	1.0085
Southwest	0.8441	0.6290	1.3357	1.0101	0.9547	1.0023	0.9919	1.0030	0.8826	1.0912	1.0517
2002-2007											
Northeast	0.9656	0.6180	1.2294	1.0099	1.0560	1.0012	1.0037	1.0005	0.9819	1.1600	1.0224
North Municipalities	0.9578	0.4954	1.5737	1.0186	1.1638	1.0023	1.0095	1.0007	0.9843	1.0145	1.0015
North Coast	1.2283	0.5781	2.2598	1.0120	0.9524	0.9957	1.0012	1.0010	0.9181	1.0218	1.0126
East Coast	1.0650	0.7147	1.4517	1.0053	0.9872	0.9998	1.0359	1.0002	0.9933	1.0093	0.9916
South Coast	1.1296	0.8306	1.2267	1.0054	0.9759	0.9991	1.1317	1.0001	0.9601	1.0059	1.0067
Central Region	1.0843	0.6386	1.4753	1.0217	1.0154	1.0034	1.0008	1.0022	0.9808	1.0549	1.0255
Northwest	1.2729	0.8753	1.1864	1.0160	1.0825	1.0021	1.0060	1.0014	1.0024	1.0574	1.0102
Southwest	1.1276	0.7623	1.4507	1.0164	0.9179	1.0015	1.0024	1.0015	0.9463	1.0897	1.0238
2007-2012											
Northeast	0.7367	0.9691	0.8736	0.9954	1.0044	1.0027	0.9937	1.0000	0.9705	0.8830	1.0190
North Municipalities	0.6550	0.8022	0.9177	1.0061	0.9165	0.9981	0.9915	0.9999	0.8841	1.0695	1.0298
North Coast	0.7078	0.8491	0.8395	1.0002	0.9850	1.0050	0.9920	0.9992	0.9392	1.1101	0.9659
East Coast	0.7224	0.9269	0.8661	0.9976	0.9557	0.9987	0.9978	1.0000	0.9289	0.9921	1.0302
South Coast	0.7600	0.9470	0.8902	1.0000	0.9896	0.9990	0.9761	1.0002	0.9698	0.9978	0.9626
Central Region	0.7306	0.8360	0.8756	0.9912	1.0508	1.0080	0.9997	0.9997	0.9011	1.0552	0.9945
Northwest	0.9940	0.9923	1.0359	0.9941	1.0150	1.0153	1.0037	0.9992	0.8850	1.0565	0.9984
Southwest	0.7486	0.8251	0.9207	0.9938	1.0400	1.0008	0.9895	1.0014	0.9327	1.0014	1.0272

Notes: The factors contributing to the changes in emission intensity (EI) are: λ , effect of changes in carbon emissions per unit of output; T^* , effect of changes in production technology; Φ , effect of changes in inter-regional intermediate trade structure; S , effect of changes in substitution effect between domestic and imported intermediate inputs; F , effect of changes in domestic final demand structure; e , effect of changes in export structure.

Table A5.2.3 Decomposition results of changes in China's regional EI for exports
(corresponding to Table 5.5), 2002-2012

Region	Change in EI for exports	λ	T^*	Φ	S	x	h	b
2002-2012								
Northeast	0.7861	0.5455	1.1172	0.9926	1.0192	1.0214	1.1531	1.0824
North Municipalities	0.5099	0.2219	1.3760	1.3287	1.0240	1.0424	1.0217	1.1526
North Coast	0.9245	0.5219	1.7439	0.9448	1.0151	1.0196	0.9563	1.0863
East Coast	0.9956	0.6738	1.2967	0.9886	1.0573	0.9969	1.0332	1.0585
South Coast	0.9316	0.8577	0.9530	0.9643	1.1203	1.0458	0.9749	1.0347
Central Region	0.7295	0.5687	1.2624	1.0219	1.0188	0.9410	0.9384	1.1053
Northwest	1.1603	0.8942	1.1489	1.0176	1.0432	1.0243	0.9336	1.1126
Southwest	0.8622	0.6377	1.2716	0.9591	1.0153	1.0055	0.9765	1.1121
China	0.9843	0.6068	1.2810	1.0243	1.0406	1.0412	1.0552	1.0813
2002-2007								
Northeast	1.1496	0.6263	1.2906	1.0717	1.0232	1.0271	1.1442	1.1036
North Municipalities	1.0154	0.4982	1.4539	1.2379	1.0271	1.0234	0.9188	1.1726
North Coast	1.3572	0.6141	2.1647	0.8970	1.0123	1.0303	0.9628	1.1334
East Coast	1.1955	0.7807	1.3813	0.9989	1.0583	0.9691	1.0205	1.0604
South Coast	1.2063	0.9283	1.0800	0.9731	1.1406	1.0107	1.0562	1.0155
Central Region	1.0390	0.6904	1.4133	0.9733	1.0227	0.9803	0.9842	1.1088
Northwest	1.1416	0.8165	1.1997	1.0681	1.0306	1.0360	0.9099	1.1231
Southwest	1.1018	0.7115	1.3897	0.9620	1.0252	1.0170	1.0110	1.0988
China	1.2768	0.7158	1.4273	1.0215	1.0456	1.0194	1.0514	1.0917
2007-2012								
Northeast	0.6838	0.8710	0.8657	0.9263	0.9961	0.9945	1.0078	0.9808
North Municipalities	0.5022	0.4454	0.9464	1.0733	0.9970	1.0185	1.1120	0.9830
North Coast	0.6812	0.8499	0.8056	1.0533	1.0027	0.9896	0.9932	0.9584
East Coast	0.8328	0.8630	0.9387	0.9897	0.9990	1.0287	1.0124	0.9982
South Coast	0.7723	0.9240	0.8824	0.9910	0.9822	1.0347	0.9230	1.0188
Central Region	0.7021	0.8237	0.8932	1.0499	0.9962	0.9599	0.9535	0.9968
Northwest	1.0164	1.0952	0.9577	0.9527	1.0122	0.9886	1.0260	0.9906
Southwest	0.7825	0.8963	0.9150	0.9970	0.9903	0.9886	0.9659	1.0120
China	0.7709	0.8477	0.8975	1.0026	0.9952	1.0214	1.0037	0.9905

Notes: The factors contributing to the changes in emission intensity (EI) are: λ , effect of changes in carbon emissions per unit of output; T^* , effect of changes in production technology; Φ , effect of changes in inter-regional intermediate trade structure; S , effect of changes in substitution effect between domestic and imported intermediate inputs; x , effect of changes in the share of processing exports in regional exports; h , effect of changes in the regional pattern of exports; and b , effect of changes in the product composition of exports.

Chapter 6

Summary and conclusions

6.1 Summary of the main findings

Production fragmentation across regions and countries has been causing wide-ranging and sometimes unforeseen changes for economies, societies and the environment. In this thesis, we conducted analyses on economic and environmental upgrading in an era of globalized and fragmented value chains.

In Chapter 2, we applied factor analysis to measure industrial upgrading in a global value chain (GVC) framework. We firstly systematically reviewed the literature and identified eight indicators for upgrading. Subsequently, we employed exploratory factor analysis (EFA) on the set of indicators to investigate the multidimensionality of industrial upgrading and ultimately identified three quantitative dimensions of industrial upgrading: process upgrading, product upgrading, and skill upgrading. With these dimensions, we compared and analyzed the upgrading levels for countries and for sectors.

We found that most countries had experienced upgrading since 1995, and almost all countries appeared to have experienced downgrading in 2009 due to the global financial crisis. The results also followed the convergence theory as developing countries such as Turkey, China and India appeared to have experienced more upgrading than did developed countries such as the USA and Japan. In terms of sectors, service sectors and technology-intensive sectors such as Electrical and optical equipment and Transport equipment experienced higher levels of upgrading than did resource- or labor- intensive sectors. The upgrading levels of technology-intensive sectors in developing countries was generally higher than in developed countries. Of course, higher upgrading levels suggest only faster growth. They do not mean that developing countries are absolutely better off positionally than are developed countries in GVCs.

In Chapter 3, we provided country-industry level empirical evidence for the

relationship between GVC participation and industrial upgrading. Using the WIOD that covers 40 countries at different stages of development, we examined the impacts of GVC participation on industrial upgrading. We measured two types of GVC participation from the backward and forward links as the explanatory variables, and used the three quantitative measures of industrial upgrading from Chapter 2 as the explained variables.

We found a positive effect of GVC participation on product and skill upgrading. This finding holds for both forward and backward GVC participation and across developed and developing countries. For process upgrading, the effects of forward integration and backward integration present different results. We found that the effect of backward GVC participation on industrial upgrading in developing countries was larger than that in developed countries. For forward participation, the contrary is the case. The results reveal that developed countries upgrade more through forward linkages, while developing countries (especially process upgrading) rely more on backward links than forward links. Comprehensively considering the effects of both types of GVC participation on the three dimensions of industrial upgrading, we concluded that GVC integration benefited industrial upgrading for both developed and developing countries.

Our results show that potential concerns about the negative effects of GVC integration in some countries (either developed countries or developing countries) are not supported by our empirical analyses. Countries that participate in GVC production are likely to upgrade and develop new competitive advantages because of the different endowments and technologies owned by developed and developing countries. We stress that industrial upgrading through GVC participation is possible, but far from automatic. It relies on proper GVC-supportive industrial policies. On the contrary, a nation that seeks to ban the international fragmentation and GVC participation may find that such resistance will hinder industrial upgrading.

In Chapter 4, We chose China as the object of study and explored potential strategies for its economic upgrading. We firstly quantified China's income gains from geographic shifts in international sourcing in the past decade. We then proposed a nonlinear optimization approach to explore which shifts in international sourcing would increase China's GDP per capita the most so as to develop strategies for further increasing China's value-added gains. The optimization model was built upon a global IO framework so that

the results of the model inform us which industries, which products, and which trading partners policy makers should focus on. In the model, the production technology and final demand in each country were kept unchanged, but international sourcing was flexible.

Our optimization results suggested two potential directions, i.e., import substitution and export promotion, for China's future policies which endeavor to narrow its income gap with developed countries. The strategy of import substitution holds in particular for China's technology-intensive industries. That is, to substitute China's imported technological inputs by domestically produced analogues. However, we emphasized that import substitution did not imply returning to autarky. Export promotion and import substitution interact and co-exist in a Ricardian world rather than in autarky. Some countries may fail to produce the required exports if their imported intermediates were limited. China's prosperous exports relied heavily on imported intermediates in the past decades. Nowadays, the country appears to enter a new stage where self-technological development is particularly crucial because China's production costs have increased substantially and its comparative advantages have changed.

We also looked at longer run where other countries also optimize their value-added gains. This is the case where all countries follow the same optimization strategy. The results suggested that trying to improve the value-added share of a certain country by changing the international sourcing could only be successful in the short run. That is, as long as no other country responds by adopting the same strategy of maximizing its value-added share. The short-run gains decrease once more and more countries follow this strategy and the gains vanish if all countries use this strategy.

In Chapter 5, we zoomed in on China's regional environmental upgrading (or downgrading) considering the effects of regional production fragmentation. We found that the emission intensities (EIs) exhibited clear heterogeneities across China's eight regions and across final demand categories. The EIs of coastal regions and the Beijing-Tianjin region were smaller than those of inland regions. In terms of final demand categories, the EIs of investments and exports were larger than those of consumption. The evolution of regional EIs showed that China's regional carbon emission performance experienced "downgrading" first and then "upgrading" during 2002-2012.

We employed a multiplicative structural decomposition analysis (SDA) to identify the determinants of China's regional EI changes over time. The SDA showed that changes in direct emission coefficients and in production technology were the major driving forces for the EI evolution of most regions. Changes in inter-regional intermediate trade structures and in inter-regional spillover effects exerted different influences on the regional EIs. They decreased the EIs of coastal regions but increased the EIs of inland regions. This finding suggested that the upgraded performance of coastal regions should partly be attributed to the fact that over time these regions imported more “dirtier” products from inland regions. The results suggested clear policy recommendations for China's central and regional governments to achieve the national target of carbon neutrality.

6.2 Limitations and future research

This thesis analyzed economic and environmental upgrading from a value chain perspective. In the end, we would like to discuss some limitations of this thesis, which are also indications for future research built upon our analyses.

In Chapter 2, we used the skill intensity of employment to measure one dimension of industrial upgrading, i.e., skill upgrading. Due to data limitations, we did not provide direct indicators for functional upgrading. Timmer et al. (2019) recently measured functional specialization in trade by distinguishing occupations into four so-called business functions: fabrication, R&D and technology development, sales and distribution activities, and other support activities (management). Future research can adopt this distinction to measure functional upgrading and further apply such measures to conduct relevant empirical studies.

In Chapter 3, we provided convincing evidence at country-sector level on the relationship between GVC participation and industrial upgrading. However, future research is necessary to improve the understanding of the function mechanism. For example, our empirical results did not provide very solid evidence for developing countries that forward GVC participation benefits their upgrading. One might argue that forward integration trigger international competition among suppliers leading to productivity improvements. Future firm-level analysis may capture such influence

channels that our industry-level data failed to capture. It is also essential for theoretical research to shed further light on how GVCs affect industrial upgrading. It is central to understand which effects dominate under which conditions and which policies could help to overcome barriers to gains from GVCs.

In Chapter 4, we proposed a nonlinear optimization model to investigate what China could do to optimize its gains in GVCs. We focused on the effect of international sourcing shifts, and did not consider that international sourcing shifts interact with production technology. To be specific, international sourcing shifts may create employment in China and increase China's national income. A rise in China's income enables the country to strength its financial supports for R&D, which may speed up China's technology advancement. This process can further improve China's production and value-added gains. Meanwhile, the increase of China's income also boosts its final demand and generate extra production and value-added across all countries in the world. Future research can extend the model by considering such interaction between international sourcing shifts and production technology or other factors.

As for our studies on environmental upgrading in Chapter 5, we disaggregated mainland China into eight regions due to data limitations. Future research can further extend it to a more disaggregated level, for example, provincial or city level. Such disaggregation may provide additional insights into important emission-related topics. For example, how do spillover effects change the emissions of a province or city? Second, the multiplicative SDA in this thesis could also be extended to a spatial multiplicative SDA framework that analyzes emission performance disparities across different regions. Third, the same method can be generalized to other countries with trade mode heterogeneity and vast regional disparities. Lastly, future studies can combine the literature on economic upgrading and studies on environmental changes, for example, exploring the effects of economic upgrading on environmental upgrading.

My research in this thesis is based on input-output tables. Both global MRIOs (WIOD and OECD-TiVA) and China's MRIOs are sectorally quite aggregated. Moreover, technology (or at least the input mix) in WIOD is smoothed over time since its research team interpolated intermediate industry flows between the benchmark years of the nations included. This suggests that there is likely to be potential noise embedded (via changes in

intra-sectoral industry mix) in any industrial “upgrading” (or “downgrading”) that is measured as exports from and imports into an industry of a country fall, rise, and fall again. WIOD is known to display high-quality estimates of trade, given the level of sectoral aggregation it embraces. Yet, it may not be the perfect dataset for the issues we explored in this dissertation. Future studies may conduct more sensitivity analyses and explore the possibilities of data that are better suited. Part of this would be a discussion of what the perfect dataset might include. For example, what if a global MRIO was built from microdata? For example, using information at establishment-level to form tables for all countries, including 1,000 industries with commodities that are traded internationally. Our work was limited by the reality of the lack of data required to do the work “perfectly”. Currently, WIOD or similar aggregated global MRIOs may be the best data available to perform the work. They also remain the best of all (poor) options for many international analyses.

Researchers have shown that the process technologies of firms that produce for export are quite different from those that produce for domestic markets. That is why we considered in Chapters 4 and 5 the heterogeneity between production for domestic markets, processing exports and non-processing exports, especially for the case of China. Such efforts, of course, can be extended by future studies for more countries. There are also efforts underway to separate input-output tables for domestic vs. foreign-owned firms (see Cadestin et al., 2018 for the OECD AMNE database). Opening the ‘black-box’ of firm heterogeneity would be fruitful for my analyses because foreign-owned firms (e.g., MNE affiliates) are likely to have different implications for economic and environmental upgrading. Foreign-owned (and export-oriented) firms also have different production structure than the average domestic firms. They use different technologies and produce exports with a higher average imported input intensity relative to the output of domestic firms. Zhang et al. (2020b) traced the carbon footprints of foreign affiliates of MNEs using the OECD AMNE database. Future studies are expected to provide a more in-depth analysis of the role of MNEs (or foreign direct investment) in a country’s economic and environmental upgrading.

Last but very importantly, the analyses in this thesis were conducted mainly in the framework of globalized value chains. As we started in Chapter 1, multilateral trade

governance has been substantially affected by Brexit and the US-China trade war. Despite the “phase one” trade deal of January 2020 between China and the USA, economic and geopolitical bilateral tensions have continued to escalate. Trade and economic conflict between China and the USA brought and will continue to cause severe impacts on global trade and economy. The COVID-19 crisis has further damaged the development of globalization (Duan et al., 2021). Many governments in developed and emerging countries have been anxious about issues of food and medical supply security, and launched initiatives to promote national production, the reshoring of manufacturing at home or its near-shoring closer to home. In the pre-COVID-19 era, debates on the costs and benefits of international trade were mainly set in terms of welfare, economic growth and job creation or destruction. In the post COVID-19 era, the costs and benefits of globalization are being increasingly assessed from the perspective of national security and geopolitical strategy (Hu et al., 2021). This fuels the trend of withering globalization and the restructuring of global supply chains. In such a context, some of research topics in this thesis will encounter new challenges. However, the framework and some methodologies developed in this thesis are still applicable to future research, for example, to study the economic and environmental impacts of withering globalization.

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Samenvatting

Fragmentatie van productie in verschillende regio's en landen heeft geleid tot grote, en soms onvoorziene, gevolgen voor economieën, samenlevingen en het milieu. In dit proefschrift beschrijven we analyses die we hebben uitgevoerd met betrekking tot economische en milieukundige upgrades in een tijdperk van geglobaliseerde en gefragmentariseerde waardeketens.

In hoofdstuk 2 hebben we factoranalyse toegepast om industriële upgradering in globale waardeketens (Global Value Chains, GVCs) te meten. Eerst hebben we systematisch de literatuur bestudeerd en acht indicatoren voor upgradering geïdentificeerd. Vervolgens hebben we Exploratory Factor Analysis (EFA) toegepast op deze set indicatoren om de multidimensionaliteit van industriële upgradering te onderzoeken. Uiteindelijk hebben we drie kwantitatieve dimensies van industriële upgradering geïdentificeerd: upgradering van processen, upgradering van producten en upgradering van vaardigheden. Aan de hand van deze dimensies hebben we de upgraderingniveaus voor landen en voor sectoren vergeleken en geanalyseerd.

Hieruit kwam naar voren dat de meeste landen sinds 1995 met upgradering te maken hebben gehad, en dat bijna alle landen in 2009 te maken hebben gehad met downgradering als gevolg van de wereldwijde financiële crisis. De resultaten sloten ook aan bij de convergentietheorie, aangezien er meer upgradering leek te hebben plaatsgevonden in zich ontwikkelende landen als Turkije, China en India, dan in ontwikkelde landen als de VS en Japan. Voor wat betreft sectoren was er in dienstverlenende sectoren en in technologie-intensieve sectoren (zoals “Elektrische en optische apparaten” en “Transportmiddelen”) sprake van meer upgradering dan in resource- of arbeidsintensieve sectoren. In technologie-intensieve sectoren vonden we over het algemeen meer upgradering in zich ontwikkelende landen dan in ontwikkelde landen. Meer upgradering wijst echter alleen op een snellere groei en betekent niet dat zich ontwikkelende landen een betere

positie in GVCs hebben dan ontwikkelde landen.

In hoofdstuk 3 leveren we empirische bewijzen per land en per industrie voor de relatie tussen GVC-participatie en industriële upgrading. Op basis van de World Input-Output Database (WIOD), die gegevens bevat over 40 landen in verschillende stadia van ontwikkeling, hebben we de effecten van GVC-participatie op industriële upgrading onderzocht. We hebben twee soorten GVC-participatie gemeten op basis van backward en forward linkages als de verklarende variabelen, en we hebben de drie kwantitatieve meetpunten van industriële upgrading uit hoofdstuk 2 gebruikt als de te verklaren variabelen.

We constateerden een positief effect van GVC-participatie op upgrading van producten en vaardigheden. Deze bevinding geldt voor zowel forward als backward GVC-participatie en voor zowel zich ontwikkelende als ontwikkelde landen. Voor upgrading van processen echter, lieten de effecten van forward- en backward-integratie verschillende resultaten zien. We constateerden dat het effect van backward GVC-participatie op industriële upgrading in zich ontwikkelende landen groter was dan in ontwikkelde landen. Voor forward participatie geldt het tegenovergestelde. De resultaten laten zien dat ontwikkelde landen meer via forward linkages upgraden, terwijl zich ontwikkelende landen (met name in het geval van upgrading van processen) het meer moeten hebben van backward linkages dan van forward linkages. Als we de effecten van beide typen GVC-participatie op de drie dimensies van industriële upgrading in overweging nemen, dan kunnen we concluderen dat industriële upgrading zowel in ontwikkelde als in zich ontwikkelende landen baat heeft gehad van GVC-integratie.

Onze resultaten laten zien dat potentiële zorgen over de negatieve effecten van GVC-integratie in sommige landen (zowel ontwikkelde als zich ontwikkelende landen) niet worden bevestigd door empirische analyses. Landen die deelnemen aan GVC-productie upgraden vaker en ontwikkelen vaker nieuwe competitieve voordelen dankzij de verschillende eigenschappen en technologieën waarover de ontwikkelde en zich

ontwikkelande landen beschikken. We benadrukken dat industriële upgradering door middel van GVC-participatie mogelijk is, maar lang niet altijd automatisch gebeurt; het hangt ervan af of het industriële beleid GVC-participatie ondersteunt. Het is zelfs zo dat een land dat internationale fragmentatie en GVC-participatie wil verbieden, soms ervaart dat dergelijke weerstand industriële upgradering in de weg staat.

In hoofdstuk 4 hebben we China als onderzoeksobject gekozen en potentiële strategieën voor economische upgradering in dit land onderzocht. We hebben eerst de inkomensgroei tengevolge van geografische verschuivingen in internationale sourcing gekwantificeerd voor China in de afgelopen tien jaar. Vervolgens hebben we een niet-lineaire optimaliseringsaanpak gebruikt om te onderzoeken welke verschuivingen in internationale sourcing het BBP per hoofd van de bevolking het meest zouden verhogen, om zo strategieën te ontwikkelen voor het verder verhogen van de toegevoegde waarden in China. Het optimaliseringsmodel is gebouwd op basis van een globaal IO-framework, zodat we uit de resultaten van het model kunnen aflezen op welke industrieën, producten en handelspartners beleidsmakers zich moeten concentreren. In het model zijn de productietechnologie en de eindvraag in elk land onveranderd gehouden, maar was de internationale sourcing flexibel.

Onze optimaliseringsresultaten suggereren twee potentiële richtingen, te weten imports substitutie en exportpromotie, voor toekomstig beleid om de inkomenskloof tussen China en ontwikkelde landen te verkleinen. De strategie van imports substitutie is met name geschikt voor de technologie-intensieve industrieën in China. Het idee is om de geïmporteerde technologische halffabricaten te vervangen door in China geproduceerde varianten. We benadrukken hierbij wel dat imports substitutie geen terugkeer naar een autarkische staat inhoudt. In een Ricardiaanse wereld kunnen exportpromotie en imports substitutie op elkaar reageren en naast elkaar bestaan, maar dat geldt niet in geval van een autarky. Sommige landen zullen misschien niet in staat zijn om de vereiste exporten te produceren als hun import van halffabricaten wordt beperkt. In de afgelopen

decennia waren de bloeiende exporten van China in grote mate afhankelijk van geïmporteerde halffabricaten. Tegenwoordig lijkt het land aan het begin van een nieuwe fase te staan waarin vooral de eigen technologische ontwikkeling essentieel is, omdat de productiekosten in China aanzienlijk zijn toegenomen en daardoor de comparatieve voordelen zijn veranderd.

We hebben ook naar de lange termijn gekeken, waarin ook andere landen hun toegevoegde waarde verhogen. Dit is het geval als alle landen dezelfde optimaliseringsstrategie volgen. De resultaten lieten zien dat pogingen om het aandeel van een bepaald land in de globale toegevoegde waarde te verhogen door de internationale sourcing te veranderen, alleen succesvol zijn op de korte termijn. Dat wil zeggen, zolang geen ander land hierop reageert door dezelfde strategie in te zetten om het eigen aandeel in de globale toegevoegde waarde te maximaliseren. De voordelen op de korte termijn nemen nog verder af als nog meer landen deze strategie volgen; de voordelen verdwijnen uiteindelijk helemaal als alle landen deze strategie volgen.

In hoofdstuk 5 kijken we naar de regionale milieu-upgrades (of downgrades) in China en naar de effecten van regionale productiefragmentatie. We constateerden dat de emissie-intensiteiten (EI) duidelijke verschillen lieten zien tussen de acht Chinese regio's en tussen de verschillende eindvraagcategorieën. De EI van kustregio's en van de regio Beijing-Tianjin was lager dan die van regio's in het binnenland. Voor wat betreft de eindvraagcategorieën was de EI hoger voor investeringen en exporten dan voor consumptie. De ontwikkeling van regionale EI-en laat zien dat de regionale CO₂ emissies in China eerst een downgrading doormaakten, gevolgd door een upgrading in de periode 2002-2012.

We gebruikten een multiplicatieve Structural Decomposition Analysis (SDA) om de factoren te identificeren die ten grondslag lagen aan de wijzigingen in de loop van de tijd in de regionale EI-en. De SDA liet zien dat veranderingen in de directe emissie coëfficiënten (CO₂ per miljoen dollar productie) en in productietechnologie de

belangrijkste redenen waren voor de EI-ontwikkelingen in de meeste regio's. Veranderingen in de interregionale handelsstructuren voor halffabricaten en in interregionale spillover-effecten zorgden voor verschillende invloeden op de regionale EI-en. Ze verlaagden de EI van kustregio's, maar verhoogden de EI van regio's in het binnenland. Deze bevinding suggereert dat de upgraded resultaten van kustregio's deels moeten worden teruggevoerd op het feit dat deze regio's in de loop van de tijd meer 'vuile' producten uit binnenlandse regio's hebben geïmporteerd. De resultaten bieden duidelijke beleidsaanbevelingen voor centrale en regionale overheden in China om het nationale doel van koolstofneutraliteit te realiseren.