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Environmental degradation and international trade: input-output analyses

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Environmental Degradation and International Trade:
Input-Output Analyses

Yan Xu

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university of
 groningen

Environmental Degradation and International Trade: Input-Output Analyses

PhD thesis

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

This thesis will be defended in public on
Thursday 5 September 2019 at 14.30 hours

by

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To my parents and my husband:
I deeply appreciate all your encouragement and support

致我的父母和爱人：
感谢你们一直以来的鼓励和支持

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Yan Xu

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Under the Kyoto Protocol, a group of developed countries (so-called Annex B countries) pledged to cut their greenhouse-gas (GHG) emissions by varying amounts (on average 5.2%) by 2012 as compared to 1990. Was the Kyoto Protocol a success? According to IEA (2014), the Annex B countries emitted 6.4% less in 2012 compared to 1990. However, in the same period the global GHG emissions soared by more than 50% (IEA, 2014). This suggests that non-Annex B countries are emitting for or “on behalf of” Annex B countries. Peters et al. (2011a) find that the net emission transfers from non-Annex B to Annex B countries have grown from 0.4 Gt CO₂ in 1990 to 1.6 Gt CO₂ in 2008 (global emissions in 2008 were 30.0 Gt CO₂). Researchers argue therefore that the effect of the Kyoto Protocol should be discounted by production offshoring to the Non-Annex B countries (Kanemoto, et al., 2014; Peters et al., 2011a). Taking this into account, Kanemoto et al. (2014) find that after assigning emissions responsibility to consumers, the Annex B countries have not recorded a decrease from 1990 to 2011 levels but rather an increase.

In recent decades, declining transaction costs of trade have led to an increase in the globalization of production processes for many goods and services. A product labeled “made in China” or “made in the US” may have many components produced elsewhere in the world. A simple example is illustrated in Figure 1.1. Consumers’ demand for the US-brand and US-designed mobile phones may not exclusively induce economic activities in the US electronics industry, but may also imply increased demand of manufacturing in China due to assembling activities (Dedrick et al., 2010). The phone’s camera and screen may be produced by Japan, memory chips and battery may be produced

by Korea, and audio chips and other parts may be produced by the US. The battery production in Korea requires lithium from Chile's mining industry. As a result, the involved industries in China, Japan, Chile and Korea could experience demand increases caused by the mobile phone sales increase in the US. In many industries have the declining transaction costs of trade, together with the revolutionary progress in communication and information technologies, enabled the globalization of production. Today, most products are "made in the world". With the globalization of production, however, the conventional trade statistics of gross import and export values may not be adequate to reflect the trade performance of countries and industries (see the overviews by Johnson, 2014, 2018; and Los, 2017). To bridge this gap, databases such as the World Input-Output Database (WIOD) (Dietzenbacher et al., 2013; Timmer et al., 2015) were developed, which will be discussed later in this chapter. Such databases enable researchers to analyze the effects of globalization on trade patterns, environmental pressures and socio-economic development.

Figure 1.1: Emission generated in production procedures of a US mobile phone

The story of different countries contributing to a single final product, applies not only to value-added but also to GHG emissions (Davis and Caldeira, 2010; Peters et al., 2011a; Wiedmann et al.,

2007), to land and water usages (Wiedmann et al., 2015), and to other environmental and ecosystem indicators (Cui et al., 2016; Dietzenbacher, 2005; Lenzen and Reynolds, 2014; Oita et al., 2016). Some recent studies extend the analyses towards social impacts (Alsamawi et al., 2017a; Malik et al., 2018; McBain, 2015; McBain and Alsamawi, 2014), including problematic labour (Gómez-Paredes et al., 2016; Simas et al., 2014), inequality (Alsamawi et al., 2014; Reyes et al., 2017), corruption (Xiao et al., 2017), conflict (Moran et al., 2015; Tisserant and Pauliuk, 2016), or occupational hazards (Alsamawi et al., 2017b).

Lower costs of transportation and co-ordination had two effects. On the one hand, trade in final products increased somewhat because access to foreign products became cheaper for consumers. On the other hand, trade in intermediate products increased enormously because firms used their increased opportunities to relocate parts of production processes (international production fragmentation), creating complex trade networks. Trade in final or intermediate products concurrently implies trade of embodied emissions. Consequently, there was a fast growth of emissions embodied in world trade during the past decades (see Chapter 2). Using the example mentioned above, Figure 1.1 illustrates that to serve the US consumers' demand of mobile phones, carbon emissions rise not only in the US (E1), but also in Japan (E2), Chile (E3), Korea (E4) and China (E5), who are involved in production. Despite that emissions generated in the US territory are only E1, total emissions generated to meet final consumption are the sum of E1 to E5

Under the trend of “made in the world”, the conventional production-based (or territorial) accounting of emissions is no longer adequate to capture what a country could be held responsible for. For instance, although emissions growth was substantial in a number of emerging markets (such as China, India and Indonesia) in the past decade, a large fraction of the growth in these countries was to satisfy the demand of consumers in developed countries (e.g. Andrew and Forgie, 2008; Malik and

Lan, 2016; Serrano and Dietzenbacher, 2010). To examine and quantify this effect, the consumption-based accounting method has been increasingly used in the recent literature.

The consumption-based accounting method indicates worldwide emissions (i.e. irrespective of *where* emissions take place) caused by the consumption of goods and services in an economy. The traditional production-based (or territorial) accounting method reports the emissions on a country's territory (i.e. irrespective of what the emissions are used for). It should be noted that neither the consumption-based or production-based emissions mentioned here include emissions directly generated by households (e.g. as caused by driving a car). Gaps between the consumption-based and the production-based accounting of emissions can be considerable (Aichele and Felbermayr, 2005; Barrett et al., 2013; Davis and Caldeira, 2010; Peters et al., 2011a; Su and Ang, 2014). For instance, Davis and Caldeira (2010) find that in 2004, China's production-based CO₂ emissions were 1.1 Gt larger than its consumption-based emissions; while the US production-based CO₂ emissions were 0.7 Gt smaller than its consumption-based emissions.¹ This implies that China was a net exporter of CO₂ emissions (of 1.1 Gt) and the US a net importer (of 0.7 Gt). Although the consumption-based accounting method has not yet been applied to international environmental negotiations, a number of statistical offices in Europe have started to calculate consumption-based emissions.²

The objective of this introductory chapter is to provide the background and motivation of the thesis, as well as an outline of the chapters to follow. The remainder of this chapter is structured as follows. Section 1.2 discusses emissions embodied in trade and some basic concepts frequently used

¹ To put this into the right perspective, global CO₂ emissions in 2004 were 27.0 Gt, and 6.2 Gt CO₂ were generated to produce traded goods and services.

² Statistical offices of many European countries, such as Denmark, the Netherlands, Germany, Sweden, France, and the UK, have carried out studies on the consumption-based emissions (Edens et al., 2011). In addition, OECD also provides calculated consumption-based CO₂ emissions for 36 OECD countries and 28 Non-OECD countries in the world (Wiebe and Yamano, 2016).

in this thesis. Section 1.3 describes several important input-output databases that are widely used in the recent literature. Two of them are employed in this thesis. Section 1.4 presents an overview of the remaining chapters in this thesis.

1.2 EMISSIONS EMBODIED IN TRADE

Emissions embodied in trade (EET) measure the emissions embodied in the gross trade flows, including emissions embodied in exports and imports. EET is not the same as the trade in embodied emissions (TEE). TEE accounts for emissions of one country directly and indirectly embodied in the final consumptions of another country. Using the example illustrated by Figure 1.1, there is no direct trade between Korea and the US, so there is no EET between Korea and the US. However, the amount of trade in embodied emissions between Korea and the US is not zero. Recall that emissions generated in the Korean electrical parts industry are E_4 in order to produce the mobile phones consumed in the US. Therefore, the trade in embodied emissions between Korea and the US is E_4 in this simple example.

In today's world economy, a highly complex web of global supply chains for manufactured products has been woven. Even services are traded directly and a substantial part of service activities is embodied in exported products (and these services are thus traded indirectly). To analyze TEE and EET in the framework of complex trade relationships, researchers have used global multiregional input-output (GMRIO) databases. The GMRIO databases contain information on how much inputs from each sector in each country are required to produce outputs in each sector in each country. Most GMRIO databases also contain environmental and other extensions in the form of inputs (like labor in hours or water use in liters) or "consequences" of production (like emissions or waste in tons). Using the GMRIO database allows tracing all emissions associated with consumed goods or services

back to the original source that generated the emissions. This tracing is possible even if products pass through several countries as intermediate products in a multiregional supply chain before they reach their final destination with a consumer.

1.3 GLOBAL INPUT-OUTPUT DATABASES

In recent years, several GMRIO databases have been developed for calculating the embodied air pollutants, virtual water, material use, biodiversity loss, and land use associated with international trade (see reviews by Tukker and Dietzenbacher, 2013 and Owen, et al., 2014). Tukker and Dietzenbacher (2013) provide a review of the global multiregional input-output tables, models and analysis, as well as an overview of the short historical development of the GMRIO frameworks. Owen, et al. (2014) made comparisons of analytical outcomes using different GMRIO databases.

In Table 1.1, six widely used GMRIO databases are presented. They are Eora (Lenzen et al., 2012a; 2012b; 2013), MRIOs based on data from the Global Trade Analysis Project (GTAP) (Aguilar et al., 2016; Peters et al., 2011b), the World Input-Output Database (WIOD) (Dietzenbacher et al., 2013; Timmer et al., 2015), EXIOBASE (Tukker et al., 2009; 2013; Wood et al., 2015; Stadler et al., 2018) and the OECD Inter-Country Input-Output (ICIO) Tables (Yamano, 2016). Each database has its own strength and weaknesses. Table 1.1 describes and compares the features of these GMRIO databases, and it lists the country coverages and year coverages of the databases in the last column.

These databases are for different years, cover different countries, and have different environmental or socio-economic extensions, because they were developed with different aims (see Tukker and Dietzenbacher, 2013). For example, EXIOBASE includes external cost values and has detailed information on the agricultural sector, which is relevant to land use. According to Table 1.1, Eora and the GTAP-MRIO cover more countries than other databases. WIOD, Eora, EXIOBASE and OECD ICIO Tables provide time series of annual tables.

Two GMRIO databases, WIOD (release 2013) and Eora, are used in this thesis. The WIOD database is used in Chapter 2, because WIOD includes a series (1995-2007) of annual IO tables that are both in current and previous year's prices. This allows us to single out the price effects when analyzing structural changes. In Chapter 3, the Eora database is used for its long time coverage and for its huge geographical coverage. Details on the database selection will be discussed in the chapter concerned.

Table 1.1: GMRIO databases for consumption-based emission accounting

Database	Description	Coverage
Eora	Public and free database provides a time series of high-resolution IO tables with matching environmental and social satellite accounts for 190 countries.	<u>Eora26 GMRIO Tables:</u> <ul style="list-style-type: none"> • 190 economies with 26 sectors (Eora26 GMRIO Tables) • 1990 to 2015
GTAP Global Trade Analysis Project	Public global database representing the world economy with bilateral trade information, transportation and protection linkages.	<u>Release 2015 – GTAP 9:</u> <ul style="list-style-type: none"> • 140 economies with 57 GTAP commodities • 2004, 2007 and 2011
WIOD World Input-Output Database	Public and free database containing time-series of world input-output tables for around forty countries worldwide and a model for the rest-of-the-world. Tables are in both current and previous years' prices. The database also includes matching socio-economic (for both releases) and environmental (for the 2013 release) satellite accounts.	<u>Release 2013:</u> <ul style="list-style-type: none"> • obtained from international supply and use tables with 35 sectors and 59 products • 40 economies plus a 'rest-of-the-world' region • 1995-2011 <u>Release 2016:</u> <ul style="list-style-type: none"> • 43 economies with 56 sectors plus a 'rest-of-the-world' region • 2000-2014
EXIOBASE	Public and free database with a focus on environmentally relevant activities. It includes external cost values and has detailed information on the agricultural sector.	<u>Release 2018 – version 3:</u> <ul style="list-style-type: none"> • 44 economies and 5 'rest-of-the-world' regions with 163 sectors • 1995-2011
OECD ICIO Tables	Public and free database containing time series of ICIO tables with comprehensive information concerning industrial activities.	<u>Release 2018:</u> <ul style="list-style-type: none"> • 63 economies with 36 sectors • 2005 to 2015

Source: Owen, et al (2014) and Inomata and Owen (2014); additional information sourced from Eora website (<http://www.worldmrio.com>), GTAP website (<https://www.gtap.agecon.purdue.edu>), WIOD website (<http://www.wiod.org>), EXIOBASE website (<https://www.exiobase.eu/index.php/about-exiobase>), and OECD ICIO Table website (<https://www.oecd.org/sti/ind/inter-country-input-output-tables.htm>)

1.4 OUTLINE OF THE THESIS

In this sub-section, we provide a brief overview of the remaining chapters. Chapter 2 uses a GMRIO model to provide a global analysis of the structural changes in EET. As we mentioned above, a substantial amount of emissions is embodied in international trade. Next to quantifying EET, it is important to identify and quantify the forces that have caused the changes in EET. For instance, several studies (e.g. Casler and Rose, 1998; de Haan, 2001) found that the emission growth due to the expansion of household consumption is partially offset by the reduction in emissions caused by efficiency improvements (i.e. lower emission intensities). The question is whether this is also the case for EET and whether the effect differs across countries. Another question is how (and how much) EET is affected by changes in international trade. Understanding the driving forces of the emissions in the trade among countries may help to design future climate and environmental policies. Chapter 2 investigates what drove the change in EET (and by how much) in the world's major economies in the period 1995-2007. In addition, it makes comparisons between different geographical regions and examines whether the sources of EET growth differ between developed and developing countries. The WIOD (2013 release) is used to estimate EET, after which a structural decomposition analysis (SDA) is applied. SDA examines shifts in a certain variable (EET in the present case) over a certain period of time by means of comparative static changes in key drivers (Skolka, 1989).

Chapter 3 re-examines the Environmental Kuznets Curve (EKC) hypothesis. The EKC hypothesizes an inverted-U relationship between the level of environmental degradation and the standard of living. That is, environmental degradation or pollution initially shows a positive relationship with per capita income, but beyond a certain income level, this trend reverses. Many empirical studies test the EKC hypothesis using territorial emissions. However, with the widespread diffusion and improvements of information and communication technology, it has become increasingly attractive for multinational firms to offshore stages of production processes to other

countries or even continents. This has led to a surge in international trade, in particular of intermediate inputs. This implies that the location of production and the generation of its corresponding emissions has become increasingly dissociated with the location of consumption of final products (which is related to the standard of living). The research question in this chapter is: Do such relocated emissions have a significant impact on the existence of the EKC, in particular given that offshoring generally involves relocation of activities from advanced to emerging or developing countries? Chapter 3 tests the EKC hypothesis using GHG emissions obtained from both consumption-based and production-based accounting. If evidence of the EKC is found when production-based accounting is used, but not found when consumption-based accounting is used, the downward-sloping part of the territorial EKC might merely be a reflection of emission relocation from wealthier to poorer economies. On the contrary, economic development might lead to reduced pressure on the environment, if an EKC would exist also in the case of consumption-based emission accounting.

In Chapters 2 and 3, we focus on the amount of emissions relocated by international trade. However, relocated emissions may have further health and social-economic impacts. For instance, large amounts of sulfur dioxide emissions can lead to acid rain, which in turn may cause deaths of forests, damages of properties, reductions in agricultural productivity, as well as negative effects on human health. Such negative impacts are costly to the local community and the economy as a whole. Much of the existing research on emissions transfer via international trade has been primarily focused on quantities of pollutants and the impacts measured in *physical* terms (Hertwich and Peters, 2009; Liu and Wang, 2009; Wiedmann et al., 2011). Chapter 4 quantifies the *monetary* values of the health and social-economic impacts associated with displaced emissions by trade. Because of the data we use, the chapter focuses on the US economy, the world's largest emissions importer.

In Chapter 4, we estimate how much US damage is generated due to its exports, and how much damage in the US is forgone by its imports (implying that these goods were not produced at

home). An input–output framework of the US economy is employed together with a comprehensive database on damages generated by one additional ton of air pollutants. The emission damage values are estimated by Muller et al. (2011) using a so-called Air Pollution Emission Experiments and Policy (APEEP) analysis, where emissions in each industry are linked to economic costs in monetary terms. Six major air pollutants are included in this study. They are: sulfur dioxide (SO_2); fine particulate matter ($\text{PM}_{2.5}$); coarse particulate matter (PM_{10}); nitrogen oxides (NO_x); volatile organic compounds (VOC); and ammonia (NH_3).

In Chapter 5, we focus on the issue of data, which is often considered as one of the key issues in the GMRIO studies. Although GMRIO databases are a powerful tool for analyzing a variety of questions, the quality of the answers depends on the quality of the data. Data availability and data quality are often cited as barriers to timely and robust studies. In all existing GMRIO databases, approximations have been used to construct the input-output tables. Limited information and poor data quality in some countries introduce (or increase) uncertainties to the results obtained with GMRIO databases. Chapter 5 investigates errors caused by various approximations of the full GMRIO table. Our research question is whether (and to what extent) it matters for the estimation of countries' consumer responsibilities if only limited information is available for some countries or regions. Chapter 5 mimics the actual situation by assuming that the world consists of countries in the WIOD (2013 release). Every simulation run, one country is omitted from the world input-output table and this omitted country then plays the role of the region for which no or limited information is available. A series of sensitivity analyses are carried out with different scenarios reflecting the amount of available information with respect to this region. Emissions calculated with the consumption-based accounting approach are used to compare and evaluate the scenarios.

Chapter 6 summarizes the main research findings of this thesis and discusses directions for future research.

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CHAPTER 2

A STRUCTURAL DECOMPOSITION ANALYSIS OF THE EMISSION EMBODIED IN TRADE³

As we mentioned in Chapter 1, a substantial amount of emissions is embodied in international trade. A growing trend of emissions embodied in trade (EET) has been found by a number of previous studies. What are the key driving forces behind the changes in EET? Do the key driving forces generate the same impacts across countries? The aim of Chapter 2 is twofold. Firstly, to quantify the driving forces behind the growth of EET. Secondly, to understand impacts from the driving forces on the transfer of emissions among countries. This chapter ends by explaining the uneven growth of EET between developed countries and emerging countries.

2.1 INTRODUCTION

Significant and due attention has been given recently to the effects of rapid globalization and escalating international trade on environmental impacts at the national level (Wiedmann et al., 2007). Many studies show a growing influence of international trade on national emission trends and find strong regional disparities. For example, Peters et al. (2011a) found that most developed countries have increased their consumption-based emissions (for which consumers in a country are responsible) more than their territorial emissions. This implies that the emissions embodied in imports (EEI) in developed countries have grown more than their emissions embodied in exports (EEE) did. At a global level, growth in international trade thus undermines national efforts to regulate emissions in countries where EEI grows more than EEE. Therefore, effective environmental policies require

³ This chapter is based on Xu and Dietzenbacher (2014).

cooperation of countries all over the world. A better understanding of global emissions embodied in trade (EET) can facilitate developing global environmental policies.

In recognition of trade effects, a number of recent studies have quantified the emissions embodied in global trade (e.g. Davis and Caldeira, 2010). For example, Peters et al. (2011a) found that emissions from the production of traded goods and services have increased from 4.3 Gt CO₂ in 1990 to 7.8 Gt CO₂ in 2008. However, next to quantifying EET it is important to identify and quantify the forces that have caused the changes in EET. For instance, several studies (e.g. Casler and Rose, 1998; de Haan, 2001) found that the emission growth from expansion of household consumption is partially offset by reductions in emissions through efficiency improvements (i.e. lower emission intensities). The question is whether this is also the case for EET and whether the effect differs across countries? Another question is how much changes in EET are affected by changes in international trade? Understanding the driving forces for the transfer of emissions among countries may assist in the design of future climate and environmental policies.

To quantify the driving forces of EET changes, this chapter applies a structural decomposition analysis (SDA) within a global multi-regional input-output (GMRIO) framework. To our knowledge, this has not been done before. SDA has been applied to analyze: energy indices for a group of countries using single-region input-output (SRIO) models (Alcántara and Duarte, 2004; De Nooij et al., 2003); EET using a bilateral trade input-output (BTIO) model for China (Du et al., 2011); and CO₂ emissions for a single country (Norway) using a GMRIO model (Yamakawa and Peters, 2011). This study, however, uses a GMRIO model to analyze structural changes of EET all over the world. Our aim is to investigate how and why EET changed in 40 countries (which cover more than 85% of the world's GDP) in the period 1995-2007. In addition, we make comparisons between different geographical

regions and examine whether the sources of EET growth differ between developed and developing countries.

The reason for using a GMRIO model is that it provides much more accurate estimates than BTIO or SRIO models. Based on inter-country and within-country flows of products and services between industries, a GMRIO model reflects the entire production process including the part that takes place abroad with the same level of detail. A GMRIO framework allows for tracing all emissions that are associated with final products back to the country that generated the emissions. This holds, even if the production process lingers through many countries, i.e. in the case of a global supply chain. For instance, an iPhone shipped from China to the US contains components that have been produced in Korea which themselves embody CO₂ emissions generated in the US. BTIO and SRIO models cannot take such complex relations into account and are unable to cover such feedback effects.

There is growing evidence that cross-border supply chains have become more prevalent in the global economy (De Backer and Yamano, 2007). This highlights the importance of taking account of inter-country spillover and feedback effects when estimating embodied CO₂ flows, particularly for countries with much processing trade such as China. Trefler (1995) and Hakura (2001) have shown that it is important to incorporate regional technology differences and full inter-regional connections when predicting trade patterns. When comparing models with and without feedback effects, Peters and Hertwich (2006) find a difference of more than 20% for Norway's net carbon embodied in trade. For the US, Weber and Matthews (2007) also find a difference around 20%. Therefore, full supply chains should be considered when decomposing EET, which is particularly relevant for open economies.

The data requirements in a GMRIO framework are considerably larger than in a BTIO or SRIO model. Moreover, an SDA requires data for at least two points in time and an SDA of emission

changes even requires input-output data in constant prices. This is because one of the potential driving forces are the emission intensities, for each industry measured as emissions per dollar of output. Using input-output data in current prices will seriously bias the results. To make this point clear, suppose that a certain industry produces exactly the same amount of goods (in kg) and emits exactly the same amount of CO₂ in 2007 as it did in 1995. The emission intensities thus have remained the same. Because the output prices have—in general—increased over the years due to inflation, the calculated emission coefficients will show a decrease when output values in current prices are used.

GMRIO tables in constant prices, however, do not exist (yet). For our empirical analysis we have used the tables from the recently finished World Input-Output Database (WIOD) project. This database includes a time series (1995-2007) of annual GMRIO tables (covering 40 countries) in current prices and in previous year's prices. We use a so-called "chaining technique" (De Haan, 2001) to eliminate the price effects in order to obtain the physical quantity effects. For example, subtracting the output in 1995 in current prices from the output in 1996 in previous year's prices gives the volume growth of output between 1995 and 1996, because goods and services are expressed in 1995 prices. This is done by using the price indexes for 1996 (with 1995 = 100). In the same fashion, using outputs expressed in 1996 prices provides the volume growth between 1996 and 1997. Adding both volume growths then gives the volume change between 1995 and 1997.

Tables in constant prices express all data in prices of the same base year (1995, in this example) whereas the chaining technique uses annually changing base years. To obtain the values in constant prices, commonly Laspeyres and Fisher price indexes (ISWGNA, 1994) are used. They calculate the price of a basket of goods in two years where the composition of the basket is the composition in the base year (Eurostat, 2002). Because data in constant prices use the same base year, their accuracy generally decreases as one moves further away from the base year (Eurostat, 2001). Using series of

annual tables in previous year's prices implies that the basket of goods (which is used to determine the price index) is updated every year. The chaining technique thus avoids an accumulation of biases.

In this chapter we will decompose the changes in EEI and EEE between 1995 and 2007. Three main driving forces are involved in the decomposition analysis: changes in emission intensities, changes in production technology and changes in demand for final products. The changes in the trade structure are included by splitting changes in production technology into changes in domestic inputs and changes in imported inputs, and by splitting changes in final demands into changes in demand for domestic final products and imported final products. After discussing the background for this study in Section 2.2, the details of our analytic approach are described in Section 2.3 (i.e. the estimation of EET and the chaining technique applied to SDA). Section 2.4 discusses the data we have used, and Section 2.5 presents and analyzes the results from the SDA. Finally, conclusions are presented in Section 2.6.

2.2 BACKGROUND

With the growing concern about climate change and related energy and environmental issues, input-output analysis has become an important tool in environmental policy analysis. Estimating emissions embodied in trade and analyzing emission indicators with structural decomposition analyses are two popular areas in environmental input-output (IO) analysis. With respect to the first area, EET studies enable us to understand: the embodied emission flows through international trade; the net bilateral emission transfers via trade from one country or region to another, and the resulting "carbon leakage"; the differences between territorial-based and consumption-based emissions; and a country's responsibility for global emissions which underlies its carbon footprint. With respect to the second area, SDA studies enable us to understand the driving forces behind the historical changes of an

aggregate indicator, such as CO₂ emissions, EET, or energy consumption. The effect brought about by each of the driving forces can be quantified and evaluated

In a comprehensive survey of the empirical literature on embodied carbon in trade, Sato (2012) reports that large and growing volumes of EET have been found. For example, in 2004 about 4 to 6 Gt of CO₂ was embodied in global trade, which equals 15-25% of the annual global emissions. In 2008, however, this figure has increased to 7.8 Gt (Peters et al., 2011a) or 28% of global emissions. This is in line with ongoing globalization and international integration of supply chains in the past decade. The world has seen a rapid growth in global merchandise trade by 460% in value terms between 1990 and 2008. During the same period, population and global GDP grew by 21% and 64%, respectively (Heston et al., 2011).

Other reviews have focused on the literature on methodological issues (e.g. Hertwich and Peters, 2009; Liu and Wang, 2009; Lutter et al., 2008; Peters and Solli, 2010; Wiedmann, 2009; Wiedmann et al., 2011). Three approaches in environmentally extended input-output analysis have been used to calculate EET: the single-region input-output (SRIO) model; the bilateral trade input-output (BTIO) model; and the global multi-regional input-output (GMRIO) model. The distinctions between the three models are in the way in which imported intermediate goods are treated and in the assumptions that are made about technology and emissions.

The GMRIO models combine domestic input coefficients matrices with import matrices for multiple countries into one large coefficients matrix. They capture the full global supply chain and are able to cover feedback effects. Several reviews have concluded that GMRIO models are the most appropriate approach for EET quantification at country level (Liu and Wang, 2009; Peters and Solli, 2010; Rodrigues et al., 2010). It should be stressed, however, that GMRIO models are quite demanding in terms of data requirements. Because not all data are available, GMRIO models rest to some extent

on estimates. Also, not all available data are of the same quality which leads to several types of uncertainties, e.g. in international trade data, emission data, aggregation, currency conversion, and the rest of the world (Andrew et al., 2009; Lenzen et al., 2004, 2010; Rodrigues and Domingos, 2007; Weber, 2008; Wiedmann et al., 2010; Wilting, 2012).

Recently, several MRIO datasets with a global coverage and environmental extensions have been developed. They include: Eora (Lenzen et al., 2012, 2013); EXIOBASE (Tukker et al., 2009, 2013); GTAP-MRIO (Andrew and Peters, 2013; Peters et al., 2011b); WIOD (Dietzenbacher et al., 2013); OECD database (Nakano, et al., 2009); and GRAM (Bruckner et al., 2012; Wiebe et al., 2012). These datasets are for different years, cover different countries, and have different environmental extensions and sectors. This is because they were developed with different aims (see Tukker and Dietzenbacher, 2013, for an overview). For example, EXIOBASE includes external cost values and has detailed information on the agricultural sector, which is relevant for land use, Eora and GTAP-MRIO cover more than 100 countries, and the time periods covered by Eora and WIOD are the longest. In this study, we employ the WIOD database because it includes a series (1995-2007) of annual IO tables that are both in current prices and in previous-year's prices. This is necessary to single out the price effects when analyzing structural changes. Further details will be described in Section 4.

The environmentally extended IO framework allows for the extension of SDA to study changes in energy and emissions. SDA examines shifts within an economy over a certain period of time by means of comparative static changes in key sets of parameters (Skolka, 1989). In the past decade, SDA studies have been carried out to analyze energy and emissions changes in Australia (Wood, 2009; Wood and Lenzen, 2009), Brazil (Wachsmann et al., 2009), China (Cao et al., 2010; Chai et al., 2009; Guan et al., 2008; Liu et al., 2010; Peters et al., 2007; Zhang, 2009, 2010), Denmark (Jacobsen, 2000; Munksgaard et al., 2000), Germany (Seibel, 2003), India (Mukhopadhyay, 2002;

Mukhopadhyay and Forssell, 2005), Japan (Gerilla et al., 2005; Okushima and Tamura, 2007, 2010; Yabe, 2004), Korea (Chung and Rhee, 2001; Park and Heo, 2008; Rhee and Chung, 2006), the Netherlands (De Haan, 2001), Norway (Yamakawa and Peters, 2011), Spain (Llop, 2007; Roca and Serrano, 2007), the UK (Baiocchi and Minx, 2010), and the US (Weber, 2009). A few studies examine a group of countries (each within an SRIO framework), such as De Nooij et al. (2003) for 8 OECD countries, and Alcántara and Duarte (2004) for 14 EU countries.

Some of these studies (like Peng and Shi, 2011; Peters et al., 2007; Rhee and Chung, 2006; Yamakawa and Peters, 2011) specifically focus on how changes in trade affect total emissions in a single country. An SDA for a large number of countries with a GMRIO model, however, has not yet been carried out. Also analyzing changes in EET has received only little attention so far. We are aware of only two case studies (Dong et al., 2010; Du et al., 2011). Both used BTIO models to analyze CO₂ emissions embodied in exports and both estimated the effects of changes in the bilateral trade volumes, the trade structure, and the emission intensities. Dong et al. (2010) used an index decomposition analysis to disentangle the emissions embodied in the bilateral trade between China and Japan and Du et al. (2011) applied an SDA to the case of China and the US. This study fills both gaps and studies the driving forces of global, regional and national changes in EET for a large set of countries, using GMRIO tables.

2.3 METHODS

2.3.1 Estimating Emissions Embodied in Trade

In this section we discuss the empirical methods. Since the early work of Leontief (1970), input-output analysis (IOA) has been used for numerous environmental applications. The core of the IO model are the inter-industry requirements. They are given as a matrix of intermediate deliveries,⁴

$$\mathbf{Z} = \begin{bmatrix} \mathbf{Z}^{11} & \mathbf{Z}^{12} & \dots & \mathbf{Z}^{1,N-1} & \mathbf{Z}^{1N} \\ \mathbf{Z}^{21} & \mathbf{Z}^{22} & \dots & \mathbf{Z}^{2,N-1} & \mathbf{Z}^{2N} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{Z}^{N-1,1} & \mathbf{Z}^{N-1,2} & \dots & \mathbf{Z}^{N-1,N-1} & \mathbf{Z}^{N-1,N} \\ \mathbf{Z}^{N1} & \mathbf{Z}^{N2} & \dots & \mathbf{Z}^{N,N-1} & \mathbf{Z}^{NN} \end{bmatrix}, \quad (2.1)$$

where $\mathbf{Z}^{rs}$ for $r, s = 1, 2, \dots, N$, represents the matrix with intermediate deliveries (in million dollars) z_{ij}^{rs} from sector i in country r to sector j in country s (with $i, j = 1, 2, \dots, n$). $\mathbf{Z}^{rr}$ reflects intermediate product flows within one country, while $\mathbf{Z}^{rs}$ ($r \neq s$) reflects imports of country s from country r . In our empirical application we have $n = 35$ sectors and $N = 41$ countries (the last “country” being the RoW). The input coefficients are obtained as $a_{ij}^{rs} = z_{ij}^{rs}/x_j^s$, where x_j^s gives the gross domestic output of sector j in country s . The $Nn \times Nn$ input matrix $\mathbf{A}$, which has the same structure as $\mathbf{Z}$, reflects the production technology. Its columns indicate the input from each sector in each country required to produce *one unit* of gross output in a certain sector in a certain country.

⁴ Matrices are indicated by boldfaced capital letters (e.g. $\mathbf{A}$), vectors are columns by definition and are indicated by boldfaced lowercase letters (e.g. $\mathbf{x}$), and scalars (including elements of matrices or vectors) are indicated by italicized lowercase letters (e.g. c or a). A prime indicates transposition (e.g. $\mathbf{x}'$).

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} & \dots & \mathbf{A}^{1,N-1} & \mathbf{A}^{1N} \\ \mathbf{A}^{21} & \mathbf{A}^{22} & \dots & \mathbf{A}^{2,N-1} & \mathbf{A}^{2N} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{A}^{N-1,1} & \mathbf{A}^{N-1,2} & \dots & \mathbf{A}^{N-1,N-1} & \mathbf{A}^{N-1,N} \\ \mathbf{A}^{N1} & \mathbf{A}^{N2} & \dots & \mathbf{A}^{N,N-1} & \mathbf{A}^{NN} \end{bmatrix} \quad \mathbf{x} = \begin{bmatrix} \mathbf{x}^1 \\ \mathbf{x}^2 \\ \vdots \\ \mathbf{x}^{N-1} \\ \mathbf{x}^N \end{bmatrix} \quad (2.2)$$

The $Nn \times N$ final demand matrix $\mathbf{F}$ consists of the vectors $\mathbf{f}^{rs}$ that give the sectoral final demands (i.e. household consumption, private investments and government expenditures) in region s for products from country r . That is,

$$\mathbf{F} = \begin{bmatrix} \mathbf{f}^{11} & \mathbf{f}^{12} & \dots & \mathbf{f}^{1,N-1} & \mathbf{f}^{1N} \\ \mathbf{f}^{21} & \mathbf{f}^{22} & \dots & \mathbf{f}^{2,N-1} & \mathbf{f}^{2N} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{f}^{N-1,1} & \mathbf{f}^{N-1,2} & \dots & \mathbf{f}^{N-1,N-1} & \mathbf{f}^{N-1,N} \\ \mathbf{f}^{N1} & \mathbf{f}^{N2} & \dots & \mathbf{f}^{N,N-1} & \mathbf{f}^{NN} \end{bmatrix}. \quad (2.3)$$

The simple accounting identity expresses that all gross output from country r is sold to producers (either at home or abroad) and to final users (at home or abroad). That is, $\mathbf{x}^r = \sum_{s=1}^N \mathbf{Z}^{rs} \mathbf{u} + \sum_{s=1}^N \mathbf{f}^{rs}$ where $\mathbf{u}$ indicates a summation vector (i.e. consisting of ones) of appropriate length. For the whole set of countries, we can write $\mathbf{x} = \mathbf{Z}\mathbf{u} + \mathbf{F}\mathbf{u}$. Using the definition of the input coefficients we can write $\mathbf{Z}\mathbf{u} = \mathbf{A}\mathbf{x}$, which gives the IO model $\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{F}\mathbf{u}$. Its solution is given by $\mathbf{x} = \mathbf{M}\mathbf{F}\mathbf{u}$, where $\mathbf{M} \equiv (\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse or multiplier matrix.

The direct emission coefficients for country r are given by the vector $\mathbf{w}^r$, where its element $w_j^r = e_j^r / x_j^r$ gives the amount of CO₂ emissions (in kilotons) in sector j of country r per million US dollars of its production. The full Nn -element vector $\mathbf{w}$ for all countries, is obtained by stacking the vectors $\mathbf{w}^r$. That is, $\mathbf{w}' = [(\mathbf{w}^1)' \dots (\mathbf{w}^r)' \dots (\mathbf{w}^N)']'$. In order to determine the emissions embodied in trade, it is convenient to define a new $N \times Nn$ matrix $\mathbf{V}$ as follows.

$$\mathbf{V} = \begin{bmatrix} (\mathbf{v}^{11})' & (\mathbf{v}^{12})' & \dots & (\mathbf{v}^{1,N-1})' & (\mathbf{v}^{1N})' \\ (\mathbf{v}^{21})' & (\mathbf{v}^{22})' & \dots & (\mathbf{v}^{2,N-1})' & (\mathbf{v}^{2N})' \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ (\mathbf{v}^{N-1,1})' & (\mathbf{v}^{N-1,2})' & \dots & (\mathbf{v}^{N-1,N-1})' & (\mathbf{v}^{N-1,N})' \\ (\mathbf{v}^{N1})' & (\mathbf{v}^{N2})' & \dots & (\mathbf{v}^{N,N-1})' & (\mathbf{v}^{NN})' \end{bmatrix}, \quad (2.4)$$

where $(\mathbf{v}^{rs})' = (\mathbf{w}^r)' \mathbf{M}^{rs}$. Its element v_j^{rs} gives the CO₂ emissions (directly and indirectly) generated in country r for one unit (i.e. million dollars) of final demand in country s for good j produced in country r .

The EET for any country r consists of two parts: emissions embodied in exports (EEE) and emissions embodied in imports (EEI). Extending the methodology developed for two countries in Serrano and Dietzenbacher (2010) to the case of N countries, the EEE for country r is given by

$$\mathbf{EEE}^r = \underbrace{\left[\sum_{k=1}^N (\mathbf{v}^{kr})' \right] (\sum_{s \neq r}^N \mathbf{f}^{rs})}_{\text{A}} + \underbrace{\sum_{s \neq r}^N [(\mathbf{v}^{rs})' (\sum_{k=1}^N \mathbf{f}^{sk})]}_{\text{B}}. \quad (2.5)$$

Part A represents the emissions (generated anywhere in the world) that are embodied in the exports of *final products* by country r to *consumers* in any other country. $\sum_{k=1}^N (\mathbf{v}^{kr})'$ is a row vector of emissions generated in all countries that are necessary for (and thus embodied in) one unit of final goods and services produced in a specific sector in country r . The column vector $\sum_{s \neq r}^N \mathbf{f}^{rs}$ gives each sector's final goods and services, produced in country r for final users in all the other countries. Part B represents the country r emissions embodied in the *intermediate products* it exports to *producers* in all the other countries, which are then used for the production of final goods and services. The row vector $(\mathbf{v}^{rs})'$ gives the emissions in country r as embodied in one unit of final goods and services produced in each sector in country s ($\neq r$). The column vector $\sum_{k=1}^N \mathbf{f}^{sk}$ gives the final goods and services produced in country s for final users all over the world (including country r). The product of $(\mathbf{v}^{rs})'$ and $\sum_{k=1}^N \mathbf{f}^{sk}$ captures the amount of emissions in country r in the intermediate products that

end up in the final goods and services produced in any other country s . Together we have the global emissions embodied in the exports of final products by country r (i.e. A) and the emissions in country r that are ultimately embodied in the final products of other countries (i.e. B).

The EEI is determined analogously and yields

$$\mathbf{EEI}^r = \underbrace{\sum_{s \neq r}^N [\sum_{k=1}^N (\mathbf{v}^{ks})']}_{\text{C}} \mathbf{f}^{sr} + \underbrace{[\sum_{s \neq r}^N (\mathbf{v}^{sr})'] (\sum_{k=1}^N \mathbf{f}^{rk})}_{\text{D}}. \quad (2.6)$$

Part C represents the global emissions embodied in the imports by country r of *final products for consumers* in country r . $\sum_{k=1}^N (\mathbf{v}^{ks})'$ gives the global emissions embodied in one unit final goods and services produced in country s and $\mathbf{f}^{sr}$ gives the imports by country r of final goods and services produced in s . The product gives the global emissions embodied in the final products of s that are imported by final users in r . Part D gives the emissions in other countries that are embodied in the *intermediate products* imported by *producers* in country r to make final products. The row vector $\sum_{s \neq r}^N (\mathbf{v}^{sr})'$ gives the emissions generated in all other countries for one unit of final goods and services produced in country r . The column vector $\sum_{k=1}^N \mathbf{f}^{rk}$ gives all final goods and services produced in country r .

2.3.2 Structural Decomposition Analysis

The matrix $\mathbf{A}$ in equation (2.2) contains the input coefficients. They measure the intermediate inputs per unit (million dollars) of output where the intermediate inputs are distinguished according to country of origin. For production, however, it does not matter whether a certain intermediate product comes from one country or another, what matters is how much is needed per unit of output. This is

reflected by the so-called technological coefficients. For country r they are given by the $n \times n$ matrix $\mathbf{H}^r$, which is obtained by summing all input matrices for country r . That is,

$$\mathbf{H}^r = \sum_{s=1}^N \mathbf{A}^{sr} \quad (2.7)$$

Given certain technological input requirements, the question what the origin of the inputs is, is answered by a matrix $\mathbf{T}$ that reflects the trade structure.

$$\mathbf{T} = \begin{bmatrix} \mathbf{T}^{11} & \mathbf{T}^{12} & \dots & \mathbf{T}^{1,N-1} & \mathbf{T}^{1N} \\ \mathbf{T}^{21} & \mathbf{T}^{22} & \dots & \mathbf{T}^{2,N-1} & \mathbf{T}^{2N} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{T}^{N-1,1} & \mathbf{T}^{N-1,2} & \dots & \mathbf{T}^{N-1,N-1} & \mathbf{T}^{N-1,N} \\ \mathbf{T}^{N1} & \mathbf{T}^{N2} & \dots & \mathbf{T}^{N,N-1} & \mathbf{T}^{NN} \end{bmatrix}, \quad (2.8)$$

where the elements in $\mathbf{T}^{sr}$ are given by

$$t_{ij}^{sr} = a_{ij}^{sr} / h_{ij}^r \quad (2.9)$$

It follows from (2.9) that

$$\mathbf{A}^{sr} = \mathbf{T}^{sr} \otimes \mathbf{H}^r \quad (2.10)$$

where $\otimes$ indicates the Hadamard product of elementwise multiplication. Note that $\sum_{s=1}^N t_{ij}^{sr} = 1$, $\forall r, \forall i, j$ and that the element t_{ij}^{rr} of matrix $\mathbf{T}^{rr}$ gives the share of all inputs of good i (as required per unit of output by sector j in country r) that originates in country r . The matrix $\mathbf{A}$ in equation (2.2) can thus be rewritten as

$$\mathbf{A} = \begin{bmatrix} \mathbf{T}^{11} \otimes \mathbf{H}^1 & \dots & \mathbf{T}^{1N} \otimes \mathbf{H}^N \\ \vdots & \ddots & \vdots \\ \mathbf{T}^{N1} \otimes \mathbf{H}^1 & \dots & \mathbf{T}^{NN} \otimes \mathbf{H}^N \end{bmatrix}. \quad (2.11)$$

In a similar way, we split the final demand matrix $\mathbf{F}$ in equation (2.3) into a part that reflects the levels of final demand and a part that reflects the trade in final products. Define the overall level of the final demand vector in country r as

$$\mathbf{q}^r = \sum_{s=1}^N \mathbf{f}^{sr}. \quad (2.12)$$

Let the trade structure for final products be given by the matrix $\mathbf{D}$

$$\mathbf{D} = \begin{bmatrix} \mathbf{d}^{11} & \mathbf{d}^{12} & \dots & \mathbf{d}^{1,N-1} & \mathbf{d}^{1N} \\ \mathbf{d}^{21} & \mathbf{d}^{22} & \dots & \mathbf{d}^{2,N-1} & \mathbf{d}^{2N} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{d}^{N-1,1} & \mathbf{d}^{N-1,2} & \dots & \mathbf{d}^{N-1,N-1} & \mathbf{d}^{N-1,N} \\ \mathbf{d}^{N1} & \mathbf{d}^{N2} & \dots & \mathbf{d}^{N,N-1} & \mathbf{d}^{NN} \end{bmatrix} \quad (2.13)$$

where the elements of the vector $\mathbf{d}^{sr}$ are given by

$$d_j^{sr} = f_j^{sr} / q_j^r. \quad (2.14)$$

This implies that

$$\mathbf{f}^{sr} = \mathbf{d}^{sr} \otimes \mathbf{q}^r \quad (2.15)$$

which yields

$$\mathbf{F} = \begin{bmatrix} \mathbf{d}^{11} \otimes \mathbf{q}^1 & \dots & \mathbf{d}^{1N} \otimes \mathbf{q}^N \\ \vdots & \ddots & \vdots \\ \mathbf{d}^{N1} \otimes \mathbf{q}^1 & \dots & \mathbf{d}^{NN} \otimes \mathbf{q}^N \end{bmatrix}. \quad (2.16)$$

A structural decomposition analysis disentangles the changes in EEE and EEI over time and quantifies how much a certain component has contributed. In so doing, we want to distinguish

between the changes (in such a component) at home and the changes abroad.⁵ We do this for the changes in emission intensities, in technology, in final demand, and in the trade structure. Thus, we define for the case of country r ($= 1, \dots, N$)

$$\begin{aligned}
 \mathbf{w} &= \mathbf{w}^{(r)} + \mathbf{w}^{(-r)} \\
 \mathbf{T} &= \mathbf{T}^{(r)} + \mathbf{T}^{(-r)} \\
 \mathbf{H} &= \mathbf{H}^{(r)} + \mathbf{H}^{(-r)} \\
 \mathbf{D} &= \mathbf{D}^{(r)} + \mathbf{D}^{(-r)} \\
 \mathbf{q} &= \mathbf{q}^{(r)} + \mathbf{q}^{(-r)}.
 \end{aligned} \tag{2.17}$$

For example, the Nn -element vector $\mathbf{w}^{(r)}$ only includes the elements of the emission coefficients at home and other elements are zero, $(\mathbf{w}^{(r)})' = [0' \dots 0' (\mathbf{w}^r)' 0' \dots 0']'$. The Nn -element vector $\mathbf{w}^{(-r)}$ includes the elements of the emission coefficients abroad and zeros for the elements corresponding to country r , $(\mathbf{w}^{(-r)})' = [(\mathbf{w}^1)' \dots (\mathbf{w}^{r-1})' 0' (\mathbf{w}^{r+1})' \dots (\mathbf{w}^N)']'$. A similar structure applies to the split of the Nn -element vector $\mathbf{q}$ and the $n \times Nn$ matrix $\mathbf{H} = [\mathbf{H}^1 \mathbf{H}^2 \dots \mathbf{H}^N]$. For splitting the $Nn \times Nn$ matrix $\mathbf{T}$ we have

$$\mathbf{T}^{(r)} = \begin{bmatrix} \mathbf{0} & \dots & \mathbf{0} & \mathbf{T}^{1r} & \mathbf{0} & \dots & \mathbf{0} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \dots & \mathbf{0} & \mathbf{T}^{r-1,r} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{T}^{r1} & \dots & \mathbf{T}^{r,r-1} & \mathbf{T}^{rr} & \mathbf{T}^{r,r+1} & \dots & \mathbf{T}^{rN} \\ \mathbf{0} & \dots & \mathbf{0} & \mathbf{T}^{r+1,r} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \dots & \mathbf{0} & \mathbf{T}^{Nr} & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix} \text{ and } \mathbf{T}^{(-r)} = \mathbf{T} - \mathbf{T}^{(r)} \tag{2.18}$$

and the $Nn \times N$ matrix $\mathbf{D}$ is split similarly.

⁵ In this study, “abroad” consists of all non-focal countries (i.e. countries other than r). We only consider the overall effects. It is possible, however, to determine the effects from changes in each single country “abroad” (i.e. for each country $s \neq r$), which might be relevant in other studies.

The values of EEE^r in equation (2.5) and EEI^r in equation (2.6) depend on the matrices $\mathbf{V}$ and $\mathbf{F}$. In its turn, $\mathbf{V}$ is obtained from $\mathbf{w}$ and $\mathbf{M} \equiv (\mathbf{I} - \mathbf{A})^{-1}$. Hence, EEE^r and EEI^r depend on $\mathbf{w}$, $\mathbf{A}$ and $\mathbf{F}$. Next, $\mathbf{A}$ depends on $\mathbf{T}$ and $\mathbf{H}$, according to equation (2.11), and $\mathbf{F}$ depends on $\mathbf{D}$ and $\mathbf{q}$, according to equation (2.16). Finally, $\mathbf{w}$, $\mathbf{T}$, $\mathbf{H}$, $\mathbf{D}$ and $\mathbf{q}$ are split into two parts (home and abroad) according to equation (2.17). Without writing out the explicit definition in matrix notation for EEE^r and EEI^r , it is clear that the expression is a function of ten matrices and vectors. That is,

$$\begin{aligned} EEE^r &= f^r(\mathbf{w}^{(r)}, \mathbf{w}^{(-r)}, \mathbf{T}^{(r)}, \mathbf{T}^{(-r)}, \mathbf{H}^{(r)}, \mathbf{H}^{(-r)}, \mathbf{D}^{(r)}, \mathbf{D}^{(-r)}, \mathbf{q}^{(r)}, \mathbf{q}^{(-r)}) \\ EEI^r &= g^r(\mathbf{w}^{(r)}, \mathbf{w}^{(-r)}, \mathbf{T}^{(r)}, \mathbf{T}^{(-r)}, \mathbf{H}^{(r)}, \mathbf{H}^{(-r)}, \mathbf{D}^{(r)}, \mathbf{D}^{(-r)}, \mathbf{q}^{(r)}, \mathbf{q}^{(-r)}) \end{aligned} \quad (2.19)$$

It has long been recognized in the literature on SDA that there is not a unique way to do a decomposition. The results may differ significantly across the alternative procedures (see e.g. Dietzenbacher and Los, 1998; De Haan, 2001; De Boer, 2008; Ang et al., 2009 for comparisons). To overcome the “non-uniqueness problem”, Dietzenbacher and Los (1998) have proposed to use the average of all possible decomposition forms. In the case of k determinants (or variables), the number of alternative decompositions is $k!$. In the present study we have $k = 10$, implying 3,628,800 alternatives. Dietzenbacher and Los (1998) also showed that the average of all decompositions can be adequately approximated by the average of the two so-called polar decomposition forms. De Haan (2001) subsequently indicated that these polar decomposition forms themselves are not unique and that the average of any pair of polar forms provides a good approximation of the overall average. For index decompositions, Sun (1998) proposed a complete decomposition model that becomes particularly relevant when the number of variables increases. His approach yields exactly the same results as the average of the $k!$ different outcomes (see Hoekstra and van den Bergh, 2003).

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, i.e. changing the last variable first, followed by changing the one but last variable, etcetera. The two polar forms, that appear to be “mirror images” of each other, are given in the Appendix. The growth in EEE^r between year $t-1$ and year t is in this chapter decomposed by f_{polar1}^r and f_{polar2}^r , after which the geometric average is taken. The decomposition of EEl^r is obtained from the geometric average of the two polar decompositions g_{polar1}^r and g_{polar2}^r . The full expressions for the polar forms are presented in Appendix A.

$$\begin{aligned}\Delta EEE_{t-1,t}^r &= \frac{\Delta EEE_t^r}{\Delta EEE_{t-1}^r} = \sqrt{f_{polar1}^r \times f_{polar2}^r} \\ \Delta EEI_{t-1,t}^r &= \frac{\Delta EEI_t^r}{\Delta EEI_{t-1}^r} = \sqrt{g_{polar1}^r \times g_{polar2}^r}\end{aligned}\tag{2.20}$$

Because our calculations are based on tables in previous year's prices, the changes between two years $t-1$ and t are related to only volume changes. For the decomposition over a period of years, a chaining technique is applied by multiplying consecutive one-year decompositions. The total changes from year 0 to year t can be expressed as,

$$\begin{aligned}\Delta EEE_{0-t}^r &= \frac{EEE_t^r}{EEE_0^r} = \frac{EEE_1^r}{EEE_0^r} \times \frac{EEE_2^r}{EEE_1^r} \times \dots \times \frac{EEE_t^r}{EEE_{t-1}^r} \\ &= \Delta EEE_{0,1}^r \times \Delta EEE_{1,2}^r \times \dots \times \Delta EEE_{t-1,t}^r \\ \Delta EEI_{0-t}^r &= \frac{EEI_t^r}{EEI_0^r} = \frac{EEI_1^r}{EEI_0^r} \times \frac{EEI_2^r}{EEI_1^r} \times \dots \times \frac{EEI_t^r}{EEI_{t-1}^r} \\ &= \Delta EEI_{0,1}^r \times \Delta EEI_{1,2}^r \times \dots \times \Delta EEI_{t-1,t}^r\end{aligned}\tag{2.21}$$

Using expression (2.20), the growth in EEE and in EEI for country r between 1995 and 2007 is disentangled into the contribution of ten components as described in Table 2.1.

Table 2.1: Description of structural decomposition components

Factors	Description
	The change in total CO ₂ emissions embodied in imports/exports due to changes in:
$\Delta \mathbf{w}^{(r)}$	Emission intensities at home
$\Delta \mathbf{w}^{(-r)}$	Emission intensities abroad
$\Delta \mathbf{T}^{(r)}$	Trade structure of intermediate products at home
$\Delta \mathbf{T}^{(-r)}$	Trade structure of intermediate products abroad
$\Delta \mathbf{H}^{(r)}$	Production technology at home
$\Delta \mathbf{H}^{(-r)}$	Production technology abroad
$\Delta \mathbf{D}^{(r)}$	Trade structure of final products at home
$\Delta \mathbf{D}^{(-r)}$	Trade structure of final products abroad
$\Delta \mathbf{q}^{(r)}$	Total final demands at home
$\Delta \mathbf{q}^{(-r)}$	Total final demands abroad

2.4 DATA

The data in this study come from the World Input-Output Database (WIOD). This database combines detailed information on national production activities and international trade data. For each country, national supply and use tables (SUTs)—with 59 products and 35 industries—have been harmonized and taken as a starting-point. Bilateral trade data have been used to distinguish the use of intermediate inputs according to country of origin, which led to the international SUTs for each of 40 countries. Next, these international SUTs have been stacked into a full 40-country SUT which was then converted into a 40-country IO table of the industry-by-industry type, using the so-called “fixed product sales structure” assumption. This IO table included matrices for imports from the RoW, but only a vector of gross exports to the RoW. In a final step, the RoW has been added as a single 41st “country”, to proxy all other countries in the world. For its estimation the UN National Accounts have been used and it was assumed that the input structure in the RoW equals that of an average

emerging country (for which the structures of Brazil, Russia, India, China, Indonesia, and Mexico have been used).

The world IO tables in WIOD cover 40 countries (all 27 EU countries and 13 major other countries), plus estimates for the rest of the world. They are available as an annual series for the time period 1995-2007 (and estimates for 2008 and 2009); both in current prices while “deflated” tables are given in previous year’s prices.⁶ For the tables in previous year’s prices, row-wise deflation using industry output deflators from the National Accounts has been applied. All data in WIOD are obtained from official national statistics and are consistent with the National Accounts. The full database is publicly and free of charge available at: <http://www.wiod.org/database/index.htm> (details of the construction of the WIOD database are given by Dietzenbacher et al., 2013).

For CO₂ emission data in the WIOD, a major source of information was the full EU27 NAMEA-air dataset from Eurostat (2012). It covers time series from 1995 to 2009. For non-EU countries, only international air emission inventories have been used. Information on CO₂ emission factors were gathered from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) as well as from UNFCCC (2011) emission reports that also contain country-specific emission factors. Although the household emission data are available, it should be emphasized that we focus in this study only on the CO₂ emission from production. Household emissions are thus not included in our EET analysis.

⁶ We conduct our decomposition analysis only up to the year 2007, because the data for 2008 and 2009 are less reliable. At the same time, 2007 is a “peak year” and the steadily increasing trade dependencies, for example, start to decline due to the crisis. So, even if good data had been available, we would have preferred to analyze the periods 1995-2007 and 2007-2009 separately, rather than 1995-2009 in its entirety.

2.5 RESULTS AND DISCUSSIONS

2.5.1 Overall Results

Figure 2.1 shows the world CO₂ EET, which is the summation of national values for EEE (EEI) plus those for the RoW, and the total CO₂ emissions in the world from production.⁷ During the period 1995-2007, the total emissions from production have increased by 32% from 19.0 Gt in 1995 to 25.3 Gt in 2007. In contrast, the world's EET has increased by 80%. We find that emissions embodied in traded goods and services (including both final and intermediate products) have increased from 4.6 Gt (24% of global emissions in production) in 1995 to 8.3 Gt (33%) in 2006. These findings are close to the results in Davis and Caldeira (2010) and other studies, but are not exactly the same due to differences in the definitions.⁸ These findings indicate a faster percentage increase of EET than of the total emissions from production. In other words, we find an increasing share of EET in the total emissions from production, which was also found by Peters et al. (2011a). This trend clearly coincides with the increasing geographical separation between production and consumption. The question, however, is: How much of the changes in EEE and EEI is due to changes in the trade structure or in any of the other underlying driving forces of EET?

Tables 2.2 and 2.3 present the detailed SDA results for EEE and EEI, respectively. We decompose the EEE and EEI changes into the following components: changes in emission intensities ($\Delta\mathbf{w}$), changes in the trade structure of intermediate products ($\Delta\mathbf{T}$), changes in the production technology change ($\Delta\mathbf{H}$), changes in the trade structure of final products ($\Delta\mathbf{D}$), and changes in the

⁷ With regard to the total emissions from production, the direct CO₂ emissions from households are not included.

⁸ Davis and Caldeira (2010) estimated 6.2 Gt of EET in 2004 which is in their case 23% of global CO₂ emissions. In our study, EET in 2004 is 7.0 Gt or 31% of global emissions from production. The ratios of EET and total emissions are larger in our study, because we divide EET by the total emissions from production whereas Davis and Caldeira (2010) divide EET by total emissions, which include emissions from production and direct emissions from household consumption. In addition, the definition of EET in this study differs slightly from Davis and Caldeira (2010) in the sense that we take into account the emissions embodied in the exports of intermediate products. Summing over countries implies that some double-counting is involved in our results for the world EET.

levels of final demand ($\Delta \mathbf{q}$). Each component (say $\Delta \mathbf{X}$) has two complementary parts, to distinguish changes at home ($\Delta \mathbf{X}^{(r)}$) and changes abroad ($\Delta \mathbf{X}^{(-r)}$). The columns show the percentage changes in EEE or EEI due to each of the ten components, and the last column indicates the total percentage changes in EEE or EEI. The rows represent the 40 countries and the last row represents the RoW.

For example, if only Australia's emission intensities ($\Delta \mathbf{w}^{(r)}$) would have changed as they actually have and all other components would have remained constant, Australia's EEE would have increased by 3%. According to the definition, the total change ΔEEE (ΔEEI) and the changes caused by each separate component have the following relationship:

$$\Delta \text{EEE} + 1 = (\Delta \mathbf{w}^{(r)} + 1) \times (\Delta \mathbf{w}^{(-r)} + 1) \times (\Delta \mathbf{T}^{(r)} + 1) \times \dots \times (\Delta \mathbf{q}^{(-r)} + 1) \quad (2.22)$$

In the example of Australia, we have:

$$1.46 = 1.03 \times 0.98 \times 0.92 \times 0.96 \times 0.98 \times 1.07 \times 1 \times 1.02 \times 1 \times 1.51.$$

Figure 2.1: Emissions Embodied in Trade (EET) and Global Emissions in Production (GEP)

Table 2.2: Structural decomposition results EEE (1995-2007)

countries	$\Delta w^{(r)}$	$\Delta w^{(-r)}$	$\Delta T^{(r)}$	$\Delta T^{(-r)}$	$\Delta H^{(r)}$	$\Delta H^{(-r)}$	$\Delta D^{(r)}$	$\Delta D^{(-r)}$	$\Delta q^{(r)}$	$\Delta q^{(-r)}$	ΔEEE
Australia	3%	-2%	-8%	-4%	-2%	7%	0%	2%	0%	51%	46%
Austria	-33%	-11%	-3%	31%	6%	5%	0%	36%	0%	45%	70%
Belgium	-20%	-13%	4%	-1%	2%	8%	0%	-4%	0%	49%	14%
Bulgaria	-53%	-2%	-20%	-3%	27%	25%	0%	16%	0%	52%	0%
Brazil	15%	-3%	-1%	21%	11%	1%	0%	20%	0%	47%	166%
Canada	-20%	-4%	0%	8%	-3%	1%	0%	2%	0%	46%	20%
China	-57%	-2%	-5%	119%	13%	4%	0%	95%	1%	50%	207%
Cyprus	-36%	-5%	-8%	25%	17%	14%	0%	11%	0%	51%	58%
Czech	-31%	-6%	-14%	34%	-14%	4%	0%	42%	0%	48%	40%
Germany	-25%	-9%	0%	24%	6%	5%	1%	20%	0%	58%	81%
Denmark	4%	-6%	-2%	16%	2%	18%	0%	3%	0%	58%	116%
Spain	-17%	-8%	-2%	14%	13%	7%	0%	19%	0%	48%	83%
Estonia	8%	-5%	-13%	21%	-42%	10%	0%	9%	0%	63%	23%
Finland	-17%	-6%	0%	12%	-13%	2%	0%	5%	0%	57%	26%
France	-34%	-11%	2%	-1%	-5%	8%	0%	16%	0%	51%	6%
UK	-14%	-8%	1%	-13%	-1%	8%	0%	-10%	0%	58%	8%
Greece	-30%	-2%	-3%	112%	0%	19%	0%	34%	0%	62%	267%
Hungary	-12%	-11%	-11%	18%	-15%	5%	0%	55%	0%	53%	74%
Indonesia	22%	-3%	-1%	8%	10%	2%	0%	8%	0%	50%	131%
India	-16%	-3%	-9%	48%	-13%	-1%	0%	66%	0%	44%	125%
Ireland	-26%	-14%	-5%	37%	3%	2%	0%	24%	0%	57%	69%
Italy	-12%	-11%	-1%	-5%	13%	6%	0%	-5%	0%	50%	26%
Japan	-3%	-5%	0%	-3%	-4%	16%	0%	4%	0%	77%	86%
Korea	-28%	-6%	-1%	29%	-7%	10%	0%	24%	0%	67%	84%
Lithuania	-18%	-6%	-9%	10%	-11%	4%	0%	18%	0%	55%	31%
Luxembourg	-28%	-7%	0%	41%	4%	2%	0%	19%	0%	55%	86%
Latvia	-44%	-6%	-10%	28%	0%	3%	0%	10%	0%	57%	7%
Mexico	-13%	-9%	5%	14%	-8%	1%	0%	17%	0%	58%	66%
Malta	-39%	-5%	1%	14%	19%	13%	0%	20%	0%	52%	63%
Netherlands	-33%	-8%	0%	-6%	5%	7%	0%	-1%	0%	40%	-9%
Poland	-43%	-3%	-11%	64%	-26%	5%	0%	55%	0%	40%	36%
Portugal	-15%	-7%	-2%	15%	6%	5%	0%	-1%	0%	45%	43%
Romania	-38%	-2%	-22%	3%	-14%	8%	0%	15%	0%	51%	-21%
Russia	-13%	0%	-2%	-15%	-5%	21%	0%	0%	0%	49%	25%
Slovakia	-29%	-6%	-14%	22%	-28%	8%	0%	63%	0%	48%	31%
Slovenia	-7%	-12%	-6%	26%	-8%	8%	0%	36%	0%	44%	88%
Sweden	-21%	-12%	6%	0%	-3%	8%	0%	7%	0%	60%	32%
Turkey	-35%	-8%	-3%	95%	-3%	2%	0%	94%	0%	44%	213%
Taiwan	-28%	-6%	2%	49%	5%	8%	0%	0%	0%	75%	107%
US	-8%	-4%	-1%	-10%	-15%	10%	1%	-1%	3%	58%	18%
RoW	-39%	-3%	-4%	47%	27%	13%	1%	19%	1%	52%	123%

Table 2.3: Structural decomposition results EEI (1995-2007)

countries	$\Delta \mathbf{w}^{(r)}$	$\Delta \mathbf{w}^{(-r)}$	$\Delta \mathbf{T}^{(r)}$	$\Delta \mathbf{T}^{(-r)}$	$\Delta \mathbf{H}^{(r)}$	$\Delta \mathbf{H}^{(-r)}$	$\Delta \mathbf{D}^{(r)}$	$\Delta \mathbf{D}^{(-r)}$	$\Delta \mathbf{q}^{(r)}$	$\Delta \mathbf{q}^{(-r)}$	ΔEEI
Australia	0%	-33%	39%	2%	2%	10%	28%	0%	72%	1%	133%
Austria	0%	-33%	6%	1%	12%	7%	14%	9%	21%	6%	37%
Belgium	0%	-36%	21%	2%	5%	10%	11%	-3%	19%	10%	31%
Bulgaria	0%	-23%	-43%	0%	81%	10%	-4%	8%	74%	5%	66%
Brazil	0%	-34%	47%	3%	10%	9%	16%	2%	28%	2%	85%
Canada	0%	-29%	10%	4%	10%	1%	13%	0%	60%	7%	77%
China	-1%	-26%	20%	-2%	24%	2%	2%	26%	187%	8%	330%
Cyprus	0%	-30%	-18%	1%	24%	8%	-4%	1%	56%	2%	20%
Czech	0%	-31%	10%	0%	18%	3%	10%	20%	48%	11%	99%
Germany	0%	-34%	16%	1%	7%	4%	23%	4%	7%	8%	27%
Denmark	0%	-33%	11%	4%	11%	6%	15%	-1%	24%	9%	38%
Spain	0%	-34%	22%	3%	19%	10%	22%	4%	66%	5%	140%
Estonia	0%	-27%	-8%	1%	28%	0%	3%	6%	137%	10%	147%
Finland	0%	-27%	10%	2%	6%	1%	3%	3%	46%	9%	46%
France	0%	-33%	3%	3%	8%	9%	10%	5%	43%	6%	47%
UK	0%	-34%	22%	3%	4%	6%	29%	-2%	44%	5%	76%
Greece	0%	-33%	21%	1%	12%	10%	16%	4%	74%	2%	116%
Hungary	0%	-30%	11%	1%	22%	4%	10%	25%	39%	11%	111%
Indonesia	0%	-36%	22%	1%	10%	13%	17%	3%	29%	4%	58%
India	0%	-40%	64%	2%	15%	15%	23%	14%	131%	2%	338%
Ireland	0%	-30%	8%	5%	19%	1%	10%	9%	87%	16%	148%
Italy	0%	-36%	7%	2%	30%	8%	16%	-1%	23%	5%	47%
Japan	0%	-38%	23%	1%	3%	13%	23%	1%	-6%	4%	8%
Korea	0%	-36%	12%	1%	17%	13%	15%	10%	43%	10%	87%
Lithuania	0%	-18%	-2%	0%	20%	0%	0%	6%	135%	6%	154%
Luxembourg	0%	-35%	5%	6%	7%	8%	-3%	7%	51%	12%	50%
Latvia	0%	-27%	-13%	-1%	42%	-5%	-4%	2%	162%	4%	128%
Mexico	0%	-28%	41%	4%	13%	-4%	22%	7%	81%	12%	205%
Malta	0%	-30%	-1%	1%	24%	11%	14%	2%	14%	7%	36%
Netherlands	0%	-35%	13%	3%	6%	11%	8%	0%	24%	8%	28%
Poland	0%	-28%	24%	1%	18%	6%	14%	16%	103%	4%	217%
Portugal	0%	-33%	8%	4%	22%	12%	7%	-1%	39%	5%	60%
Romania	0%	-29%	25%	0%	8%	7%	12%	6%	119%	3%	174%
Russia	0%	-38%	15%	2%	7%	11%	11%	-1%	132%	1%	121%
Slovakia	0%	-30%	10%	-1%	10%	1%	5%	37%	73%	10%	130%
Slovenia	0%	-33%	10%	-2%	8%	13%	11%	13%	45%	9%	77%
Sweden	0%	-32%	23%	2%	4%	5%	12%	3%	34%	10%	60%
Turkey	0%	-33%	5%	0%	40%	10%	13%	15%	85%	4%	176%
Taiwan	0%	-34%	0%	2%	-3%	8%	4%	-3%	34%	16%	11%
US	0%	-38%	37%	3%	2%	9%	28%	0%	47%	2%	88%
RoW	-1%	-27%	28%	-1%	7%	3%	16%	5%	55%	5%	99%

Growth in EEE and EEI, occurred in almost all countries and in 8 (16) countries the EEE (EEI) more than doubled.⁹ Considering the total amounts of the increases in Gt of CO₂, rather than the percentage increases, it appears that the growth of EEE and EEI is concentrated in a handful of countries. Figure 2.2 shows that the top 10 countries accounted for more than 50% of the total EET increases (in Gt). Growth in the emissions embodied in exports from China exceeded those from any other country and was responsible for 34% of the world's total EEE growth. The following 9 countries also took about 1/3 of total EEE growth. With regard to EEI, growth in the US is the highest, accounting for 18% of the world's EEI growth, followed by China (10%), India (5%) and the UK (4%). Changes in these large countries brought about significant effects in the changes in world EET. Analyzing the driving forces of EET in these countries is therefore relatively more important. In the next sub-section, we will further analyze the detailed SDA results at the national level for some of these important countries.

Figure 2.2: Growth share of top 10 countries in ΔEEE and ΔEEI

Note: other top 10 of ΔEEE are Japan, Russia, Korea, Taiwan, the US, Indonesia, and Spain; other top 10 of ΔEEI are the UK, Spain, Germany, France, Mexico, Korea and Canada

⁹ There are two exceptions: the EEE of the Netherlands and Romania show a negative growth.

From Figure 2.2, it also follows that growth in EEE had a high regional concentration, with 7 out of the 10 top countries being Asian.¹⁰ From the last column in Table 2.3, we see that Asian countries such as China, India, Indonesia, and Taiwan all had more than 100% growth in EEE during 1995-2007; whereas in North America the US and Canada both had an EEE growth of approximately 20%. As a result, among the top 10 countries, the 7 Asian countries take approximately 53% of the world's EEE growth, the 2 European countries (Germany and Spain) take 7% and the one American country (the US) takes only about 2%. In contrast, the distribution of the top 10 countries was almost evenly spread across regions for EEI growth. That is, 3 Asian countries (accounting for 17% of the world's EEI growth), 4 European countries (14%), and 3 American countries (24%). Although the American countries take a much larger share of the total EEI growth, due to the substantial growth in the US, the difference between the top region (America) and the next two regions (Asia and Europe) is much smaller than the regional differences associated with EEE.

The large growth of EEE in Asian countries reflects their growing importance in the world economy. It is surprising that the strong growth is not restricted to emerging markets, such as China, India, Indonesia and Russia, but is also found in more developed and industrialized economies, such as Japan, Korea and Taiwan. A possible explanation is the increasingly tighter production and trade interdependencies among Asian countries, as suggested in Eichengreen et al. (2004). Table 2.4 shows trade within and with Asian countries. In the period 1995-2007, the trade in intermediate products within Asia increased from 6% of total world trade in intermediate products to 7%. Exports from Asia to non-Asian countries increased from 14% to 16% and exports from non-Asia to Asia increased from 12% to 14% of the world total. This suggests a more important role for Asian countries in global value chains. For final products, however, the trade within Asia remains the same during 1995-2007

¹⁰ Asian countries include China, India, Indonesia, Japan, Korea, Taiwan and Russia. The top 10 countries that are not shown in the graphs are indicated by "Other top 10" in Figure 2.2 and listed in the note.

and accounts for 5% of total world trade in final products. Exports of final products from Asia to non-Asian countries have increased from 16% to 20%, while imports from non-Asia to Asia have decreased from 11% to 9%. That is, trade in final products increases for one direction (i.e. from Asia to the rest of the world) but decreases for the opposite direction, which points at a stronger competitive position for the Asian countries.

Table 2.4: International trade flows within and outside of Asia (1995, 2007)

Intermediate goods and services trade					
1995			2007		
	Asia	Non-Asia		Asia	Non-Asia
Asia	0.06	0.14	Asia	0.07	0.16
Non-Asia	0.12	0.68	Non-Asia	0.14	0.63
Final goods and services trade					
1995			2007		
	Asia	Non-Asia		Asia	Non-Asia
Asia	0.05	0.16	Asia	0.05	0.20
Non-Asia	0.11	0.68	Non-Asia	0.09	0.66

Note: Asian countries include China, India, Indonesia, Japan, Korea, Taiwan and Russia. Excluding Russia does not change the figures in the table.

Figure 2.3 presents the simple arithmetic average contribution of each decomposition factor, where countries have been weighted equally. We find a strong growth due to the changes in the final demand levels ($\Delta \mathbf{q}^{(r)}$ and $\Delta \mathbf{q}^{(-r)}$), i.e. the EET would have increased by more than 50% on average. The reduction due to the changes emission intensities ($\Delta \mathbf{w}^{(r)}$ and $\Delta \mathbf{w}^{(-r)}$) is significant (approximately 30%, on average). These findings are consistent with other SDA studies (e.g. Du et al., 2011; Yamakawa and Peters, 2011). The net effects are positive, in the sense that the additional emissions through final demand increases outweigh the emission reductions from emission intensity

improvements. Also the average effects of the total changes in the trade structures ($\Delta \mathbf{D}^{(r)}$, $\Delta \mathbf{D}^{(-r)}$, $\Delta \mathbf{T}^{(r)}$ and $\Delta \mathbf{T}^{(-r)}$) are substantial (between 40 and 50%). When compared to the other factors, technological changes ($\Delta \mathbf{H}^{(r)}$ and $\Delta \mathbf{H}^{(-r)}$) cause relatively small effects (between 5 and 25%, on average). In particular in developed countries, production technology has been fairly stable in this period of 13 years.

Figure 2.3: Average contribution of each factor over 40 countries and RoW

It follows from Tables 2.2 and 2.3 and from Figure 2.3 that the contributions of the decomposition factors $\Delta \mathbf{D}^{(r)}$ and $\Delta \mathbf{q}^{(r)}$ on EEE and of $\Delta \mathbf{w}^{(r)}$ on EEI are close to zero. There are only few exceptions, where the contribution is 1-3%, for large countries such as China, Russia and the US. The reason is that these effects are very indirect. They are related to the term $\sum_{s \neq r} \mathbf{v}^{rs} \mathbf{f}^{sr}$ in equations (2.5) and (2.6), i.e. the emissions in country r that are embodied in the final products abroad that are imported by country r . These emissions are exported first by country r and imported again at

a later stage, which is why they appear both in (5) and in (6). In general, EEE is affected most by demand abroad and production at home, while EEI is largely determined by demand at home and production abroad, which is quite intuitive. Following this line of reasoning, one might be inclined to expect that also the opposite holds. That is, the effects of changes in the foreign trade structure and the level of final products ($\Delta \mathbf{D}^{(-r)}$ and $\Delta \mathbf{q}^{(-r)}$) on EEI and of changes in foreign emission intensities ($\Delta \mathbf{w}^{(-r)}$) on EEE are close to zero. This is not the case, however, because a multitude of indirect effects is involved. For example, included are the emissions in any country k ($\neq r$) that are embodied in the final products that country r exports to any country s ($\neq r$).

Looking at the columns in Tables 2.2 and 2.3, we see that the emission intensity effect $\Delta \mathbf{w}^{(-r)}$ on EEI is very similar across countries (ranging between -25% and -40%), whereas the emission intensity effect $\Delta \mathbf{w}^{(r)}$ on EEE differs considerably across countries (e.g. -57% for China and +22% for Indonesia). A similar finding applies to the effects of changes in the final demand levels. The effects of $\Delta \mathbf{q}^{(-r)}$ on EEE are large and similar across countries (accounting for about 40-55%), whereas the effects of $\Delta \mathbf{q}^{(r)}$ on EEI differ substantially across countries (from -6% in Japan to 187% in China). Figure 2.4 depicts the histograms indicating the dispersion of the outcomes. These results imply that, for the effects of emission intensity changes and final demand level changes, the differences between countries are caused by home features. Foreign influences are more or less the same. This finding addresses the intuition. If the changes in emission intensities differ largely between countries r and s , we will find large differences for the effects of $\Delta \mathbf{w}^{(r)}$ and $\Delta \mathbf{w}^{(s)}$. The differences between the effects of $\Delta \mathbf{w}^{(-r)}$ and $\Delta \mathbf{w}^{(-s)}$, however, will be relatively small because these effects both include the emission intensity changes in the 39 other countries k ($\neq r, s$). That is, the “world abroad” shows a large overlap for any pair of countries.

Figure 2.4: Histograms of emission intensity and overall level of final demand effects

With regard to changes in production technology, it follows from Figure 2.3 that $\Delta \mathbf{H}^{(r)}$ induces a 15% increase in EEI on average. This is because one dollar of output contains more intermediate inputs and less value added in 2007 than in 1995. This applies to 32 out of 35 sectors (the exceptions being “Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sales of Fuel”, “Hotels and Restaurants”, and “Private households with employed persons”). A larger dependence on intermediate inputs implies that per dollar of final demand more production is required and hence more emissions are generated.

When production activities shift from rich, developed countries to emerging economies, e.g. due to trade, this leads to carbon leakage. In general, EEI growth tends to remain substantial (and in some cases even high) in many developed countries, although their EEI levels are already considerably higher than those in developing countries. At the same time, their growth in EEE is much lower. For example, the last columns in Tables 2.2 and 2.3 show that EEI growth in France, the UK, and the US was more than 4 times as high as their EEE growth (and their EEE levels in 1995 were between 55-70% of their EEI levels). For the UK, Wiedmann et al. (2010) report similar findings. They found that the EEI are higher than the EEE for all years from 1992 to 2004, and a clear trend of an increasing deficit in this balance (defined as EEE minus EEI). The amount of deficit was 27Mt of CO₂ in 1992 (4.3% of total emissions from production) and peaked in 2002 with 121Mt (20%).

The percentage and absolute changes (which are not shown in Tables 2.2 and 2.3) in EEE and EEI indicate that the emerging economies, especially China and India, are playing an increasingly important role in the trade of emissions. From the lists of emerging markets published by IMF, The Economist, S&P, and Dow Jones, 9 countries in our dataset appear on each list. These are: Brazil, China, Hungary, India, Indonesia, Mexico, Poland, Russia, and Turkey. In total, they are responsible for 47% of the world growth in EEE and for 26% in EEI growth. Although the percentage growth figures for EEI in individual countries are very large (more than 100% or even 200%, except in Brazil, Indonesia and Russia), the amount of the increase in EEI is only half of that in EEE. This is due to much lower values of EEI in 1995 in these countries. So, although emerging economies are expanding their EEI they still exhibit an increasing surplus on their emission balance (i.e. an increasing gap between EEE and EEI). In addition, we see that the RoW has a higher EEE than EEI growth, both as a percentage and in absolute values. A similar finding was reported by Peters et al. (2011a), who found that the net transfer of emissions from developing to developed countries increased from 0.4

Gt CO₂ in 1990 to 1.6 Gt CO₂ in 2008. This increase was larger than the reduction of CO₂ emissions in developed countries during the same period.

The changes in the trade structure of final products ($\Delta \mathbf{D}^{(-r)}$) induce an increase in EEE of 21% on average. This reflects the ongoing globalization where consumers buy more foreign products. Changes abroad in the product mix of the consumption bundle affect EEE and changes at home affect EEI. We find (in Tables 2.2 and 2.3, and Figure 2.3) that the influence of $\Delta \mathbf{D}^{(-r)}$ on EEE is usually smaller than 30%, but it is especially large in some emerging economies. For example, in China, Hungary, India, Poland, Russia and Turkey the increase is more than 50%, while in Australia, Canada, Japan, the UK, and the US it is less than 5% or even negative. With regard to the influence of $\Delta \mathbf{D}^{(r)}$ on EEI, which is 12% on average, we find that the larger positive effects tend to occur in developed countries. For instance, Australia, the UK, and the US are the countries with an increase in EEI of more than 25%. Perhaps somewhat surprising is the positive effect of $\Delta \mathbf{D}^{(-r)}$ on EEI. Although it is only 6% on average, in some emerging economies like China, Hungary, India, Poland, and Turkey (next to the Czech Republic, Slovakia, and Slovenia) the EEI growth would be more 10%. Note that in most of the aforementioned countries $\Delta \mathbf{D}^{(r)}$ has a larger effect on EEI than $\Delta \mathbf{D}^{(-r)}$. It should be stressed that the effect of $\Delta \mathbf{D}^{(-r)}$ is very indirect. For example, because final users all over the world buy relatively more Chinese products and because Chinese production of final products depends on imported intermediate inputs, the EEI in China increases. Because this indirect effect covers many channels (in which China produces and exports the final products) the accumulation may become substantial (inducing 26% growth in EEI in China).

The effects of changes in the trade structure of intermediate products show a similar pattern as the effects of changes in the trade structure of final products. That is, changes abroad increase the EEE at home (by 23% on average) and changes at home increase the EEI (by 14% on average). The

ongoing international fragmentation implies that production has become more dependent on imported intermediate products (see e.g. Hummels et al., 2001). The increased role of emerging countries is very clear. For instance, $\Delta \mathbf{T}^{(-r)}$ led to a more than 45% increase in EEE in China, India, Poland and Turkey. In contrast, countries like the UK and the US seem to have lost somewhat of their position in the sense that $\Delta \mathbf{T}^{(-r)}$ caused a reduction in EEE that was more than 10% EEE. Smaller reductions are observed for Australia, France, Japan, Italy and the Netherlands.

Our findings above show that even though the growth in final demand levels increases EEE the most, also the changes in the trade structure of intermediate and of final products lead to considerable effects. On average, both the increased trade in intermediates and the increased trade in final products are each responsible for approximately 20% growth of EEE. In addition have we seen a shift in trade where emerging countries have become more important because of their increased participation in global value chains. In China, India, Poland and Turkey, changes in the foreign trade structure of intermediate/final products led to more than 50% growth in EEE. The changes in the trade structure have contributed considerably to the increased transfer of emissions from developed to emerging countries. By shifting emissions towards emerging countries such as China and India, developed countries could maintain their high levels CO₂ consumption.

2.5.2 Specific Countries

In this subsection, we look at two specific countries (the US and China) and discuss their EEE/EEI results in Tables 2.2 and 2.3 in more detail.¹¹ The US is the typical rich, developed country, in which EEI has increased to a larger extent than EEE. It tends to have reduced the increase in emissions at

¹¹ The discussion of the results for two other countries (Germany and Japan) is given in the Appendix.

home by importing goods and services from abroad. China is the typical emerging country in Asia. During 1995-2007, its EEE and EEI have increased significantly. Apart from a large demand increase at home also the increased demand from abroad for both final and intermediate products have led to huge increases in its EEE.

The US

The US is the largest economy among the developed countries. The EEE in the US has grown little during the 12 year period 1995-2007 (18%), much less than the world EEE growth (80%). When compared to other countries, this was not caused by lower growth of final demand abroad or by a larger reduction of the US emission intensities. The changes in the levels of final demand abroad ($\Delta \mathbf{q}^{(-r)}$) led to a 58% increase of EEE, which is close to the average (53%, see Figure 2.3). Changes in the US emission intensities ($\Delta \mathbf{w}^{(r)}$) brought only an 8% reduction in EEE, which is much smaller than the average reduction (21%). Important factors that reduced the EEE in the US considerably are: (i) the changes in production technology at home ($\Delta \mathbf{H}^{(r)}$, causing -15% growth), expressing that the average dollar of US output contained more domestic value added than before, and (ii) the decrease in the foreign dependence on US intermediate products ($\Delta \mathbf{T}^{(-r)}$, causing -10% growth). This differs largely from the average effects for these two factors (-1% for $\Delta \mathbf{H}^{(r)}$ and 23% for $\Delta \mathbf{T}^{(-r)}$).

The EEI in the US has increased by 88%. Although the percentage increase was not the largest in the world, the increase in kilotons of EEI was by far the largest (e.g. twice as large as the increase in China). Important components were changes in emission intensities abroad ($\Delta \mathbf{w}^{(-r)}$, -38%) and the changes in the level of US final demands ($\Delta \mathbf{q}^{(-r)}$, 47%). Both components had very average effects (-32% respectively 53%). Changes that had large positive effects on the US EEI were the changes in

its trade structures, indicating that the US became more dependent on intermediate as well as final products imported from abroad. $\Delta \mathbf{T}^{(r)}$ led to 37% of EEI growth (14% for the average country) and $\Delta \mathbf{D}^{(r)}$ led to 28% growth in EEI (12% on average).

When comparing the effects of the different components on EEE and EEI in the US, we have seen the importance of changes in the world's trade structure. Although the changes in final demand levels and emission intensities had—not surprisingly—relatively larger effects, the changes in trade structure are key to the differences of EET between the US and other countries. Changes in the world trade structure of intermediate products (i.e. the combination of $\Delta \mathbf{T}^{(r)}$ and $\Delta \mathbf{T}^{(-r)}$) have increased the US EEI by 41% ($1.37 \cdot 1.03 - 1$) and have reduced the US EEE by 11% ($0.99 \cdot 0.90 - 1$). Besides, changes in the world trade structure of final demand ($\Delta \mathbf{D}^{(r)}$ and $\Delta \mathbf{D}^{(-r)}$) increased the US EEI by 25% ($1.25 \cdot 1.00 - 1$) and left the US EEE almost unchanged ($1.01 \cdot 0.99 - 1$). The changes above are caused by two factors: (i) the importance of the US as a supplier of intermediate and final goods and services lessened between 1995 and 2007; (ii) the US shifted from using intermediate and final goods and services produced by low emission intensity countries (including itself) to importing them from high emission intensity countries. The share of the US in the exports of intermediates products decreased by 4% (from 15% to 11%) and the US share in the exports of final products decreased by 2% (from 12% to 9%). The US imports of intermediate products from the 9 emerging countries amounted to 13% of the total US intermediate imports in 1995 and increased to 24% in 2007. Similarly, the share of the 9 emerging countries in the US imports of final products increased by 16% during this period (from 18% to 34%).

The EEE of China increased by 207% between 1995 and 2007. The changes in the foreign trade structure of production ($\Delta \mathbf{T}^{(-r)}$) played the most important role in the increase of CO₂ emissions embodied in exports, accounting for an increase of 119%. Changes in the foreign trade structure of final demand ($\Delta \mathbf{D}^{(-r)}$) closely followed and have induced an increase of 95%. These results reflect that a considerable share of world production has shifted to China, resulting in a significant increase of Chinese EEE. Simply put, producers all over the world use more Chinese intermediate goods and services and consumers all over the world demand more Chinese final products. Bilateral trade data support this finding. The share of China in the world's total amount of exports of intermediate products was 2% in 1995, which increased to 7% in 2007. Similarly, China's share in the total amount of exports of final products increased from 4% to 13%. Another important factor have been the changes in the Chinese emission intensities (i.e. $\Delta \mathbf{w}^{(r)}$), which accounted for a serious reduction (-57%) of the EEE. This improvement of emission intensities in China is quite considerable and its effect is larger than in many other countries, given a world average of -21%. The changes in foreign final demands ($\Delta \mathbf{q}^{(-r)}$) were also substantial and accounted for a 50% increase of EEE, but were—at the same time—very much in line with the effects in other countries (the world average being 53%). So, despite a larger than average reduction of EEE in China due to its lower emission intensities, the increased reliance of foreign producers and consumers on imports from China have led to the enormous growth of its EEE.

The EEE in China was 5.5 times as large as its EEI in 1995 and this gap has decreased considerably between 1995 and 2006, when EEE was “only” 3.9 times as large as EEI. This was because the EEI has grown by an impressive 330% which was much larger than China's EEE growth. The most important factor, which accounted for 187% EEI growth, was the increase in the volume

of Chinese final demand. Final demands in China were 2% of the total final demands in the world in 1995 and grew to 6% of the world total in 2007 due to the country's economic development.

The changes in the Chinese trade structure of intermediate products ($\Delta \mathbf{T}^{(r)}$) have led to a reduction (-5%) in EEE and a rise in EEI (20%). International fragmentation of the world's production processes and China's involvement in processing trade implied that also China became more dependent on imported intermediate imports. The trade data show that 91% of China's intermediate inputs were produced domestically (and 9% was thus imported) in 1995. This decreased to 89% (and the share of imported intermediates increased to 11%) in 2007. Next to the change in the import share, also the change in the origin of the imports matters. The shares of imported intermediate products from Korea, Turkey and Taiwan increased the most, while the share of imports from Japan decreased the most. So, next to an increase in the use of foreign intermediate products, a larger share of these imported intermediates came from countries with relatively large emission intensities.

The changes in the Chinese production technology ($\Delta \mathbf{H}^{(r)}$) induced 24% growth of EEI and 13% growth of EEE. The input-output data show that the intermediate input requirements per unit of output increased in 26 out of 35 sectors between 1995 and 2007. In other words, the domestic value added per dollar of output has decreased in these sectors. In addition, it turns out that these sectors are responsible for about 91% of total Chinese exports. So, any given bundle of exports requires more intermediate products in 2007 than in 1995 and, hence, more emissions (including Chinese emissions), which explains why EEE has grown. The same 26 sectors are also responsible for about 98% of imports of intermediate products. So, any given production level uses more intermediate inputs in 2007 than in 1995 in these 26 sectors. Because these are the sectors that rely on imported inputs, also the imports of emissions will be larger in 2007 than in 1995.

2.6 CONCLUSIONS

In this chapter, we have decomposed and compared emissions embodied in trade (EET) for 40 countries in the period from 1995 to 2007. Our analysis shows that the share of global emissions that result from the production of internationally traded goods and services has grown significantly. Moreover, EET growth was larger than the growth of global emissions. This has led to an increased geographical separation between the generation (or “production”) of emissions and the “consumption” of emissions. Our results also show that in many developed countries the emissions embodied in imports (EEI) were larger than the emissions embodied in exports and this gap has become larger over time. This is because EEI growth in rich, developed countries was usually higher than their EEE growth, and because EEE growth was particularly large in some of the emerging economies. These findings indicate that the imbalance—in emissions embodied in trade—between rich, developed countries and emerging countries has only grown larger between 1995 and 2007.

Our findings show that the distinguishing feature in explaining the uneven growth of EET between rich, developed and emerging countries were the changes in the trade structure. When buying intermediate inputs, producers all over the world shifted from importing inputs from developed countries to importing inputs from emerging countries or buying them at home. For example, the reduction of foreign dependence on US intermediate products ($\Delta \mathbf{T}^{(-r)}$) has caused a negative EEE growth (-10%) in the US. Similar findings hold for Australia (-4%), UK (-13%), Japan (-3%), the Netherlands (-6%) and some other developed countries. In contrast, the increase of foreign dependence on some emerging markets, such as China, India, Poland and Turkey, increased their EEE growth with more than 45%. Also consumers shifted their import pattern when purchasing final goods and services. On average, the changes in the foreign trade structure of final products ($\Delta \mathbf{D}^{(-r)}$) led to an increase in EEE of 21%. However, in some emerging markets, such as China, India, Poland and

Turkey, the increase was more than 50%; and in some developed countries, such as Australia, Canada, Japan, the UK and the US, the increase was less than 5%.

It turns out that increases in final demand levels and decreases in emission intensities (and to a lesser extent changes in production technology) have been important factors in explaining the growth of EET. On average, the increase in the final demand levels led to more than 50% EEE (EEI) growth; while the decrease in the emission intensities brought about 30% EEE (EEI) reduction. However, these changes have been rather comparable across countries and did not determine the grown imbalance between developed and emerging economies. Had the trade structures not changed between 1995 and 2007, the gap between EEE growth and EEI growth would have been much smaller. This holds for the negative gap in developed countries and for the positive gap in emerging countries.

The crucial point in our analysis is that developed countries did not play the same role in world production in 2007 as they did in 1995. Some of the emerging economies have gained in importance. As a result, developed countries maintained a high growth of “consuming” emissions but had a relatively low growth of their territorial emissions, at the expense of environmental conditions elsewhere. For example, the US share in the total amount of exports of intermediate products reduced by 4% and its share in total exports of final products by 2%. The export shares of China have increased by 5% (intermediate products) and 9% (final products). Summarized, we found that shifts in trade have increased the global EET and have led to an uneven EET growth between rich, developed and emerging countries, which caused more carbon leakage worldwide.

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$$\begin{aligned}
& f_{\text{polar}2}^r \\
&= \frac{f^r(w_1^{(r)}, w_0^{(-r)}, T_0^{(r)}, T_0^{(-r)}, H_0^{(r)}, H_0^{(-r)}, D_0^{(r)}, D_0^{(-r)}, q_0^{(r)}, q_0^{(-r)})}{f^r(w_0^{(r)}, w_0^{(-r)}, T_0^{(r)}, T_0^{(-r)}, H_0^{(r)}, H_0^{(-r)}, D_0^{(r)}, D_0^{(-r)}, q_0^{(r)}, q_0^{(-r)})} \times \frac{f^r(w_1^{(r)}, w_1^{(-r)}, T_0^{(r)}, T_0^{(-r)}, H_0^{(r)}, H_0^{(-r)}, D_0^{(r)}, D_0^{(-r)}, q_0^{(r)}, q_0^{(-r)})}{f^r(w_1^{(r)}, w_1^{(-r)}, T_1^{(r)}, T_1^{(-r)}, H_0^{(r)}, H_0^{(-r)}, D_0^{(r)}, D_0^{(-r)}, q_0^{(r)}, q_0^{(-r)})} \\
&\times \frac{f^r(w_1^{(r)}, w_1^{(-r)}, T_1^{(r)}, T_1^{(-r)}, H_0^{(r)}, H_0^{(-r)}, D_0^{(r)}, D_0^{(-r)}, q_0^{(r)}, q_0^{(-r)})}{f^r(w_1^{(r)}, w_1^{(-r)}, T_1^{(r)}, T_1^{(-r)}, H_1^{(r)}, H_1^{(-r)}, D_0^{(r)}, D_0^{(-r)}, q_0^{(r)}, q_0^{(-r)})} \times \frac{f^r(w_1^{(r)}, w_1^{(-r)}, T_1^{(r)}, T_1^{(-r)}, H_1^{(r)}, H_1^{(-r)}, D_0^{(r)}, D_0^{(-r)}, q_0^{(r)}, q_0^{(-r)})}{f^r(w_1^{(r)}, w_1^{(-r)}, T_1^{(r)}, T_1^{(-r)}, H_1^{(r)}, H_1^{(-r)}, D_1^{(r)}, D_1^{(-r)}, q_0^{(r)}, q_0^{(-r)})} \\
&\times \frac{f^r(w_1^{(r)}, w_1^{(-r)}, T_1^{(r)}, T_1^{(-r)}, H_1^{(r)}, H_1^{(-r)}, D_1^{(r)}, D_1^{(-r)}, q_0^{(r)}, q_0^{(-r)})}{f^r(w_1^{(r)}, w_1^{(-r)}, T_1^{(r)}, T_1^{(-r)}, H_1^{(r)}, H_1^{(-r)}, D_1^{(r)}, D_1^{(-r)}, q_1^{(r)}, q_1^{(-r)})} \times \frac{f^r(w_1^{(r)}, w_1^{(-r)}, T_1^{(r)}, T_1^{(-r)}, H_1^{(r)}, H_1^{(-r)}, D_1^{(r)}, D_1^{(-r)}, q_1^{(r)}, q_1^{(-r)})}{f^r(w_1^{(r)}, w_1^{(-r)}, T_1^{(r)}, T_1^{(-r)}, H_1^{(r)}, H_1^{(-r)}, D_1^{(r)}, D_1^{(-r)}, q_1^{(r)}, q_1^{(-r)})}
\end{aligned}$$

2.8.2 Appendix B

In this Appendix we discuss the results for Germany and Japan in more detail. Germany and Japan are two special countries in Europe and Asia, respectively. Although they are rich, developed countries, they exhibited a strong export expansion during 1995-2007, which is quite similar to some of the emerging economies. Instead of shifting production and emissions to other countries, they have produced and emitted more at home.

Germany

The German EEE has increased by 81% and this increase is the second largest increase in EEE when measured in kilotons of CO₂. The factors that have caused this change appear to be very average on first sight. That is, changes in the final demands abroad ($\Delta \mathbf{q}^{(-r)}$) accounted for 58% EEE growth (world average 53%); changes in the trade structure of production abroad ($\Delta \mathbf{T}^{(-r)}$) accounted for 24% (world average 23%); and changes in foreign trade structure of final demands ($\Delta \mathbf{D}^{(-r)}$) accounted for 20% (world average 21%). Clearly, when compared to the findings for China, all three factors had a much smaller effect on EEE in Germany. However, when compared to other rich, developed countries, such as the US, the UK and Japan, the effects of changes in the trade structures abroad had much larger effects on the growth of EEE in Germany. The IO data show that the share of German intermediate and final goods and services has increased largely in some European countries (and in particular in neighboring countries such as Austria, the Czech Republic and Poland, and in Hungary) and has increased slightly in large countries such as China and the US.

The EEI of Germany has only increased by 27%, which is much lower than the world average of 101%. The effects of the underlying factors are in Germany not very different from those in the

US and the UK, changes in the trade structure at home ($\Delta \mathbf{T}^{(r)}$ and $\Delta \mathbf{D}^{(r)}$) contributed again considerably to EEI growth (16% and 23%). However, the changes in the final demand levels in Germany ($\Delta \mathbf{q}^{(r)}$) have led to much less EEI growth (7%) than the world average (53%) and than for many other rich, developed countries. The contribution of final demand changes at home is only smaller in Japan (-6%).

Data from the German statistical office show that in the past decade, the wage rate of German workers has increased much less than in the other 26 EU countries. The costs of an hour of work in Germany rose by 19% between 2001 and 2011, which was the lowest growth in the EU27. These low wage increases have led to a higher competitiveness of German products, which in turn has resulted in an increase in exports. At the same time, it has led to a serious slowdown of domestic final demand growth in Germany.

Japan

The percentage increase of EEI in Japan is the lowest among 40 countries (8%). It is the only country where the changes in the final demand levels at home have led to a reduction in EEI (i.e. the effect for $\Delta \mathbf{q}^{(r)}$ is -6%). The input-output data show that the total final demand in Japan has decreased by 18% during 1995-2007. The largest reduction was for “Wood and Products of Wood Cork” and in 16 out of 35 sectors final demands decreased by more than 20%. Japan has experienced a disastrous decade of economic stagnation and deflation between 1991 and 2001. Bubbles in the stock market, a collapse of the land prices, over-investments in the 1980s and contractionary government policies, led to very low Japanese economic growth in the 1990s. Although temporary recoveries of growth occurred in 1996 and 1999 in response to expansionary fiscal and monetary policies, Japan entered a

recession again in 1997 and 2001. Over the whole 1995-2006 period, Japan's stagnant economic growth induced a drop in its consumption levels.

Japanese EEE increased by 86%, which was mainly brought about by changes in the final demand levels abroad (accounting for 77% EEE growth). Although the demand for Japanese products didn't change very much when measured as shares (reflected by $\Delta \mathbf{T}^{(-r)}$ and $\Delta \mathbf{D}^{(-r)}$), there has been an enormous size effect. For instance, due to the largely increased production and consumption levels in China, the exports from Japan to China have increased significantly. As an indication, the bilateral trade has tripled during the past decade and China has become Japan's major export market. The emergence of China had positive effects on high-income Asian economies that export mainly capital goods. Japan has benefited from China's demand for imported machinery and equipment and Japanese investments in China in recent years have been twice the size of the US and South Korean investments.

CHAPTER 3

RELOCATIONS OF EMISSIONS AND THE EXISTENCE OF THE ENVIRONMENTAL KUZNETS CURVE

As explained in Chapter 1, territorial emissions consider emissions generated in a particular country, while consumption-based emissions consider global emissions associated with the consumption in a particular country. Most empirical studies on the Environmental Kuznets Curve (EKC) use territorial emissions in tests of the inverted-U relationship between a country's income and pollution levels. However, emissions related to consumption partly happen elsewhere, in particular in a world in which many production processes have increasingly become organized in supplier networks spanning multiple countries. In Chapter 2, we find that shifts in international trade have increased the global emission embodied in trade (EET) and have led to an uneven EET growth across countries. This chapter re-examines the EKC hypothesis using data on both consumption-based and territorial greenhouse gas (GHG) emissions. We find evidence of the EKC when the territorial emissions are used, but not when the consumption-based emissions are used. We also find evidence of a positive relationship between income and the difference between consumption-based and territorial emissions. We argue that the consequences of these two findings do not bode well for a world that is developing.

3.1 INTRODUCTION

The Environmental Kuznets Curve (EKC) hypothesizes an inverted-U relationship between pollution levels and standards of living. That is, pollution shows a positive relationship with per capita income

at lower income levels, but this trend reverses beyond a certain income level. Continued economic growth would then lead to lower emissions in per capita terms.

Over the past three decades, the Environmental Kuznets Curve hypothesis has been the subject of many empirical tests. In general, results suggest that the EKC may exist (e.g., Carson et al., 1997; Cole et al., 1997; Dijkgraaf et al., 2005; Grossman and Krueger, 1991; 1995; Piaggio and Padilla, 2012; Selden and Song, 1994; Shafik and Bandyopadhyay, 1992), although the findings vary across methodologies (see, e.g. Stern, 2004). Nevertheless, conventional EKC tests have a critical limitation: they are only based on territorial emissions (GHGs emitted within the borders of the country). As a consequence, such EKCs cannot reflect whether emission reductions at high income levels come from lifestyle changes and technological improvements or from the relocation of polluting activities in the production process to other countries.

Emissions and consumption do not necessarily take place in the same country, due to international trade in both final and intermediate products. Trade in final products has grown steadily, mainly as a consequence of reduced costs of international transportation. With the widespread diffusion and improvements of information and communication technology and continuing global trade liberalization in the late 1990s and the first decade of the millennium, it has become attractive for many multinational firms to relocate stages of production processes to other countries or even continents (the emergence of Global Value Chains, see Baldwin, 2016). This has led to a surge in international trade in intermediate inputs. Both trends imply that the location of emissions in production have become increasingly dissociated with the location of consumption. This leads to an important question: Do such relocated emissions have significant impacts on the existence of the EKC, in particular given that offshoring generally involves relocation of activities from advanced to emerging or developing countries (where multinationals can benefit from lower wage costs)?

To answer this question, we test the EKC hypothesis using both territorial and consumption-based measures. Consumption-based measures indicate the amount of pollutants emitted globally due to the consumption of goods and services in a certain economy. These global emissions thus explicitly capture relocated emissions. Davis and Caldeira (2010) found evidence that gaps between territorial and consumption-based GHG emissions are substantial for a number of high-income countries indeed, which reinforces our expectation that the two approaches will lead to different conclusions regarding the EKC hypothesis.

We test the EKC hypothesis using both territorial and consumption-based emissions by using data for GHG emissions in more than 150 countries and global input-output tables including data for the same set of countries for the period 1970 to 2011. These data are taken from the Eora database (see Lenzen et al., 2013a,b). In addition, the relationship between outsourced emissions and income is also investigated and discussed. In the next section, we briefly review the previous literature on the Environmental Kuznets Curve. Section 3.3 describes the empirical methods and the data. Section 3.4 presents empirical results. Section 3.5 is devoted to discussion and final remarks.

3.2 BACKGROUND

Grossman and Krueger (1995) suggested three channels that might explain the EKC: the scale effect, the composition effect, and the technological effect. They argue that the first stage of development (starting from a situation in which subsistence farming is the dominant activity) requires more natural resources and therefore leads to more pollution generation. This is the scale effect. When the economy continues to develop, the economic structure shifts toward activities (such as services) that involve less pollution. Such changes in economic structure are referred to as the composition effect. Higher standards of living also allow countries to develop advanced cleaner technologies and to invest in the

diffusion of these, which causes the technological effect. If the composition effect and the technological effect taken together are larger than the scale effect, emissions start to decline with further development.

Other theories that explain the EKC hypothesis incorporate related changes, such as the demand for environmental quality (e.g., Cole, 2000; de Bruyn, 2000), the substitution between pollutants (e.g., de Bruyn, 2000; Devlin and Grafton, 1994), and increasing returns to scale in abatement activities (e.g., Andreoni and Levinson, 2001). From the perspective of this chapter, the most important cause is emission relocation through international trade, as discussed by e.g. Cole (2004), Kearsley and Riddel (2010) and Suri and Chapman (1998).

With the increase of globalization, gaps between territorial emissions and consumption-based emissions have become larger and larger in many economies (Peters and Hertwich, 2008). A number of empirical studies have analyzed impacts of trade on the EKC. Stern (1998) observed that the poorest US states tend to host more polluting industries, while the richest states have specialized in considerably cleaner service sectors. The findings of Carson et al. (1997) and Roach (2013) that an EKC for US states exists could thus possibly be explained by relocation of emissions, next to scale, composition, and technology effects.

Lucas et al. (1992) presented evidence that stricter environmental regulations in OECD countries have led to a relocation of dirty industries towards poorer countries. Lots of embodied emissions are found in imports of OECD countries from poorer countries. Suri and Chapman (1998) tested EKCs for energy consumption, using export-manufacturing ratios and import-manufacturing ratios to capture trade effects.¹² They also found that most industrialized countries had "avoided"

¹² Suri and Chapman (1998) defined the export-manufacturing ratio as the ratio of exports values of manufactured goods to domestic value added in manufacturing. For the import-manufacturing ratio a similar definition was used.

domestic energy consumption by increasing imports. Correcting for the impact of trade led to substantially higher turning points of EKC, i.e. higher income levels have to be attained beyond which per capita pollution levels start decreasing.

Trade indicators related to those employed by Suri and Chapman (1998) were employed by Antweiler et al. (2001), Cole (2004), Cole et al. (2011), Harbaugh et al. (2002), Kaufmann et al. (1998) and Kearsley and Riddel (2010). These studies present mixed evidence on the EKC hypothesis. One reason might be that the trade indicators used in these studies do not fully capture trade effects. Importing a car that used to be produced domestically will generally not only lead to reductions in emissions in the car manufacturing industry itself, but also in the production of metal products, for example. Conventional trade indicators will not show that imports of metal products have increased, although these products are embodied in the imported car (Los et al., 2015). The full incorporation of the effects of relocated emissions requires the use of consumption-based measures. Their calculation is based on a multi-region input-output model that includes all countries in the world as regions.

Until recently, little empirical work on the EKC has been carried out using consumption-based emissions. The main reason for this is data availability and data quality issues related to the estimation of consumption-based emissions. The consumption-based emissions are obtained from global multi-region input-output tables which were not available until the early 2000s. However, in recent years, the data availability and data quality have greatly improved (Tukker and Dietzenbacher, 2013). Some global input-output databases are publicly available, and they allow researchers to use data with high industry detail on (i) international flows of intermediate products, (ii) exports and imports of final goods and services, and (iii) emissions of pollutants by industry and country. As a result, relocated emissions and consumption-based emissions have been estimated and analyzed in more and more recent empirical studies (e.g. Davis and Caldeira, 2010; Dietzenbacher et al., 2012; Peters and Hertwich, 2008; Serrano and Dietzenbacher, 2010). Global input-output tables also enable us to test the EKC hypothesis with consumption-based emissions and to directly assess the impacts of relocated emissions on differences in the test results for territorial emissions and consumption-based emissions.

3.3 EMPIRICAL METHOD AND DATA

The Environmental Kuznets Curve hypothesizes an inverted-U relationship between environmental degradation and income level. The basic EKC model is given by:

$$y_i = \alpha + \beta_1 GDP_i + \beta_2 GDP_i^2 + \varepsilon_i, \quad (3.1)$$

in which y_i is per capita territorial or consumption-based greenhouse-gas emissions of country i (in quantities), GDP_i is gross domestic product per capita of country i (in constant dollars), and ε_i is a random disturbance term. As in many previous EKC studies (e.g., Grossman and Krueger, 1995; Cole, 2004; Kearsley and Riddel, 2010), we use GDP per capita as a measure of income. However, we need to keep in mind that GDP accounts for income within a country's border, including that received by foreign firms and residents within the country's territory. We use sequential cross-sectional data for more than 150 countries, using annual data from 1970 to 2011.

If results for Equation (3.1) would provide evidence for the existence of EKC using territorial emissions, but could not provide such evidence using consumption-based emissions, relocated emissions would have significant impacts on the existence and shape of EKCs. A plausible explanation for this would be that wealthy countries (directly or indirectly) import sizable shares of pollution-generating products from poorer countries.

This brings up another question: Are the net imports of emissions larger in wealthier economies indeed? To answer this question, we run regressions of net imports of emissions on income levels. The net emission imports are defined as the difference between a country's imports of emissions (i.e. emissions generated abroad, but necessary for – or embodied in – this country's consumption) and this country's exports of emissions (i.e. emissions generated in this country but

embodied in foreign consumption). It can be shown (e.g. Serrano and Dietzenbacher, 2010) that the net imports of emissions are equal to the difference between the consumption-based and the territorial emissions. If a country is a “factory for the world” (China has this nickname, but the line of reasoning also applies to Mexico and some East-European countries), its territorial emissions are larger than its consumption-based emissions. The net imports of emissions of this country are negative. The model to test relationship between income and net imports of emissions is given by Equation (3.2):

$$M_i = \alpha + \beta_1 GDP_i + \varepsilon_i, \quad (3.2)$$

in which M_i gives the net imports of emissions by country i (in quantities), GDP_i is the per capita gross domestic product of country i (in constant prices expressed in a common currency), and ε_i is the error term. In these regressions, sequential cross-sectional data is used as well.

In this chapter, territorial and consumption-based GHG emissions are directly taken from the Eora Database (Lenzen et al., 2012; 2013).¹³ The Eora Database covers 182 countries for the period 1970-2011. It employs multiple sources of GHG data, such as the EDGAR (European Commission Joint Research Centre (JRC)/Netherlands Environmental Assessment Agency (PBL), 2009) and the UNFCCC (1997) databases. GHG emissions are measured in equivalents of tons of CO₂. In this chapter, we focus on all emissions generated by human activities, which includes direct emissions by households.

Population data have been taken from the Total Population Database maintained by the United Nations.¹⁴ Country level GDP levels at constant 2005 prices in US dollars have been obtained from

¹³ Eora database website: <http://www.worldmrio.com>. The data were downloaded on June 26th, 2014.

¹⁴ The Total Population Database website is: <http://esa.un.org/unpd/wpp/Excel-Data/population.htm>.

the United Nations' National Accounts Main Aggregates Database.¹⁵ As a consequence of the use of deflated income levels, the estimated turning points of EKC's are comparable among years.

We prefer to employ the Eora database rather than other global input-output databases for two main reasons. First, Eora covers a longer time period. This coverage enables us to study the relationships between pollution and income over a period in which many countries attained high economic growth rates. Second, Eora covers a large number of countries. A number of developing countries that are not included in databases such as EXIOBASE and WIOD might be the destinations of outsourced emissions. Missing these countries in the sample might lead to biased results. We should remain cautious in interpreting the results, however. The quality of data provided by national statistical institutes in many developing and underdeveloped countries is still low, mainly as a consequence of scarce resources. Moran et al. (2013) show that national consumption-based CO₂ emissions calculated on the basis of the Eora database are comparable to those calculated based on the GTAP database (Andrew and Peters, 2013; Davis et al, 2011; Peters et al., 2011), for countries included in both databases.

In our empirical analyses, we approach the data as annual cross-sections rather than as true panel data. The reason is that the data on consumption-based emissions are based on input-output tables that were published at low frequencies (especially in the early part of the period analyzed). A full time series was obtained by using interpolation techniques. Using the data as if they were a panel of observed data might well cause spurious regression results. To avoid this problem while maximizing the use of available data, we opted for annual cross-sectional regressions.

¹⁵ The National Accounts Main Aggregates Database website is: <https://unstats.un.org/unsd/snaama/Introduction.asp>. The data compilers converted data initially collected at national level using market exchange rates as reported by the IMF.

3.4 RESULTS

This section presents the results of our empirical analysis. In subsection 3.4.1, estimation results using territorial and consumption-based GHG emissions are presented and compared. In subsection 3.4.2, additional analyses regarding the relationship between income and net outsourced emissions are carried out.

3.4.1 Consumption-Based versus Territorial Emissions

In this subsection, empirical results using territorial emissions and consumption-based emissions are presented and compared. Table 3.1 gives an overview of the results for 1970, 1975, 1980, etc., until 2010.¹⁶

Table 3.1 shows that an EKC is found for the territorial emissions from 1995 onwards. For those years, the estimated coefficient for GDP is positive and significant and for GDP squared it is statistically significant and negative. However, when the consumption-based emissions are analyzed, an EKC cannot be observed: we generally find that only the level of GDP is statistically significant, while the estimate for the quadratic term of GDP is never significant.

¹⁶ Data is not available for 6 countries in 1970s and 1980s. These are Estonia, Lithuania, Latvia, Russia, the Czech Republic and the Slovak Republic. The first four countries were part of the Soviet Union and did not become independent until 1991. The Czech and Slovak Republics jointly formed Czechoslovakia until 1993. For better comparisons of results across years, we carry out additional regressions by excluding these six countries in all years from 1970-2011. Summaries on the regression results are presented in Tables A1 and A2 of the Appendix. We do not find qualitative differences: excluding these countries from the sample does not change our conclusions.

Table 3.1: Test results of the territorial and the consumption-based emissions in selected years

VARIABLES	Territorial GHG Emissions								
	1970	1975	1980	1985	1990	1995	2000	2005	2010
GDP	0.0893 (0.264)	0.117 (0.156)	0.221 (0.146)	0.392** (0.165)	0.447*** (0.138)	0.530*** (0.149)	0.518*** (0.103)	0.489*** (0.103)	0.430*** (0.101)
GDP ²	6.75e-06** (3.06e-06)	8.87e-06*** (2.28e-06)	3.23e-06 (3.13e-06)	-1.99e-06 (4.94e-06)	-4.82e-06 (3.05e-06)	-5.96e-06** (2.86e-06)	-4.87e-06** (1.97e-06)	-4.07e-06** (1.94e-06)	-3.98e-06** (1.86e-06)
Constant	10.00e03*** (2,723)	6.98e03*** (1,311)	7.44e03*** (1,409)	5.10e03*** (796.0)	6.37e03*** (1,191)	5.22e03*** (890.8)	4.21e03*** (547.3)	4.38e03*** (567.9)	4.50e03*** (662.3)
Observations	147	147	147	147	153	153	153	153	153
R-squared	0.096	0.294	0.155	0.236	0.103	0.182	0.303	0.309	0.237

VARIABLES	Consumption-Based GHG Emissions								
	1970	1975	1980	1985	1990	1995	2000	2005	2010
GDP	0.427* (0.252)	0.381*** (0.134)	0.320** (0.130)	0.344*** (0.119)	0.403*** (0.124)	0.647*** (0.140)	0.576*** (0.123)	0.566*** (0.134)	0.444*** (0.158)
GDP ²	-4.39e-08 (2.93e-06)	1.24e-06 (1.74e-06)	3.19e-06 (2.31e-06)	2.38e-06 (2.92e-06)	-2.48e-07 (2.71e-06)	-4.70e-06 (2.95e-06)	-3.95e-06 (2.58e-06)	-2.79e-06 (2.48e-06)	-1.56e-06 (2.66e-06)
Constant	9.55e03*** (2.49e03)	6.79e03*** (1.36e03)	7.59e03*** (1.39e03)	5.39e03*** (0.78e03)	6.40e03*** (1.12e03)	5.00e03*** (1.03e03)	3.85e03*** (0.84e03)	4.23e03*** (1.01e03)	5.19e03*** (1.77e03)
Observations	147	147	147	147	153	153	153	153	153
R-squared	0.068	0.186	0.240	0.390	0.239	0.329	0.423	0.413	0.174

Note: The independent variable is *per capita* territorial or consumption-based greenhouse-gas emissions (in kilos) of country, and dependent variables are *per capita* gross domestic products (in 2005 dollars) and its quadratic term. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.2 summarizes the values of estimated turning points and the number of countries with GDP levels higher than these turning points. We only consider these turning points if the estimated coefficients for both GDP and GDP squared are statistically significant at the 5% level and have the expected signs (+ for GDP and – for GDP²).

Table 3.2: EKC turning points for territorial emissions and consumption-based emissions (1970 – 2011)

Years	Territorial GHG Emissions		Consumption-based GHG Emissions	
	TP (\$)	# Countries	TP (\$)	# Countries
1970-1985	—	—	—	—
1986	41,235	5	—	—
1987	—	—	—	—
1988	42,914	5	—	—
1989-1994	—	—	—	—
1995	44,463	5	—	—
1996	41,277	8	—	—
1997	47,084	5	49,576	4
1998	47,755	6	58,027	4
1999	48,482	6	62,700	3
2000	53,183	4	—	—
2001	50,196	6	—	—
2002	54,318	4	—	—
2003	56,004	4	—	—
2004	—	—	—	—
2005	60,074	4	—	—
2006	61,370	4	—	—
2007	—	—	—	—
2008	55,131	7	—	—
2009	52,564	7	—	—
2010	54,020	6	—	—
2011	54,617	6	—	—

Note: The turning points are assumed to exist only if the estimated coefficients for both GDP and GDP squared are statistically significant at 5%) and have the expected signs.

With respect to territorial emissions, we find the EKC in 17 (out of 42) years. According to our results, it existed in almost all the years after 1995. The income (in 2005 dollars) per capita level associated with the estimated turning point increased almost monotonically until 2006, which implies that the composition effect and technological effect started to dominate the scale effect at ever higher levels of development. After 2006, the income levels at which these effects started to dominate the scale effect stabilized. Still, also in the most recent years included in this analysis, only six or seven countries were in the income range in which decreasing pollution levels (in per capita terms) might be expected. These countries were small to very small countries, many of which are specialized in providing services: Cayman Islands, Liechtenstein, Luxemburg, Monaco, Norway, Qatar and

Switzerland. Despite these important side notes, the signs of the estimated coefficients and their statistical significance indicate that a territorial EKC *might* exist.

However, this should not lead to optimism about the prospects of declining emissions when income levels increase. An EKC based on consumption-based emissions is only found for three years, in the late 1990s. Moreover, the estimated turning points are much higher than those related to territorial emissions. As a consequence, even fewer countries attained the income levels required to be in the range in which further growth might be accompanied by lower emission levels.

3.4.2 Income and Net Imports of Emissions

In this subsection, empirical results with respect to the relationship between income and net imports of emissions are presented and discussed. Table 3 gives an overview of the estimation results for 1970, 1975, 1980, etc., until 2010.

The results in Table 3.3 reveal a positive relationship between the net imports of emissions and income levels in the period from 1980 to 2010. From the early 1980s onwards, wealthier countries tended to be net importers of emissions and their net imports were larger the larger their GDP per capita. Vice versa, poorer countries were the net exporters and their net exports were larger the lower their per capita GDP. With the advent of international fragmentation of production processes (the emergence of Global Value Chains), especially after 1990, stronger trade effects started to have increasing impacts on the GHG emissions of countries. Rich countries import more and more emissions from poor countries and the gap increases with income differences and over time.

Table 3.3: Regression results for net imports of emissions in selected years

Years	GDP
1970	-0.0871
1975	-0.110
1980	0.0968*
1985	0.122**
1990	0.148***
1995	0.171***
2000	0.105*
2005	0.148***
2010	0.147***

Note: The dependent variable is net imports of GHG emissions (in ton per capita) and the independent variable is GDP per capita (in 2005 dollars). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The question whether changes in international trade have affected global GHG emissions has been investigated also by Arto and Dietzenbacher (2014). They did not analyze changes in each and every economy included in our analysis but looked into the geographical distribution of drivers of changes in worldwide emissions. They found that all changes in the emerging economies (Brazil, Russia, India, Indonesia and China) have caused 44% of global emission growth during 1995-2008, while the increase in their territorial emissions accounted for 59% of emission growth in the same period. This means that 15% of extra global GHG emissions during 1995-2008 have been emitted in these emerging countries, but were caused by changes in other countries. This finding of Arto and Dietzenbacher (2014) aligns well with the results found in this chapter: emission relocations have played an important role in the mitigation of the territorial emissions of wealthy nations and the gap between rich and poor countries has grown over time.

3.5 DISCUSSION AND CONCLUSIONS

To investigate the impact of international trade, this chapter estimated and compared EKC's for both territorial and consumption-based emissions. Weak evidence for the existence of an EKC is found if territorial emissions are analyzed. The turning point of the territorial EKC is found at very high income levels, the number of countries in the downward-sloping part is small, and these are (very) small countries with a strong specialization in services. If we, despite these side notes, assume that the territorial EKC exists, another finding becomes relevant.

We find a positive relationship between income and net imports of emissions, which indicates that countries with higher incomes tend to relocate emission intensive production to countries with a lower income and import instead of produce at home. This effect has increased over time and we conclude that international trade is a key driver of the existence of territorial EKC's. The consequences of this finding are twofold.

First, the downward-sloping part of the territorial EKC might merely be a reflection of emissions that the wealthier countries import from the poorer countries. Furthermore, this effect is strongest for the richest countries. For the consumption-based EKC, this implies that the downward-sloping part becomes flatter and may not even be downward sloping anymore. Our findings corroborate this argument as GDP squared is statistically far from significant. Second, the poor countries are the net exporters of emissions and the poorer they are the more emissions they export. This implies that the consumption based EKC has an upward-sloping part that is steeper than the upward-sloping part of the territorial EKC. Both aspects do not bode well for a world that is developing. If poor countries increase their GDP per capita, this will increase global emissions more than suggested by the territorial EKC. If rich countries increase their GDP per capita, this will not decrease emissions (if at all) as much as suggested by the territorial EKC. Taking into account that

only very few, small countries are located in the downward-sloping part of the territorial EKC, this suggests a linear upward-sloping consumption-based EKC. The implication is that any increase in GDP per capita will increase global emissions.

Economists have long argued that environmental degradation is not an inevitable consequence of economic growth. The opinions that economies adapt well and that the least uncertain way to achieve environmental quality is to get rich are still around. These opinions do carry weight in policy circles and part of the EKC literature provides empirical support for these. We showed that the EKC does not exist if the consumption-based emissions are used. Moreover, the territorial EKC may well exist only because of international trade. Replacing GHG emissions in one country by GHG emissions in other countries cannot stop global warming. Moreover, if more countries show GDP growth, demand (by rich countries) for imports of emission will increase, while supply (by poor countries) decreases. This is not possible so that only the richest countries will be able to import emissions. This means that the turning point of territorial emissions EKC shifts to higher income levels. With a constant or growing population, development might only lead to reduced pressures on the environment if an EKC would exist for consumption-based emission indicators.

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3.7 Appendix

Table A3.1: EKC turning points excluding the former Soviet Union countries, the Czech Republic and the Slovak Republic (1970-2011)

Years	Territorial GHG Emissions		Consumption-based GHG Emissions	
	TP (\$)	# Countries	TP (\$)	# Countries
1970-1985	—	—	—	—
1986	41,235	5	—	—
1987	—	—	—	—
1988	42,914	5	—	—
1989-1994	—	—	—	—
1995	45,399	5	—	—
1996	42,257	6	—	—
1997	48,390	5	50,362	4
1998	48,582	5	59,091	4
1999	49,179	5	63,963	3
2000	54,237	4	—	—
2001	51,111	5	—	—
2002	56,235	4	—	—
2003	58,237	4	—	—
2004	—	—	—	—
2005	62,632	3	—	—
2006	64,385	3	—	—
2007	—	—	—	—
2008	57,161	7	—	—
2009	54,750	7	—	—
2010	56,658	5	—	—
2011	57,703	5	—	—

Note: Countries excluded from the analyses are Estonia, Lithuania, Latvia, Russia, Czech Republic and Slovak Republic. The turning point exists only when both level and quadratic terms of GDP are statistically significant (at 5% level) and have the expected signs.

Table A3.2: Regressions results on net imports of emissions excluding the former Soviet Union countries, the Czech Republic and the Slovak Republic (1970-2011)

Years	GDP	Years	GDP
1970	-0.0871	1991	1.157**
1971	-0.238**	1992	0.212***
1972	-0.229*	1993	0.151***
1973	-0.264**	1994	0.167***
1974	-0.210**	1995	0.170***
1975	-0.110	1996	0.161***
1976	-0.0817	1997	0.0963*
1977	0.00190	1998	0.132**
1978	-0.0211	1999	0.114**
1979	0.0655	2000	0.105*
1980	0.0968*	2001	0.111**
1981	0.134***	2002	0.113**
1982	0.172***	2003	0.120***
1983	0.190***	2004	0.131***
1984	0.141*	2005	0.147***
1985	0.122**	2006	0.152***
1986	0.120**	2007	0.186***
1987	0.159***	2008	0.159***
1988	0.126**	2009	0.146***
1989	0.121**	2010	0.146***
1990	0.149***	2011	0.151**

Note: Countries excluded from the analyses are Estonia, Lithuania, Latvia, Russia, Czech Republic and Slovak Republic. The dependent variable is outsourced GHG emissions (in ton per capita) and the independent variable is GDP per capita (in 2005 dollars). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

CHAPTER 4

INTERNATIONAL TRADE AND AIR POLLUTION DAMAGES IN THE UNITED STATES

In previous chapters, we estimated quantities of CO₂ that are the consequence of consumption and investment demand in a specific country, but that are emitted elsewhere. We labeled the difference "relocated emissions". Emissions of pollutants are known to have health and social-economic impacts. For instance, large amounts of SO₂ emissions might lead to acid rain, which in turn will cause death of forests, damaged properties, reductions in agricultural productivity, as well as a number of negative effects on human health. Consequently, importing the output of activities that cause emissions leads to reductions of negative local impacts compared to a situation in which the country would host these activities within its own borders. The mirror image is that exporting output of polluting activities causes more local damages than if the country would just support its domestic consumption and investment demand. How can such effects be analyzed in a framework that also takes the effects of trade on value added creation into account? This chapter aims to estimate the *monetary* values of the health and socio-economic impacts of emissions in the US as implied by its international trade pattern in 2002.

4.1 INTRODUCTION

Reports by the US Environmental Protection Agency (EPA) show that emissions of air pollutants in the US decreased substantially since 1980. Such improvements are often linked to stricter regulations and improved environmental efficiency of production processes (Chestnut and Rowe, 1990; USEPA, 1999; 2011). Empirical studies, however, indicate that the stabilization of emissions in developed

countries like the US has partially been due to growing imports from developing countries. Weber and Matthews (2007), for example, find a large increase of the relocation of US air emissions to other countries, between 1997 and 2004. These are caused by increasing quantities of products imported by the US. In Chapter 3 of this thesis, we found similar results for other developed countries.¹⁷

Much of the existing research on emissions relocation via international trade has focused on emitted quantities of pollutants. In contrast, this chapter analyzes the impacts of the relocated emissions in terms of monetary values. Air pollutants are responsible for many adverse environmental effects, such as photochemical smog, acid rain, death of forests, and reduced atmospheric visibility. Polluted air can also directly harm human health, cause damages to property, and reduce agricultural productivity. The United States reduces its home damages when it imports products from abroad instead of producing these products domestically. In the same vein, the US increases its home damages when it produces for export purposes.

What are the benefits of using monetary terms in the impact assessment? First, using a common monetary unit allows for direct comparisons of damages generated by various air pollutants and computation of the total effects of all air pollutants. Second, unlike physical indicators, monetary indicators provide a natural link between the economic and the environmental consequences of trade. This implies that agents in the trade policy arena can compare alternative policies on the basis of indicators that internalize negative external effects of production activities. Of course, monetary valuation has its own limitations and involves the use of subjective prices for these externalities. Still, previous studies provide useful estimates in this respect.¹⁸

¹⁷ See Lutter et al. (2008), Hertwich and Peters (2009), Liu and Wang (2009), Wiedmann (2009), Peters and Solli (2010), Wiedmann et al. (2011) and Kanemoto et al. (2014) for other studies related to the impacts of international trade on the location of emissions, see Arto and Dietzenbacher (2014) for an analysis of changes over time.

¹⁸ See e.g. Freeman (2002), Ho and Jorgenson (2007), Muller and Mendelsohn (2007; 2009) and USEPA (2011).

This study investigates the net damage changes through international trade for the US economy in 2002. That is, we estimate the environmental damages in the US generated by its exports and subtract the damages in the US if its imports would have been produced at home. To this end, we employ a detailed input–output (IO) table for the US economy (needed to take the required US production of raw materials, parts and components and business services into account), complemented by a comprehensive database on the damages generated by additional emissions of several air pollutants. These emission damage values were estimated by Muller et al. (2011), using the so-called Air Pollution Emission Experiments and Policy (APEEP) model. The six major local air pollutants included in their study are SO_2 , $\text{PM}_{2.5}$, PM_{10} , NO_x , VOC, and NH_3 . We cannot but limit our analysis to the US, in view of two data constraints. First, Muller et al.’s (2011) estimates of the damages of emissions in monetary terms are very specific for the US. Second, we do not have IO tables at the same level of detail (400 industries) for the majority of the most important trade partners of the US. Hence, our results do not address the impacts of US trade elsewhere in the world.

This chapter is structured as follows. After discussing the background of this study in Section 4.2, the details of our approaches are described in Section 4.3. Section 4.4 discusses the data we used in this chapter. Section 4.5 is devoted to the main results. We report on sensitivity analyses in Section 4.6, and present conclusions in Section 4.7.

4.2 BACKGROUND

Global environmental challenges have prompted increased attention to the environmental performance of individual countries, for example in relation to pledges made by countries in various international treaties. Such a focus disregards that the growing intensity of international trade in both intermediate inputs and final products has led to increasing differences between the location of emissions and the location of the use of the associated final products: substituting domestically

produced goods by imports contributes to reducing domestically emitted pollutants, but increases these elsewhere. There is a growing literature on environmental degradation focusing on these emissions relocated by trade (see the comprehensive surveys of Jayadevappa and Chhatre, 2000; Wiedmann et al., 2007; and Sato, 2012). One of the earliest empirical contributions was Walter (1973). Recent studies employ global input-output tables that allow for more accurate estimations of traded emissions (e.g., Davis and Caldeira, 2010; Peters et al., 2011; Moran et al., 2013). Chapters 1 and 2 have presented detailed discussions on this strand of literature.

Another part of the literature on environmental degradation focuses on "emission-damage analysis". Emission-damage analysis has been widely used to evaluate social impacts of policy changes related to emissions. For instance, USEPA (2011) analyzed benefits due to the reduction of emissions as a consequence of the Clean Air Act. It found that the total estimated direct benefit (related to human health and welfare) in the year 2010 amounted to around \$1,300 billion. Furthermore, it estimated the total present value of direct benefits from the Clean Air Act from 1990 to 2020 to be about \$12 trillion.

In this chapter, we demonstrate that combining the literature on emissions embodied in trade and the literature on damages yields additional insights. We connect the two strands of literature and estimate the monetary consequences of emissions in the US implied by its exports and of emissions that have been "avoided" by importing rather than producing at home.

Muller and Mendelsohn (2007; 2009) used a so-called Air Pollution Emissions Experiments and Policy (APEEP) model to calculate the marginal damage associated with emitting an additional ton of pollution in the US. Air emission data used by the authors were provided by the US Environmental Protection Agency's National Emission Inventory (NEI), which encompasses all anthropogenic emissions of six air pollutants (SO_2 , $\text{PM}_{2.5}$, PM_{10} , NO_x , VOC, and NH_3) in the 48 contiguous states of the US (USEPA, 2006; 2009). The APEEP model first connects emissions of air

pollutants to physical effects. These physical effects include adverse effects on human health, decreased timber and agriculture yields, reduced visibility, accelerated depreciation of materials, and reductions in recreation services. In the next step, the model translates the physical effects into monetary terms using standard estimates of mortality and morbidity risks, market values of goods and services, and results of other valuation studies (e.g. Chestnut and Rowe, 1990; McClelland et al., 1993).

Muller and Mendelsohn (2007; 2009) first calculated baseline damages of the emissions in 2002 emissions, and then calculate damages of one additional ton of emission. They followed this procedure for each of the six pollutants in each of 10,000 locations that act as sources of pollution, such as factories. The estimated marginal damage, $MD_{s,j}$, indicates the value of damages caused by one additional ton of pollutant s in location j . Muller and Mendelsohn (2007) compared the gross damages to value added ratios by industry. They found that these ratios were larger than one in six industries (Stone Quarrying, Solid Waste Incineration, Sewage Treatment Plants, Oil and Coal Fired Power Plants, Marinas, and Petroleum-Coal Product Manufacturing). This implies that the environmental impacts of production can be so large that their monetary value exceeds the direct economic impacts. Muller and Mendelsohn (2007) also found that emissions of VOC, NH_3 , SO_2 and $\text{PM}_{2.5}$ generated about 80% of total damages, although they account for only half of all emissions in terms of weight.¹⁹ Muller and Mendelsohn (2009) used these data on source-specific marginal damages to identify more efficient market-based pollution policies: They calculated the welfare gains from making the US trading program in sulfur dioxide allowances for power plants more efficient.

Based on these data from Muller and Mendelsohn (2007; 2009), Muller et al. (2011) presented a framework to include environmental impacts into the system of national accounts. They estimated

¹⁹ Previous studies, such as Fann et al. (2009) and Levy et al. (2009), find evidence of heterogeneity among pollutants, too. However, both studies had scopes that are somewhat different from Muller and Mendelsohn's (2007; 2009). Fann et al. (2009) computed damages per ton for 9 urban areas rather than for the whole country. Levy et al. (2009) focused entirely on coal-fired power plants, so only one industry was covered by their study.

the air pollution damages for each industry in the United States. In Muller et al. (2011), gross external damage by industry is calculated by multiplying the industrial emissions in each location to the pollutant-specific marginal damage in the same location. In this study, we divide these industry-level gross external damage indicators by industry-level gross output figures. In the next section, we discuss how these ratios (or damage coefficients) can be used to estimate the effects of US trade on pollution damage in this country, using input-output analysis.²⁰

4.3 METHODS

In this study, we use input-output analysis. Input-output analysis explicitly takes into account that exporting products requires intermediate inputs, the production of which might have environmental impacts. A simple, highly stylized illustration is given in Figure 4.1. The production of cars to be exported from the US requires activities in the automotive industry. Besides labor, capital and possibly damaging emissions, these activities require components produced by, for example, the machinery industry. The (potentially polluting) activities in this industry require inputs from the metals and mining industries. Hence, damages are not only generated in the automotive industry itself (D3 in the figure), but also in other industries (D1 and D2). Indirect effects like these should be taken into account in the quantification of damages due to trade.

²⁰ In our analysis of the damages that are avoided by importing products, we do not include so-called “non-comparable imports”. These are imports of products that US industries cannot produce themselves, like specific raw materials. Hence, analyzing what would happen if these products would be produced in the US is not meaningful. Just for information, the share of non-comparable imports in the value of total imports amounted in 2002 to roughly 10%.

Figure 4.1: Industries involved in final demand of a US-produced car

Previous chapters focused on global pollutants and calculated global effects for which global IO tables were used. The research question of this chapter focuses on local pollutants and we calculate the effects in the US using the national IO table. Since we are interested in damages occurring on US soil (and the avoidance of such damages by US imports) rather than the environmental impacts of US production or consumption on the rest of the world, we should use information on the US production structure. An advantage that comes with these limited data requirements is that using the US input-output account data allows us to estimate damages at a detailed level of industry detail. The US input-output tables from the Bureau of Economic Analysis (BEA) contain data for more than 400 industries, which implies that we can meaningfully link them to the also detailed damage data.

Using an input-output table for the US, we obtain a vector of output changes for each industry due to a dollar of final demand (i.e. household consumption, private investment, government expenditures or exports) for the output of industry i . It is expressed as $(\mathbf{I} - \mathbf{A}_{\text{US}})^{-1} \boldsymbol{\delta}^i$, where $\mathbf{I}$ is the identity matrix, $\mathbf{A}_{\text{US}}$ is the industry-by-industry direct domestic input coefficient matrix for the US, and $\boldsymbol{\delta}^i$ is a column vector with the i^{th} element equal to one and zeros elsewhere. The matrix $(\mathbf{I} - \mathbf{A}_{\text{US}})^{-1}$ is usually called the Leontief inverse. It takes the indirect effects depicted in Figure 4.1

into account.

For pollutant s , we define “unit damage” as the damage generated by one dollar of final demand for the output of industry i and denote it by $UD_{s,i}$. In a similar vein, we define “unit value-added” as the value-added generated by one dollar of final demand for industry i ’s product. We denote it by u_i . We have

$$UD_{s,i} = \mathbf{d}'_s (\mathbf{I} - \mathbf{A}_{US})^{-1} \boldsymbol{\delta}^i, \quad (4.1)$$

$$u_i = \mathbf{v}' (\mathbf{I} - \mathbf{A}_{US})^{-1} \boldsymbol{\delta}^i, \quad (4.2)$$

in which $\mathbf{d}_s$ is the damage coefficients vector that gives—for each of the industries—the damages in dollars related to pollutant s per dollar of gross output, and $\mathbf{v}$ is value added coefficient vector that gives the value added per dollar of gross output.²¹

The damage coefficients vectors $\mathbf{d}_s$ has been computed in a number of steps:

$$d_{s,i} = GED_{s,i}/x_i, \quad (4.3)$$

in which x_i is the gross output in dollars in industry i and $GED_{s,i}$ denotes the dollar value of damages attributed to pollutant s generated by industry i . To obtain $GED_{s,i}$, we aggregated the $GED_{s,i,j}$ in Muller et al. (2011) across locations j :

$$GED_{s,i} = \sum_j GED_{s,i,j}, \quad (4.4)$$

²¹ Primes stand for transposition.

As mentioned in Section 4.2, Muller et al. (2011) calculated the $GED_{s,i,j}$ by multiplying the industrial emissions in each location to the pollutant-specific marginal damage in the same location. Therefore, we can re-write Equation (4.4) as:

$$GED_{s,i,j} = E_{s,i,j} MD_{s,j}. \quad (4.5)$$

where $E_{s,i,j}$ is the industrial emissions of pollutant s in location j in industry i , and $MD_{s,j}$ is the marginal damage of pollutant s in location j .

Equations (4.1) and (4.5) yield $d_{s,i} = \sum_j (MD_{s,j} E_{s,i,j}) / x_i$ and reflect an important assumption in this study. To estimate “unit damages”, we assume that the shares of locations in the emissions of all industries directly and indirectly involved in the production of one dollar of final output of industry i are equal to the industry averages. For example, if the US exports of cars are increased by 2%, we implicitly assume that factories all over the US will increase their production of cars by 2% and the same is assumed regarding the intermediate inputs for cars. Most likely, this assumption is far from true, since exported products might generally well be produced closer to borders and ports than products for domestic markets. Since the marginal damages MD in Equation (4.5) are dependent on location j , our results for UD in (4.1) would be biased if exported products would tend to be produced in locations with marginal damages that are far from the average. We would need an interregional input-output table (with fine-grained geographical detail) to relax this assumption, but such a table is not available for the US.

The elements v_i of the value added coefficients vector $\mathbf{v}$ (see Equation 4.2) are computed as

$$v_i = va_i / x_i, \quad (4.6)$$

in which va_i is the value-added of industry i and x_i is the gross output in industry i . The required information is available in the input-output table itself.

Having defined “unit-damage” and “unit value added”, we can calculate damages associated to producing exports and damages avoided by imports. Damages generated by producing exports of the output of industry i are denoted by $DEX_{s,i}$:

$$DEX_{s,i} = UD_{s,i}e_i, \quad (4.7)$$

in which e_i is the value of US industry i 's exports. The total amount, $\sum_s \sum_i DEX_{s,i}$, can be interpreted as the damages in the US associated with production to meet demand from other countries. We assume that traded and non-traded products are produced in the US using the same input mix, which is an assumption often adopted in input-output analyses. To relax this strict assumption, input-output tables in which industries are split into sub-industries producing export products and producing products for domestic markets (based on firm-level data) would be needed. Such tables are not available for the US.²²

Next, we analyze the impacts of imports, by estimating the damages avoided by importing. Everything else equal, purchasing foreign goods and services rather than producing these at home reduces damages in the US. How much additional damages would the US have faced if it had not relied on any imports? We adopt an approach that is identical to Levinson's (2009), who focused on reduced pollution volumes. The avoided damages due to pollutant s in the US through importing goods and services produced by industry i in foreign countries are

²² Very recently, BEA has published a report on its efforts to construct an input-output table in which data for multinational firms and for non-multinationals have been separated (see Fetzer et al., 2018).

$$DIM_{s,i} = UD_{s,i}m_i, \quad (4.8)$$

in which m_i is the value of imported products (of both final products and intermediate inputs) from foreign counterparts of industry i .

The impacts of exports and imports on value added changes in industry i are denoted as VEX_i and VIM_i , respectively:

$$VEX_i = u_i e_i, \quad (4.9)$$

$$VIM_i = u_i m_i. \quad (4.10)$$

We define the net costs of trade in the output of industry i regarding pollutant s as the difference between $DEX_{s,i}$ and $DIM_{s,i}$ and denote it as $\Delta D_{s,i}$:

$$\Delta D_{s,i} = DEX_{s,i} - DIM_{s,i} = UD_{s,i}(e_i - m_i). \quad (4.11)$$

In a similar vein, we define the net value added gain of trade in the output of industry i (ΔVA_i) as the difference between VEX_i and VIM_i

$$\Delta VA_i = VEX_i - VIM_i = u_i(e_i - m_i). \quad (4.12)$$

4.4. DATA

We use the gross external damages (GED) for 2002 as estimated by Muller et al. (2011). They

employed emissions to air data from the US Environmental Protection Agency's national emission inventory (USEPA 2006; 2009). This covers all anthropogenic emissions of six air pollutants (SO_2 , $\text{PM}_{2.5}$, PM_{10} , NO_x , VOC , and NH_3) in the 48 contiguous states of the US (i.e., excluding Alaska and Hawaii). The GED data are available for about 840 industries (at the six-digit level in the North American Industry Classification System, NAICS). This implies $s = 6$, $i \approx 840$, and $j = 48$.

To account for indirect effects (output of intermediate products to be used in other industries), we employ Input-Output Accounts (make and use tables) data from the BEA. Given that damages data are only available for 2002, we use the IO table for the same year. The details of the procedures to arrive at the IO table from the make and use tables can be found in Appendix A, but two aspects are too important to be left undiscussed here.

First, we remove imported intermediate inputs from the use table. The use table is a matrix that shows the use of products by each industry and by final users. The inter-industry commodity flow data used to construct the US use table do not distinguish between the use of domestically sourced products and products purchased abroad. Since we focus on damages in the US, removing the imported intermediate products is a necessary step. To attain this, we use an import matrix from the BEA. The import matrix documents the values of uses of imports by industries and final users, by product.²³

The second issue relates to the matching of the industry classification of the IO table to the NAICS industry classification of the damages data. The US IO table contains data for 426 industries.²⁴ As we mentioned above, emissions and damages data are available for many more industries. Aggregating the more detailed industries in the emissions data into the broader industries in the IO

²³ Horowitz and Planting (2009) give a more detailed discussion on this “domestication” issue, especially for the description and construction of the import matrix.

²⁴ Our analyses are based on 418 industries. We left out the industries that are called “Special industries” in BEA publications. For these industries damages data are not available. Most of these industries are government enterprises, which are only marginally involved in international trade and mainly supply to domestic final users.

data proved unproblematic in most cases (apart from the fact that aggregation bias is inevitable as soon as we start attributing damages to exports or imports). There are two categories of exceptions, however. First, we have 20 IO industries to which we cannot match any NAICS industry. This implies that we do not have information on damages for those 20 IO industries. In the baseline model, we assume that damages in these 20 industries are equal to zero. Another category of exceptions relates to agricultural industries and construction industries, for which the damages data contain less industry detail than the IO table. Disaggregating GEDs is necessary with respect to those industries.²⁵ In the baseline model, we simply allocate GEDs in agricultural and construction industries proportionally to value added.²⁶ In Section 4.6, we report on sensitivity analyses to assess the extent to which results change if we adopt alternative approaches to deal with these issues.

For expositional reasons, we aggregate our analytical results for IO industries into 42 sectors.²⁷ Hereafter, we refer to the 6-digit IO industries as ‘industries’, and refer to the 42 aggregated IO sectors as ‘sectors’. In addition, we sometimes aggregate results for the 42 sectors into results for three broad aggregates: the primary sector, the secondary sector, and the tertiary sector (see Table A4.6 in Appendix C for the aggregation of the 42 sectors into three).

We also addressed several issues with respect to prices. The first price issue is about the type of prices in which the IO table is expressed. It would be optimal to use data in basic prices. The basic price is the price received by the producer for goods and services that are sold, excluding taxes and subsidies. The make and use tables from the US BEA, however, are expressed in producers’ prices (which equal the basic prices plus taxes on products minus subsidies on products). Tables in basic prices are not available from public US official sources and would have to be estimated. Therefore,

²⁵ Alternatively, we could have aggregated industries in the IO table, but that would have meant a neglect of interdependencies between the industries involved.

²⁶ The procedures to handle these two exceptional categories are explained in more detail in Appendix B.

²⁷ We aggregate the results after having conducted the analysis. Aggregating data before doing the analyses would yield aggregation biases.

the IO table in producers' prices is used. Part of our robustness analysis assesses the sensitivity of our results to the choice of a price concept: We repeat our analysis using the 2002 US IO table in basic prices obtained from the 2013 release of the World Input-Output Database (WIOD) (Dietzenbacher et al., 2013). This table is much more aggregated, however. It contains 35 sectors, based on the European NACE classification. Detailed discussions can be found in Appendix D.

The second issue relates to the price concepts used for imports and exports. The exports data as published in the BEA IO table are in producers' prices, which is the same as is used for all domestically produced commodities. Imports, however, are expressed in two different prices: the "foreign border prices" and the "US border prices". The foreign border price of imports is the value of commodities at the foreign port. Usually, it referred to as the "fob (free on board) price". The US border price is the price of a product when it enters the US, which is equal to the foreign border price plus transportation costs, insurance and custom duties. An internationally more common label for this price concept is the "cif (cost, insurance and freight) price". According to Horowitz and Planting (2009), the US border prices are comparable to producer prices of US domestic production. Therefore, in the baseline model, we use imports valued in US border prices. To assess the sensitivity of our results, we also present the results for imports in foreign border prices in Appendix D.

The third price issue is about changes in prices over time. The damage values taken from Muller et al. (2011) are expressed in dollars of 2000. The input-output tables from BEA, however, are expressed in prices of 2002. In the baseline analysis, we convert damage values to values in 2002 prices, using GDP deflators. We choose to use the Federal Reserve Bank's Implicit Price Deflator of GDP.²⁸ Damages involve aspects that have an impact in several spheres of the economy, including human health, agricultural productivity, visibility, and recreation. We feel that using a "broad" deflator like

²⁸ See <http://research.stlouisfed.org/fred2/series/GDPDEF/>.

the GDP is more appropriate than using a specific deflator like the consumer price index or the industry-level output deflator. Inflation between 2000 and 2002 as measured using this GDP deflator amounted to 3.71%. Hence, total GED in 2002 equaled \$184 billion if expressed in 2000's prices, but approximately \$191 billion in 2002's prices. A sector level summary of GEDs by pollutants is presented in Table A4.9 of Appendix E. An alternative approach would be to adjust the value added and other input-output data from 2002's prices to 2000's prices. This approach requires deflators at the industry level. In the sensitivity analysis, we consider the results obtained by using the deflated IO table from WIOD, see Appendix D.

4.5 RESULTS

4.5.1 Damages Associated with Trade

We present our main results for damages associated with international trade of the US in Table 4.1.²⁹ Let us first focus on results for a single sector. The first row, for example, shows that the exports of Crop Products generated approximately \$2.4 billion of damages (DEX), and accounted for about \$14.8 billion of value added (VEX), in all sectors of the US taken together. If the imports of crop products would have been produced domestically instead, \$2.2 billion of damages (DIM) and \$11.0 billion of value added (VIM) would have been generated (assuming that sufficient production factors would have been available). Hence, net damages (ΔD) generated by trade of Crop Products amounted to \$106 million, which accounts for 2.8% of net value added created by trade ($\Delta D/\Delta VA$) of crop products ($\Delta VA=3.7$ billion). That is, on average, for each \$1,000 of value-added generated by net exports of crop products, additional air pollution would have caused \$28 of damages. In the Crop

²⁹ Table 4.1 only lists the results for those sectors that matter most in this respect, plus results for the three major aggregates. The complete sectoral results for all 42 sectors, can be found in Table A4.10 of Appendix E.

Production sector, the net exports are \$4.4 billion and the value added contained in these exports adjusted for damages from air pollutants is \$3.6 billion ($\Delta VA - \Delta D$).

Table 4.1: Damages in US associated with trade, 2002 (in millions of \$). Selected industries.

IO code	Sectors	Exports		Imports		Exports minus Imports		Comparisons		Net Exports (\$1million)
		DEX ^a	VEX ^b	DIM ^c	VIM ^d	ΔD^e	ΔVA^f	$\Delta D / \Delta VA$	$\Delta VA - \Delta D^g$	
111	Crop Production	2351	14754	2246	11020	106	3734	2.83%	3628	4368
112	Animal Production	326	1071	745	2639	-419	-1568	26.72%	-1149	-1698
113	Forestry and Logging	146	1191	105	1015	41	176	23.48%	135	155
211	Oil and gas extraction	34	2039	1521	90128	-1486	-88089	1.69%	-86603	-92322
212-213	Mining, except oil and gas	185	4298	201	3159	-16	1139	-1.40%	1155	1217
	Primary Sector Total	3060	25518	4889	116320	-1827	-90802	2.01%	-88975	-95021
221	Utilities	111	416	291	1038	-180	-621	28.95%	-441	-648
311-312	Food and beverage and tobacco products	2278	26225	2139	35413	139	-9189	-1.51%	-9328	-11418
315-316	Apparel and leather and allied products	141	5765	1236	84887	-1095	-79123	1.38%	-78028	-89656
331	Primary metals	582	8825	2298	26870	-1716	-18045	9.51%	-16329	-21806
336	Transportation Equipment	1383	98496	3113	183596	-1729	-85100	2.03%	-83371	-110970
	Secondary Sector Total	11608	422910	21272	846611	-9663	-423702	2.28%	-414039	-509490
42	Wholesale trade	381	65259	19	3299	362	61959	0.58%	61597	64159
48-49	Transportation and Warehousing	6306	58243	6354	37844	-48	20400	-0.23%	20448	21259
53	Real Estate and Rental and Leasing	170	39963	1	113	170	39850	0.43%	39680	40896
55	Management of Companies and Enterprises	147	34023	0	41	147	33981	0.43%	33834	34879
71	Arts, Entertainment and Recreation	3	888	3	162	-0.2	725	-0.03%	725.2	739
	Tertiary Sector Total	7349	282875	6559	83774	787	199098	0.40%	198311	205861
	Total	22017	731301	32722	1046705	-10705	-315405	3.39%	-304700	-398650

a: DEX denotes damages generated by producing exports

b: VEX denotes value added contribution of exports

c: DIM denotes damages avoided by importing goods and services

d: VIM denotes value added forgone due to imports

e: ΔD is the differences between DEX and DIM ($\Delta D = \text{DEX} - \text{DIM}$)

f: ΔVA is the difference between VEX and VIM ($\Delta VA = \text{VEX} - \text{VIM}$)

g: $\Delta VA - \Delta D$ is the net value added gain contribution corrected for environmental damages

Shaded rows indicate sectors with negative damage to value added ratios.

The sectoral ratios between DEX and VEX are not necessarily identical to the ratios between DIM and VIM, and between ΔD and ΔVA . For example, for Crop Products we have $DEX/VEX = 15.93\%$, $DIM/VIM = 20.38\%$, and $\Delta D/\Delta VA = 2.84\%$. At the *industry* level, it follows from equations (4.7) - (4.12) that $DEX_{s,i}/VEX_{s,i} = DIM_{s,i}/VIM_{s,i} = \Delta D_{s,i}/\Delta VA_{s,i} = UD_{s,i}/u_i$. At the *sector* level, however, several *industries* are involved in Crop Products (and in sectors selling intermediate inputs to the crops sector). The sector ratios are weighted averages of the industry ratios. The weights for DEX/VEX are the industry VEXes as share of the sector VEX, the weights for DIM/VIM are the industry VIMs as share of the sector VIM, and the weights for $\Delta D/\Delta VA$ are the VA changes in the industries as share of the sector's VA change. The weights are thus different for the three ratios, which explains why the ratios yield different outcomes at the sector level. This also explains why ΔD and ΔVA have opposite signs for some sectors (corresponding to the shaded rows in Table 4.1). At the industry level they must have the same sign, as follows from $\Delta D_{s,i} = UD_{s,i} \cdot (e_i - m_i)$ and $\Delta VA_i = u_i \cdot (e_i - m_i)$.

Shifting the focus to economy-wide effects, we find that international trade had significant environmental impacts on the 2002 US economy. The total damages associated with exports amounted to approximately \$22.0 billion, and we estimate that the total damages avoided by importing were approximately \$32.7 billion. Thus, about \$10.7 billion of damages were avoided through net imports, which can be considered as net damage benefits of trade. To put the figure of \$10.7 billion into perspective, this value is larger than the GDPs in 2002 of countries such as Iceland and Paraguay. Seen from the perspective of the US, these avoided damages could be subtracted from the structurally large trade deficit that the country has been incurring over a prolonged period of time. It accounts for 2.7% of the trade deficit (as conventionally measured, i.e. in terms of gross exports and imports) in 2002 (\$399 billion), and 3.4% of the US value added associated with trade (see Table 4.1).

The economy-wide damage to value added ratio of 3.4% at the national level hides a lot of heterogeneity at the detailed industry level. For instance, in the Carbon Black Manufacturing industry and the All Other Petroleum and Coal Products Manufacturing industry, damage to value added ratios were as high as 51% and 54%, respectively (see Table A4.11 in Appendix E). This implies that additional production by these industries (due to exports of any type of product requiring inputs from these industries) are so detrimental to the environment that more than half of its value added contributions would disappear if we would take its environmental damages properly into account.³⁰ At the more aggregated sectoral level, large but less extreme ratios are found (see Table 4.1), such as for Animal Production ($\Delta D/\Delta VA=26.72\%$), Forestry and Logging ($\Delta D/\Delta VA=23.48\%$), and Utilities ($\Delta D/\Delta VA=28.95\%$).

Table 4.1 also shows that net environmental benefits (or costs) associated with trade differ significantly among sectors. Consider the three broad sectoral aggregates, for example. Net trade in products from the primary sector led to a reduction of about \$1.8 billion of damages, while these amounted to about \$9.7 billion for trade in products of the secondary sector. Net trade in products of the tertiary sector, however, added to environmental damages by about \$0.8 billion. Furthermore, the damage to value added ratios differed to a large extent. For the primary and secondary sectors, these were larger than 2%, while they amounted to less than 0.5% of value added in the tertiary sectors.

Table 4.1 shows that the largest net environmental benefits were generated by trade in products from the Transportation Equipment, Primary Metals, Oil and Gas Extraction, and Apparel and Leather and allied Products sectors, with avoided damages of \$1.7 billion, \$1.7 billion, \$1.5 billion, and \$1.1 billion, respectively. The largest net environmental costs of trade were generated by exports of the Wholesale trade sector (-\$362 million), followed by those of the Real Estate and Rental and

³⁰ Damage to value added ratios at the industry level are available from the author upon request.

Leasing (-\$170 million), the Management of Companies and Enterprises (-\$147 million), the Food and Beverage, Tobacco Product (-\$139 million), and the Crop Production (-\$106 million) sectors.³¹

4.5.2 Unit Damages

We also find that the signs of the net damages did not always correspond to the signs of net exports. This shows that a trade deficit does not automatically imply damage benefits. The four sectors for which we find such a negative damage to value added ratio are highlighted in Table 4.1. For instance, we find that the US had a trade surplus in products from the Transportation and Warehousing sector (\$21.3 billion). Trade in these products generated a positive net effect on value added ($\Delta VA = \$20.4$ billion) but a negative net effect on the damages ($\Delta D = -\$48$ million). Trade thus leads to more income and less damages. Similar findings are observed for the Mining, Except Oil and Gas sector, and the Arts, and Entertainment and Recreation sector. The opposite effect (trade induces less income but more damages) is observed for the Food, Beverage, and Tobacco Products sector. Everything else equal, it is—for the net effect on damages—beneficial for a country to import products with high unit damages and exports products with low unit damages.³² We calculated these unit damages (defined as damages generated by \$1,000 exports or avoided by \$1,000 imports. In Table 4.2, we present these unit damages at the sectoral level.³³

³¹ The top 10 and bottom 10 industries regarding ΔD for each pollutant are presented in Tables A4.12 and A4.13 of Appendix E.

³² In the same fashion, everything else equal, it is—for the net effect on value added—beneficial for a country to export products with high unit VA and import products with low unit VA.

³³ The top-10 and bottom-10 industry level “unit damages” are presented in Table A4.14 in Appendix E.

Table 4.2: Unit damages of trade (\$ damages per \$1000 of exports or imports) by sector

IO code	Sectors	Exports			Imports			Net exports (\$1million)
		%Exports (Weights)	\$ Damages per \$1000 of exports		%Imports (Weights)	\$ Damages per \$1000 of imports		
			Total	\$Damages of intermediate		Total	\$Damages of intermediate	
111	Crop Production	2.00%	145.22	21.67 (14.92%)	1.00%	189.94	19.65 (10.35%)	4368
113	Forestry and Logging	0.20%	116.71	35.06 (30.04%)	0.10%	95.64	23.81 (25.05%)	155
211	Oil and Gas Extraction	0.30%	16.10	8.80 (54.66%)	7.70%	16.10	8.80 (54.66%)	-92322
212-213	Mining, Except Oil and Gas	0.60%	40.36	23.58 (58.42%)	0.30%	59.63	24.87 (41.71%)	1217
Primary Sector Total		3.30%	110.62	21.11 (19.08%)	10.00%	39.85	11.14 (27.95%)	-95021
221	Utilities	0.10%	253.35	8.37 (3.30%)	0.10%	267.72	7.68 (2.87%)	-648
311-312	Food and Beverage and Tobacco Products	3.50%	78.35	72.91 (93.06%)	3.30%	52.83	48.41 (91.63%)	-11418
315-316	Apparel and Leather and Allied Products	0.80%	21.74	21.30 (97.98%)	7.80%	12.86	12.65 (98.37)	-89656
325	Chemical Products	7.80%	36.19	21.59 (59.66%)	8.20%	24.59	14.23 (57.87%)	-36448
331	Primary Metals	1.30%	54.06	27.16 (50.24%)	2.70%	70.55	29.04 (41.16%)	-21806
333	Machinery	7.10%	11.90	11.41 (95.88%)	5.30%	11.88	11.38 (95.79%)	-6617
334	Computer and Electronic Products	12.10%	8.45	8.24 (97.51%)	14.50%	7.74	7.60 (98.19%)	-77435
336	Transportation Equipment	14.40%	11.63	10.67 (91.75%)	18.70%	13.54	11.40 (84.19%)	-110970
Secondary Sector Total		60.20%	23.29	17.44 (74.88%)	82.20%	21.10	14.86 (70.43%)	-509490
42	Wholesale trade	8.16%	5.64	4.20 (74.47%)	0.28%	5.64	4.20 (74.47%)	64159
4A	Retail Trade	8.03%	9.05	7.33 (80.99%)	3.69%	9.05	7.33 (80.99%)	-2416
48-49	Transportation and Warehousing	0.10%	94.84	8.19 (8.64%)	0.27%	140.47	8.64 (6.15%)	21259
52	Finance and Insurance	4.57%	2.18	2.18 (100%)	2.24%	1.89	1.89 (100%)	10441
53	Real Estate and Rental and Leasing	4.95%	4.15	4.15 (100%)	0.01%	4.58	4.56 (99.56%)	40896
61	Educational Services	0.05%	18.01	18.01 (100%)	0.02%	18.10	18.10 (100%)	164
71	Arts, Entertainment and Recreation	0.11%	3.44	2.87 (83.43%)	0.01%	19.94	6.06 (39.39%)	739
Tertiary Sector Total		36.50%	24.44	4.87 (19.93%)	7.80%	68.40	5.97 (8.73%)	205861
Total		100%	26.63	12.98 (48.74%)	100%	26.69	13.79 (51.67%)	-398650

Note: The primary sectors, secondary sectors, and tertiary sectors are separated by horizontal lines. Selected sectors are included in this table. Please see Tables A4.15 and A4.16 in Appendix E of “unit damage” with respect to exports and imports of all sectors by pollutants. The shaded rows indicate sectors in which more than 80% of the damages (associated with imports or exports) come from intermediate products in other sectors.

Not surprisingly, we find that an increase of exports by the tertiary sector would yield much smaller damages than if exports of the primary sector would increase by the same amount. However, the damages avoided by importing more tertiary products are larger than those avoided by increasing the imports of products from primary industries by the same value. This at first sight surprising result is mainly due to the importance of damage-intensive crops in the US's export bundle of primary products, while it is much less prominent in the import bundle of these products. In this import bundle, the output of the Oil and Gas Extraction industry (which generates much less damages per \$1,000 of imports than imports of other primary products) accounts for a much larger share.

Concerns have been voiced about so-called "pollution haven" effects. Polluting industries would relocate outside the US to save on costs incurred to comply with environmental regulations. Our data do not allow for a longitudinal analysis required to arrive at strong evidence, but a finding of more damaging imports than exports would provide a hint into this direction. Table 4.2, shows that the damages were \$26.69 per \$1,000 of imports and \$26.63 per \$1,000 of imports. This negligible difference suggests that multinational companies had not massively relocated damaging activities from the US to other countries in 2002. Still, a few more caveats apply. First, we implicitly assume that US industries conduct the same activities as their foreign counterparts. This is not necessarily true. The US Computer and Electronic Products industry has specialized in R&D, design and marketing activities, while the manufacturing activities mainly take place in various Asian countries (see e.g. Dedrick et al., 2010). These activities have very different impacts on the environment. Second, international trade in intermediate inputs started booming after 2001, in the so-called "second wave" of globalization (which also included the emergence of China as a location for manufacturing activities) (see Baldwin, 2016). Hence, we cannot generalize the absence of "pollution haven" effects to recent periods.

Trade surpluses and deficits are defined in terms of gross exports and imports and are

therefore different from the net value added generation due to exports and imports, as explained in Section 4.3. One might develop a trade strategy to maximize the gains and minimize the losses, leaving the trade balance the same. Importing from industries with high unit damage (\$ damage per \$1000 dollar of imports or exports) and exporting in industries with low unit damage will lower the losses. At the sector level, Table 4.2 showed that Crop Production and Machinery qualify as such. Importing an additional billion dollar of crop products and increasing exports machinery products by the same amount would have yielded lower losses (i.e. damages) and more gains (i.e. value added) in the US, while leaving the trade deficit unchanged.

Table 4.2 also shows that damages associated with producing intermediate products (products that are not exported themselves but are used to produce exported products) are considerable. For instance, we find that virtually all damages associated with trades in three major service sectors (Finance and Insurance, Real Estate and Education Services) are generated in the production of intermediate products. At the national level, damages associated with intermediate products account for about half of the total “unit damage” of both exports and imports (49% and 52%, respectively). If intermediate products would not be taken into consideration, the unit damages of imports and exports would be more than 80% lower in as many as nine sectors: Food and Beverage and Tobacco Products, Apparel and Leather and Allied Products, Machinery, Computer and Electronic Products, Transportation Equipment, Retail Trade, Finance and Insurance, Real Estate, and Education Services. This is to an important extent due to the fact that these sectors require electricity to produce. Power generation (which is part of the sector Utilities) is a very damaging activity, which is reflected in the very high unit damages of this sector reported in Table 4.2. A substantial part of the damages embodied in the exports of a product is thus associated with the production of its intermediate products. This finding indicates that it is important to study damages in trade in an input-output (IO) analysis. Next to the direct effects of trade, IO studies also take all indirect effects into full account.

4.5.3 Damages by Pollutant

In Figure 4.2, we present a pie chart to show the composition of the net \$10.7 billion environmental benefits of US trade in 2002, by pollutant. SO₂ was clearly the most important pollutant. It accounted for almost half of total ΔD (48%), followed by fine particles (PM_{2.5}) and volatile organic compounds (VOC). Through international trade, about \$5 billion of damages caused by SO₂ were avoided. Tables A4.13 in Appendix E shows that most of the trade related damages were clustered in trade and transportation sectors. Other sectors in the top-10 of sectors with damaging SO₂-related effects of net trade include other services sectors, farming and (in particular) manufacturing sectors.

With respect to the Animal Production sector and the Forestry and Logging sector, NH₃ is responsible for more than 85% of damages related to both exports and imports. We also find that NH₃ emissions were particularly important regarding trade in products of some manufacturing sectors, such as the Food and Beverage and Tobacco Products and the Wood Products sectors, which are highly dependent on agricultural inputs.

Figure 4.2: Composition of the damages of net trade (ΔD) by pollutant

4.6 SENSITIVITY ANALYSIS

As discussed in Section 4.4, we had to make several choices with respect to the data. Each of these choices could have impacts on the results. In this section, we redo the analysis nine times (Case II to Case X) with approaches or assumptions different from the baseline model (Case I, in what follows), for which we have already reported the results. Case II, Case V and Case VI address the issues regarding prices. Case III and Case VI deal with the industrial GED data issues. Cases VII to X deal with assumptions with respect to the marginal damage estimation in Muller et al. (2011). Summary results of these sensitivity analyses are presented in Table 4.3.

Table 4.3: Sensitivity Analyses

Cases	Description	ΔD (\$1M)	$\Delta D / \Delta VA$
Case I	Baseline	-10705	3.39%
Case II	Foreign Border Prices	-9446	3.43%
Case III	Split by Output	-9989	3.17%
Case IV	No Missing Damages	-10414	3.31%
Case V	Basic Prices 2002	-8898	2.84%
Case VI	Basic Prices 2000	-8550	2.65%
Case VII	Laden	-11883	3.77%
Case VIII	VSL6m	-12243	3.88%
Case IX	VSLY2m	-10052	3.19%
Case X	VSLY10m	-11339	3.59%

Note: ΔD is negative, because there are more damages avoided by imports than damages generated by exports. Case I is the baseline model. Case II excludes costs of duties, freight and insurance from the imports. Case III splits the GED of agricultural and construction industries by gross output. Case IV estimates some missing damage values using data from other industries producing similar goods or services. Case V uses IO data from WIOD in basic prices. Case VI uses IO data from WIOD in basic prices and deflated IO data from 2002 to 2000. Case VII uses the adult mortality dose-response function for $PM_{2.5}$ from Laden et al. (2006). Case VIII employs the same value for premature mortality to the populations of all ages. Case IX changes the Value per Statistical Life (VSL) to \$2 million. Case X changes the VSL to \$10 million. Cases I, VI and VII employ premature mortality values that are heterogeneous across ages.

In Case II, we value imports at foreign border prices instead of the US border prices, to assess the sensitivity of results to differences in price concepts. The foreign border prices are roughly equal to the ex-factory price plus the margins for transport and trade within the exporter country. The US border prices employed in the baseline model is equal to the foreign border values plus the freight,

insurances, and custom duties associated with international trade. Hence, for a given quantity of imported products, values of imports are smaller if the foreign border prices are employed. Consequently, we find smaller values of damages and lower value added associated with these imports. Given that we assume that everything else is the same, the net damage avoided by trade is lower than as found in the baseline model. In the baseline model (or Case I), we found that \$10.7 billion net damages were avoided by trade. This value is reduced to \$9.4 billion in Case II, which implies a difference of about 12%. If we focus on the $\Delta D/\Delta VA$ ratio, however, the difference is very small: 3.39% in Case I versus 3.43% in Case II.

As we mentioned in Section 4.4, we had to disaggregate GED values with regard to some agricultural industries and construction industries. In the baseline model, the disaggregation of agricultural industries is carried out proportionally to value added by industry. In some other studies, gross output shares have been employed instead. Therefore, in Case III, we change the disaggregation approach by using gross output shares (see Tables A4.7a and A4.7b of the Appendix D). We find the ΔD is -\$10.0 billion in Case III, which implies that the avoided damages are \$716 million smaller than in Case I. The $\Delta D/\Delta VA$ ratio is 3.17%, which is 0.22% lower than the ratio in Case I.

Another issue relates to the fact that we do not have information on GED values in 20 industries. Among them, 18 are industries in the tertiary sector. In the baseline analysis, we assumed that the gross environmental damages of these industries are zero. In Case IV we analyze the sensitivity of the results to this choice, by assuming that the unknown damage intensities (GED_i/x_i) are equal to those of industries producing similar goods or services. For instance, we assume that the damage per unit of output in the Tortilla Manufacturing industry is the same as the damage per unit of output in the Cookie, Cracker and Pasta Manufacturing industry.³⁴ Case IV gives very similar results compared

³⁴ The selected "proxy industries" and the estimated damages per dollar of output are presented in Table A4.8 of Appendix D.

to the baseline model. Both the avoided damages and the overall $\Delta D/\Delta VA$ ratio are slightly smaller than in the baseline model (-\$10.4 billion and 3.31%, respectively).

In Case V, we assess the sensitivity of our results to the choice of price concept by using IO data in basic prices, which are obtained from WIOD (Dietzenbacher et al., 2013). On the one hand, basic prices (which exclude taxes and subsidies from producer prices) are the preferred type of prices. On the other hand, the WIOD tables are more aggregated, distinguishing only 35 sectors. Moreover, the sector classification is aligned with the European NACE, which implies that we need to match damage data for North-American NAICS sectors to NACE sectors. To this end, we used a conversion table from the US Census Bureau.³⁵ Table 4.3 shows that the US avoided \$8.9 billion of damages by trading according to this analysis, which is \$1.8 billion or 17% less than in Case I (the baseline). The reduction in value added is also much less (30%) in Case V than it is in Case I. The economy-wide $\Delta D/\Delta VA$ ratio is therefore 0.55% lower if based on WIOD. It is not straightforward to compare sectoral results from Case V to those from the baseline model, because of the different classification systems.³⁶ Nevertheless, we find that the $\Delta D/\Delta VA$ ratios are fairly close in many sectors (see Tables A4.17 and A4.18 in Appendix E). The $\Delta D/\Delta VA$ ratios of Electricity, Gas and Water Supply (Case V) and the Utility sector (Case I) are both around 29%, and these ratios are close to 0.55% for the Wholesale Trade sector in both tables. The $\Delta D/\Delta VA$ ratios are also fairly close in sectors related to textile products, wood products, transportation equipment, accommodation and food services (hotel and restaurants), financial intermediates, real estate activities, and education. However, for some sectors heavily involved in trade, like Petroleum and Coal products, the differences are sizable (7.73% in Case I, but only 3.65% in Case V).

³⁵ The table can be obtained from <https://www.census.gov/eos/www/naics>

³⁶ Additional errors might be introduced during the conversion of damage data from NAICS codes to NACE codes (the match is not perfect), and estimation results can be less accurate because a relatively aggregated input-output table is employed.

In all the cases we discussed so far, the estimation results are in 2002's prices. Recall that the original damage data (for 2002) are in prices of 2000 and have been converted to prices of 2002 with a GDP deflator. In Case VI, we keep damage data in 2000's prices, but convert IO data from 2002's prices to 2000's prices. For this, we used data from WIOD and applied the "chaining technique" explained in Appendix D (also see Chapter 2). Data from the WIOD is in basic prices, so the basic prices are used in Case VI as well. The estimated total net damages in Case VI are only slightly smaller than in Case V, and the $\Delta D/\Delta VA$ ratios of Cases V and VI are quite close. The results thus appear to be insensitive to the way in which deflation is done.

Cases VII to X follow Muller et al. (2011) in assessing the effects of uncertainties in marginal damages, regarding three aspects. First, the $PM_{2.5}$ mortality dose-response function from Pope et al. (2002) is used in the baseline estimates. In Case VII, we use a more sensitive dose-response function, from Laden et al. (2006). As a result, the total damages avoided by trade move up to \$11.9 billion, and the overall ratio of $\Delta D/\Delta VA$ increases to 3.77%. Second, in the baseline model, we assume that the costs of premature mortality varies with age.³⁷ In Case VIII, the value of premature mortality is assumed to be identical across ages. This change raises the value of damages avoided by trade to \$12.2 billion and the overall $\Delta D/\Delta VA$ ratio to 3.88%, which are the highest among all cases. Third, in the baseline model, the value of statistical life (VSL) (Viscusi and Aldy, 2003) equals \$6 million, and this VSL value is used to determine the annual mortality risk premium (Muller et al., 2011). In Case IX, we assume the VSL equals \$2 million (following Mrozek and Taylor, 2002), which leads to a reduction of the avoided damages by \$653 million. In Case X, we assume that the VSL equals \$10 million (following Viscusi and Moore, 1989). This causes an increase in the avoided damages by \$634 million.

³⁷ For example, the mortality value faced by elderly people is relatively low, because they have fewer life-years remaining. However, this assumption is controversial. One could also argue that the value society places on mortality risks should not vary by age.

Summarizing the cases, we find that the estimated values of US-wide damages avoided by trade vary from \$8.6 billion to \$12.2 billion, which correspond to deviations from the baseline model between -17% and +14%. The overall $\Delta D/\Delta VA$ ratio ranges from 2.65% to 3.88%. In most sectors, the differences between the sectoral $\Delta D/\Delta VA$ ratios across cases are small (see Tables A4.17 to A4.19 in the Appendix E), and the relative rankings across sectors remain roughly the same under different assumptions. Although the magnitudes of the welfare impacts vary, we consider the results from the baseline model as good indications, in particular with respect to the $\Delta D/\Delta VA$ ratios.

4.7 CONCLUSIONS

This chapter estimated the monetary values of the health and social-economic impacts associated with emissions generated in activities required for US exports by trade and the emissions on US territory that are avoided by importing products. Using these monetary values allowed us to compare damages with economic effects of trade, and to compute trade balance indicators with a wider scope. Here, we summarize some key findings.

First, damages associated with international trade are considerable and cannot be neglected. For 2002, we found that the US avoided \$32.7 billion of damages by importing, and at the same time generated \$22.0 billion of damages to produce its exports (both directly by exporting industries, and indirectly by domestic suppliers of these industries). This implied that the net trade effect was a reduction of damages caused by emissions to air of about \$10.7 billion in 2002. Economy-wide, every \$1000 of net value added generated by trade caused emission-related net damages of \$33.9 on average. At the industry level, we found that such damage to value added ratios can exceed 50%, such as in the Carbon Black Manufacturing (51%) and the All the Other Petroleum and Coal Products Manufacturing industry (54%). However, in other industries, such as Legal Services, only \$2 of damages were associated with \$1,000 of value added generated by trade.

Second, a considerable amount of damage was generated through the production of intermediate products, so it is important to use input-output analysis in this study. Damages associated with emissions by producers of intermediate inputs embodied in US exports (and in imported products if they would have been produced domestically) accounted for about half of the total “unit damage”: \$12.98 out of \$26.63 of damages in an average \$1000 of exports and \$13.79 out of \$26.69 of damages in an average \$1000 of imports.

The finding that the US avoided more damages on its own territory by importing than that it generated to produce its exports is strongly related to its massive trade deficit. Still, we found that for some sectors a trade deficit and positive damages due to trade coexisted. The US had a trade deficit of \$11.4 billion regarding products of the Food, Beverage, and Tobacco Product sector, for example, but net trade in these products generated a net effect of \$139 million damages. This is the consequence of differences in the compositions of imports and exports. Even within rather homogeneous sectors, products sold by industries (defined at a more fine-grained level) can vary considerably in terms of the damages they cause.

We did some sensitivity analyses regarding assumptions with respect to price concepts, missing data, and the marginal monetary damage value of emissions. We found that the sensitivity of the results to some of the assumptions is not negligible, in the sense that the net effect of both the damages and the value added generation can change by about 15% in either direction, in particular if different price concepts are used in the valuation of economic transactions. However, differences in the damage to value added ratios are rather small at the economy-wide level and small to moderate in most sectors.

Currently, the persistent and large trade deficit of the United States attracts a lot of attention, both in policy circles and among academic scholars. Although this trade deficit is the direct consequence of low savings by Americans, President Trump feels that he can reduce it by import substitution policies, mainly implemented via high tariffs that might lead to a trade war with countries

like China. This study shows that the true US trade deficit is about 3% smaller if the costs of pollution to society are taken into account. By importing much more than exporting, the US avoids pollution-related damages that it would have incurred if the imported products would have been produced in the country itself. In their attempts to curb imports by means of tariffs, policymakers could take such damages into account.

Future research along the lines set out in this chapter are definitely possible. First, only damages from emissions to air are included in this study. Other external effects, such as damages related to pollution of water and soil, or to noise, are not taken into account. Second, at the time this study was carried out, damages occurred in years more recent than 2002 could not be assessed due to data availability.³⁸ Finally, we focused on damages related to trade in the US, because there is no marginal damage data on emissions in the other countries. If such data would be available, we could consider trade as a worldwide phenomenon and study whether its environmental consequences in monetary terms are positive or negative.

³⁸ According to Muller (2018), more recent damage data are available for years of 2005, 2008 and 2011.

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4.9 APPENDICES

4.9.1 Appendix A: Construction of the 2002 Input-Output Table

A1. Input-Output Data

The industry-by-industry input-output (IO) table in this study is constructed based on the 2002-benchmark input-output accounts from the US Bureau of Economic Analysis (BEA).³⁹ This section outlines the methodology and data sources used.

The 2002 make and use tables, published in October 2007, were compiled in accordance with the 2002 version of the North American Industry Classification System (NAICS). They present data at a highly disaggregated level of detail, with 427 commodities and 426 industries.⁴⁰ The make table is a matrix that shows the value of each commodity produced by each industry, expressed in producers' prices (see Figure A4.1). The entries in a row corresponding to an industry represent the dollar value of the commodities indicated by the columns, as produced by that industry.

The use table is a matrix that shows the use of commodities (indicated by the rows) by each industry and by final users (indicated by the columns, see Figure A4.2). The total output of each commodity is the sum of all intermediate uses of the commodity by industries and all sales to final users. Additional rows provide information on components of value added generated by industries. Double-entry bookkeeping procedures ensure that the total output of each industry in the make table is equal to the sum of its intermediate use of all commodities and its value added, i.e. the sum of the entries in a column of the use matrix. Furthermore, for the economy as a whole, the total of all final uses of commodities equals the sum of all value added by all industries (GDP).

³⁹ See US Bureau of Economic Analysis, "Benchmark Input-Output Accounts", available at http://bea.gov/industry/io_benchmark.htm.

⁴⁰ In the construction of the matrix with intermediate input coefficients, we disregard BEA's "Special industries" related to the provision of government services. As a consequence, this matrix has 418 rows and columns. Implicitly, we consider these special industries as parts of the primary inputs block and of final demand.

Figure A4.1: Make table

		COMMODITIES																TOTAL INDUSTRY OUTPUT	
		Agriculture, forestry, fishing and hunting	Mining	Utilities	Construction	Manufacturing	Wholesale trade	Retail trade	Transportation and warehousing	Information	Finance, insurance, real estate, rental, and leasing	Professional and business services	Educational services, health care, and social assistance	Arts, entertainment, recreation, accommodation, and food	Other services, except government	Government	Other		Scrap, used and secondhand goods
INDUSTRIES	Agriculture, forestry, fishing and hunting																		
	Mining																		
	Utilities																		
	Construction																		
	Manufacturing																		
	Wholesale trade																		
	Retail trade																		
	Transportation and warehousing																		
	Information																		
	Finance, insurance, real estate, rental, and leasing																		
	Professional and business services																		
	Educational services, health care, and social assistance																		
	Arts, entertainment, recreation, accommodation, and food services																		
	Other services, except government																		
Government																			
TOTAL COMMODITY OUTPUT																			

	Total industry output
	Total commodity output

Source: Horowitz and Planting (2009)

Figure A4.2: Use table

		INDUSTRIES																FINAL USES (GDP)								
		Agriculture, forestry, fishing and hunting	Mining	Utilities	Construction	Manufacturing	Wholesale trade	Retail trade	Transportation and warehousing	Information	Finance, insurance, real estate, rental, and leasing	Professional and business services	Educational services, health care, and social assistance	Arts, entertainment, recreation, accommodation, and food services	Other services, except government	Government	Total intermediated	Personal consumption expenditures	Private fixed investment	Change in inventories	Exports of goods and services	Imports of goods and services	Government consumption expenditure and gross	Total final uses (GDP)	TOTAL COMMODITY	
COMMODITIES	Agriculture, forestry, fishing and hunting																									
	Mining																									
	Utilities																									
	Construction																									
	Manufacturing																									
	Wholesale trade																									
	Retail trade																									
	Transportation and warehousing																									
	Information																									
	Finance, insurance, real estate, rental, and leasing																									
	Professional and business services																									
	Educational services, health care, and social assistance																									
	Arts, entertainment, recreation, accommodation, and food services																									
	Other services, except government																									
	Government																									
	Other																									
	Scrap, used and secondhand goods																									
	Total intermediate																									
VALUE ADDED	Compensation of employees																									
	Taxes less subsidies																									
	Gross operation surplus																									
	Total value added																									
TOTAL INDUSTRY OUTPUT																										

Total industry output

Total commodity output

Source: Horowitz and Planting (2009)

To see how these two tables relate to each other in more detail, we illustrate the structure of make and use tables using matrices and vectors in Table A4.1. The part of the use matrix related to use by industries is represented by $\mathbf{U}$. Its typical element u_{ij} indicates the value of commodity i used by industry j . The part of the use matrix representing final use is given by the vector $\mathbf{d} + \mathbf{e} - \mathbf{m}$, in which $\mathbf{d}$, $\mathbf{e}$ and $\mathbf{m}$ stand for domestic final demand, exports and imports, respectively. The part of the use matrix containing value added by industry is given by the row vector $\mathbf{va}'$. $\mathbf{V}$ stands for the make matrix. The typical element of this matrix, v_{ij} indicates output of commodity j as produced by domestic industry i .

Table A4.1: Structure of make and use tables from BEA

	Commodities	Industries	Final Demand	Total output
Commodities		$\mathbf{U}$	$\mathbf{d} + \mathbf{e} - \mathbf{m}$	$\mathbf{q}$
Industries	$\mathbf{V}$			$\mathbf{x}$
Value Added		$\mathbf{va}'$		
Total Input	$\mathbf{q}'$	$\mathbf{x}'$		

Total industry output $\mathbf{x}$ can be obtained by summing over all commodities produced by an industry:

$$\mathbf{x} = \mathbf{V}\mathbf{t}, \quad (\text{A4.1})$$

in which $\mathbf{t}$ is a suitably sized vector of ones.

We should note three things with respect to the BEA's make and use tables. First, transactions in the make and use table show sales of goods and services expressed in producers' prices, which are equal to the basic prices plus commodity taxes.⁴¹ Second, costs of transporting goods and costs associated with

⁴¹ Commodity taxes consist of sales taxes and excise taxes, which are included in industry and commodity output. "Taxes less subsidies" in the use table consists of a variety of taxes, including commodity taxes, custom duties, property taxes, motor vehicle licenses, severance taxes, and other taxes.

wholesaling or retailing these goods have been estimated as margins and were recorded as service inputs of the transportation and trade sectors. Third, BEA's matrix $\mathbf{U}$ includes commodity inputs from foreign as well as domestic sources. The industry inputs from foreign sources need to be removed, before we use the make and use tables to construct an input-output table from which we can derive a matrix with domestic input coefficients. We should divide the matrix $\mathbf{U}$ into two parts, a part with domestic transaction values and a part with transactions related to imports:

$$\mathbf{U} = \mathbf{U}^D + \mathbf{M}, \quad (\text{A4.2})$$

in which $\mathbf{U}^D$ is the matrix with domestic input transactions only and $\mathbf{M}$ is the matrix of imported intermediate inputs transactions. The vector of total commodity output $\mathbf{q}$ can be obtained as

$$\mathbf{q} = \mathbf{U}\mathbf{t} + \mathbf{d} + \mathbf{e} - \mathbf{m}, \quad (\text{A4.3})$$

Since total supply must be equal to total use for each commodity, the elements of $\mathbf{q}$ in the use matrix are equal to the sums of the elements in columns of $\mathbf{V}$, indicated by $\mathbf{q}'$ in the bottom row.

A2. Input-Output Table Construction

The import vector $\mathbf{m}$ from BEA's use table includes imported commodities, for intermediate and for final use taken together. Hence, the vector $\mathbf{m}$ can be split into three parts,

$$\mathbf{m} = \mathbf{M} + \mathbf{m}^f - \mathbf{r} \quad (\text{A4.4})$$

Imports used in production are denoted by the matrix $\mathbf{M}$ (as in the previous section), imports for final use are given by the vector $\mathbf{m}^f$, and $\mathbf{r}$ is an adjustment vector related to international trade and transportation margins. The import vector $\mathbf{m}$ contains values expressed in US border prices, which include costs of custom duties and of US freight and insurance services. In order to avoid double-counting, such costs are subtracted from the imports and included in an adjustment vector $\mathbf{r}$.⁴² This vector $\mathbf{r}$ contains zeros for all commodities, except for water freight (\$25,506 million), air freight (\$1,232 million), couriers and messengers (\$6,468 million), insurance carriers (\$369 million) and wholesale trade (for custom duties values \$19,917 million). These are the commodities to which international margins are attributed.

Some of the costs in $\mathbf{r}$ are incurred to import goods and services for final use, $\mathbf{r}^f$, while the remainder is related to imports of goods and services for production activities, $\mathbf{r}^M$:

$$\mathbf{r} = \mathbf{r}^M + \mathbf{r}^f, \quad (\text{A4.5})$$

The two terms on the right hand side of Equation (A4.5) play a role in BEA's estimation of the import matrix $\mathbf{M}$. Data on the use of imports by industries and final uses are not available from BEA's statistical data sources.⁴³ To develop an import matrix for 2002, BEA assumed that imports are used in a single proportion to domestic products, uniform across all using industries and final uses: $m_{ij} = \left(\frac{u_{ij}}{\sum_j u_{ij} + f_i} \right) m_i$ and $m_i^f = \left(\frac{f_i}{\sum_j u_{ij} + f_i} \right) m_i$. Using the same approach, we can split $\mathbf{r}^M$ into a matrix associated with intermediate imports $\mathbf{R}^M$ ($\mathbf{R}^M \mathbf{t} = \mathbf{r}^M$).

Using Equations (A4.4) and (A4.5), Equation (A4.3) can now be rewritten as

⁴² See Horowitz and Planting (2009) for details.

⁴³ For more information, see Meade et al. (2003).

$$\mathbf{q} = \mathbf{U}\mathbf{t} + \mathbf{d} + \mathbf{e} - \mathbf{m} = (\mathbf{U} - \mathbf{M} + \mathbf{R}^M)\mathbf{t} + \mathbf{d} + \mathbf{e} - \mathbf{m}^f + \mathbf{r}^f \quad (\text{A4.3}^*)$$

Table A4.2 gives the structure of the make and use tables after these adjustments.

Table A4.2: Structure of make and use tables with adjustments of imports

	Commodities	Industries	Final Demands	Total output
Commodities		$\mathbf{U} - \mathbf{M} + \mathbf{R}^M$	$\mathbf{d} + \mathbf{e} - (\mathbf{m}^f - \mathbf{r}^f)$	$\mathbf{q}$
Imports		$\mathbf{M} - \mathbf{R}^M$	$\mathbf{m}^f - \mathbf{r}^f$	$\mathbf{m}$
Industries	$\mathbf{V}$			$\mathbf{x}$
Value Added		$\mathbf{va}'$		
Total Input	$\mathbf{q}'$	$\mathbf{x}'$		

From Table A4.2, we can start deriving a total domestic requirements table (the Leontief inverse), which shows the levels of gross output by industry required to produce specified levels of final demand. Given that the environmental damages data to which our input-output table will be linked provides information on damages attributed to industries rather than to commodities, our requirements table should be of the industry-by-industry type (instead of the commodity-by-commodity type). To construct such a table, we use the approach proposed by Jackson (1998). The first step is to calculate a direct requirements table (also known as the input coefficients table) based on the domestic part of the use table. The commodity inputs in the use table are divided by each industry's output to derive the coefficients for the table that gives the requirements of each commodity that each industry requires to produce one unit of output:⁴⁴

⁴⁴ A hat above a vector denotes a diagonal matrix with the elements of the vector on the main diagonal and zeros elsewhere.

$$\mathbf{B} = (\mathbf{U} - \mathbf{M} + \mathbf{R}^M)\hat{\mathbf{x}}^{-1} \quad (\text{A4.6})$$

The second step is to derive the so-called market shares matrix $\mathbf{D}$, which shows the proportion of commodity output produced by each industry. This matrix is derived from the make matrix by dividing the elements of each row in $\mathbf{V}$ by the total commodity output vector.

$$\mathbf{D} = \mathbf{V}\hat{\mathbf{q}}^{-1}, \quad (\text{A4.7})$$

Finally, the industry-by-industry direct domestic input coefficients matrix $\mathbf{A}_{\text{US}}$ is obtained by

$$\mathbf{A}_{\text{US}} = \mathbf{D}\mathbf{B}. \quad (\text{A4.8})$$

Exports and imports of each industry are derived using

$$\mathbf{e}_{\text{US}} = \mathbf{D}\mathbf{e} \text{ and} \quad (\text{A4.9})$$

$$\mathbf{m}_{\text{US}} = \mathbf{D}(\mathbf{M}\mathbf{t} + \mathbf{m}^f). \quad (\text{A4.10})$$

By using $(\mathbf{M}\mathbf{t} + \mathbf{m}^f)$ in Equation (A4.10), we measure the value of imported products using prices at the US border. An alternative approach would measure imports at foreign border prices, before the products were shipped. The reasons for using US border prices in this study are as follows. The purpose

of this study is to compare damages generated by exports to the damages saved by imports. We are interested in showing the imports at their substitution value for domestically produced goods or services, that is, at their value entering the US economy. Thus, no matter who provides the transportation or insurances services and no matter who charges the custom duties, those costs should not be subtracted from imports for a meaningful comparison. Including custom duties, transportation costs and insurances costs in imports will make the comparison more reliable. Note that the transportation costs and trade margins that are required to move exports from the producer to the port of exit are included in the transportation and trade rows of the use table. Therefore, the domestic port values of imports with adjustment of vector $\mathbf{r}$ are more comparable to the domestically produced goods or services (Horowitz and Planting, 2009). If imports would not be expressed according to a price concept comparable to domestically produced goods, we might undervalue the damages saved by imports.

In the sensitivity analysis, Case II, we use imports valued at the foreign border prices (see Appendix D1).

A3. Additional Data Adjustments

For reasons of exposition, we did not discuss several additional adjustments of the data in the previous section. In this section, we discuss these additional adjustments in some detail.

First, the nonmonetary gold is treated in a special way in the exports and imports of the input-output accounts. The exports of gold is always zero, and the imports of gold is the excess of the value of gold in gross domestic purchases over the value of U.S. production of gold. Because U.S. production was for a long time not sufficient to satisfy the demand for industrial uses, the BEA input-output accounts follow the convention of setting exports to zero and entering the net value as an import. The reason of such treatment is explained in detail in Chapter 7 of Horowitz and Planting (2009). However, nowadays, the U.S. produces more gold than required to satisfy its own demand. The value of net exports in 2002

was \$2.1 billion. Therefore, it would be more appropriate to set imports to zero and entering the net values as an export. This adjustment should be made before we do any calculations with regard to exports and imports.

By such an adjustment, we do not change the net exports (or net imports) of gold or final uses of gold. It is just the way of recording net gold exports which we change. In other words, the effect of this adjustment to the net damages saved by trade is negligible. By doing this, we made exports of the industry Gold, Silver, and Other Metal Ore Mining larger, and turned the imports of this industry from an unreasonable negative value to a positive value. This avoids problems caused by a negative value when we calculate import ratios.

Second, rows labeled “non-comparable imports” and “ROW adjustment” are removed from the use table. These figures represent statistical adjustments by BEA to reflect commodities produced overseas that are used in U.S. production, because there is no domestic industry that produces these items. They are excluded from the use table before industry-by-industry relationships can be estimated.

Finally, rows labeled “scrap” and “used and second-hand goods” in the use table are merged with rows corresponding to other commodities. Before an industry-by-industry table can be derived, these data must be attributed to specific row commodities. As a rough approximation, we distribute the use of scrap and used goods by each industry proportionally to all other commodities purchased by them.

4.9.2 Appendix B: Adjustments regarding Gross External Damages

In order to obtain GED values for each industry appearing in the input-output table, we have to match the Gross External Damage (GED) for the 850 industries with 6-digit NAICS code to the 416 industries with BEA’s IO industry codes. As BEA’s IO industry codes are largely based on NAICS, we can successfully allocate damage values to as much as 95% of the IO industries in rather straightforward ways:

(i) For about 20% of the IO industries, especially in manufacturing, a single NAICS industry represents a single IO industry and a one-to-one match is possible.

(ii) For about 70% of the IO industries, 2-4 industries in NAICS code are aggregated into a single IO industry.

(iii) For a few industries in the Wholesale trade and the Retail trade sectors, more than 10 NAICS industries are aggregated into one IO industry.

More complicated procedures have to be adopted to arrive at GED values for about 5% of the IO industries. These procedures fall in either of two categories:

(iv) With respect to 20 IO industries, GED information for matching NAICS industries is absent. This happens for 1 agricultural industry, 1 manufacturing industry and 18 service industries. In our baseline model, we assume that damages and emissions of these industries are zero. The industry names and the impacts on their output of international trade are listed in Table A4.3. In one sensitivity analysis, Case IV, we use damage values in similar industries to estimate the damages of these industries. Detailed methods are explained in Section A4.

Table A4.3: Industries without GED values

IO Code	Name	Output due to economywide exports	Output reduction due to economywide imports
115000	Support activities for agriculture and forestry	2283	3192
311830	Tortilla manufacturing	19	12
511130	Book publishers	1823	1984
5111A0	Directory, mailing list, and other publishers	1788	2212
511200	Software publishers	14371	9810
532230	Video tape and disc rental	5	5
533000	Lessors of nonfinancial intangible assets	47059	27803
541200	Accounting, tax preparation, bookkeeping, and payroll services	7069	9107
541920	Photographic services	272	352
561300	Employment services	9228	10999
561600	Investigation and security services	1935	2738
611100	Elementary and secondary schools	10	12
611A00	Junior colleges, colleges, universities, and professional schools	786	1114
621600	Home health care services	21	20
624400	Child day care services	5	7
711100	Performing arts companies	435	394
713950	Bowling centers	18	21
813A00	Grant making, giving, and social advocacy organizations	5	6
490000	Postal Services	4981	4539
S00800	Owner-occupied dwellings	73	78
Total		92187	74405

Note: values in \$1mln.

(v) For 18 IO industries, splitting GED values for more aggregated NAICS industries is necessary. The 3-digit NAICS industries Crop Production, Livestock Production, Forestry, and Fishing and Hunting (for which GED information is available) are more aggregated than the IO industries covering these parts of the economy. In the baseline model, we assume that all IO industries that are part of one of these 3-digits NAICS industries generate the same amount of damages per dollar of value added. The results can be found in Table A4.4.

Table A4.4: Estimated GED for agricultural industries, using a value added-based approach

NAICS Code	Industry	GED Baseline (\$1M)	IO Code	Name	Value Added (\$1M)	GED /Sum(VA)	Estimated GED (\$1M)
111000	Crop Production	15844	1111A0	Oilseed farming	6212	0.34	2132
			1111B0	Grain farming	6069	0.34	2083
			111200	Vegetable and melon farming	8720	0.34	2992
			1113A0	Fruit farming	5599	0.34	1921
			111335	Tree nut farming	1221	0.34	419
			111400	Greenhouse, nursery, and floriculture production	9753	0.34	3347
			111910	Tobacco farming	239	0.34	82
			111920	Cotton farming	672	0.34	230
			1119A0	Sugarcane and sugar beet farming	907	0.34	311
			1119B0	All other crop farming	6780	0.34	2327
112000	Livestock Production	15327	1121A0	Cattle ranching and farming	7218	0.56	4028
			112120	Dairy cattle and milk production	8053	0.56	4494
			112A00	Animal production, except cattle and poultry and eggs	8301	0.56	4632
			112300	Poultry and egg production	3894	0.56	2173
113000	Forestry	2043	113A00	Forest nurseries, forest products, and timber tracts	2658	0.18	483
			113300	Logging	8582	0.18	1560
114000	Fishing Hunting	0.007	114100	Fishing	1948	2.31E-06	0.0045
			114200	Hunting and trapping	1007	2.31E-06	0.0023

(vi) A more complicated situation emerges regarding the construction industries. Construction data published by BEA at the detail level do not align with 2002 NAICS industries. In NAICS, some construction industries have been defined by disaggregating more broadly defined construction sectors along occupational lines, such as Flooring Contractors, Plumbing, Heating and Airconditioning Contractors, and Electrical Contractors. BEA's IO industries, however, are the results of disaggregating parts of the broad construction sector according to the type of product that is delivered, such as Residential Permanent Structures, Nonresidential Manufacturing Structures, and Nonresidential Commercial and Healthcare Structures.

To address this problem, we first match some industries by the type of structure. Table A4.5 shows that we match the NAICS industry New Single Family Housing Construction to the IO industry Residential Permanent Site Single- and Multi- Family Structures. Similar matches are possible to obtain GED values for the IO industries Other Residential Structures, Nonresidential Commercial and Healthcare Structures, and Other Nonresidential Structures. In addition, several NAICS industries can be matched to the IO industry Nonresidential Manufacturing Structures (see Table A4.5).

In addition, we cannot match 12 NAICS industries to single IO industries. These 12 industries can be categorized into two groups. The first group is related to the foundation and exterior of buildings, and the second group to the inner decoration and equipment of buildings. We attribute the total GED values of each group to related IO industries in proportion to their value added levels. Thus, the first group's GED is split among all IO industries related to construction, with the exception of the two industries devoted to repair and maintenance activities. We attribute the GED of the second group of NAICS industries proportionally to all the construction industries in the IO classification, including maintenance and repair. The estimated GED values for the IO industries are documented in the last column of Table A4.5.

Table A4.5: Estimated GEDs for construction industries, using a value added-based approach

NAICS Code		GED (\$1M)	IO Code		Estimated GED (\$1M)
236115	New Single Family Housing Construction	0.71	230201	Residential permanent site single- and multi-family structures	468.82
236118	Residential Remodelers	0.03	230202	Other residential structures	228.68
236210	Industrial Building Construction	0.32	230102	Nonresidential manufacturing structures	13574
237110	Water and Sewer Line Construction	0.19			
237120	Oil and Gas Pipeline Construction	0.66			
237130	Power and Communication Line Construction	1.52			
237210	Land Subdivision	0.19			
237310	Highway, Street, and Bridge Construction	0.26			
236220	Commercial and Industrial Building Construction	13524	230101	Nonresidential commercial and health care structures	242.91
237990	Other Heavy and Civil Engineering Construction	0.11	230103	Other nonresidential structures	516.58
			230301	Nonresidential maintenance and repair	209.66
			230302	Residential maintenance and repair	74.22
238110	Poured Concrete Foundation Contractors	0.06	aggregate and then attribute to 230201, 230202, 230102, 230101, 230103		
238140	Masonry Contractors	0.02			
238170	Siding Contractors	1.41			
238910	Site Preparation Contractors	8.91			
238190	Other Foundation and Building Exterior Contractors	0.01			
238210	Electrical Contractors	0.07	aggregate and attribute to all IO construction industries		
238220	Plumbing, Heating, and Air-Conditioning Contractors	0.27			
238290	Other Building Equipment Contractors	0.08			
238320	Painting and Wall Covering Contractors	6.86			
238330	Flooring Contractors	0.01			
238350	Finish Carpentry Contractors	1765			
238990	All other specialty trade contractors	4.20			

4.9.3 Appendix C: Aggregation of IO Sectors into Broad Primary, Secondary and Tertiary Sectors

Sectors related to agriculture, forestry, fishing, hunting, mining and quarrying, oil and gas extraction activities together constitute the broad primary sector. Sectors related to utilities, constructions, and manufacturing activities form the broad secondary sector. The remaining sectors, which are in general related to service activities, fall into the category of the broad tertiary sector. See Table A4.6 for the details.

Table A4.6: Primary, secondary and tertiary sectors

IO code	Categories	Sectors
111	Primary Sector	Crop Production
112		Animal Production
113		Forestry and Logging
114		Fishing Hunting and Trapping
115		Support Activities for Agriculture and Forestry
211		Oil and gas extraction
212-213		Mining, except oil and gas
221	Secondary Sector	Utilities
230		Construction
311-312		Food and beverage and tobacco products
313-314		Textile mills and textile product mills
315-316		Apparel and leather and allied products
321		Wood products
322		Paper products
323		Printing and related support activities
324		Petroleum and coal products
325		Chemical products
326		Plastics and rubber products
327		Nonmetallic mineral products
331		Primary metals
332		Fabricated metal products
333		Machinery
334		Computer and electronic products
335		Electrical equipment, appliances, and components
336		Transportation Equipment
337		Furniture and related products
339		Miscellaneous manufacturing
42	Tertiary Sector	Wholesale trade
4A		Retail Trade
48-49		Transportation and Warehousing
51		Information and Cultural Industries
52		Finance and Insurance
53		Real Estate and Rental and Leasing
54		Professional, Scientific and Technical Services
55		Management of Companies and Enterprises
56		Administrative and Support, Waste Management and Remediation Services
61		Educational Services
62		Health Care and Social Assistance
71		Arts, Entertainment and Recreation
72		Accommodation and Food Services
81		Other Services (except Public Administration)
S0		Government Enterprises and Services

4.9.4 Appendix D: Sensitivity Analysis

D1. Case II: Foreign Border Prices

In the baseline model, we measure imports using US border prices, which include costs of custom duties, freight and insurances. In this sensitivity analysis, we use the imports expressed in foreign border prices instead.

In Section A1.2 we adjust the imports in domestic border prices $(\mathbf{M}\mathbf{t} + \mathbf{m}^f)$ by a vector $\mathbf{r}$, which includes the freight costs, insurance costs, and custom duties for each imported final commodities. Due to limited data availability, we only know about the total value of these costs: water freight (\$25.5 billion), air freight (\$1.2 billion), couriers and messengers (\$6.5 billion), insurance carriers (\$0.4 billion) and custom duties (\$20.0 billion), which add up to \$53.5 billion. We denote these total costs by c . For this sensitivity analysis, however, we need to obtain foreign border prices for each commodity. To allocate the importing costs to specific commodities, we adopt the crude assumption that each dollar of imported commodity requires the same costs in freight, insurance and custom duties. The costs of importing commodity i are then equal to

$$\Delta_i = c \times \left(\frac{\mathbf{t}'_i(\mathbf{M}\mathbf{t} + \mathbf{m}^f)}{\mathbf{t}'(\mathbf{M}\mathbf{t} + \mathbf{m}^f)} \right), \quad (\text{A4.11})$$

in which $\mathbf{t}_i$ is a column vector with the i th element equal to 1 and zeros elsewhere, and $\mathbf{t}$ is a summation vector of ones. The vector Δ contains the estimated costs of freight, insurances and custom duties for each commodity. The imports expressed in foreign border prices are obtained subsequently, by subtracting importing costs from $(\mathbf{M}\mathbf{t} + \mathbf{m}^f)$,

$$\mathbf{m}^{\text{FBP}} = (\mathbf{M}\mathbf{l} + \mathbf{m}^{\text{f}}) - \mathbf{\Delta}, \quad (\text{A4.12})$$

Next, we need to replace the expression in Equation (A4.10) (which transforms the imports data in the use table to the imports vector in the IO table) by Equation (A4.10*):

$$\mathbf{m}_{\text{US}} = \mathbf{D}\mathbf{m}^{\text{FBP}}. \quad (\text{A4.10*})$$

This import vector can subsequently be used in a straightforward way in the computations of damages avoided by US imports.

D2. Case III: Split GED by Gross Output

During the process of matching the Gross External Damage (GED) values of NAICS industries to IO industries, we sometimes have to split GED of a single broader aggregate into GEDs of multiple IO industries (see Appendix B). In the baseline model, GEDs are attributed to IO industries in proportion to their *value added*. However, several previous studies used *gross output* shares to attain such a disaggregation. The values of estimated GEDs obtained in this way (using information directly observable in the IO table) are presented in Table A4.7a and A4.7b, which could be compared to the base case Tables A4.4 and A4.5, respectively.

Table A4.7a: Estimated GED for agricultural industries, using a gross output-based approach

NAICS	Industry	GED Baseline (\$1M)	IO Code	Name	Gross Output x (\$1M)	GED/x	Estimated GED(\$1M)
111000	Crop Production	15844	1111A0	Oilseed farming	14602	0.13	1936
			1111B0	Grain farming	28794	0.13	3817
			111200	Vegetable and melon farming	17788	0.13	2358
			1113A0	Fruit farming	10942	0.13	1450
			111335	Tree nut farming	2214	0.13	293
			111400	Greenhouse, nursery, and floriculture production	15654	0.13	2075
			111910	Tobacco farming	1226	0.13	162
			111920	Cotton farming	3376	0.13	448
			1119A0	Sugarcane and sugar beet farming	2139	0.13	284
			1119B0	All other crop farming	22788	0.13	3021
112000	Livestock Production	15327	1121A0	Cattle ranching and farming	42259	0.15	6421
			112120	Dairy cattle and milk production	21057	0.15	3199
			112A00	Animal production, except cattle and poultry and eggs	16411	0.15	2493
			112300	Poultry and egg production	21152	0.15	3214
113000	Forestry	2043	113A00	Forest nurseries, forest products, and timber tracts	7048	0.06	449
			113300	Logging	25012	0.06	1594
114000	Fishing Hunting	0.0068	114100	Fishing	3177	1.26E-06	0.0040
			114200	Hunting and trapping	2247	1.26E-06	0.0028

Table A4.7b: Estimated GED for construction industries, using a gross output-based approach

NAICS Code		GED (\$1M)	IO Code		Estimated GED (\$1M)
236115	New Single Family Housing Construction	0.71	230201	Residential permanent site single- and multi-family structures	530.23
236118	Residential Remodelers	0.03	230202	Other residential structures	246.37
236210	Industrial Building Construction	0.32	230102	Nonresidential manufacturing structures	13568
237110	Water and Sewer Line Construction	0.19			
237120	Oil and Gas Pipeline Construction	0.66			
237130	Power and Communication Line Construction	1.52			
237210	Land Subdivision	0.19			
237310	Highway, Street, and Bridge Construction	0.26			
236220	Commercial and Industrial Building Construction	13524	230101	Nonresidential commercial and health care structures	226.09
237990	Other Heavy and Civil Engineering Construction	0.11	230103	Other nonresidential structures	505.10
			230301	Nonresidential maintenance and repair	180.26
			230302	Residential maintenance and repair	58.86
238110	Poured Concrete Foundation Contractors	0.06	sum up and then split among 230201, 230202, 230102, 230101, 230103		
238140	Masonry Contractors	0.02			
238170	Siding Contractors	1.41			
238910	Site Preparation Contractors	8.91			
238190	Other Foundation and Building Exterior Contractors	0.01			
238210	Electrical Contractors	0.07	sum up and then split among all the construction IO industries		
238220	Plumbing, Heating, and Air-Conditioning Contractors	0.27			
238290	Other Building Equipment Contractors	0.08			
238320	Painting and Wall Covering Contractors	6.86			
238330	Flooring Contractors	0.01			
238350	Finish Carpentry Contractors	1765			
238990	All other specialty trade contractors	4.20			

D3. Case IV: No Missing Damages

In the baseline model, we have 20 IO industries without corresponding GED values (see Table A4.3). Although imports and exports of these sectors themselves are not considerable, they supply inputs to other, possibly more trade-intensive industries. Consequently, the base case results might be sensitive to the assumption of zero damages in these industries. To investigate this, we also estimate the missing damage values by using damage per unit of output values from industries producing similar goods or services (if a similar industry exist).

For instance, we assume in this analysis that the damage per unit of output in the Tortilla Manufacturing is the same as in the Cookie, Cracker and Pasta Manufacturing. For 19 of the industries with missing values, we manage to assign damage values in this way. Only with regard to the Support Activities for Agriculture and Forestry industry, no information from a similar industry can be used. For this industry we estimate the damage per unit of output by using the arithmetic average values of all the industries in the agriculture and forestry sectors.

The estimated damage per unit of gross output and the similar industries on which these are based are presented in Table A4.8.

Table A4.8: Estimated damage per output for industries without GED data

Missing GED Industries		Similar Industry		Estimated GED/x (10 ⁻⁶)
IO Code	Name	IO Code	Name	
115000	Support activities for agriculture and forestry		Average of all agriculture and forestry industries*	116384
311830	Tortilla manufacturing	311820	Cookie, cracker and pasta manufacturing	647.74
511130	Book publishers	511110	Newspaper publishers	258.72
5111A0	Directory, mailing list, and other publishers	511110	Newspaper publishers	258.72
511200	Software publishers	516110	Internet publishing and broadcasting	233.02
532230	Video tape and disc rental	532A00	General and consumer goods rental	355.73
533000	Lessors of nonfinancial intangible assets	532400	Commercial and industrial machinery and equipment rental and leasing	7.97
541200	Accounting, tax preparation, bookkeeping, and payroll services	541100	Legal services	0.07
541920	Photographic services	5419A0	All other miscellaneous professional, scientific and technical services	5.24
561300	Employment services	561900	Other support services	11.35
561600	Investigation and security services	561900	Other support services	11.35
611100	Elementary and secondary schools	611B00	Other educational services	15.01
611A00	Junior colleges, colleges, universities, and professional schools	611B00	Other educational services	15.01
621600	Home health care services	621A00	Offices of physicians, dentists and other health practitioners	43.49
624400	Child day care services	624A00	Individual and family services	9.64
711100	Performing arts companies	711A00	Promoters of performing arts and sports and agents for public figures	212.98
713950	Bowling centers	713940	Fitness and recreational sports centers	2.85
813A00	Grant making, giving, and social advocacy organizations	813B00	Civic, social, professional and similar organizations	0.15
490000	Postal Services	492000	Couriers and messengers	11.67
S00800	Owner-occupied dwellings	531000	Real estate	51.37

Note:* We cannot find a single industry close to Support activities for agriculture and forestry industry. Therefore, the (unweighted arithmetic) average of GED/x in agricultural and forestry industries is used.

D4. Case V: Basic Prices 2002

In Case V, we use the US national IO table for 2002 from the World Input-Output Database (WIOD, 2013 release), which contains values in basic prices. The basic price is the price for a product received by the producer, minus payable taxes and plus receivable subsidies for producing or selling it. It excludes transportation costs and insurance costs. The WIOD data are far more aggregated than the BEA IO data, i.e. the WIOD IO table contains 35 sectors. All data in WIOD are obtained from official national statistics and are consistent with the National Accounts.⁴⁵

In addition, the tables are structured according to a different statistical classification of industries called Statistical Classification of Economic Activities in the European Community (NACE). Therefore, damage data for industries in the North American Industry Classification System (NAICS) should be converted first. We use a table named ‘2002 NAICS to NACE’ from the US Census Bureau to match GEDs to the WIOD sectors.⁴⁶

D5. Case VI: Basic Prices 2000

In the cases discussed so far, estimation results are in 2002 prices by converting damage values for 2000 into values for 2002, using the GDP deflator. In this Case VI, we keep the damage data in 2000 prices, but convert the input-output data from 2002 prices to 2000 prices using the chaining technique.

Cell-wise dividing the IO table for 2002 in current prices by that for 2002 in previous year’s prices (this table is also taken from WIOD, since the required data is not available for the detailed BEA IO table) gives the price changes between 2001 and 2002, Π_1 . Similarly, dividing the IO table in 2001 in current prices by those in 2001 in previous years’ prices give the price changes between 2000 and 2001, Π_2 . The element-wise multiplication of Π_1 and Π_2 then gives the price changes between 2000 and 2002. To obtain

⁴⁵ The full database is publicly and free of charge available at: <http://www.wiod.org/database/index.htm>. (details of the construction of the WIOD database are given by Dietzenbacher et al., 2013).

⁴⁶ The table can be obtained from: <https://www.census.gov/eos/www/naics/concordances>

the IO table for 2002 in 2000 prices, we need to divide the IO table in current prices cell-wise by this element-wise product of $\mathbf{\Pi}_1$ and $\mathbf{\Pi}_2$.

4.9.5 Appendix E: Additional Tables and Figures

Table A4.9: US Gross External Damages in the year 2002 (in millions of 2002 US\$)

IO code	Sectors	GED	%GED of Total	GED/VA	GED					
					SO ₂	PM _{2.5}	PM ₁₀	NO _x	VOC	NH ₃
111	Crop Production	15844	8.30%	34.32%	95	7019	978	34	1	7716
112	Animal Production	15327	8.03%	55.80%	2	481	62	1	75	14707
113	Forestry and Logging	2043	1.07%	18.17%	16	20	1	-36	87	1956
114	Fishing Hunting and Trapping	0.007	0.00%	0.00%	0.000	0.005	0.000	0.001	0.000	0.000
211	Oil and gas extraction	746	0.39%	1.41%	261	82	3	296	104	1
212-213	Mining, except oil and gas	2669	1.40%	6.82%	219	2104	252	74	10	10
221	Utilities	64757	33.94%	34.68%	52465	4742	182	4913	1435	1020
230	Construction	15314	8.03%	3.17%	982	8990	1524	1327	2367	124
311-312	Food and beverage and tobacco products	1804	0.95%	1.17%	782	633	33	99	181	75
313-314	Textile mills and textile product mills	214	0.11%	0.90%	125	55	2	5	22	4
315-316	Apparel and leather and allied products	14	0.01%	0.07%	7	3	0.1	0.3	4	0.4
321	Wood products	578	0.30%	2.17%	19	366	18	13	159	3
322	Paper products	2993	1.57%	5.40%	1800	714	33	194	172	80
323	Printing and related support activities	188	0.10%	0.41%	2	30	1	4	146	5
324	Petroleum and coal products	6241	3.27%	28.06%	3479	1370	59	288	539	506
325	Chemical products	5455	2.86%	3.63%	2372	879	37	331	1506	330
326	Plastics and rubber products	395	0.21%	0.61%	118	89	5	9	164	11
327	Nonmetallic mineral products	3527	1.85%	8.68%	1583	1320	78	421	43	81
331	Primary metals	3320	1.74%	8.13%	1456	1470	56	118	111	109
332	Fabricated metal products	597	0.31%	0.58%	50	141	6	11	379	10
333	Machinery	107	0.06%	0.12%	28	36	2	10	24	7
334	Computer and electronic products	64	0.03%	0.05%	5	22	1	3	21	12
335	Electrical equipment, appliances, and components	172	0.09%	0.40%	89	57	2	7	15	1
336	Transportation Equipment	973	0.51%	0.54%	55	122	5	16	766	8
337	Furniture and related products	652	0.34%	2.13%	11	104	4	-5	537	0
339	Miscellaneous manufacturing	112	0.06%	0.18%	2	41	2	2	52	14
42	Wholesale trade	1220	0.64%	0.20%	3	63	5	14	1136	1
4A	Retail Trade	1736	0.91%	0.26%	2	9	1	1	1722	1
48-49	Transportation and Warehousing	24061	12.61%	7.11%	6298	6302	220	9267	1656	316
51	Information and Cultural Industries	21	0.01%	0.00%	1	8	0.3	1	11	0.3
52	Finance and Insurance	1	0.00%	0.00%	0.1	0.2	0.0	0.1	0.4	0.1
53	Real Estate and Rental and Leasing	50	0.03%	0.01%	18	17	1	10	3	1
54	Professional, Scientific and Technical Services	53	0.03%	0.01%	16	23	1	4	7	2
55	Management of Companies and Enterprises	0.2	0.00%	0.00%	0.1	0.0	0.0	0.0	0.0	0.0
56	Administrative and Support, Waste Management and Remediation Services	11123	5.83%	3.44%	312	5682	178	260	4102	587
61	Educational Services	1	0.00%	0.00%	0.3	0.1	0.0	0.0	0.1	0.1
62	Health Care and Social Assistance	677	0.35%	0.10%	398	174	7	62	21	15
71	Arts, Entertainment and Recreation	2319	1.22%	2.32%	53	603	18	111	1509	25
72	Accommodation and Food Services	4401	2.31%	1.46%	4	3984	140	6	223	46
81	Other Services (except Public Administration)	1025	0.54%	0.41%	2	17	1	1	1003	1
	Total	190794 (100%)	100%	2.20%	73131 (38%)	47772 (25%)	3920 (2%)	17872 (9%)	20315 (11%)	27786 (15%)

Note: The broad primary sector, secondary sector, and tertiary sector have been separated by horizontal lines.

Table A4.10: Net damages saved by trade (in millions of 2002 US\$)

IO code	Sectors	Exports			Imports			Exports - Imports		
		DEX	%DEX of total	VEX ^a	DIM	%DIM of total	VIM ^b	ΔD	ΔVA ^c	ΔD /ΔVA
111	Crop Production	2351	10.68%	14754	2246	6.86%	11020	106	3734	2.83%
112	Animal Production	326	1.48%	1071	745	2.28%	2639	-419	-1568	26.72%
113	Forestry and Logging	146	0.66%	1191	105	0.32%	1015	41	176	23.48%
114	Fishing Hunting and Trapping	18	0.08%	2149	68	0.21%	8227	-50	-6078	0.82%
115	Support Activities for Agriculture and Forestry	0	0.00%	16	3	0.01%	132	-3	-116	2.57%
211	Oil and gas extraction	34	0.16%	2039	1521	4.65%	90128	-1486	-88089	1.69%
212-213	Mining, except oil and gas	185	0.84%	4298	201	0.62%	3159	-16	1139	-1.40%
	Primary Sector Total	3060	13.90%	25518	4889	14.95%	116320	-1827	-90802	2.01%
221	Utilities	111	0.50%	416	291	0.89%	1038	-180	-621	28.95%
230	Construction	1	0.00%	60	0	0.00%	0	1	60	1.60%
311-312	Food and beverage and tobacco products	2278	10.34%	26225	2139	6.54%	35413	139	-9189	-1.51%
313-314	Textile mills and textile product mills	253	1.15%	7443	444	1.36%	15187	-190	-7744	2.46%
315-316	Apparel and leather and allied products	141	0.64%	5765	1236	3.78%	84887	-1095	-79123	1.38%
321	Wood products	208	0.95%	3246	933	2.85%	14958	-724	-11712	6.18%
322	Paper products	864	3.93%	10627	1261	3.85%	16359	-397	-5731	6.93%
323	Printing and related support activities	31	0.14%	1779	34	0.10%	1935	-3	-156	2.05%
324	Petroleum and coal products	512	2.33%	5243	1029	3.15%	11932	-517	-6689	7.73%
325	Chemical products	2327	10.57%	54257	2477	7.57%	88548	-151	-34291	0.44%
326	Plastics and rubber products	339	1.54%	12536	536	1.64%	18382	-197	-5846	3.38%
327	Nonmetallic mineral products	252	1.14%	4890	875	2.67%	14318	-623	-9428	6.61%
331	Primary metals	582	2.64%	8825	2298	7.02%	26870	-1716	-18045	9.51%
332	Fabricated metal products	274	1.24%	15211	488	1.49%	27763	-214	-12551	1.71%
333	Machinery	701	3.18%	51028	778	2.38%	57028	-77	-6001	1.29%
334	Computer and electronic products	845	3.84%	84705	1373	4.20%	145786	-529	-61081	0.87%
335	Electrical equipment, appliances, and components	254	1.15%	14988	545	1.67%	35387	-291	-20399	1.43%
336	Transportation Equipment	1383	6.28%	98496	3113	9.51%	183596	-1729	-85100	2.03%
337	Furniture and related products	68	0.31%	2065	692	2.11%	16745	-623	-14680	4.25%
339	Miscellaneous manufacturing	184	0.83%	15105	730	2.23%	50479	-547	-35375	1.55%
	Secondary Sector Total	11608	52.70%	422910	21272	65.01%	846611	-9663	-423702	2.28%
42	Wholesale trade	381	1.73%	65259	19	0.06%	3299	362	61959	0.58%
4A	Retail Trade	8	0.03%	814	29	0.09%	3152	-22	-2338	0.94%
48-49	Transportation and Warehousing	6306	28.64%	58243	6354	19.42%	37844	-48	20400	-0.23%
51	Information and Cultural Industries	108	0.49%	27379	24	0.07%	4560	83	22819	0.37%
52	Finance and Insurance	83	0.38%	36494	52	0.16%	25978	31	10516	0.29%
53	Real Estate and Rental and Leasing	170	0.77%	39963	1	0.00%	113	170	39850	0.43%
54	Professional, Scientific and Technical Services	66	0.30%	16883	31	0.10%	6883	34	10001	0.34%
55	Management of Companies and Enterprises	147	0.67%	34023	0	0.00%	41	147	33981	0.43%
56	Administrative and Support, Waste Management and Remediation Services	56	0.25%	1790	31	0.10%	311	24	1479	1.64%
61	Educational Services	7	0.03%	388	4	0.01%	229	3	159	1.85%
62	Health Care and Social Assistance	1	0.01%	165	1	0.00%	106	0.25	58	0.43%
71	Arts, Entertainment and Recreation	3	0.01%	888	3	0.01%	162	-0.20	725	-0.03%
72	Accommodation and Food Services	11	0.05%	405	1	0.00%	24	10	381	2.75%
81	Other Services (except Public Administration)	2	0.01%	180	9	0.03%	1072	-7	-893	0.81%
S0	Government Enterprises and Services	0	0.00%	1	0	0.00%	0	0.002	1	0.33%
	Tertiary Sector Total	7349	33.37%	282875	6559	20.05%	83774	787	199098	0.40%
	Total	22017	100.00%	731301	32722	100.0%	1046705	-10705	-315405	3.39%

Note: The broad primary sector, secondary sector, and tertiary sector have been separated by horizontal lines.

a: VEX denotes value added due to exports.

b: VIM denotes value added forgone due to imports.

c: ΔVA is the difference between VEX and VIM (ΔVA=VEX-VIM).

Table A4.11: The top 10 and bottom 10 industries for $\Delta D/\Delta VA$

#	IO Code	Top 10 Industries	$\Delta D/\Delta VA$
1	324199	All other petroleum and coal products manufacturing	54.0%
2	325182	Carbon black manufacturing	51.2%
3	483000	Water transportation	38.1%
4	112A00	Animal production, except cattle and poultry and eggs	36.1%
5	221300	Water, sewage and other systems	34.7%
6	221100	Electric power generation, transmission, and distribution	29.1%
7	112120	Dairy cattle and milk production	28.0%
8	327310	Cement manufacturing	27.7%
9	322110	Pulp mills	26.5%
10	111400	Greenhouse, nursery, and floriculture production	26.0%
#	IO Code	Bottom 10 Industries	$\Delta D/\Delta VA$
1	541200	Accounting, tax preparation, bookkeeping, and payroll services	0.28%
2	525000	Funds, trusts, and other financial vehicles	0.28%
3	523000	Securities, commodity contracts, investments, and related activities	0.27%
4	522A00	Nondepository credit intermediation and related activities	0.27%
5	541511	Custom computer programming services	0.26%
6	541100	Legal services	0.25%
7	561300	Employment services	0.22%
8	711500	Independent artists, writers, and performers	0.20%
9	52A000	Monetary authorities and depository credit intermediation	0.20%
10	524100	Insurance carriers	0.20%

Table A4.12: Top 10 industries in the net damages saved (-ΔD) through trade by pollutant (in \$1million)

Top 10 industries in net damage saved (-ΔD)		
IO code	Description	Total saved damages
211000	Oil and gas extraction	1486
483000	Water transportation	1115
336111	Automobile Manufacturing	855
1113A0	Fruit farming	810
336112	Light truck and utility vehicle manufacturing	625
331110	Iron and steel mills and ferroalloy manufacturing	567
324110	Petroleum refineries	546
325412	Pharmaceutical preparation manufacturing	489
336300	Motor vehicle parts manufacturing	437
331419	Primary smelting and refining of nonferrous metal (except copper and aluminum)	422

IO code	Description	SO ₂	IO code	Description	PM _{2.5}
211000	Oil and gas extraction	714	1113A0	Fruit farming	336
483000	Water transportation	652	483000	Water transportation	245
331419	Primary smelting and refining of nonferrous metal (except copper and aluminum)	376	331110	Iron and steel mills and ferroalloy manufacturing	215
324110	Petroleum refineries	298	211000	Oil and gas extraction	207
336112	Light truck and utility vehicle manufacturing	276	111200	Vegetable and melon farming	153
33131A	Alumina refining and primary aluminum production	270	336112	Light truck and utility vehicle manufacturing	146
331110	Iron and steel mills and ferroalloy manufacturing	241	336111	Automobile Manufacturing	136
336111	Automobile Manufacturing	234	336300	Motor vehicle parts manufacturing	118
322120	Paper mills	213	111400	Greenhouse, nursery, and floriculture production	109
336300	Motor vehicle parts manufacturing	203	324110	Petroleum refineries	102

IO code	Description	PM ₁₀	IO code	Description	NO _x
1113A0	Fruit farming	46	211000	Oil and gas extraction	373
111200	Vegetable and melon farming	21	483000	Water transportation	185
111400	Greenhouse, nursery, and floriculture production	15	336112	Light truck and utility vehicle manufacturing	75
211000	Oil and gas extraction	10	336111	Automobile Manufacturing	65
483000	Water transportation	9	324110	Petroleum refineries	63
331110	Iron and steel mills and ferroalloy manufacturing	8	331110	Iron and steel mills and ferroalloy manufacturing	54
336112	Light truck and utility vehicle manufacturing	6	336300	Motor vehicle parts manufacturing	47
336111	Automobile Manufacturing	6	327310	Cement manufacturing	41
212310	Stone mining and quarrying	6	315230	Women's and girls' cut and sew apparel manufacturing	41
336300	Motor vehicle parts manufacturing	5	325412	Pharmaceutical preparation manufacturing	31

IO code	Description	VOC	IO code	Description	NH ₃
336111	Automobile Manufacturing	384	1113A0	Fruit farming	373
325412	Pharmaceutical preparation manufacturing	220	321100	Sawmills and wood preservation	244
337122	Nonupholstered wood household furniture manufacturing	213	1121A0	Cattle ranching and farming	198
211000	Oil and gas extraction	154	111200	Vegetable and melon farming	169
33712A	Metal and other household furniture (except wood) manufacturing	119	112A00	Animal production, except cattle and poultry and eggs	166
336112	Light truck and utility vehicle manufacturing	90	111400	Greenhouse, nursery, and floriculture production	119
336300	Motor vehicle parts manufacturing	41	316100	Leather and hide tanning and finishing	67
324110	Petroleum refineries	37	311513	Cheese manufacturing	65
334300	Audio and video equipment manufacturing	30	113A00	Forest nurseries, forest products, and timber tracts	54
315230	Women's and girls' cut and sew apparel manufacturing	28	322120	Paper mills	48

Table A4.13: Top 10 industries for net generated damage (ΔD) through trade by pollutant (in \$1million)

Top 10 industries for net generated damage (ΔD)				
IO code	Description	Total generated damage		
31122A	Soybean and other oilseed processing	146		
550000	Management of companies and enterprises	147		
111920	Cotton farming	157		
325211	Plastics material and resin manufacturing	163		
31161A	Animal (except poultry) slaughtering, rendering, and processing	252		
482000	Rail transportation	265		
420000	Wholesale trade	362		
1111B0	Grain farming	525		
484000	Truck transportation	673		
1111A0	Oilseed farming	837		

IO code	Description	SO ₂	IO code	Description	PM _{2.5}
420000	Wholesale trade	138	1111A0	Oilseed farming	352
533000	Lessors of nonfinancial intangible assets	100	1111B0	Grain farming	204
484000	Truck transportation	94	484000	Truck transportation	203
325211	Plastics material and resin manufacturing	86	111920	Cotton farming	59
550000	Management of companies and enterprises	81	31122A	Soybean and other oilseed processing	57
334413	Semiconductor and related device manufacturing	67	482000	Rail transportation	57
482000	Rail transportation	56	420000	Wholesale trade	55
1111B0	Grain farming	54	325211	Plastics material and resin manufacturing	32
336411	Aircraft manufacturing	50	550000	Management of companies and enterprises	27
336413	Other aircraft parts and auxiliary equipment manufacturing	46	31161A	Animal (except poultry) slaughtering, rendering, and processing	25

IO code	Description	PM ₁₀	IO code	Description	NO _x
1111A0	Oilseed farming	48	484000	Truck transportation	306
1111B0	Grain farming	27	482000	Rail transportation	133
111920	Cotton farming	8	486000	Pipeline transportation	39
31122A	Soybean and other oilseed processing	7	420000	Wholesale trade	30
484000	Truck transportation	7	325211	Plastics material and resin manufacturing	18
31161A	Animal (except poultry) slaughtering, rendering, and processing	3	325110	Petrochemical manufacturing	16
420000	Wholesale trade	3	550000	Management of companies and enterprises	15
111335	Tree nut farming	3	1111B0	Grain farming	14
482000	Rail transportation	2	336413	Other aircraft parts and auxiliary equipment manufacturing	13
311221	Wet corn milling	2	533000	Lessors of nonfinancial intangible assets	13

IO code	Description	VOC	IO code	Description	NH ₃
420000	Wholesale trade	114	1111A0	Oilseed farming	385
484000	Truck transportation	44	1111B0	Grain farming	220
325520	Adhesive manufacturing	37	31161A	Animal (except poultry) slaughtering, rendering, and processing	197
550000	Management of companies and enterprises	17	113300	Logging	90
336411	Aircraft manufacturing	16	311615	Poultry processing	80
325211	Plastics material and resin manufacturing	15	111920	Cotton farming	63
48A000	Scenic and sightseeing transportation and support activities for transportation	13	31122A	Soybean and other oilseed processing	57
482000	Rail transportation	12	112300	Poultry and egg production	25
486000	Pipeline transportation	12	111335	Tree nut farming	21
533000	Lessors of nonfinancial intangible assets	9	420000	Wholesale trade	21

Table A4.14: Unit damage of trade (\$ damages per \$1000 of exports or imports) of selected industries

IO Code	Top 10 Industries	Damage Per \$1,000 Exports or Imports (\$)
230102	Nonresidential manufacturing structures	620
324199	All other petroleum and coal products manufacturing	395
325182	Carbon black manufacturing	380
112A00	Animal production, except cattle and poultry and eggs	341
221300	Water, sewage and other systems	339
483000	Water transportation	306
221100	Electric power generation, transmission, and distribution	279
112120	Dairy cattle and milk production	259
327310	Cement manufacturing	257
111400	Greenhouse, nursery, and floriculture production	246
IO Code	Bottom 10 Industries	Damage Per \$1,000 Exports or Imports (\$)
525000	Funds, trusts, and other financial vehicles	3
522A00	Non-depository credit intermediation and related activities	3
523000	Securities, commodity contracts, investments, and related activities	3
541511	Custom computer programming services	3
541100	Legal services	2
561300	Employment services	2
711500	Independent artists, writers, and performers	2
52A000	Monetary authorities and depository credit intermediation	2
524100	Insurance carriers	2
814000	Private households	0.01

Table A4.15: Unite damage (\$ damages per \$1000 of exports) by sector

IO code	Sectors	%Exports (weights)	\$ Damages per \$1000 of exports							
			Damages from intermediate products in the other	Total	SO ₂	PM _{2.5}	PM ₁₀	NO _x	VOC	NH ₃
111	Crop Production	2.00%	21.67	145.22	10.02	59.21	7.99	2.35	1.08	64.57
112	Animal Production	0.10%	38.79	284.63	9.43	19.43	2.36	2.59	2.17	248.65
113	Forestry and Logging	0.20%	35.06	116.71	3.87	7.10	0.75	-0.35	4.82	100.53
114	Fishing Hunting and Trapping	0.30%	7.55	7.55	3.46	1.52	0.07	0.95	0.86	0.69
115	Support Activities for Agriculture and Forestry	0.00%	23.65	23.65	6.15	4.52	0.43	1.60	0.75	10.19
211	Oil and gas extraction	0.30%	8.80	16.10	7.73	2.25	0.10	4.04	1.67	0.31
212-213	Mining, except oil and gas	0.60%	23.58	40.36	17.99	15.18	1.44	4.19	0.77	0.78
	Primary Sector Total	3.30%	21.11	110.62	10.31	38.59	5.06	2.55	1.27	52.84
221	Utilities	0.10%	8.37	253.35	202.65	19.90	0.79	21.57	4.95	3.50
230	Construction	0.00%	12.99	15.14	4.12	4.87	0.44	1.25	3.30	1.16
311-312	Food and beverage and tobacco products	3.50%	72.91	78.35	12.47	16.51	1.81	3.30	2.11	42.15
313-314	Textile mills and textile product mills	1.00%	26.88	29.22	13.82	5.84	0.41	2.31	2.16	4.67
315-316	Apparel and leather and allied products	0.80%	21.30	21.74	5.96	3.20	0.24	1.51	1.27	9.56
321	Wood products	0.40%	49.02	58.05	7.27	10.67	0.71	1.99	5.64	31.77
322	Paper products	1.50%	30.11	71.63	37.75	15.59	0.79	5.09	4.61	7.80
323	Printing and related support activities	0.20%	13.75	15.72	7.36	2.75	0.12	1.42	2.91	1.15
324	Petroleum and coal products	1.20%	13.12	51.79	29.70	10.48	0.45	4.95	3.05	3.15
325	Chemical products	7.80%	21.59	36.19	18.57	6.62	0.32	3.71	4.60	2.38
326	Plastics and rubber products	1.80%	20.53	23.19	12.87	4.10	0.19	2.32	2.56	1.16
327	Nonmetallic mineral products	0.70%	20.83	46.61	19.60	15.41	0.76	7.04	1.98	1.83
331	Primary metals	1.30%	27.16	54.06	31.33	14.37	0.61	4.05	2.21	1.50
332	Fabricated metal products	2.00%	14.10	16.28	7.49	4.24	0.17	1.57	2.27	0.53
333	Machinery	7.10%	11.41	11.90	5.60	3.17	0.13	1.30	1.16	0.54
334	Computer and electronic products	12.10%	8.24	8.45	4.70	1.58	0.07	0.89	0.85	0.37
335	Electrical equipment, appliances, and components	2.10%	11.77	14.62	8.08	3.43	0.14	1.44	1.07	0.47
336	Transportation Equipment	14.40%	10.67	11.63	5.22	2.83	0.12	1.30	1.64	0.51
337	Furniture and related products	0.30%	15.78	29.21	6.05	5.22	0.25	1.49	13.50	2.70
339	Miscellaneous manufacturing	2.00%	9.90	10.88	4.91	2.35	0.11	1.20	1.47	0.84
	Secondary Sector Total	60.20%	17.44	23.29	10.05	4.98	0.29	2.01	2.07	3.88
42	Wholesale trade	8.16%	4.20	5.64	2.15	0.86	0.04	0.47	1.78	0.33
4A	Retail Trade	8.03%	7.33	9.05	3.89	1.34	0.07	0.74	2.26	0.75
48-49	Transportation and Warehousing	0.10%	8.19	94.84	45.19	22.90	0.81	20.86	4.26	0.81
51	Information and Cultural Industries	3.42%	3.79	3.80	1.86	0.78	0.03	0.38	0.56	0.21
52	Finance and Insurance	4.57%	2.18	2.18	0.96	0.48	0.02	0.19	0.41	0.13
53	Real Estate and Rental and Leasing	4.95%	4.15	4.15	2.72	0.58	0.02	0.37	0.32	0.13
54	Professional, Scientific and Technical Services	2.10%	9.60	4.00	1.71	0.90	0.04	0.38	0.52	0.23
55	Management of Companies and Enterprises	4.22%	3.73	4.00	2.31	0.77	0.03	0.43	0.48	0.18
56	Administrative and Support, Waste Management	0.22%	4.21	30.00	2.96	19.65	0.63	0.86	3.54	2.32
61	Educational Services	0.05%	4.45	18.00	9.65	2.45	0.13	1.48	1.44	2.85
62	Health Care and Social Assistance	0.02%	18.01	8.00	3.85	1.39	0.07	0.67	0.71	1.08
71	Arts, Entertainment and Recreation	0.11%	6.75	3.00	1.44	0.78	0.03	0.34	0.68	0.17
72	Accommodation and Food Services	0.05%	2.87	26.00	6.50	12.05	0.51	1.19	1.45	4.41
81	Other Services (except Public Administration)	0.02%	15.64	8.00	4.03	1.64	0.07	0.71	1.24	0.59
S0	Government Enterprises and Services	0.45%	7.87	9.60	3.63	2.61	0.14	1.01	1.24	0.97
	Tertiary Sector Total	36.50%	4.87	24.44	11.56	5.77	0.21	4.90	1.62	0.38
	Total	100%	12.98	26.63	10.61	6.39	0.42	3.09	1.88	4.24

Note: The broad primary sector, secondary sector, and tertiary sector have been separated by horizontal lines. The UD's are average damage values weighted with export shares.

Table A4.16: Unite damage (\$ damages per \$1000 of imports) by sector

IO code	Sectors	%Imports (weights)	\$ Damages per \$1000 of imports							
			Damages from intermediate products in the other	Total	SO ₂	PM _{2.5}	PM ₁₀	NO _x	VOC	NH ₃
111	Crop Production	1.00%	19.65	189.94	10.10	78.89	10.79	2.09	0.96	87.11
112	Animal Production	0.20%	43.13	261.99	9.69	20.64	2.54	2.51	2.02	224.59
113	Forestry and Logging	0.10%	23.81	95.64	3.97	5.49	0.54	-0.29	4.01	81.92
114	Fishing Hunting and Trapping	0.70%	7.55	7.55	3.46	1.52	0.07	0.95	0.86	0.69
115	Support Activities for Agriculture and Forestry	0.00%	23.65	23.65	6.15	4.52	0.43	1.60	0.75	10.19
211	Oil and gas extraction	7.70%	8.80	16.10	7.73	2.25	0.10	4.04	1.67	0.31
212-213	Mining, except oil and gas	0.30%	24.87	59.63	20.82	27.47	2.92	6.68	0.96	0.77
	Primary Sector Total	10.00%	11.14	39.85	8.02	10.73	1.27	3.62	1.55	14.66
221	Utilities	0.10%	7.68	267.72	219.87	21.14	0.84	22.59	1.24	2.04
230	Construction	0.00%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
311-312	Food and beverage and tobacco products	3.30%	48.41	52.83	9.45	12.72	1.21	2.51	2.04	24.90
313-314	Textile mills and textile product mills	1.50%	22.99	24.74	11.86	4.92	0.34	2.08	1.80	3.75
315-316	Apparel and leather and allied products	7.80%	12.65	12.86	5.38	2.31	0.14	1.28	1.03	2.71
321	Wood products	1.40%	46.85	56.24	7.63	11.13	0.72	2.11	5.18	29.48
322	Paper products	1.50%	29.99	67.90	36.50	13.97	0.70	4.96	3.97	7.79
323	Printing and related support activities	0.20%	13.91	15.93	7.45	2.79	0.13	1.43	2.96	1.17
324	Petroleum and coal products	1.90%	12.70	44.80	24.92	8.65	0.36	4.81	2.90	3.16
325	Chemical products	8.20%	14.23	24.59	11.86	4.21	0.21	2.28	4.45	1.58
326	Plastics and rubber products	1.70%	21.41	24.99	14.56	4.26	0.20	2.30	2.48	1.19
327	Nonmetallic mineral products	1.30%	19.98	56.10	29.04	16.08	0.95	6.97	1.85	1.22
331	Primary metals	2.70%	29.04	70.55	44.04	17.06	0.73	4.75	2.18	1.78
332	Fabricated metal products	2.50%	13.94	15.91	7.39	4.20	0.17	1.56	2.05	0.53
333	Machinery	5.30%	11.38	11.88	5.63	3.14	0.13	1.30	1.16	0.52
334	Computer and electronic products	14.50%	7.60	7.74	4.02	1.56	0.07	0.84	0.89	0.37
335	Electrical equipment, appliances, and components	3.30%	11.80	13.37	7.05	3.16	0.13	1.41	1.10	0.51
336	Transportation Equipment	18.70%	11.40	13.54	5.41	3.02	0.13	1.38	2.99	0.61
337	Furniture and related products	1.50%	15.92	36.45	5.99	5.57	0.26	1.41	20.21	3.01
339	Miscellaneous manufacturing	4.80%	11.19	12.49	5.70	2.61	0.12	1.36	1.52	1.18
	Secondary Sector Total	82.20%	14.86	21.10	9.35	4.48	0.24	1.82	2.53	2.69
42	Wholesale trade	0.28%	4.20	5.64	2.15	0.86	0.04	0.47	1.78	0.33
4A	Retail Trade	3.69%	7.33	9.05	3.89	1.34	0.07	0.74	2.26	0.75
48-49	Transportation and Warehousing	0.27%	8.64	140.47	76.77	32.92	1.16	24.02	5.01	0.59
51	Information and Cultural Industries	0.39%	5.09	5.12	2.45	1.05	0.05	0.54	0.70	0.33
52	Finance and Insurance	2.24%	1.89	1.89	0.87	0.40	0.02	0.16	0.34	0.10
53	Real Estate and Rental and Leasing	0.01%	4.56	4.58	2.09	0.97	0.04	0.43	0.77	0.28
54	Professional, Scientific and Technical Services	0.58%	7.85	4.43	2.04	1.03	0.04	0.47	0.57	0.26
55	Management of Companies and Enterprises	0.00%	4.37	4.21	2.31	0.77	0.03	0.43	0.48	0.18
56	Administrative and Support, Waste Management	0.03%	4.21	96.64	5.38	70.52	2.22	1.87	8.77	7.88
61	Educational Services	0.02%	4.44	18.10	9.71	2.46	0.13	1.49	1.45	2.87
62	Health Care and Social Assistance	0.01%	18.10	9.74	4.91	1.68	0.08	0.82	0.76	1.48
71	Arts, Entertainment and Recreation	0.01%	8.14	19.94	3.50	4.76	0.16	1.28	9.61	0.62
72	Accommodation and Food Services	0.00%	6.06	27.04	6.51	12.68	0.54	1.20	1.47	4.63
81	Other Services (except Public Administration)	0.09%	15.92	7.65	3.51	1.57	0.07	0.66	1.49	0.36
S0	Government Enterprises and Services	0.24%	6.70	7.85	2.89	2.06	0.10	0.72	1.09	1.00
	Tertiary Sector Total	7.80%	5.97	68.40	36.99	16.13	0.57	11.48	2.77	0.45
	Total	100%	13.79	26.69	11.39	6.02	0.37	2.76	2.45	3.71

Note: The broad primary sector, secondary sector, and tertiary sector have been separated by horizontal lines. The UD's are average damage values weighted with import shares.

Table A4.17: Sensitivity Analysis CaseII-IV (in \$1million)

IO code	Sectors	Case I Baseline		Case II Foreign Border Prices		Case III Split by Output		Case IV Missing Damages Proxied	
		ΔD	$\frac{\Delta D}{\Delta v_a}$	ΔD	$\frac{\Delta D}{\Delta v_a}$	ΔD	$\frac{\Delta D}{\Delta v_a}$	ΔD	$\frac{\Delta D}{\Delta v_a}$
111	Crop Production	-106	2.83%	-192	4.62%	-805	21.57%	-113	3.03%
112	Animal Production	419	26.72%	390	26.62%	453	28.90%	412	26.28%
113	Forestry and Logging	-41	23.48%	-45	21.08%	-48	27.22%	-26	14.98%
114	Fishing Hunting and Trapping	50	0.82%	47	0.82%	50	0.82%	48	0.80%
115	Support Activities for Agriculture and Forestry	3	2.57%	3	2.57%	3	2.16%	18	15.16%
211	Oil and gas extraction	1486	1.69%	1428	1.69%	1486	1.69%	1430	1.62%
212-213	Mining, except oil and gas	16	-1.40%	8	-0.65%	16	-1.38%	15	-1.34%
221	Utilities	180	28.95%	169	29.01%	180	28.95%	173	27.84%
230	Construction	-1	1.60%	-1	1.60%	-1	1.58%	-1	1.56%
311-312	Food and beverage and tobacco products	-139	1.51%	-221	-2.82%	276	3.00%	-139	-1.51%
313-314	Textile mills and textile product mills	190	2.46%	173	2.42%	203	2.62%	186	2.40%
315-316	Apparel and leather and allied products	1095	1.38%	1048	1.38%	1152	1.46%	1070	1.35%
321	Wood products	724	6.18%	688	6.18%	737	6.29%	749	6.40%
322	Paper products	397	6.93%	348	6.83%	399	6.96%	387	6.75%
323	Printing and related support activities	3	2.05%	2	2.31%	3	2.06%	3	1.98%
324	Petroleum and coal products	517	7.73%	477	7.66%	517	7.73%	499	7.46%
325	Chemical products	151	0.44%	55	0.18%	150	0.44%	145	0.42%
326	Plastics and rubber products	197	3.38%	177	3.44%	198	3.39%	191	3.27%
327	Nonmetallic mineral products	623	6.61%	589	6.64%	623	6.61%	601	6.37%
331	Primary metals	1716	9.51%	1628	9.57%	1717	9.51%	1660	9.20%
332	Fabricated metal products	214	1.71%	196	1.70%	215	1.71%	207	1.65%
333	Machinery	77	1.29%	48	1.25%	78	1.29%	75	1.25%
334	Computer and electronic products	529	0.87%	476	0.86%	530	0.87%	513	0.84%
335	Electrical equipment, appliances, and components	291	1.43%	270	1.42%	292	1.43%	281	1.38%
336	Transportation Equipment	1729	2.03%	1610	2.06%	1737	2.04%	1670	1.96%
337	Furniture and related products	623	4.25%	597	4.25%	626	4.26%	607	4.13%
339	Miscellaneous manufacturing	547	1.55%	519	1.55%	548	1.55%	530	1.50%
42	Wholesale trade	-362	0.58%	-362	0.58%	-365	0.59%	-350	0.56%
4A	Retail Trade	22	0.94%	21	0.94%	22	0.93%	21	0.91%
48-49	Transportation and Warehousing	48	0.23%	-196	0.90%	48	0.23%	46	-0.22%
51	Information and Cultural Industries	-83	0.37%	-84	0.37%	-84	0.37%	-83	0.36%
52	Finance and Insurance	-31	0.29%	-33	0.29%	-31	0.29%	-30	0.28%
53	Real Estate and Rental and Leasing	-170	0.43%	-170	0.43%	-170	0.43%	-164	0.41%
54	Professional, Scientific and Technical Services	-34	0.34%	-36	0.35%	-35	0.35%	-33	0.33%
55	Management of Companies and Enterprises	-147	0.43%	-147	0.43%	-147	0.43%	-142	0.42%
56	Administrative and Support, Waste Management and Remediation Services	-24	1.64%	-26	1.71%	-24	1.64%	-24	1.59%
61	Educational Services	-3	1.85%	-3	1.85%	-3	1.86%	-3	1.79%
62	Health Care and Social Assistance	0	0.43%	0	0.47%	0	0.43%	0	0.42%
71	Arts, Entertainment and Recreation	0	0.03%	0	-0.01%	0	0.03%	0	-0.02%
72	Accommodation and Food Services	-10	2.75%	-11	2.75%	-11	2.78%	-10	2.68%
81	Other Services (except Public Administration)	7	0.81%	7	0.81%	7	0.81%	7	0.78%
S0	Government Enterprises and Services	0	0.33%	0	0.33%	0	0.33%	-12	1.66%
	Total	10705	3.39%	9446	3.43%	9989	3.17%	10414	3.31%

Note: Case I is the baseline model. Case II subtracts costs of duties, freight and insurance from the imports. Case III splits the GED of agricultural and construction industries using gross output weights. Case IV estimates missing damage values using data from other industries producing similar goods or services.

Table A4.18: Sensitivity Analysis with World Input-Output Database (in \$1million)

IO code	Sectors	Case V Basic Prices 2002		Case VI Basic Prices 2000	
		ΔD	$\frac{\Delta D}{\Delta va}$	ΔD	$\frac{\Delta D}{\Delta va}$
1	Agriculture, Hunting, Forestry and Fishing	710	23.02%	583	22.04%
2	Mining and Quarrying	2815	3.71%	2486	3.25%
3	Food, Beverages and Tobacco	512	6.88%	537	6.97%
4	Textiles and Textile Products	1600	2.63%	1557	2.52%
5	Leather, Leather and Footwear	753	4.31%	741	4.40%
6	Wood and Products of Wood and Cork	698	6.49%	696	6.13%
7	Pulp, Paper, Paper , Printing and Publishing	36	2.57%	60	2.48%
8	Coke, Refined Petroleum and Nuclear Fuel	276	3.65%	245	2.95%
9	Chemicals and Chemical Products	908	3.21%	911	3.14%
10	Rubber and Plastics	170	2.32%	185	2.25%
11	Other Non-Metallic Mineral	1210	14.36%	1206	14.10%
12	Basic Metals and Fabricated Metal	938	3.00%	971	2.86%
13	Machinery, Nec	96	1.71%	125	1.65%
14	Electrical and Optical Equipment	825	1.06%	707	0.88%
15	Transport Equipment	1266	2.04%	1269	1.94%
16	Manufacturing, Nec; Recycling	989	2.25%	979	2.21%
17	Electricity, Gas and Water Supply	388	29.25%	399	32.23%
18	Construction	22	2.87%	21	2.93%
19	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	7	2.17%	6	2.07%
20	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	-425	0.53%	-412	0.50%
21	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	26	0.51%	24	0.48%
22	Hotels and Restaurants	14	2.44%	15	2.48%
23	Inland Transport	-740	6.11%	-710	6.16%
24	Water Transport	-3941	35.14%	-3759	36.59%
25	Air Transport	2	2.47%	-26	2.23%
26	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	-71	0.66%	-68	0.67%
27	Post and Telecommunications	-73	0.66%	-70	0.66%
28	Financial Intermediation	-123	0.27%	-121	0.27%
29	Real Estate Activities	5	0.54%	6	0.56%
30	Renting of M&Eq and Other Business Activities	159	0.47%	138	0.46%
31	Public Admin and Defense; Compulsory Social Security	-43	0.92%	-41	0.94%
32	Education	8	1.65%	7	1.64%
33	Health and Social Work	3	0.76%	3	0.78%
34	Other Community, Social and Personal Services	-124	2.23%	-118	2.24%
35	Private Households with Employed Persons	0	0.00%	0	0.00%
	Total	8898	2.84%	8550	2.65%

Note: Case V uses IO data from WIOD in basic prices. Case VI uses deflated IO data from WIOD in basic prices.

Table A4.19: Sensitivity Analysis of Marginal Damages (in \$1million)

IO code	Sectors	Case VII Laden		Case VIII VSL6m		Case IX VSLY2m		Case X VSLY10m	
		ΔD	$\frac{\Delta D}{\Delta va}$	ΔD	$\frac{\Delta D}{\Delta va}$	ΔD	$\frac{\Delta D}{\Delta va}$	ΔD	$\frac{\Delta D}{\Delta va}$
111	Crop Production	-122	3.26%	-127	3.39%	-97	2.59%	-114	3.06%
112	Animal Production	874	55.77%	1008	64.27%	166	10.56%	665	42.40%
113	Forestry and Logging	-90	51.27%	-105	60.01%	-14	8.20%	-67	38.35%
114	Fishing Hunting and Trapping	54	0.89%	55	0.91%	48	0.79%	52	0.86%
115	Support Activities for Agriculture and Forestry	5	4.04%	5	4.48%	2	1.75%	4	3.37%
211	Oil and gas extraction	1521	1.73%	1533	1.74%	1467	1.66%	1506	1.71%
212-213	Mining, except oil and gas	15	-	15	-	16	-	15	-
			1.32%		1.30%		1.44%		1.35%
221	Utilities	180	28.98%	180	28.99%	180	28.93%	180	28.97%
230	Construction	-1	1.99%	-1	2.14%	-1	1.37%	-1	1.82%
311-312	Food and beverage and tobacco products	-446	-	-536	-	32	0.35%	-305	-
			4.85%		5.84%				3.32%
313-314	Textile mills and textile product mills	230	2.97%	242	3.12%	168	2.17%	212	2.73%
315-316	Apparel and leather and allied products	1354	1.71%	1431	1.81%	951	1.20%	1235	1.56%
321	Wood products	1227	10.47%	1383	11.81%	448	3.82%	993	8.48%
322	Paper products	455	7.95%	474	8.27%	365	6.36%	428	7.47%
323	Printing and related support activities	3	2.20%	4	2.25%	3	1.96%	3	2.13%
324	Petroleum and coal products	520	7.78%	521	7.79%	515	7.70%	519	7.76%
325	Chemical products	160	0.47%	163	0.48%	145	0.42%	156	0.45%
326	Plastics and rubber products	206	3.52%	208	3.56%	193	3.30%	202	3.45%
327	Nonmetallic mineral products	629	6.67%	631	6.69%	620	6.57%	626	6.64%
331	Primary metals	1726	9.56%	1729	9.58%	1711	9.48%	1721	9.54%
332	Fabricated metal products	219	1.74%	220	1.75%	212	1.69%	217	1.73%
333	Machinery	79	1.32%	80	1.33%	76	1.27%	78	1.31%
334	Computer and electronic products	555	0.91%	563	0.92%	514	0.84%	543	0.89%
335	Electrical equipment, appliances, and components	299	1.47%	301	1.48%	287	1.40%	295	1.45%
336	Transportation Equipment	1797	2.11%	1818	2.14%	1692	1.99%	1766	2.08%
337	Furniture and related products	687	4.68%	707	4.82%	588	4.01%	658	4.48%
339	Miscellaneous manufacturing	587	1.66%	600	1.70%	524	1.48%	569	1.61%
42	Wholesale trade	-385	0.62%	-392	0.63%	-349	0.56%	-374	0.60%
4A	Retail Trade	24	1.04%	25	1.08%	20	0.88%	23	0.99%
48-49	Transportation and Warehousing	39	-	36	-	53	-	43	-
			0.19%		0.18%		0.26%		0.21%
51	Information and Cultural Industries	-88	0.38%	-89	0.39%	-81	0.36%	-86	0.38%
52	Finance and Insurance	-34	0.32%	-34	0.33%	-29	0.28%	-32	0.31%
53	Real Estate and Rental and Leasing	-174	0.44%	-176	0.44%	-167	0.42%	-172	0.43%
54	Professional, Scientific and Technical Services	-37	0.37%	-37	0.37%	-33	0.33%	-36	0.36%
55	Management of Companies and Enterprises	-153	0.45%	-155	0.46%	-143	0.42%	-150	0.44%
56	Administrative and Support, Waste Management and Remediation Services	-25	1.67%	-25	1.68%	-24	1.63%	-25	1.66%
61	Educational Services	-3	2.18%	-4	2.28%	-3	1.66%	-3	2.03%
62	Health Care and Social Assistance	0	0.47%	0	0.48%	0	0.41%	0	0.45%
71	Arts, Entertainment and Recreation	0	-	0	-	0	-	0	-
			0.02%		0.02%		0.03%		0.02%
72	Accommodation and Food Services	-13	3.36%	-13	3.54%	-9	2.41%	-12	3.08%
81	Other Services (except Public Administration)	7	0.84%	8	0.85%	7	0.79%	7	0.83%
S0	Government Enterprises and Services	0	0.38%	0	0.39%	0	0.30%	0	0.35%
	Total	1188	3.77%	1224	3.88%	1005	3.19%	1133	3.59%
		3		3		2		9	

Note: Case IV uses the adult mortality dose-response function for PM_{2.5} from Laden et al. (2006). Case V employs a single, uniform value for premature mortality for all ages. Case VI changes the VSL (value of a statistical life) to \$2 million. Case VII changes the VSL to \$10 million VSL. Cases I, VI and VII employ heterogeneous premature mortality values across ages.

4.9.6 References of Appendix

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CHAPTER 5

DOES THE REST OF THE WORLD MATTER? A SENSITIVITY ANALYSIS WITH RESPECT TO DATA AVAILABILITY

A full multi-regional input-output (MRIO) model should include all the countries in the world, but none of the current databases covers all. Therefore, countries not covered by the MRIO databases, i.e. the rest of the world (RoW), are estimated with limited information. The central question in this study is: what is the role of the RoW? In this chapter, we investigate whether and to what extent it matters for the estimation of countries' consumer responsibilities in case that we only have limited information for the RoW. A sensitivity analysis will be carried out including different scenarios reflecting the amount of available information. We mimic the actual situation by assuming that the world consists of countries in the World Input-Output Database (WIOD). One country is omitted from the world input-output table, which then plays the role of RoW. We find that serious biases can occur when the true emission coefficients are estimated by average emission coefficients, and when the true technical coefficients matrix of the omitted country is estimated by the average matrix. Also, omitting a "large" country from the world can affect the estimation of the consumer responsibility of its "small" neighbors or trading partners. Using a so-called 'regional representative' method to estimate the true technical coefficients can reduce the estimation errors of consumer responsibility considerably.

5.1 INTRODUCTION

In recent years, there has been a considerable development of multi-regional input-output (MRIO) databases with global coverage (see Tukker and Dietzenbacher, 2013, for an overview). Examples are

Eora (Lenzen et al., 2012, 2013), EXIOBASE (Tukker et al., 2009, 2013), GTAP-MRIO (Peters et al., 2011; Andrew and Peters, 2013), WIOD (Dietzenbacher et al., 2013), the OECD database (Nakano et al., 2009) and GRAM (Bruckner et al., 2012; Wiebe et al., 2012). The number of countries involved in these databases ranges from 40 (WIOD) to 187 (Eora). Although these databases represent more than 85% of world GDP, none of them covers every country in the world. This implies that some representation is needed of the rest of the world (RoW), for which we have only very limited information. The central question in this study is: what is the role of the RoW? That is, to what extent does it matter that we only have limited information for the RoW?

The answer to this question is important, because it will influence the amount of time we will have to spend on the RoW in the future. If it matters little, it is not necessary to put much effort in getting additional information or estimating data for the RoW. If it matters considerably, the implication is that serious errors in our calculations are likely and that a better coverage of the RoW is essential. Several sensitivity analyses have been carried out for MRIO models, for example to study the effects of uncertainties in international trade data, emission data, aggregation, and currency conversion (Lenzen et al., 2004, 2010; Rodrigues and Domingos, 2007; Weber, 2008; Wiedmann et al., 2010; Wilting, 2012). Little attention, however, has been paid to the role of the RoW or to comparing alternative approaches to estimate the RoW.

We will perform a sensitivity analysis, mimicking the actual situation. The application is with respect to the calculation of each country's consumer responsibility for global CO₂ emissions. This consumer responsibility equals the part of the carbon footprint that is related to emissions involved in the production of goods and services. The other part is related to the actual consumption of these goods and services and is not included in our study. To mimic the actual situation, we will assume that the entire world consists of just the 41 countries (i.e. the 40 WIOD countries and the RoW in WIOD

as the 41st country). This gives us *the* world input-output table (WIOT). Next, we will omit one country from this WIOT, which then plays the role of RoW. This exercise is repeated 41 times, implying that we cover a wide variety of possibilities. For example, the RoW may be very large (when the US is omitted) or very small (when Malta or Cyprus is omitted), it may depend much on imports (Belgium) or its exports may be important for others (Germany), it may have small (Netherlands) or large (China) emission intensities.

In our sensitivity analysis, we will discuss five types of cases. The cases are: a full neglect of the RoW; using information on the imports from the RoW; adding a very crude estimate of the RoW's production structure; adding an estimate of RoW's structure of domestic deliveries and imported intermediate inputs; and adding the RoW's true production structure. In all cases, we calculate the consumer responsibility of the remaining 40 countries (recall that one country is taken as RoW) and compare it with the true outcome as obtained from the WIOT (with 41 countries).

To our knowledge, one other study (Andrew et al., 2009) is available that performs a similar sensitivity analysis. It should be stressed though that the perspective differs. Andrew et al. (2009) focus on the calculation of the carbon footprint of a single country (for which they have 87 candidates). Their central question is: what approximation of the full model gives an answer that comes closest to the true answer as obtained from the 87-country MRIO table that they constructed on the basis of the GTAP6 database? Our starting-point is different. We are not interested in finding an answer for a single country but aim at running calculations that include all countries. This implies that one of the models that Andrew et al. (2009) consider (i.e. the so-called unidirectional model for a single country) is not of interest for the present study. Building 41 unidirectional models requires just as much information as a full 41-country MRIO table. The results in Andrew et al. (2009) show that estimating the RoW by using the world-average IOT and world-average emission intensities lead, in general, to

less than 1% error. The world-average IOT often provides a good representation of the aggregate RoW.

Our analysis covers two aspects. These are, estimating the RoW in the WIOT and estimating the emission intensities in the RoW. With respect to estimating the RoW, several studies, have used other economies as proxies of the RoW's production technology. For example, Lenzen et al. (2004) used Australia. Other studies have used information from more than one economy to produce proxies. For example, Lenzen et al. (2004) also used the world-average technology (as an alternative to using Australia's technology). Peters and Hertwich (2006a) assigned the German, Danish or Swedish technology to most European countries, the Japanese technology to highly industrialized Asian countries, and the Chinese technology to developing countries. The GTAP database divides the world into geo-political regions and each region has a 'Rest of the Region' (Dimaranan, 2006). For example, the North American region includes Canada, the US and Rest of North America, which covers Bermuda, Greenland, and Saint Pierre and Miquelon. The technology in the Rest of North America is a weighted average of Canada and the US. This 'Rest of the Region' approach allows a greater geographical distinction without extra data requirements. Weber and Matthews (2008) focus on the US economy and included the top seven trading partners. The remaining countries were each grouped with one of these seven countries, using cluster analysis and additional data from Esty et al. (2005) and the International Energy Agency (IEA, 2005). It essentially mirrors the GTAP 'Rest of the Region' approach, but using a technological rather than a geopolitical classification. Dietzenbacher et al. (2013) used the production structures of six countries (Brazil, Russia, India, China, Indonesia, Mexico) in connection with aggregate data from the UN National Accounts to estimate the domestic deliveries in RoW in WIOD.

Some studies construct a single RoW (Lenzen et al., 2004; Weber and Matthews, 2007, 2008; Dietzenbacher et al., 2013) while other studies group separate RoW countries together with the included countries on the basis of similarity (Dimaranan, 2006; Peters and Hertwich, 2006a, 2006b). Empirically, one RoW block is easier to deal with and is less demanding in terms of data requirements. In this study we, consider only the case where RoW is represented as a single block (or as a single country). We compare several of the methods mentioned above to estimate the RoW's production structure. These are: (i) use the world-average, which is the baseline model in this test; (ii) use one country's production technology, viz. Australia or the US; (iii) assign the German technology to European countries, the US technology to American countries, the Japanese technology to industrialized Asian countries, and the Chinese technology to Asian developing countries; (iv) assume that the economies in the 'Rest of the Region' employ technologies that are the unweighted average of the other countries in their region.

With respect to estimating the emission intensities in the RoW, Weber and Matthews (2007) and Weber (2008) used the US intensities as a proxy for the RoW. Weber and Matthews (2007) performed a sensitivity analysis using emission intensities in the highest and in the lowest carbon intensive economies in their database as proxy for RoW. They report a variation in the results that amounts to 20% of the total embodied emissions. Also Ahmad and Wyckoff (2003) performed a sensitivity analysis comparing the use of US, China's and France's emission intensities for the RoW. They found considerable variation due to this uncertainty, about 20% of total embodied emissions of CO₂. Andrew et al. (2009) compared using the domestic emission intensities and world-average emission intensities for the RoW in their Domestic Technology Assumption models.⁴⁷ Their results

⁴⁷ There are a focal country and a RoW in the Domestic Technology Assumption model. The emissions from the production of imported products are estimated using the domestic technology, rather than the technology of the country of origin.

show that using world-average emission intensities is generally better. In this study, we employ both the true emission intensity of the RoW and the world-average emission intensities in each model, so that we can test whether the true emission intensities of the RoW brings significant improvements in the estimations.

The next section presents the methodology and discusses the five cases. Section 3 presents the detailed results for each of the cases and Section 4 draws conclusions.

5.2 METHODOLOGY

5.2.1 The Benchmark Model

The benchmark model we adopt is based on the MRIO table in the WIOD database. The table is for 2006 and the data are in millions of US dollars. It lists 35 sectors and 40 countries, and is matched to data for sectoral CO₂ emissions. The total GDP of the 40 countries is approximately 85% of the global GDP. The WIOD table includes an estimate for RoW as a 41st country. We will term it Zutopia in this study (to avoid confusion between the RoW from the WIOD table, which we take as given, and the 41 RoWs that we will estimate in this study). The matrix of intermediate deliveries from the 41-country MRIO table is given by

$$\mathbf{Z} = \begin{bmatrix} \mathbf{Z}^{11} & \mathbf{Z}^{12} & \dots & \mathbf{Z}^{1,N-1} & \mathbf{Z}^{1N} \\ \mathbf{Z}^{21} & \mathbf{Z}^{22} & \dots & \mathbf{Z}^{2,N-1} & \mathbf{Z}^{2N} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{Z}^{N-1,1} & \mathbf{Z}^{N-1,2} & \dots & \mathbf{Z}^{N-1,N-1} & \mathbf{Z}^{N-1,N} \\ \mathbf{Z}^{N1} & \mathbf{Z}^{N2} & \dots & \mathbf{Z}^{N,N-1} & \mathbf{Z}^{NN} \end{bmatrix} \quad (5.1)$$

where $\mathbf{Z}^{rs}$ for $r, s = 1, 2, \dots, N$, represents the matrix with intermediate deliveries z_{ij}^{rs} from sector i in region r to sector j in region s (with $i, j = 1, 2, \dots, n$). In our empirical application we have $n = 35$ and $N = 41$. The input coefficients are obtained as $a_{ij}^{rs} = z_{ij}^{rs}/x_j^s$, where x_j^s gives the gross domestic output of sector j in region s . The input matrix $\mathbf{A}$ has the same structure as the matrix $\mathbf{Z}$ in (1), replacing $\mathbf{Z}^{rs}$ by $\mathbf{A}^{rs}$. The final demands are given by the matrix $\mathbf{F}$ and the direct emission coefficients by the vector $\mathbf{w}$. That is,

$$\mathbf{F} = \begin{bmatrix} \mathbf{f}^{11} & \mathbf{f}^{12} & \dots & \mathbf{f}^{1,N-1} & \mathbf{f}^{1N} \\ \mathbf{f}^{21} & \mathbf{f}^{22} & \dots & \mathbf{f}^{2,N-1} & \mathbf{f}^{2N} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{f}^{N-1,1} & \mathbf{f}^{N-1,2} & \dots & \mathbf{f}^{N-1,N-1} & \mathbf{f}^{N-1,N} \\ \mathbf{f}^{N1} & \mathbf{f}^{N2} & \dots & \mathbf{f}^{N,N-1} & \mathbf{f}^{NN} \end{bmatrix} \text{ and } \mathbf{w} = \begin{bmatrix} \mathbf{w}^1 \\ \mathbf{w}^2 \\ \vdots \\ \mathbf{w}^{N-1} \\ \mathbf{w}^N \end{bmatrix} \quad (5.2)$$

where $\mathbf{f}^{rs}$ gives the final demand vector (for household consumption, private investments and government expenditures) in region s for products produced in region r . The direct emission coefficients in $\mathbf{w}^r$ for region r are given by $w_j^r = e_j^r/x_j^r$, the total amount of direct CO₂ emissions (in Kilotons) in sector j in region r per million US dollar of its production.

The global CO₂ emissions involved in the final demands (both domestically produced and imported) of the ‘consumers’ (i.e. households, government and investors) of country r are given by

$$p_r = \mathbf{w}'(\mathbf{I} - \mathbf{A})^{-1}\mathbf{f}^{\bullet r} \quad (5.3)$$

Where $\mathbf{f}^{\bullet r}$ indicates the r th column of the matrix $\mathbf{F}$. p_r is also known as the consumer responsibility of country r and reflects the part of the carbon footprint that is related to the production of goods

and services (the other part is related to the actual consumption of goods and services). Note that the consumer responsibility of country r is given by the r th element of the vector $\mathbf{p}' = \mathbf{w}'(\mathbf{I} - \mathbf{A})^{-1}\mathbf{F}$.

The results from equation (5.3) are viewed as the “true” emissions that will be used later to make comparisons with results obtained with tables with imperfect information. In this study, we will discuss various possibilities for the case where information for one country is lacking. This “missing” country then plays the role of the RoW and we can check how the errors depend on the size and type of the RoW and on the amount of missing information.

5.2.2 The Model when Information for One Country is Incomplete

In this model, we assume that the data for one country are not available or only partly available. For the sake of notational convenience, we will assume that this is the case for country N . Note that country N may be interpreted as RoW, because the original dataset is a full world IO table, i.e. it covers all countries. Comparing the outcomes obtained from this model with the outcomes from the benchmark model, thus sheds light on the role of RoW. In practical cases, it is impossible to obtain a true world IO table, which means that there is always an RoW for which (part of the) information is lacking. In the empirical application we will run the calculations for the deletion of each of 41 countries. Some countries are large (e.g. US) and others are small but highly dependent on imports (e.g. Belgium). In this way we will have a substantial variation in the characteristics of the RoW.

For this model, we distinguish several cases, depending on the amount of information that is available for the RoW (i.e. country N). In case A, we assume that no information is available. That is, the consumer responsibilities in (5.3) are calculated for $r = 1, 2, \dots, N-1$, where $\mathbf{A}$ and $\mathbf{f}^r$ are now replaced by

$$\tilde{\mathbf{A}} = \begin{bmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} & \dots & \mathbf{A}^{1,N-1} & \mathbf{0} \\ \mathbf{A}^{21} & \mathbf{A}^{22} & \dots & \mathbf{A}^{2,N-1} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{A}^{N-1,1} & \mathbf{A}^{N-1,2} & \dots & \mathbf{A}^{N-1,N-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \end{bmatrix} \text{ and } \tilde{\mathbf{f}}^{\bullet r} = \begin{bmatrix} \mathbf{f}^{1r} \\ \mathbf{f}^{2r} \\ \vdots \\ \mathbf{f}^{N-1,r} \\ \mathbf{0} \end{bmatrix} \quad (5.4)$$

For case B, it assumed that each country j ($j = 1, 2, \dots, N-1$) has information on its own intermediate and final imports from RoW (i.e. country N). Again, the consumer responsibilities in (5.3) are calculated for $r = 1, 2, \dots, N-1$, and where $\mathbf{A}$ and $\tilde{\mathbf{f}}^{\bullet r}$ are replaced by

$$\tilde{\mathbf{A}} = \begin{bmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} & \dots & \mathbf{A}^{1,N-1} & \mathbf{0} \\ \mathbf{A}^{21} & \mathbf{A}^{22} & \dots & \mathbf{A}^{2,N-1} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{A}^{N-1,1} & \mathbf{A}^{N-1,2} & \dots & \mathbf{A}^{N-1,N-1} & \mathbf{0} \\ \mathbf{A}^{N1} & \mathbf{A}^{N2} & \dots & \mathbf{A}^{N,N-1} & \mathbf{0} \end{bmatrix} \text{ and } \tilde{\mathbf{f}}^{\bullet r} = \begin{bmatrix} \mathbf{f}^{1r} \\ \mathbf{f}^{2r} \\ \vdots \\ \mathbf{f}^{N-1,r} \\ \mathbf{f}^{Nr} \end{bmatrix} \quad (5.5)$$

It is clear that case A yields an underestimate of case B, which itself underestimates the “true” outcomes from the benchmark model.

In case C, we assume that information is available for the matrix of technical input coefficients of country N . That is, the consumer responsibilities in (5.3) are calculated for $r = 1, 2, \dots, N-1$, where $\tilde{\mathbf{A}}$ and $\tilde{\mathbf{f}}^{\bullet r}$ are given by

$$\tilde{\mathbf{A}} = \begin{bmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} & \dots & \mathbf{A}^{1,N-1} & \mathbf{0} \\ \mathbf{A}^{21} & \mathbf{A}^{22} & \dots & \mathbf{A}^{2,N-1} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{A}^{N-1,1} & \mathbf{A}^{N-1,2} & \dots & \mathbf{A}^{N-1,N-1} & \mathbf{0} \\ \mathbf{A}^{N1} & \mathbf{A}^{N2} & \dots & \mathbf{A}^{N,N-1} & \mathbf{A}^N \end{bmatrix} \text{ and } \tilde{\mathbf{f}}^{\bullet r} = \begin{bmatrix} \mathbf{f}^{1r} \\ \mathbf{f}^{2r} \\ \vdots \\ \mathbf{f}^{N-1,r} \\ \mathbf{f}^{Nr} \end{bmatrix} \quad (5.6)$$

and $\mathbf{A}^N = \sum_{r=1}^N \mathbf{A}^{rN}$. When using (5.5) in model B, the direct emissions for producing the imports from RoW were included, but not the indirect emissions. Using (5.6) in model C assumes that the imports from the RoW are entirely produced in the RoW (i.e. require no imports from any of the countries 1, 2, ..., N-1). In particular when the production in country N relies heavily on imported inputs and the direct emission coefficients of country N differ substantially from those in other countries, model C may be expected to yield considerable differences with the benchmark case.

Case D also employs (5.6), but it is assumed that the matrix of technical input coefficients for country N is not known (which reflects the actual situation). Instead, it is estimated by the unweighted average of technical input matrices of the other 40 countries. That is, define the technical input matrix for country s ($= 1, 2, \dots, N-1$) as $\mathbf{A}^s = \sum_{r=1}^N \mathbf{A}^{rs}$. The average matrix is then given by $\bar{\mathbf{A}}^N = \sum_{r=1}^{N-1} \mathbf{A}^r / (N-1)$. For model D, $\mathbf{A}^N$ in (5.6) is replaced by $\bar{\mathbf{A}}^N$.

In case E, we assume that information is available for the total exports from country r ($r = 1, 2, \dots, N-1$) to the RoW and total domestic deliveries of the RoW (i.e. country N). This vector can be expressed as,

$$\mathbf{e}^{\bullet N} = \begin{bmatrix} \mathbf{Z}^{1N} \\ \mathbf{Z}^{2N} \\ \vdots \\ \mathbf{Z}^{N-1,N} \\ \mathbf{Z}^{NN} \end{bmatrix} \mathbf{1} + \begin{bmatrix} \mathbf{f}^{1N} \\ \mathbf{f}^{2N} \\ \vdots \\ \mathbf{f}^{N-1,N} \\ \mathbf{f}^{NN} \end{bmatrix} = \begin{bmatrix} \mathbf{e}^{1N} \\ \mathbf{e}^{2N} \\ \vdots \\ \mathbf{e}^{N-1,N} \\ \mathbf{e}^{NN} \end{bmatrix} \quad (5.7)$$

where $\mathbf{1}$ is a column vector of n ones. The technical coefficients of country N , $\mathbf{A}^N$ in (5.6), can be split into the N matrices using the information from $\mathbf{e}^{\bullet N}$. Define the imports from r (in case $r \neq N$) or the domestic deliveries of N (in case $r = N$) as a share of the total supply in country N of good j as

$$\sigma_j^{rN} = e_j^{rN} / \sum_{r=1}^N e_j^{rN}$$

The split of $\mathbf{A}^N$ yields the following estimates for $\mathbf{A}^{rN}$

$$\tilde{\mathbf{A}}^{rN} = \hat{\sigma}^{rN} \mathbf{A}^N \quad (5.8)$$

where a “hat” is used to indicate a diagonal matrix. The consumer responsibilities in (5.3) are calculated for $r = 1, 2, \dots, N-1$, where $\tilde{\mathbf{A}}$ and $\tilde{\mathbf{f}}^{\bullet r}$ are given by

$$\tilde{\mathbf{A}} = \begin{bmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} & \dots & \mathbf{A}^{1,N-1} & \tilde{\mathbf{A}}^{1N} \\ \mathbf{A}^{21} & \mathbf{A}^{22} & \dots & \mathbf{A}^{2,N-1} & \tilde{\mathbf{A}}^{2N} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{A}^{N-1,1} & \mathbf{A}^{N-1,2} & \dots & \mathbf{A}^{N-1,N-1} & \tilde{\mathbf{A}}^{N-1,N} \\ \mathbf{A}^{N1} & \mathbf{A}^{N2} & \dots & \mathbf{A}^{N,N-1} & \tilde{\mathbf{A}}^{NN} \end{bmatrix} \text{ and } \tilde{\mathbf{f}}^{\bullet r} = \begin{bmatrix} \mathbf{f}^{1r} \\ \mathbf{f}^{2r} \\ \vdots \\ \mathbf{f}^{N-1,r} \\ \mathbf{f}^{Nr} \end{bmatrix} \quad (5.9)$$

In general, it is unlikely that information for the emission coefficients in the RoW is known. In order to estimate the effect of this we run the five models above twice.⁴⁸ Models A, B1, C1, D1 and E1 apply equation (5.3) straightforwardly, i.e. $\tilde{\mathbf{p}}_r = \mathbf{w}'(\mathbf{I} - \mathbf{A})^{-1} \tilde{\mathbf{f}}^{\bullet r}$. Models B2, C2, D2 and E2 also use this equation, but the emission coefficients of RoW (i.e. country N) are estimated by the average emission coefficients of the other 40 countries. That is, in equation (5.2), $\mathbf{w}^N$ is replaced by

⁴⁸ Because model A assumes that no information on the RoW is available, it does not use any emission coefficients for the RoW. Hence there is only one model type A.

$\bar{\mathbf{w}}^N = \sum_{r=1}^{N-1} \mathbf{w}^r / (N-1)$ which gives us $\tilde{\mathbf{w}}$. The consumer responsibility of country r is then obtained as $\tilde{p}_r = \tilde{\mathbf{w}}'(\mathbf{I} - \mathbf{A})^{-1}\tilde{\mathbf{f}}^r$.

In our empirical application, we will calculate the average effect (as a percentage error) on the consumer responsibility. For the benchmark model we have $p_r = \mathbf{w}'(\mathbf{I} - \mathbf{A})^{-1}\tilde{\mathbf{f}}^r$, and for each of the nine types of the model without country N , we have $\tilde{p}_r = \mathbf{w}'(\mathbf{I} - \mathbf{A})^{-1}\tilde{\mathbf{f}}^r$ or $\tilde{p}_r = \tilde{\mathbf{w}}'(\mathbf{I} - \mathbf{A})^{-1}\tilde{\mathbf{f}}^r$ for $r = 1, 2, \dots, N-1$. The percentage error in the consumer responsibility of country r is given by $100 \times (\tilde{p}_r - p_r)/p_r$. For the ease of exposition, we have designated the country that is omitted from the benchmark model as country N . Clearly this can be any one of the 41 countries. Omitting country i ($= 1, \dots, 41$) yields a percentage error for country j ($= 1, \dots, 41, j \neq i$), PE_{ij} .

The weighted average percentage error (WAPE, which is often used for this type of analysis, see e.g. Lahr, 2001) for omitted country i is given by $WAPE_i = 100 \times \sum_{j \neq i} PE_{ij} (p_j / \sum_{j \neq i} p_j)$. The idea of using true consumer responsibilities as weights is that it is more important to have small errors for countries with large responsibilities than for countries with small responsibilities. Note that this WAPE also gives us the error in the total emissions (i.e. those related to the production of goods and services) of the remaining 40 countries, due to the omission of country i . For many purposes, this is a very reasonable perspective. However, less so when taking a policy viewpoint (e.g. each country aims at reducing its responsibility by 10%, in which case also the errors for countries with small responsibilities are relevant). Therefore, we also calculate the simple (i.e. unweighted) average percentage error (APE) for country i , which is given by $APE_i = 100/(N-1) \times \sum_{j \neq i} PE_{ij}$. Finally, to check which country is “hurt” most, we calculate the percentage error for country j , averaged over all 40 cases where country i ($\neq j$) is omitted. That is, $APE2_j = 100/(N-1) \times \sum_{i \neq j} PE_{ij}$.

5.2.3 Different Methods to Estimate the RoW's technology in Case E

In Case E the matrix of technical input coefficients $\mathbf{A}^N$ for country N is estimated by the unweighted average of technical input matrices of the other 40 countries. Instead, we could also apply other methods, which were adopted in previous studies. First, we assign one country's production technology to the RoW. Weber and Matthews (2007) used the US, while Lenzen et al. (2004) used Australia. We ran models E twice, once using Australia's technology and once using the US technology. Second, similar to Peters and Hertwich (2006a), we separate countries according to their region and assign a representative country to the countries in the region. In this experiment, we assign the German technology to the RoW in case a European country is missing. Similarly, the US technology is used if an American country is missing (and thus plays the role of RoW), the Japanese technology if an industrialized Asian country is missing and the Chinese technology if an Asian developing country is missing. Each country's regional representative country is listed in Table A5.1 of the Appendix. Finally, we apply the 'Rest of Region' approach by dividing countries into three regions: Europe, Asia and America. Each missing country will be estimated by the average technology of the other countries in its own region. For example, if the US is the missing country and is thus considered as RoW, its production technology will be estimated by the average of the other American countries in WIOD. The name of countries and their region are presented in Table A5.1 in the Appendix. Note that in the last two approaches, the country Zutopia does not belong to any single region. The technical input coefficients of Zutopia are estimated by the average coefficients of all 40 other countries. Similar to the estimations in subsection 5.2.2, the true emission coefficients are known under model E1, in model E2 they are estimated by the average emission coefficients of the other 40 countries.

5.3 RESULTS

5.3.1 The case where no information is available for the RoW

The results for model A are shown in the columns 2 to 4 of Table 5.1. Omitting a country from the world IO table and assuming that no information is available for this country, induces a underestimation of the consumer responsibility in each of the other 40 countries. For example, omitting Australia underestimates the consumer responsibility in Austria, in Belgium, etcetera. On average, this underestimation amounts to -0.5% if the weighted average (WAPE) is used and -0.4% if the unweighted average (APE) is used.⁴⁹ For 32 countries we find that their omission produces an underestimation of the average consumer responsibility by no more than 1.0%. For Germany, India, Japan, Korea, Russia, Taiwan and the US, the average error is between -1.0% and -3.0%. The only cases with considerable average errors are China and Zutopia with an underestimation of the true responsibility with 8.7% and 10.0%, respectively.

This suggests that a complete lack of information on a single country produces relatively small errors, even when the omitted country is very large and/or influential, China being the single exception. Clearly, China is an important producer of goods that are imported by many countries and the imports from China are not included in model A.⁵⁰ Hence also the emissions involved in producing these imports are not included. In the case of China, another factor that plays a substantial role (as we will show later) is that its emission intensities are relatively large. Both aspects explain why the errors are so large in the case of China. Zutopia is the actual RoW in the WIOD database and contains more than one hundred countries. Missing Zutopia causes a 10% underestimation of the consumer responsibility on average. This suggests that leaving out a large group of countries may lead to a

⁴⁹ Hereafter, “average error” will refer to the weighted average percentage error (WAPE).

⁵⁰ Also the exports from any country to China (i.e. China’s imports) are not taken into account. In the case of model A, however, they only have a second-order effect.

serious underestimation of consumer responsibilities, even though their total GDP only takes less than 15% of the world total. The explanation for the size of the average error is similar to that for China. That is, all countries depend on imports from the true RoW (i.e. Zutopia) and the RoW exhibits large emission intensities.

Comparing the weighted and the unweighted averages (i.e. WAPes and APes), we see that for most countries the findings are very comparable. There are a few exceptions, however. For example, for Germany we see that the unweighted average error is -6.1%, whereas the weighted average error is only -2.4%. The reason is that omitting Germany leads to relatively large errors (more than 10%, up to 23%) in small countries (Austria, Belgium, Luxemburg and Slovenia) that rely on imports from Germany but are not so relevant in terms of emissions. The same is observed (but to a lesser extent) for a couple of other European countries and for Russia. Observe that almost all countries have a WAPE that is smaller (in absolute sense) than the APE, Canada and China being the most important exceptions. In the case of China, all countries import Chinese intermediate products, including the major contributors to global emissions. These major contributors have a large weight in the WAPE calculation and show an error in their consumer responsibility that is usually larger (in absolute sense) than -8.1% (i.e. the value of the APE). In the case of Canada, the difference between APE and WAPE stems from the -2.8% error in the consumer responsibility of the US (which plays a substantial role in terms of emissions).

Table 5.1: Average % errors for models A to E.

Models	A			B1	B2	C1	C2	D1	D2	E1	E2
Countries	WAPE	APE	APE2	WAPE	WAPE	WAPE	WAPE	WAPE	WAPE	WAPE	WAPE
Australia	-0.5	-0.4	-1.0	-0.3	-0.1	0.0	0.1	0.1	0.2	0.1	0.2
Austria	-0.3	-0.8	-2.6	-0.2	-0.1	-0.1	0.3	-0.1	0.2	0.0	0.2
Belgium	-0.6	-1.7	-2.6	-0.4	-0.2	-0.2	0.4	-0.2	0.5	0.0	0.3
Brazil	-0.3	-0.3	-1.0	-0.2	-0.1	0.0	0.2	0.0	0.2	0.0	0.2
Bulgaria	-0.1	-0.4	-1.1	-0.1	-0.1	0.0	0.0	0.0	-0.1	0.0	-0.1
Canada	-1.0	-0.6	-1.4	-0.6	-0.4	-0.1	0.2	0.2	0.6	0.2	0.6
China	-8.7	-8.1	-0.3	-7.6	-7.8	2.2	-2.6	-2.8	-5.3	-3.2	-5.4
Cyprus	0.0	0.0	-1.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Czech Republic	-0.4	-1.1	-1.3	-0.3	-0.3	0.1	0.0	0.0	0.0	0.0	0.0
Denmark	-0.4	-0.6	-2.2	-0.2	-0.1	-0.1	0.1	0.0	0.2	0.0	0.1
Estonia	0.0	-0.3	-1.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Finland	-0.2	-0.6	-1.7	-0.2	-0.1	0.0	0.1	0.0	0.1	0.0	0.1
France	-0.8	-1.6	-2.1	-0.6	-0.2	-0.2	0.8	-0.2	1.1	0.1	0.9
Germany	-2.4	-6.1	-1.8	-1.7	-1.2	-0.5	0.9	0.1	1.8	0.5	1.6
Greece	-0.2	-0.4	-1.3	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0
Hungary	-0.2	-0.5	-1.9	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0
India	-1.2	-1.2	-0.5	-0.9	-1.0	0.2	-0.5	0.1	-0.6	-0.1	-0.6
Indonesia	-0.5	-0.5	-0.7	-0.2	-0.3	0.0	-0.2	0.4	-0.1	0.2	-0.1
Ireland	-0.2	-0.2	-2.1	-0.1	0.0	-0.1	0.1	0.0	0.3	0.0	0.2
Italy	-0.9	-2.1	-1.7	-0.7	-0.4	-0.2	0.8	-0.3	0.7	0.0	0.6
Japan	-1.5	-1.3	-1.1	-1.1	-0.9	-0.1	0.8	-0.2	0.8	0.0	0.8
Korea	-1.2	-1.1	-1.1	-1.0	-0.9	0.3	0.3	0.0	0.0	-0.2	0.0
Latvia	0.0	-0.1	-2.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Lithuania	-0.1	-0.3	-2.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Luxembourg	-0.1	-0.1	-2.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Malta	0.0	0.0	-1.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mexico	-0.5	-0.3	-1.1	-0.4	-0.3	-0.1	0.1	0.0	0.3	0.1	0.3
Netherlands	-0.9	-1.8	-2.1	-0.5	-0.4	-0.2	0.3	-0.1	0.4	0.0	0.3
Poland	-0.6	-1.8	-0.9	-0.4	-0.4	0.1	-0.1	0.1	-0.1	0.0	-0.1
Portugal	-0.1	-0.2	-1.7	-0.1	-0.1	0.0	0.1	0.0	0.1	0.0	0.0
Romania	-0.2	-0.4	-1.1	-0.1	-0.1	0.0	0.0	0.0	-0.1	0.0	-0.1
Russia	-2.6	-6.0	-0.4	-1.6	-2.1	0.1	-1.4	-0.1	-1.5	-0.3	-1.5
Slovak Republic	-0.2	-0.5	-1.9	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0
Slovenia	-0.1	-0.1	-2.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Spain	-0.6	-1.3	-1.7	-0.4	-0.3	-0.1	0.4	-0.1	0.3	0.0	0.2
Sweden	-0.3	-0.6	-2.6	-0.2	-0.1	-0.1	0.2	-0.1	0.3	0.0	0.2
Taiwan	-1.1	-0.9	-1.2	-0.8	-0.9	2.6	-0.3	1.4	-0.4	-0.1	-0.3
Turkey	-0.3	-0.6	-1.2	-0.2	-0.2	0.0	0.0	0.0	0.0	0.0	0.0
United Kingdom	-0.9	-1.9	-1.8	-0.5	-0.3	-0.2	0.7	0.0	0.9	0.2	0.9
United States	-3.0	-3.0	-0.9	-2.0	-1.8	-0.3	0.1	1.1	1.2	1.2	1.2
Zutopia	-10.0	-13.0	-0.9	-6.0	-5.4	1.7	1.0	1.9	0.4	0.6	0.5

Note: The APE and APE2 for models B to E are not included, but they are available upon request.

The fourth column in Table 5.1 indicates which country is on average affected the most if one country is omitted from the analysis. For example, the detailed results for Australia (which are not shown in Table 5.1) indicate that its consumer responsibility is underestimated by 0.2% if Austria is omitted, 0.3% if Belgium is left out, but 2.6% and 10.1% if the US resp. China are deleted. On average, the underestimation of the Australian consumer responsibility amounts to 1.0% (as listed in Table 5.1). The largest errors (between -2.5 and -2.6%) are found for Austria, Belgium, Luxembourg and Sweden, for any other country the error is less (in absolute sense) than -2.5%. In general, most European countries are relatively small and their production depends relatively much on imported intermediate products. The average error is for them usually between -1.0 and -2.2%. The countries that are least affected are China, India and Russia, with an average underestimation of only 0.3% to 0.5%. Those countries are very large and do not depend strongly on imports for their production. From the detailed results for China, for example, we find that only the omission of Japan, Korea, Taiwan and Zutopia produces an underestimation larger than 1% (1.1%, 1.2%, 1.3%, and 4.4%, respectively). India's consumer responsibility is underestimated by more than 1% only if China (3.2%) and Zutopia (8.6%) are omitted from the world IO model. Russia's consumer responsibility is underestimated by more than 1% if China (-2.9%), Zutopia (-3.1%) or Germany (-1.3%) is omitted.

5.3.2 The case where only information is available for countries' imports from the RoW

Take for example the case of calculating the consumer responsibility of France when the US has been omitted from the model. As we have mentioned before, an important aspect in the underestimation of the French consumer responsibility in model A is that the US emissions embodied in the imported intermediate products from the US are not taken into account. The next step (i.e. model B) is to assume that information is available with respect to the full import matrices for intermediate inputs

exported by the US. In that case, the emissions in the US that are directly involved in producing its export products are included. What is still missing are the second-order effects (i.e. emissions in the inputs necessary for producing the US exports).

Columns 5 and 6 in Table 5.1 give the results for the models B (i.e. B1 and B2).⁵¹ For model B1 (using the true emission coefficients for the omitted country), it can be shown analytically that there will still be an underestimation of the consumer responsibilities but also that this underestimation is smaller than for model A. The results show that there is a reduction in the underestimation by 0.3% (i.e. the overall average underestimation reduces from 1% in model A to 0.7% in model B1). Only six countries have an average error (WAPE) that is (in absolute sense) larger than 1.0% (China, Germany, Japan, Russia, the US and Zutopia) for model B1 (which was nine countries for model A). Similar findings as for model A are found for the unweighted averages (APE) and for the average effect on a country's consumer responsibility (APE2).

Model B2 carries out the same exercise, except that the true emission coefficients for the omitted country (in model B1) are now replaced by the average sectoral emission coefficients (where the average is taken over the 40 remaining countries). At first glance, the results seem very comparable in terms of the sizes of the errors. Except for China, Germany, Russia, the US and Zutopia, omitting a country produces an average error in the consumer responsibilities of the other 40 countries that is no more than 1.0% in absolute sense. Closer inspection, however, shows that the estimation of the true emission coefficients may increase but also decrease the underestimation found in model B1. For example, omitting Canada yields an average error in the consumer responsibilities of -0.6% when the true Canadian emission coefficients are used (i.e. model B1) and -0.4% when the Canadian emission

⁵¹ The APE and APE2 for models B to E are not presented in this chapter but are available upon request.

coefficients are estimated by the average emission coefficients. For China we find the opposite result that the underestimation is increased (the average error is -7.6% in model B1 and -7.8% in model B2).

Take the case of China as an example. For the calculation of the consumer responsibility of country r (other than China), we first calculate the outputs in each and every country (including China) that produces exports to country r . The resulting outputs are exactly the same for models B1 and B2. Next, it is calculated how much emissions are involved in producing these outputs. In model B1, we use the true Chinese emission coefficients, which in most sectors are larger than the average emission coefficients that are used in model B2.⁵² Hence, in the case of China, we find that the calculated consumer responsibility for each country r is smaller for model B2 than for model B1. We know that the consumer responsibilities in model B1 underestimate the true consumer responsibilities. So, the underestimation becomes larger for countries that have emission coefficients that are larger than average. Next to China, this also applies to Indonesia, India and Russia. For relatively clean producing countries (i.e. with emission coefficients smaller than average) the opposite occurs. That is, the underestimation in model B1 becomes smaller when model B2 is used. For instance the underestimation for Germany reduces from 1.7% to 1.2% and for France it drops from 0.6% to 0.2%.

For the case of Zutopia, the underestimation reduces from 6.0% to 5.4%. Zutopia's emission intensities are larger than the world average in 7 sectors but are smaller in the other 28 sectors. Therefore, the direction of changes from B1 to B2 depends on sectoral exports of Zutopia to each country. The underestimation in model B1 becomes smaller in model B2 for 19 out of 40 countries, including the US, China, Japan and Germany. However, these 19 countries take 81% of intermediate products exports and 76% of final products exports from the Zutopia. As a result, the weighted average errors become smaller in case of Zutopia when the world average emission intensities are

⁵² The true Chinese emission coefficients are larger than the world average emission coefficients in 25 out of 35 sectors.

applied. All in all, however, our main conclusion from comparing models B1 and B2 is that estimating the emission coefficients has relatively little effect on the underestimation.

5.3.3 The case where information is available for the true technical input coefficients of the RoW

What is missing in the models of type B, are the second-order effects. Again, consider the example of calculating the consumer responsibility of France when the US has been omitted from the model. The French imports from the US require production in the US. For this production, however, inputs are required and these inputs are produced themselves, which requires further inputs, and so forth. In model C, we do take these second-order (or indirect) effects into account. That is, we assume that the true matrix with technical coefficients for country N (the US in this example) is available. These technical coefficients measure the intermediate inputs of good i (irrespective of the country of origin) per dollar of output in sector j in country N . Note however that these intermediate inputs for US production include products that are produced domestically as well as imported products (e.g. from Germany). The only difference between model C1 and the benchmark model is that model C1 performs as if all imported inputs from country N were entirely produced domestically in country N .

The results for model C1 are given in columns 7 and 8 in Table 5.1 and show that the errors are very small. The average error in measuring the consumer responsibilities of the remaining 40 countries if country N is omitted is (in absolute sense) no larger than 0.5%, except when China (+2.2%), Taiwan (+2.6%), or Zutopia (+1.7%) are omitted. Despite the fact that China has a very large domestic market, it is also heavily involved in processing trade (or offshoring) and its production structure thus shows a relatively large dependence on imported products. In the benchmark model, these imports come from countries such as the US and Germany with clean production technologies.

In model C1, however, it is assumed that these imported inputs are produced at home (i.e. in China) using the Chinese production techniques with relatively large emission coefficients. So, in comparison with the true answer (i.e. from the benchmark model), the outcomes for China from model C1 will thus be larger. This overestimation is larger for countries that strongly depend on Chinese exports than for countries that do not. For example, the consumer responsibilities of Japan and Korea are overestimated by more than 3.0%, and those of Bulgaria, the Czech Republic and Greece by less than 1.5%.⁵³

Note also that for some countries we find in column 7 an underestimation while for others we find overestimation. In terms of emissions, model C1 reports underestimation in cases where the omitted country produces in a relatively clean way. For instance, omitting Germany implies that in model C1 it is assumed that all German imports of intermediate products are entirely produced at home in Germany (and their production does not require inputs from China, for example). Because the German emission coefficients are smaller than the coefficients in most of the other countries, producing intermediate inputs entirely in Germany leads to a smaller amount of emissions than the actual production of intermediate inputs (which relies on Chinese inputs, for example). Negative average errors less than -0.1% are observed for Belgium, France, Germany, Italy, the Netherlands, the UK and the US.

The results for the unweighted average errors (APE) are very similar to those for the weighted average errors (WAPE). The errors are all extremely small for APE2, i.e. when we measure how much the consumer responsibility of a single country is on average biased due to omitting the other 40

⁵³ The detailed results showing how each country is affected by omitting country N are not included in this chapter. They are available upon request.

countries one by one. No reported average error is (in absolute sense) larger than 0.2%. This small size is to some extent explained from the fact that negative and positive errors cancel out.

The differences between the outcomes for model C1 (with true emission coefficients) and model C2 (with estimated coefficients) are qualitatively the same as the differences between models B1 and B2. That is, for clean countries (with true emission coefficients smaller than average), the underestimation for C1 is larger than for C2 (in which case they often even become an overestimation). However, quantitatively the differences between the C models are larger than those between the B models. The reason for this is as follows. Consider the example where France is deleted. Calculating the consumer responsibility of Germany for example includes imports of intermediate products from France. In model B, only the (French) emissions directly involved in producing the German imports from France are included. Model C, however, includes all production (and thus emissions) in France that is directly *and indirectly* involved in these imports of intermediates. The same applies to the German imports from France for final demand purposes (such as consumption). So, consumer responsibilities calculated with model C are larger than those obtained from model B.

This explains why the negative errors under B are less negative or even positive under C. This also enlarges the gap that is due to using estimated instead of true emission coefficients. Because more production is involved, the difference between using true emission coefficients and using average emission coefficients (with which the production is multiplied) also becomes larger. For example, for the US we have errors of -2.0% and -1.8% for models B1 and B2 respectively, and -0.3% and +0.1% for models C1 and C2 respectively. This enlargement of the gap also works in the other direction for countries with true emission coefficients that are larger than average. For China we find errors of -7.6% (B1) and -7.8% (B2), and +2.2% (C1) and -2.6% (C2).

For almost all countries, the results for C1 yield very small errors, China, Taiwan and Zutopia being the exceptions. This is because it is assumed that all inputs that are required in, for example, China to produce its exports of intermediate and final products are produced within China and therefore with Chinese emission coefficients. In reality, however, also China imports inputs and the assumption that Chinese emission coefficients (which are larger than average) are used thus yields a serious overestimation. The same applies to Taiwan and Zutopia.

5.3.4 The case where the technical input coefficients of the RoW are estimated

Model C1 rests on the assumption that the true technical coefficients matrix is known for the RoW. In the two models of type D, we estimate this matrix by the average technical coefficients matrix of the 40 countries for which full information is available. The results are given in columns 9 and 10 of Table 5.1. If we compare the outcomes for model D1 with those for model C1, we see that for the majority of countries the WAPE changes only marginally (i.e. 0.4% or less). Only for China, Germany, Taiwan and the US is the (absolute) difference between the two models 0.5% or more. Observe that these “large” differences are of a varied nature. The calculated consumer responsibilities decrease for China (turning an overestimation into an underestimation) and Taiwan, and increase for Germany and the US (in both cases turning an underestimation into an overestimation).

These results suggest that the latter countries are more efficient (in the sense of using less intermediate inputs per unit of output) than average, whereas the former two countries are less efficient than average. Recall that part of the consumer responsibility of France, for example, is determined by the Chinese emissions embodied in the French imports from China. These goods are assumed to be produced entirely in China (i.e. all inputs are produced domestically). The only difference between models C and D is for the matrix with technical input coefficients. If the results

for model C are larger than for model D (as is the case for China) the average coefficients used under D must—on average—be smaller than the true coefficients that are used under C.

Just like was the case with models B and C, also the differences between D2 and D1 essentially depend on how the true emission coefficients of the omitted country compare to the average coefficients. The differences between model D2 and D1 are very similar to those between model C2 and C1. The results of model D2 also confirm the finding in Andrew et al. (2009) that using world average technical coefficients and emission intensities for the RoW generally yield errors that are smaller than 1%.

5.3.5 The case where the import coefficients of the RoW are estimated

Although model D includes an estimate of technical coefficients for the RoW, all the inputs are assumed to be produced domestically. Model E includes a further refinement and splits the technical coefficients matrix of the RoW on the basis of the existing information of the exports at sectoral level of each country to RoW. Take, for example, the calculation of the consumer responsibility of France when the US has been omitted from the model. The French imports from the US require production in the US, but some inputs in the US production are imported from Canada, Mexico, China, and even from France. In model E, we estimate the US import coefficients by using the countries' total exports of each good to the US (which plays the role of RoW in this example) as additional information.

The results are given in the last two columns of Table 5.1. If we compare results for model E1 with those for model D1, we again find that for the majority of countries the average errors change only marginally (i.e. 0.4% or less). Taiwan and Zutopia are the exceptions and show serious reductions in their average errors. Both countries are important trading partners for many countries (including

the major players in the world) and use a large amount of imports in their production. Including an estimate of the import matrices for Taiwan and Zutopia is thus important. Observe that for China, Germany and the US, estimating import matrices does not lead to smaller (absolute) average errors. These are also the three countries with an absolute WAPE larger than 1.0% in models E.

Estimating the emission coefficients of the RoW causes the errors for model E2 to be larger than those for E1, in general. The differences between model E2 and E1 are very similar to those between model D2 and D1. When countries with the smallest emission coefficients (Japan, Germany and several other EU countries) are omitted, the estimated consumer responsibilities go up. The opposite result holds for countries with the largest emission coefficients (China, Russia, India). If we compare the outcomes for models E2 and D2, all the countries' average errors change less than 0.2%. In other words, if we have no information on the emission coefficients and the technical coefficients of the RoW, estimating import coefficients for the RoW does not improve the outcomes much.

5.3.6 Country-specific errors

So far, we have focused on average errors. It goes without saying that such averages hide a large amount of results. Therefore, Tables 5.2 and 5.3 provide an overview of all individual errors (EP_{ij}) larger than 10%, which are termed “large errors”. Table 5.2 gives the large errors in the case of model A. If Zutopia is omitted from the benchmark model, the consumer responsibility of no less than 29 (out of 40) countries is underestimated by more than 10%. If China is omitted this holds for 13 countries and for 8 countries if Germany is omitted. Observe that Austria's consumer responsibility is underestimated by 25% if Germany is omitted. This points at another clear pattern, namely that large errors occur for the consumer responsibility of “small” neighboring countries when a “large”

country is omitted. That is, Italy is large when compared to its neighbor Malta, the same applies for Netherlands and Belgium, for Spain and Portugal, and for the UK and Ireland.

Adding more information decreases the number of large errors. China and Zutopia still matter, and neighbors still matter when we compare model A with the models of type B. Neighbors matter also in the next steps of adding information, i.e. going from models B to models D. Note that estimating China's and Zutopia's production technology by the world average has considerably reduced the errors. Errors larger than 10% are no longer found in models D when China and Zutopia are omitted. Omitting Germany, however, still causes several large errors in model D2. Some neighboring European countries depend to a considerable amount on imports from Germany. In model D, the efficient German production is estimated by the average, i.e. using more inputs than it actually does. German production embodied in its exports is thus too large in model D. If moreover the German emission coefficients are estimated larger than the true coefficients (in model D2), the end result will be a gross overestimation of German emissions involved in the exports to its European partners.

More information is added when we go from models D to models C (which uses the true technical input matrix) and E. The overestimation (in model D2) that was caused by adopting an average production structure that uses more inputs than are actually used in Germany is removed in model C2, but is not removed in model E2. The cases with errors larger than 10% are almost the same for models E2 and D2, and in general the errors are just a bit smaller in model E2. Note that when the true emission coefficients are used in models C1, D1 and E1 no individual errors are found that are larger than 10%.

Table 5.2: Percentage errors larger than 10% for model A.

Deleted country i	Affected country j	EP_j	Deleted country i	Affected country j	EP_j
Belgium	Luxemburg	-18.2	Zutopia	Australia	-13.7
China	Australia	-10.1		Austria	-16.7
	Canada	-11.7		Belgium	-20.8
	France	-10.4		Brazil	-13.6
	Germany	-10.4		Cyprus	-12
	Ireland	-10.6		Denmark	-17.1
	Japan	-13.7		Finland	-10.9
	Korea	-13.7		France	-20
	Luxemburg	-12		Germany	-14.3
	Malta	-15.6		Greece	-12.2
	Netherlands	-12.5		Hungary	-10.4
	Sweden	-10.3		Indonesia	-11.4
	Taiwan	-10.1		Ireland	-15.5
	United Kingdom	-10.2		Italy	-18.4
Germany	Austria	-25.1		Japan	-14.3
	Belgium	-16.8		Korea	-12.5
	Denmark	-11.1		Latvia	-15.5
	Hungary	-11.3		Lithuania	-15.8
	Luxemburg	-16.6		Luxemburg	-12.5
	Netherlands	-10.7		Malta	-15
	Slovenia	-12.1		Netherlands	-17.1
	Sweden	-11.5		Portugal	-13.9
Italy	Malta	-10.9		Slovak Republic	-17.1
Netherlands	Belgium	-10.4		Slovenia	-18.8
Russia	Estonia	-10.6		Spain	-15.6
	Finland	-12.9		Sweden	-20
	Hungary	-14.1		Taiwan	-13.6
	Lithuania	-24.7		Turkey	-12.9
	Latvia	-16.4		United Kingdom	-16.8
	Slovak Republic	-13.5			
Spain	Portugal	-13.2			
United Kingdom	Ireland	-16.1			
United States	Canada	-16.4			
	Mexico	-12.5			

Table 5.3: Percentage errors larger than 10% for models B, C, D and E.

Deleted country i	Affected country j EP_j	Affected country j EP_j
	Model B1	Model B2
Belgium	Luxemburg -13.5	
China	Canada -10.4 Japan -11.9 Korea -11.7 Luxemburg -10.5 Malta -11.8 Netherlands -10.7	Canada -10.6 Japan -12.2 Korea -12.1 Luxemburg -11.2 Malta -12.8 Netherlands -11.2
Germany	Austria -16.1 Luxemburg -11.5	Austria -12.8
Russia	Lithuania -15.4 Latvia -10.1	Lithuania -18.7 Latvia -12.8
United Kingdom	Ireland -10.6	
USA	Canada -12	Canada -10.6
Zutopia	Belgium -10.3 France -12 Italy -11.2 Netherlands -10.3 Slovenia -10.9 Sweden -11.3	Belgium -11.3 Denmark -11.2 France -10.4 Latvia -10.9 Lithuania -10.5 Netherlands -10.1 Slovak Republic -12.8 Slovenia -10.7 Sweden -13.4 United Kingdom -10.3
	Model C2	Model D2
Belgium	Luxemburg 12.7	Luxemburg 13.4
Germany		Austria 14.1 Belgium 11.7 Luxemburg 11.8
Russia	Lithuania -11.6	Lithuania -12.2
United Kingdom	Ireland 12	Ireland 16.6
	Model E2	
Germany	Austria 11.7 Belgium 10.3 Luxemburg 10.2	
United Kingdom	Ireland 14.8	
Russia	Lithuania -12.3	

In the graphs in Figure 5.1, we plotted the errors in models B to E against those in model A, where each graph contains 1600 dots. It is clear that the majority of errors is smaller than 10% in absolute terms. Comparing the graphs for model types 1 with the graphs for model types 2, we see that information with respect to the true emission coefficients of the omitted country reduces the errors considerably. In particular the number of cases with absolute errors larger than 5% becomes smaller. Comparing models C and D, we see that knowing the true technical coefficients (C) rather than estimates (D) reduces the errors only marginally. Knowing the true emission coefficients is more important than knowing the true technical coefficients. Even if the technical coefficients of the omitted country are unknown, having information about its emission coefficients considerably reduces the errors.

5.3.7 Comparing different methods for estimating RoW's technical coefficients

To compare different methods of estimating the RoW's technical coefficients, we extended model E into several cases as discussed in Section 2.3. These were, using Australia's technical coefficients for the omitted country (AUS), using US coefficients (US), using the coefficients of the "Regional Representative" (RR), and using the average coefficients in the "Rest of the Region" (RoR). Table 5.4 presents the weighted average errors (WAPes) for each of these models. Comparing the WAPes in the last two columns of Table 5.1 with those in Table 5.4 shows that the differences are not very large. It appears that estimating the omitted country's technical coefficients using Australian or US coefficients, increases the errors somewhat if a developing country is omitted (China, India, Russia and Zutopia). The regional representative approach clearly works best for models E2. The WAPE decreases in absolute terms for all countries (except Poland) and the improvements are sizeable for China, Russia and the US.

Figure 5.1: Error comparison of Model A, B, C, D and E

The graphs in Figure 5.2 consider all individual country-specific errors, instead of the averages as in Table 5.4. They plot the errors of models E1 (AUS, US, RR, RoR) against the errors of model E1 that uses average technical coefficients (which is used as the baseline model). Using the “Rest of the Region” approach produces outcomes very close to the baseline model (i.e. its errors lie very near the 45 degree line). Using Australian or US technical coefficients are hardly better than using the average technical coefficients. At the same time it is interesting to observe that for cases where the baseline produces positive errors, the errors become smaller (and even negative). For cases where the baseline errors are negative, the errors become more negative (i.e. larger in absolute size). The “Regional Representative” approach performs the best; its errors are grouped around a line with a slope that is less than 45 degrees. This indicates that errors become smaller in size. The outcomes for the various types of model E2 (in Figure 5.3) are similar to the finding for model E1, but with larger errors in general. For model E1 the majority of errors is smaller than 5% in absolute terms, while for model E2 they are between -10% and 10%. The “Regional Representative” approach again outperforms the other options. Its errors are again centered around a line with a smaller than 45 degree slope.

Table 5.4: Weighted average % errors for four approaches in models E

Countries	E1				E2			
	AUS	US	RR	RoR	AUS	US	RR	RoR
Australia	0.0	0.0	0.0	0.2	0.1	0.1	0.1	0.2
Austria	0.0	0.0	0.0	0.0	0.2	0.1	0.1	0.2
Belgium	-0.1	-0.1	-0.1	0.0	0.2	0.2	0.2	0.3
Brazil	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.1
Bulgaria	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1
Canada	0.1	0.1	0.1	0.1	0.4	0.3	0.3	0.4
China	-4.2	-4.9	-1.9	-3.9	-5.7	-6.1	-4.7	-5.7
Cyprus	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Czech Republic	0.0	-0.1	-0.1	0.0	0.0	-0.1	-0.1	0.0
Denmark	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1
Estonia	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Finland	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
France	0.0	0.0	-0.1	0.1	0.7	0.6	0.6	0.9
Germany	0.2	0.1	0.1	0.5	1.2	0.9	0.9	1.6
Greece	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Hungary	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
India	-0.2	-0.3	0.4	-0.2	-0.7	-0.7	-0.4	-0.6
Indonesia	0.1	0.1	0.5	0.1	-0.1	-0.1	0.1	-0.1
Ireland	0.0	0.0	0.0	0.0	0.2	0.1	0.1	0.2
Italy	-0.1	-0.2	-0.2	-0.1	0.5	0.4	0.4	0.6
Japan	-0.2	-0.3	-0.3	-0.1	0.5	0.3	0.3	0.6
Korea	-0.3	-0.4	-0.2	-0.3	-0.2	-0.3	0.0	-0.1
Latvia	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Lithuania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Luxembourg	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Malta	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mexico	0.0	-0.1	-0.1	0.0	0.2	0.1	0.1	0.1
Netherlands	0.0	0.0	-0.1	0.0	0.2	0.1	0.2	0.3
Poland	-0.1	-0.1	-0.1	0.0	-0.2	-0.2	-0.2	-0.1
Portugal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Romania	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1
Russia	-0.6	-0.7	0.6	-0.6	-1.6	-1.6	-1.0	-1.6
Slovak Republic	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Slovenia	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Spain	-0.1	-0.1	-0.1	0.0	0.2	0.1	0.1	0.2
Sweden	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.2
Taiwan	-0.2	-0.3	0.0	-0.1	-0.4	-0.5	-0.3	-0.4
Turkey	-0.1	0.0	-0.1	0.0	0.0	0.0	0.0	0.0
United Kingdom	0.1	0.1	0.0	0.2	0.7	0.6	0.6	0.9
United States	0.5	0.0	0.4	0.6	0.7	0.3	0.4	0.7
Zutopia	-1.2	-1.3	0.6	0.6	-0.7	-0.9	0.5	0.5

Note: 'AUS' means using Australia's technical coefficients for the omitted country;
 'US' means using US coefficients, 'RR' means using the 'Regional Representative' approach;
 'RoR' means using the 'Rest of Region' approach.

Figure 5.2: Error comparison of Models E1

Figure 5.3: Error comparison of Models E2

5.4 CONCLUSIONS

What lessons can be learned from this chapter? We have mimicked the problems, as caused by lacking information for the RoW, by omitting one country from an existing world input-output table. The various cases show what happened when additional information was added. Comparing the cases, we are able to draw the following set of conclusions.

First, serious biases may occur when the true emission coefficients in the omitted country are estimated by average emission coefficients. The direction of the errors depends on whether the omitted country produces emission intensive or not. For example, countries like Germany, the US and Canada have emission coefficients that are clearly smaller than average. Estimating the emission coefficients by average coefficients will then yield an upward bias in the consumer responsibilities. The opposite holds for countries like China, India and Russia. Any information on the nature of the emissions in the omitted country may help to remove part of the errors.

Second, another serious bias is caused by the fact that we have estimated the true technical coefficients matrix of the omitted country by the average matrix. In particular when a country is much more (less) efficient—in the sense of requiring less (more) inputs per unit of output—than average, estimating the technical coefficients will yield an upward (downward) bias in the consumer responsibilities. It should be noted that for most countries both effects (estimating the true emission coefficients and estimating the true technical coefficients) strengthen each other.

Third, if both biases can be removed fully, we arrive at model C1. No average error was larger than 0.3% in absolute sense, except for Germany (-0.5%), China (+2.2%), Taiwan (+2.6%) and Zutopia (+1.7%). In this case, the errors are caused by missing export vectors. For example, the consumer responsibility of a country depends on the (German) emissions embodied in imports from Germany. The question is how Germany produces these exported goods and services. In reality,

German production uses imported inputs in its production processes. In model C1, however, these are assumed to be produced entirely within Germany (with its high efficiency and low emission coefficients). The German exports to other countries thus embody less emissions than in reality, which yields a downward bias in the consumer responsibilities. The opposite holds for China and Taiwan, that both rely on processing imports from countries with a high efficiency and small emission coefficients.

Fourth, estimating the import matrices of the omitted country from the export vector of each country and estimating the true technical coefficients with the average coefficients matrix gave us models E. When compared to models D, the average errors changed only marginally.

Fifth, estimating the technical coefficients with the coefficients of the ‘Regional Representative’ country, instead of by the average technical coefficients, was the best approach with model E. The outcomes were close to those for model C (which uses the true technical coefficients, but estimates no import matrices of the omitted country). The consumer responsibility of no individual country has a bias larger than 10% bias in this case, even when the emission coefficients are estimated by average emission coefficients.

Finally, in general, omitting a “large” country from the world may affect the estimation of the consumer responsibility in its “small” neighbors or trading partners. Large and small do not necessarily reflect the size of a country. Rather the “small” country depends largely on imports of the omitted “large” country. For example, Belgium depends largely on imports from the Netherlands, both of which are of a small size. Typically, however, this import dependence occurs when the “small” country is also small in size and the “large” country is also large in size.

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CHAPTER 6

SUMMARY AND DIRECTIONS FOR FUTURE RESEARCH

This thesis focused on the relationship between international trade and environmental degradations. Input-output analyses were used to answer environmental research questions in a period of ongoing globalization and, in particular, in which final goods became “made in the world” (rather than in a single country). In this final chapter, we will review the research findings of this thesis and will discuss some potential directions of future research.

6.1 SUMMARY

The main research findings of each chapter in this thesis are summarized below.

Chapter 2 studied the carbon dioxide emissions embodied in trade (EET) in 40 major economies in the period from 1995 to 2007. The findings corroborated earlier research and indicated that emissions embodied in imports (EEI) grew faster than emissions embodied in exports (EEE) for many developed economies; while for some emerging economies (such as China and India) it was the other way round and the EEE grew particularly hard. Chapter 2 applied a structural decomposition analysis to find out what drove the changes in EET. We quantified the contribution to the changes in EET for a set of selected drivers. One key finding of this chapter is that change in the trade structure was the key driver of why the growth of EET was so uneven between the developed and the emerging economies. When buying intermediate inputs, producers all over the world have shifted from importing inputs from developed economies to importing inputs from emerging economies (and, in particular in the case of China, also to buying the inputs at home). The second key finding in Chapter 2 is that increases in final demand levels and decreases in emission intensities were important drivers

of the changes in EET. On average, the increases in the final demand levels led to more than 50% EEE (EEI) growth; while the decrease in the emission intensities brought about 30% EEE (EEI) reduction. To sum up, the crucial point in Chapter 2 is that developed countries, such as the US and the UK, did not play the same role in world production in 2007 as they did in 1995. As a result, developed countries maintained a large growth in “consuming” emissions but had relatively little growth of territorial emissions. The consequence was that this occurred at the expense of environmental conditions elsewhere.

Chapter 3 re-examined the Environmental Kuznets Curve (EKC) hypothesis using data for both the consumption-based and the territorial greenhouse gas (GHG) emissions. We found (weak) evidence of the EKC for territorial emissions, but not for consumption-based emissions. Also, a positive relationship was found between income and the difference between consumption-based and territorial emissions (which measures the net imports of emissions). Both findings do not bode well for a world that is developing. On the one hand, if poor countries increase their GDP per capita, it will lead to an increase in global emissions that will be larger than the increase suggested by the territorial EKC. On the other hand, if rich countries increase their GDP per capita, the reduction in emissions will be smaller than suggested by the territorial EKC. Moreover, if more countries show GDP growth, demand (by rich countries) for imports of emission will increase, while supply (by poor countries) decreases. This is not possible so that only the richest countries will be able to import emissions. As a result, the turning point of territorial emissions EKC will shift to higher income levels. With a constant or growing population, development might only lead to reduced pressures on the environment if an EKC would exist for consumption-based emission indicators.

Chapter 4 investigated the health and economic consequences of trade, due to imported and exported emissions of various pollutants and value added. We compared the US emissions generated

for US exports and the US air emissions that were avoided by importing products. One of the main contributions of this chapter was that it considered the monetary values of the impacts. It was found that damages associated with international trade are considerable and cannot be neglected. For 2002, the US avoided \$32.7 billion of damages by importing and at the same time generated \$22.0 billion of damages to produce its exports. This implies that trade caused a net reduction of \$10.7 billion of damages in 2002. In other words, the US trade deficit would have been about 3% smaller if the pollution costs to society had been taken into account. The large US avoidance of damages on its own territory is strongly related to its massive trade deficit. Still, some sectors showed both a trade deficit and a damage surplus. This is because a sector consists of various industries (which sometimes show a considerable variation in damages). If the imports of a sector are concentrated in particular industries while the exports are concentrated in other industries, this may lead to a trade deficit and a damage surplus at the same time. Moreover, it was found that the computed "damage to value-added ratios" differed greatly across industries. Exports in some industries, such as the Carbon Black Manufacturing industry, are so hazardous that more than half of the value-added gained from extra exports would disappear due to environmental damages. These findings imply that the US might benefit more from trade by increasing its exports more in low damage-intensive industries (most of them are in the tertiary sectors) than in high damage-intensive industries (most of them are in the primary or secondary sectors).

Chapter 5 investigated the errors introduced by various approximations of the full global multiregional input-output (GMRIO) model. The question was how much a country's consumer responsibility (or footprint) changes if only limited (or no) information is available for some countries or regions. To mimic the real world situation, one country was omitted from the world input-output table and data for this country were then estimated. Chapter 5 found that serious biases may occur

when the true emission coefficients in the omitted country are estimated by average emission coefficients and when the true technical coefficients matrix of the omitted country is estimated by the average matrix. Also, omitting a country from the world can greatly affect the estimation of the consumer responsibility of neighbors and trading partners, if they depend largely on imports from the omitted country. Moreover, it was indicated that using a so-called “regional representative” to estimate the true technical coefficients of the omitted country might improve the estimation of the consumer responsibility considerably. Although researchers have put more and more efforts in obtaining detailed and reliable information for constructing full GMRIO tables, they usually face restrictions in data of sufficient quality, time and resources. The findings in Chapter 5 may facilitate researchers in the allocation of the limited resources spent on data collection and construction.

6.2 FUTURE RESEARCH

The research that has been undertaken for this thesis has highlighted a number of topics on which further research would be beneficial. These include the extension of the GMRIO data and sensitivity analyses therewith, and the use of GMRIO analyses to evaluate and improve policies.

GMRIO databases play an important role in empirical studies on international trade and environmental degradation. Although data availability and quality have been improved in the past decades due to continuous efforts of numerous researchers, there is still ample room for future data improvements and sensitivity studies. For example, Chapter 5 indicated that serious biases in the calculation of consumption-based emissions can occur when the true emission coefficients or input coefficients of some countries or regions are unavailable and are estimated using average values. Sensitivity analyses may help users of data by informing them about the impacts of potential errors. Also, large discrepancies are often found between the imports listed in the national input-output tables

and in the official trade statistics. Typically, researchers have to construct detailed trade matrices based on assumptions because additional information does not exist (Wiedmann et al., 2011). Estimated GMRIO tables just come with errors. More empirical studies are needed to get insight in the nature of these errors and their consequences. That is, what are the effects of certain, given errors on the outcomes?

Another way to use empirical sensitivity analyses is by turning the direction of the question around. That is, by asking which errors cause the largest effect on the outcomes? This clearly links to a large stream of the literature in the past. For example, research on so-called “inverse important coefficients” investigated for which input coefficients does a certain error cause the largest effect in (multipliers obtained from) the Leontief inverse matrix (see Kurz et al., 1998, for an overview). It was found that multipliers are largely determined by just a small number of elements in the input-output matrix (Jensen, 1980). In the case of limited time and resources, it seems beneficial to concentrate on precisely these elements and make sure that as much as possible information is collected and/or that they are estimated with highest accuracy. Instead of looking at the standard multipliers, one might take environmental outcomes (e.g. impacts, footprints, exports and imports of emissions) into account.

There are several other directions for further development related to the work undertaken in this thesis. Chapter 4 investigated economic impacts of air emissions embodied in international trade. A natural extension would be to take not only the damages from air pollution into account but also other types of damages. For example, according to the recent findings on biodiversity by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES, 2019), one million species face extinction. Another example is the serious worries that are raised regarding plastic soup (see <https://www.plasticsoupfoundation.org/en/>) or trade in waste in general. An input-output analysis would be able to track all these movements and include also the indirect effects. In

this way we can answer questions like: “Which countries are ultimately the sinks for US consumers?”. Clearly this requires detailed GMRIO tables with appropriate satellite accounts. In the present example that would be waste generation by each industry and by consumers, and the direct waste movements. This might be achieved by using the recently published EXIOBASE version 3 hybrid (Merciai and Schmidt, 2016; 2018), which contains supply and use of waste flows as the auxiliary information of the international supply and use table (currently only available for year 2011).

This thesis has also shed light on certain policy issues and this is another direction for future research. During recent years, the political consensus for serious climate change actions has frayed. In many major developed economies (such as the US), domestic economic problems (including structural unemployment of the lower educated and demising prospects for the middle class) increasingly preoccupy policymakers. In June 2017, US President Donald Trump announced that the US would cease participation in the 2015 Paris Agreement on climate change mitigation. Although the US withdrawal cannot legally take effect until November 2020, President Trump’s announcement gravely undermines the impact of the Paris Agreement. Moreover, there are potential trade impacts following the US withdrawal that will affect decisions of business and policymakers in other economies. For example, the German car industry expressed concerns about its ability to remain competitive in light of the US decision to withdraw. It is inevitable that Europe and others must facilitate a more cost efficient and economically feasible climate policy to remain internationally competitive.

A wide range of policy questions can be researched with GMRIO databases that have been augmented with environmental and social satellite accounts. For example, Chapter 3 suggested that the consumption-based EKC does not exist. Thus, it is unlikely to be true that getting richer will lead to better environmental quality. This raises several questions. What kind of environmental policy or trade regulation should be implemented in order to advocate international cooperation on

environmental issues? How to promote leadership from large developing countries to cope with or combat climate change? To what extent will knowledge sharing and technological progress help to slow down or even reverse environmental degradation? Another example is Chapter 2, which investigated the driving forces behind the growth of carbon dioxide emission embodied in trade. It demonstrated that developed countries did not play the same role in world production in 2007 as they did in 1995. Some of the emerging economies, such as China and India, had gained in terms of importance. This shift in the role of countries will continue and will raise further questions. What share of the responsibility for climate actions is “fair” to expect from emerging countries like China and India? How can we construct international environmental policies that incorporate the changing trade structures?

GMRIO tables and analyses cannot provide the answers to these questions. However, they can assist in arriving at the answers. This is because IO can be (and has been successfully) used to evaluate the effects and as a consequence to adapt the original answers so as to optimize the effects.

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SAMENVATTING

In dit proefschrift is de aandacht gericht op het verband tussen internationale handel en aantasting van het milieu. Er zijn input-outputanalyses gebruikt om milieu-onderzoeksvragen in een periode van voortgaande globalisering te beantwoorden. In deze periode is men eindproducten gaan beschouwen als *made in the world* in plaats van geproduceerd in een enkel land. Hierna volgt de samenvatting van de belangrijkste onderzoeksresultaten per hoofdstuk van dit proefschrift.

Hoofdstuk 2 focust op de uitstoot van koolstofdioxide die is ingebed in de handel (*emissions embodied in trade*, EET) van 40 grote economieën in de periode van 1995 tot 2007. Onze onderzoeksresultaten komen overeen met de uitkomsten van eerdere studies. Ze laten zien dat in vele ontwikkelde economieën de emissies ingebed in importen (EEI) sneller groeiden dan de uitstoot ingebed in exporten (EEE), terwijl dit in sommige opkomende economieën (zoals China en India) andersom was en de EEE juist bijzonder hard stegen. Hoofdstuk 2 past een structurele decompositieanalyse toe om te onderzoeken wat de drijvende krachten achter deze veranderingen in de EET waren. Wij berekenden de bijdrage van een aantal geselecteerde factoren aan de veranderingen in de EET. Een van de voornaamste bevindingen van dit hoofdstuk was dat veranderingen in de structuur van de handel de belangrijkste verklaring zijn voor het grote verschil tussen ontwikkelde en opkomende economieën in de groei van de EET. Producenten overal ter wereld zijn ertoe overgegaan hun componenten en halffabricaten te kopen in opkomende economieën in plaats van in ontwikkelde economieën. In het geval van China betekent dit dat producenten hun inkopen ook in eigen land doen. De tweede belangrijke onderzoeksuitkomst van hoofdstuk 2 is dat toenames in de grootte van de finale vraag en afnames in de uitstoot-intensiteit van de productie in belangrijke mate verantwoordelijk waren voor veranderingen in de EET. Gemiddeld leidden toenames in de eindvraag tot meer dan 50% groei in de EEE (EEI), terwijl een afname in de intensiteit van de uitstoot leidde tot een vermindering

van 30% in de EEE (EEI). Kortom, het cruciale punt in hoofdstuk 2 is dat ontwikkelde landen zoals de VS en het VK in 2007 niet dezelfde rol speelden in de mondiale productie als in 1995. Dientengevolge bleef in de ontwikkelde landen de “consumptie” van emissies sterk groeien, terwijl hun territoriale emissies relatief weinig toenamen. Dit ging dus ten koste van het milieu in andere delen van de wereld.

Hoofdstuk 3 onderwerpt de hypothese van de zogenaamde Kuznets-milieucurve (EKC) aan een nieuwe toetsing. Daarbij werd gebruik gemaakt van gegevens omtrent de uitstoot van broeikasgassen die op twee verschillende wijzen werd toegerekend. Enerzijds aan de gebruikers van eindproducten (zeg ‘consumenten’), anderzijds aan degenen die de gassen uitstoot (zeg ‘producenten’). Wij vonden dat de broeikasgassen zoals toegerekend aan producenten in zwakke mate overeenkomen met de EKC. Dat gold niet voor de emissies zoals toegerekend aan de consumenten. Wij vonden ook een positief verband tussen enerzijds inkomen en anderzijds het verschil tussen op consumptie en op productie gebaseerde emissies (een maat voor de netto import van emissies). Deze twee uitkomsten beloven weinig goeds voor ontwikkelingslanden. Als arme landen hun bruto binnenlands product (BBP) per inwoner verhogen, zal dat leiden tot mondiale emissies die groter zijn dan je op grond van de EKC met op productie gebaseerde emissies zou verwachten. Maar als rijke landen hetzelfde doen, zal de afname van emissies kleiner zijn dan diezelfde EKC voorspelt. Bovendien: als meer landen een groei van het BBP vertonen, zal de vraag (van rijke landen) naar importen van emissies toenemen, terwijl het aanbod (door arme landen) zal afnemen. Aangezien dit onmogelijk is, zullen alleen de rijkste landen emissies kunnen importeren. Dientengevolge zal het omslagpunt van de EKC met op productie gebaseerde emissies naar hogere inkomensniveaus verschuiven. Bij een gelijkblijvende of groeiende bevolking kan economische ontwikkeling alleen tot een geringere belasting van het milieu leiden indien op consumptie gebaseerde emissies de vorm van een EKC hebben.

Hoofdstuk 4 richt zich op de gevolgen van handel voor de volksgezondheid en de economie. Deze worden veroorzaakt door in- en uitvoer van emissies die leiden tot luchtverontreiniging, respectievelijk, toegevoegde waarde. Wij vergeleken de Amerikaanse emissies ten gevolge van de exporten van de VS met de Amerikaanse emissies die vermeden worden als gevolg van de importen van de VS. Een van de voornaamste bijdragen van dit hoofdstuk is dat we de gevolgen in geld hebben kunnen uitdrukken. Zo vonden wij dat de schade verbonden aan de internationale handel aanzienlijk is en niet genegeerd kan worden. In 2002 vermeden de VS milieuschade ter waarde van \$32,7 miljard door goederen te importeren. Tegelijkertijd veroorzaakten Amerikaanse exporten milieuschade ter hoogte van \$22,0 miljard. Dat houdt in dat de internationale handel een netto vermindering van milieuschade ter hoogte van \$10,7 miljard tot gevolg had. Met andere woorden, de Amerikaanse handelsbalans zou in 2002 ongeveer 3% kleiner zijn geweest als de maatschappelijke kosten van milieuvervuiling in aanmerking waren genomen. De grootschalige vermijding van milieuschade in de VS houdt in hoge mate verband met het enorme Amerikaanse handelstekort. Toch vertonen sommige bedrijfstakken niet alleen een handelstekort maar tegelijkertijd een overschot aan schade. De oorzaak ligt in het feit dat een sector uit verschillende industrieën bestaat, die soms aanzienlijk verschillen ten aanzien van de milieuschade die zij aanrichten. Als de importen van een sector in bepaalde industrieën geconcentreerd zijn, terwijl de exporten uit andere industrieën komen, dan kan dit tegelijkertijd leiden tot een handelstekort en een groei van de schade. Tevens bleek dat de verhouding tussen de milieuschade en de toegevoegde waarde in hoge mate kan verschillen tussen de ene industrie en de andere. In sommige bedrijfstakken, zoals de productie van zwarte koolstof, zijn exporten zo schadelijk voor het milieu dat meer dan de helft van de toegevoegde waarde die exporten voortbrengen verloren gaan aan milieuschade. Deze bevindingen doen vermoeden dat de VS meer profijt van zijn handel zouden hebben als hun exporten meer zouden groeien in de relatief onschadelijke bedrijfstakken (die

meestal in de tertiaire sector liggen) dan in de zeer milieuschadelijke industrieën (die meestal in de primaire en secundaire sector liggen).

Hoofdstuk 5 focust op de fouten die voortkomen uit de uiteenlopende schattingen van het globale, multi-regionale input-output model (het GMRIO-model). Hierbij vroegen wij ons af in hoeverre de verantwoordelijkheid van de consumenten (of voetafdruk van de consumptie) in een land verandert indien weinig of geen informatie voorhanden is omtrent bepaalde landen of regio's. Om de werkelijkheid na te bootsen, lieten wij één land weg uit de input-output tabel voor de hele wereld en schatten vervolgens de gegevens voor dit ontbrekende land. Hierdoor kwam aan het licht dat er ernstige afwijkingen kunnen ontstaan wanneer in plaats van de werkelijke emissiecoëfficiënten voor het weggelaten land geschatte gemiddelde coëfficiënten worden gebruikt, of wanneer de 'ware' technische coëfficiënten van het ontbrekende land vervangen worden door een schatting gebaseerd op gemiddelde coëfficiënten. Verder kan het weglaten van een land uit de mondiale gegevens grote gevolgen hebben voor de schatting van de consumentenverantwoordelijkheid van naburige landen en handelspartners, indien deze in hoge mate afhankelijk zijn van importen uit het weggelaten land. Wij stelden vast dat het gebruik van een 'regionale vertegenwoordiger' om de ware technische coëfficiënten van een weggelaten land te schatten tot veel betere schattingen van de consumentenverantwoordelijkheid kan leiden. Hoewel onderzoekers zich in toenemende mate hebben ingespannen om aan gedetailleerde en betrouwbare informatie voor het opstellen van volledige GMRIO-tabellen te komen, lijden zij onder allerlei beperkingen op het gebied van kwaliteit, tijd en middelen die het verzamelen van de gegevens bemoeilijken. De uitkomsten van hoofdstuk 5 kunnen onderzoekers helpen om hun beperkte middelen doelmatiger te gebruiken voor het verzamelen en genereren van data.