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Midpoint and Endpoint Sustainability Assessment of U.S. and China Manufacturing: A Comparative MRIO+Recipe Analysis

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MIDPOINT AND ENDPOINT SUSTAINABILITY ASSESSMENT OF U.S. AND CHINA MANUFACTURING: A COMPARATIVE MRIO+RECIPE ANALYSIS

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ABSTRACT

Manufacturing is among the most important industries for an economy, which creates value-added, fosters innovation, stimulates employment and economic growth. Therefore, manufacturing industries are crucial for a country's sustainable development not only for economic reasons but also for social (.e.g. employment, tax, etc.) and environmental ones. Thus, manufacturing activities' contribution to the economy is critically related with environmental and social impacts. Sustainable economic growth is essential and necessary for a country to provide all necessary goods and services to its growing population. And, this is highly linke with the creation of new jobs and in this context, manufacturing jobs have a substaintial multiplier impact on the employment and economic growht in manufacturing and other industries as a whole. Sustainable economic growth is crutically important for both developed and developing countries in the world from triple bottom line sustainable development perspective. Maufacturing industries have substaintial impacts on both economic and environmental domains of sustainable development. Among the largest economies of the world, the United States (U.S.) and China manufacturing industries have been in steeply rising competition, which results in considerable economic and environmental impacts for both of the countries and the rest of the world.

In this thesis, the U.S. and China manufacturing activities were studied from economic, and environmental life cycle sustainability perspectives for the period between 1995 and 2014. Multi-region input-output (MRIO) models were built by using World Input Output Database (WIOD) as the primary database, global input output tables, environmental impact and economic output multipliers, and manufacturing final demand. A MRIO model is built for each year in the 20-year study period, and it is comprised of 40 major economies and the rest of the world (ROW is considered as a country). In parallel with WIOD classification, each of the 41 country of major economies consists of 16 manufacturing and 19 service industries, which make up the whole economy for the corresponding country. MRIO models were used to derive economic output that occurs at the domestic and global supply chains as well as in each of the manufacturing industries as well as selected GHG emissions. Life Cycle Inventory (LCI) results were

obtained from MRIO models. Moreover, the ReCiPe, a life cycle impact assessment (LCIA) methodoloy, was merged with the LCI to quantify the assocaited midpoint and endpoint impacts. The U.S. and China manufacturing industries impacts were studied individually, and compared analytically. Finally, structural decomposition analysis was employed to investigate how the change in terms of the model will drive the greenhouse gas emissions.

The results indicated that China's manufacturing total economic output in 2014 only was approximately twice higher than the U.S. manufacturing total economic output, while China's manufacturing global GHG emissions appraximatedly three times higher than the U.S. manufacturing GHG emissions.

In terms of the midpoint impacts, in 2014, China's manufacturing impact on global warming was 285% larger than the impact of the U.S. manufacturing. Additionally, the impact of China's manufactruing on ozone depletion was 338% higher than the U.S. manufacturing impact. Regarding the endpoint impact, the damage to human health and to the ecosystem from China's manufacturing with 315% more than the U.S.

Furthermore, the time series analysis of LCI results showed that China manufacturing started to exceed the U.S. manufacturing gobal economic output after 2007, which is correlated with the 2008 stock market crash. In terms of GHG emissions, China manufacturing began to surpass the U.S. manufacturing significantly after 2002, which draws attention worse emissions intensity per million dollar economic activity compared to the U.S. Additionally, the U.S. manufacturing global economic output has had a cumulative of 75% growth in global economic output while the increase in GHG emissions for the same period was almost 28% during the period between 1995 and 2014. For China, the cumulative economic growth, of the country's manufacturing has been nearly 266%, and the growth in GHG emissions has been 121% for the same period.

Similarly, the time series analysis of LCIA showed that the Global Warming Potential (GWP) impact from the U.S. manufacturing has grown by a cumulative of 40% since 1995, while the impact from China's manufacturing is 108% for the same period. Moreover, the growth of the impact to ozone depletion potential from US manufacturing is 45% and 87% from China's manufacturing. Likewise, the growth of damage to human health and the damage to ecosystem from the U.S. manufacturing since 1995 is 37% while the growth is 89% from China's manufacturing.

Finally, the structural decomposition analysis (SDA) results showed that GHG emissions per million dollar output drives the total GHG emissions in the reduction direction, while the changes in final demand drives the GHG emissions positively and increases the total GHG emissions for both countries. Overall, technological advancements in manufacturing industries typically decreased the emissions intensity per million-dollar economic activity in both economies. However, this did not create a substantial decrease in the emissions inventory due to the dominating impact of growing final demand and economic output. Especially, the inter-industry flows of China's economy has not been able to successfully make the emissions' intensity reduce the GHG emissions cumulative inventory levels as a whole in the last two decades. U.S. had the same problem with China in terms of total GHG emissions, however, the U.S. GHG emissions intensity had been more rapidly declining then the China.

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CHAPTER 1: INTRODUCTION

Manufacturing plays a substantial role in any economy. In 2013, twelve million Americans were employed in manufacturing industry (Scott, 2015), representing 8.8% of the employment in the United States (U.S.). The gross output of U.S. manufacturing in 2013 was $5.9 trillion which was equivalent to 35.4% of U.S. GDP in 2013 (Scott, 2015). Thus, manufacturing has been one of the most critical sectors in term of employment and contribution to the GDP in the U.S. It is important to note that, in a typical national economy, environmental, social, and economic impacts of production activities are highly correlated due to the substantial portion of the overall material and energy use that is attributed to manufacturing industries (Egilmez et al., 2013). Therefore, production processes environmental cleanliness, as well as their positive impacts on the economy and society, are in dire need of continuous alignment toward realizing sustainable development goals in a 21st-century economy.

In this context, stabilizing and mitigating climate change impacts is still an essential task for sustainable development. As a matter of fact, climate change related impacts on the ecosystem and on the lives humans and species are severely deteriorated across the planet. The impacts are visible in various scientific reports, which mentiones areas such as rising sea levels (Pachauri & L.A. Meyer, 2014), shifted seasons, loss in the volume and height of glaciers (Roe, Baker, & Herla, 2017), rising ocean temperatures and acidification levels. According to National Center for Environmental Information NCEI, (2009), since the early years of the 20th century, the average surface temperature has increased by approximately 1.4 degrees Fahrenheit (0.8 degrees Celsius). Furthermore, according to independent analyses by NASA and the National Oceanic and Atmospheric Administration (NASA, (2017), the planet's surface temperature in 2016 was the hottest ever recorded since the start of record keeping in 1880. In the same analysis, they stated that the global average temperatures were 1.78 degrees Fahrenheit (0.99 degrees Celsius) higher than the mean surface temperature in the mid-twentieth century. Moreover, the 2016 was the third consecutive year to set another record for global mean surface temperatures. Similarly, the oceans have retained quite a bit of this increase in temperature within the 700 meters (about 2,300 feet) of depth in oceans indicates

warming of 0.302 degrees Fahrenheit since 1969 according to Levitus et al., (2009). Figure 1-1 illustrates the change in global surface temperature since 1880. The data of Figure 1-1 can be retrieved from NASA, (2017).

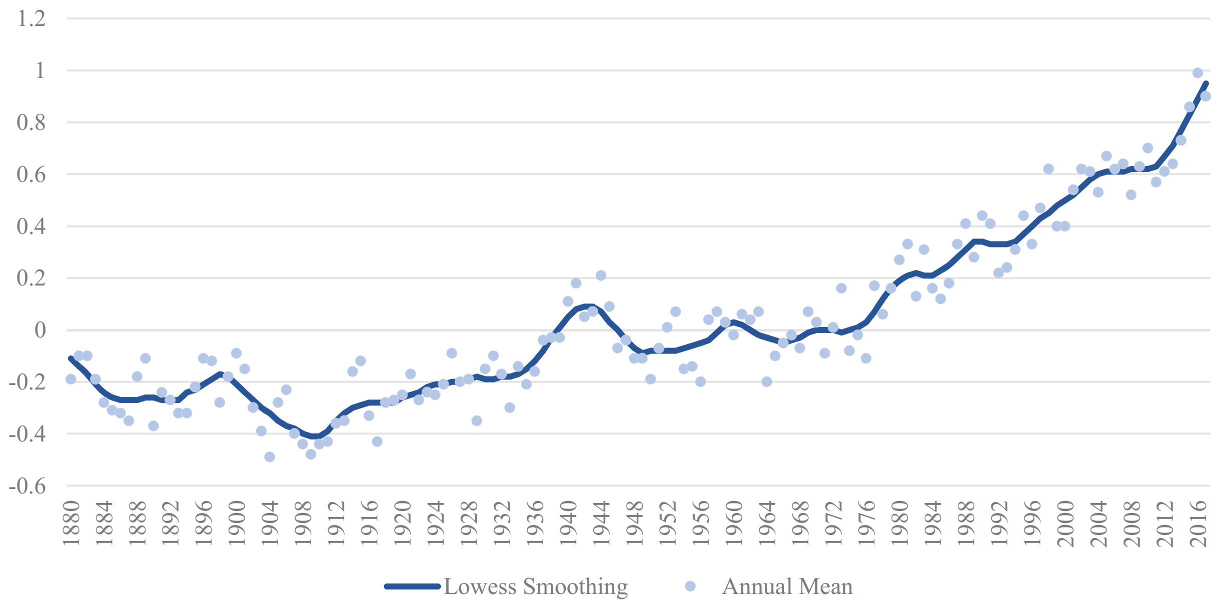

Figure 1-1: Change in global surface temperature (NASA, 2017)

Recent reports state that the primary driver of global warming is the **human expansion** of the "greenhouse effect" (Climate Change Synthesis Report for Policymakers, 2014). According to NASA, (2008), the greenhouse effect is the increase in temperature that results from trapping earth's radiating heat towards space by the atmosphere. The greenhouse effect has midpoint and endpoint impacts. Moreover, the main difference between midpoint and endpoint impacts could be understood by the respective different stages in the cause and effect chain when calculating the effect. For example, one of the midpoint impacts of Nitrous oxide (N_2O) emissions to air is *ozone depletion*. On the other hand, the endpoint impact of N_2O emissions, which refers to looking at the end of the cause-effect chain, is the damage to human health due to ozone depletion. In other words, N_2O emissions will eventually damage the human health through ozone depletion.

According to the U.S. Environmental Protection Agency (EPA), the leading greenhouse gases (GHG) are carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4), and fluorinated gases. Furthermore, Intergovernmental Panel on Climate Change, (2014) states that 65% of global GHG emissions are attributed to fossil fuel use as a result of primarily industrial processes. Another 11% is attributed to the direct and indirect emissions releases related to the deforestation and other land use such as decay in biomass. While methane (CH_4) contributes to the 16% of the total, nitrous oxide has a share of 6%. Moreover, according to the same report, the U.S. is the second largest carbon dioxide (CO_2) emitter with 15% after China with 30%.

According to United States Environmental Protection Agency, (2018), in 2016, 81% of the U.S. GHG emissions were attributed to carbon dioxide (CO_2), 10% from methane (CH_4), 6% contribution from N_2O, and 3% from fluorinated gases. The primary sources of GHG emissions in the U.S. are Transportation (28.5%), Electricity production (28.4%), Industrial production (22%), Commercial and Residential (11%), and Agriculture (9%). Indeed, industrial production is significantly linked with transportation due to the necessity to move the goods and services, and also, its tied with power production. According to U.S. Energy Information Administration, (2017), the industrial sectors are responsible for approximately one fifth of the total energy consumption in the country. All these statistics clearly indicate that it is important to study and assess sustainability of the manufacturing industries in the U.S., which is the focus of this thesis.

The primary objective of this thesis is to assess the economic and environmental (mid-point and end-point) impacts of the U.S. manufacturing industries and compare it to China manufacturing industries for the period between 1994 and 2014. Secondary obejctive of this thesis is to conduct a structural decomposition analysis (SDA) for both countries on the emission intensity, final demand, and economic output categories to understant the primary drivers of the enviromental impacts during the study period.

CHAPTER 2: LITERATURE REVIEW

2.1 Life Cycle Assessment (LCA)

The third most significant contributor to the U.S. GHG emissions inventory is the manufacturing industry (United States Environmental Protection Agency, 2018). The literature is abudant with the works that addresses the environmental sustainability impact assessment of industrial processes. Among the environmental impact assessment techniques, life cycle assessment (LCA) is the predominant approach that is typically used to trace the environmental impacts occur throughout the life cycle of products (Kucukvar, et al., 2015). This assessment incorporates all the stages of a product's life cycle including raw material extraction, distribution, consumption, and disposal (Roy et al., 2009; (Park et al., 2016). Curran, (1996) states that LCA can be used as a tool to compare products that have the same functionality, or products that undergo a modification to change the product to more "environmentally friendly." According to Roy et al., (2009), applications of LCA are classified as (1) product comparison, process comparison, or services comparison and their substitutes; (2) product or service life cycle comparison with their substitutes (3) recognizing parts of the life cycle with most prominent improvement potential.

According to the International Organization for Standardization, (2006), LCA consists of four phases, (1) the goal and scope definition, (2) the inventory analysis(LCI), (3) the impact assessment (LCIA), and (4) the interpretation. The first step is to define the goal and the scope of the LCA study. The second step is creating/computing the LCI following the with respect to the studied system. It involves the data collection necessary to reach the goals of the outlined study. The third phase, LCIA, aims to assess the impacts at the human health, ecosystem, and/or resource levels. The fourth phase is life cycle interpretation which summarizes the results of LCI, or LCIA or both. The phases of LCA is illustrated in Figure 2-1.

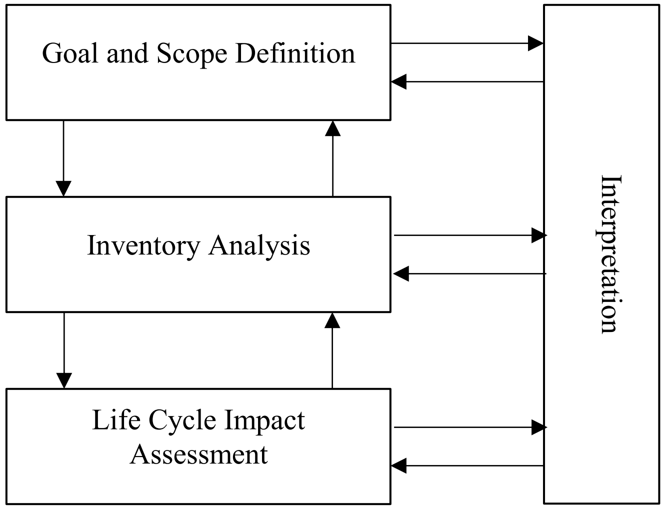

Figure 2-1: The Life Cycle Assessment Phases (Graedel and Allenby, 2010)

According to Abbood (2016), there are three types of LCA commonly used in the literature: Process-LCA (P-LCA), Economic Input-Output LCA (EIO-LCA), and Hybrid LCA (Process+Input Output LCA). P-LCA was developed by the U.S. Environmental Protection Agency and the Society of Environmental Toxicology and Chemistry. P-LCA studies the environmental impacts of products. EIO-LCA uses linear algebraic formulas to combine the economic input-output tables and environmental impacts multipliers. The fact that EIO-LCA takes into consideration direct and indirect supply chain activities makes EIO-LCA a powerful LCA methodology. The disadvantage of P-LCA is that it does not account for economic supply chain while EIO-LCA does not consider the consumption or the end of life phases of products. EIO-LCA can be applied on a single region, single region input-output (SRIO), or on multi-region, multi-region input-output (MRIO). Hybrid LCA can be implemented to achieve the benefits of P-LCA and EIO-LCA. All in all, EIO-LCA approach is the typical LCA approach if the problem domain is the entire economy or a part of economy that could be represented with input-outputa tables. Input outputa tables show the monetory flows among the industries of the corresponding economy. EIO-LCA is a very robust approach since it does not require an extensive data collection, and takes into account the entire economy depending on the scope of the EIO-LCA. The scope could be a city, state, region, country or the global economy. EIO-LCA models could be classified into two in terms of their scope: single region vs. multi-region. In single region EIO-

LCA models, domestic technology assumption is kept, where the single region could be a country, city, etc. In multi-region models, multiple regions could be linked to each other to better and more accurately quantify the monetory flows and associated environmental impacts. The most comprehensive multi region EIO LCA model would be the one that takes into account all countries and all industries in the world. Multi region EIO-LCA models are typically termed as MRIO LCA or MRIO in the literature.

2.2 Multi-region Input-Output (MRIO) LCA

World Resource Institute (WRI) and the World Business Council for Sustainable Development (WBCSD) establishes the accounting standards to trace GHG emissions of in the onsite and supply chain tiers of industries. MRIO has been used in the economy and environmental sustainability literature for various purposes. For instance, C. Zhang & Anadon, (2014), developed an MRIO model to evaluate the rate and structure of virtual water trade and consumption based water footprint in China. Moreover, Kagawa et al., (2004) used MRIO to assess the waste embedded in final consumption. Wiedmann et al., (2010) used MRIO to conduct a time series analysis of carbon footprint in the UK. Zhang et al., (2014) used MRIO to analysis regional CH_4 emissions of China. Furthermore, Cui et al., (2015) used MRIO to investigate the energy embedded in the foreign export of China. Moreover, Zhang et al., (2016) used MRIO to investigates the water withdrawals by the industries in China as well as demand-driven industrial water consumption integrated into the final demand and interregional trade.

In a recent work, Turkish manufacturing industries' carbon footprint was assessed with MRIO (Kucukvar et al., 2015). The authors found that the highest carbon footprint share was electricity, gas, and water supply among the Turkish manufacturing sectors. MRIO models were developed to assess the carbon and energy footprint of Turkish and 27 European food manufacturing industries. The results indicated that Turkish manufacturing had the highest carbon emissions. However, Spain, Germany, and France were found to be leading the overall energy footprint. As the closest work to this thesis, Abbood (2016) studied the U.S. manufacturing carbon and energy footprint impacts by using stochastic MRIO models. The results of the study indicated that 81.7% of the carbon footprint was from U.S. manufacturing and regarding

energy, U.S. manufacturing was 84%. However, the limitations of this work include: 1) the focus was only on the life cycle inventory (LCI), but the midpoint and endpoint impacts were not addressed, 2) the study period was 2000-2009 years. 3) carbon footprint impacts were studied aggregately, not in detail.

2.3 ReCiPe

Throughout the years, various LCIA methodologies were developed. Pizzol et al., (2011a) used and compared eight methods, Stepwise 2006, Impact 2002þ, EDIP 2003, Eco-indicator 99, CML 2001, TRACI 2, ReCiPe, and USEtox to assess the eco-toxicological impact of metals. The authors found out that the eco-toxicological impacts of metals differentiate based on the LCIA method employed. In a similar study of Pizzol et al., (2011b), nine different LCIA methodologies (EPS 2000 was added to the eight methods above), were compared to assess the impact of metals on human health. The authors found out that there is no agreement between the results of different methods. This study uses ReCiPe methodology for LCIA assessment due to suitability of it in terms of merging with LCI results.

Several works in the literature implemented ReCiPe as a method for impact assessment. In Slagstad & Brattebø, (2014), the authors used LCA to evaluate water and wastewater systems in Trondheim, Norway. For the impact analysis, ReCiPe midpoint was implemented. The authors found out that the water and wastewater system has a minor effect compared to the entire annual per capita GHG emissions. The authors emphasize the fact that the choice of the LCI, and the LCIA method will influence the results of LCA. Moreover, In Lamnatou & Chemisana, (2015), they used the life cycle impact assessment to investigate the environmental profile of PV-green roof, PV-bitumen, PV-gravel, gravel, extensive green, and intensive green.As the LCI approach, IPCC 2013 GWP 20a V1.00, IPCC 2013 GWP 100a V1.00 and IPCC 2013 GWP 500a V1.00 were used to calculate GWP (global warming potential) of the roofs. However, the ReCiPe endpoint method was used to assess the damage to Human health, Ecosystem, and Resources. From the endpoint analysis, they found that the extensive green roof has 20, 15, and 69 points for damage to Human health, Ecosystem, and Resources, respectively. However, the intensive green roof has about 40% higher impact than gravel and extensive green system. In another study, Lopsik, (2013)

employed LCA to determine the environmental impact of two wastewater treatment systems. In this paper, Impact 2002+ and ReCiPe were used to assess the midpoint and endpoint of the wastewater treatment systems. The LCIA of electric storage systems conducted in Oliveira et al., (2015) alsp used ReCiPe. The ReCiPe midpoint factors were climate change, human toxicity, particulate matter formation, and fossil resource depletion. Moreorver the endpoint impacts studied were the impacts of the storage systems on human health, ecosystems, and resources. The environmental footprint of a pilot unit of membrane bioreactor (MBR) is studied by Ioannou-Ttofa et al., (2016). The authors' aimed to estimate the emissions released. The authors utilized the LCA to evaluate the MBR environmentally, where LCA was merged with ReCiPe, to estimate the midpoint and endpoint impacts. There were 18 midpoint impact indicators of ReCiPe used, to name a few, impact indictors such as climate change, ozone depletion, terrestrial acidification, and etcetera were studied.

In Belboom et al., (2013), Recipe, midpoint, is used to identify best practice for municipal solid waste management in Belgium. They considered four different scenarios sanitary landfill, Incinerating the refuse-derived fuel part and using sanitary landfill for the remaining shredded organic, Incinerating the solid waste, and collecting the biodegradable part and incinerating the remainder. In another work, Chatzisymeon et al., (2013), LCA is used to assess the environmental impact of three oxidification processes of olive mill wastewater. The procedures are UV heterogenous photocatalysis (UV/TiO2), wet air oxidation (WAO), and electrochemical oxidation (EO) over boron-doped diamond electrodes. They used Recipe and IPCC 2017 to calculate global warming potential. They found that the environmental sustainability of these processes is related to the energy use, conversely. The ecological impact of these processes regarding global warming potential (GWP) decreases in the following order: UV/TiO2 > WAO > EO. In conclusion, EO was found to be the most sustainable process among the three processes for olive mill wastewater treatment. They also found that UV/TIO2 process had higher scores on damage to human health, fossil resources, and the ecosystem. In Benetto et al., (2015), the authors used ReCiPe for midpoint and endpoint life cycle assessment to assess the environmental performance and impact of the production

chain of grape marc pellets. Moreover, Pan et al., (2016), evaluated the midpoint and endpoint impacts of four process scenarios, overliming, ammonia addition, two-stage treatment, and membrane separations, for removing acidic impurities of pretreatment and conditioning of lignocellulose subtract. For assessing midpoint and endpoint impacts, ReCiPe midpoint and endpoint impact assessment is used. The midpoint indicators were water depletion potential, global warming potential, freshwater eutrophication, human toxicity, marine ecotoxicity, marine eutrophication, particulate matter formation, photochemical oxidant formation, terrestrial acidification, and terrestrial ecotoxicity. For the endpoint impact, eco-system quality, and human health were considered.

Additionally, Adam et al., (2013) developed an LCA approach to assess the environmental impact of a landfill plant. The authors used the ReCiPe midpoint method as LCIA methodology to evaluate the terrestrial and aquatic ecotoxicity of Cr(VI). The study was conducted on an industrial waste landfill in northern France that was contaminated with chromium. Furthermore, Repele & Bazbauers, (2015) assessed the environmental impacts of brick production stages and to investigate the impacts of natural gas, bio-methane, first and second generation biofuels, which were used in the industrial furnace. ReCiPe and Eco-indicator 99 was used to assess the environmental impact at the midpoint level.

Moreover, Samani et al., (2015) compared five polymers' use in novel housing solution by using ReCiPe framework. Hong Kong, Dong & Ng, (2014) conducted an assessment of the commercial buildings. The study aimed to compare the results of life cycle impact assessment of the midpoint and endpoint approached of ReCiPe. They studied 23 construction materials and a commercial building. The authors state that the difference between midpoint and endpoint approach can be noticed when several impact categories are taken into account. The paper also recommends the use of methods such as ReCiPe that has both midpoint and endpoint analysis when the goal is to assess the endpoint impacts.

As a part of their study, Park et al., (2016) assessed the midpoint and endpoint impacts of agricultural and food production in the U.S. for a single study year. The life cycle impact assessment approach was ReCipe midpoint and endpoint. They studied the midpoint impact and the endpoint impact

of 54 agricultural and food industries of the United States. Table 2-1 shows a summary of the literature on studying impact assessment from life cycle perspective.

Table 2-1: Summary of the State of Art in Mid-point and End-Point Impact Assessment

Source	**Problem Focus**	**Env. Impact Focus**		**Method(s)**
		Midpoint	**Endpoint**	
(Pizzol et al., 2011a)	Impact of metal on human health	Yes	Yes	Comparing LCIA methods
(Pizzol et al., 2011b)	Impact of metal on ecosystem	Yes	Yes	Comparing LCIA methods
(Lopsik, 2013)	Wastewater	Yes	Yes	Process-LCA + RECIPE
(Slagstad & Brattebø, 2014)	Water and wastewater system	Yes	No	Process-LCA + RECIPE Midpoint
(Oliveira et al., 2015)	LCA of electricity storage systems for grid application	Yes	Yes	Process-LCA + RECIPE
(Ioannou-Ttofa et al., 2016)	LCA of membrane bioreactor treatment process	Yes	Yes	Process LCA,IPCC 2013, RECIPE
(Lamnatou & Chemisana, 2015)	Constructin	No (other method)	Yes	Process-LCA + IPCC 2012 midpoint RECIPE endpoint
In (Belboom et al., 2013)	municipal solid waste management	Yes	No	Process-LCA + RECIPE

(Chatzisymeon et al., 2013)	Olive mill wastewater treatment	Yes	Yes	Process-LCA + RECIPE
(Benetto et al., 2015)	LCA of heat production from grape marc pellets	Yes	Yes	P-LCA + RECIPE
(Pan et al., 2016)	Energy	Yes	Yes	P-LCA + RECIPE
(Adam et al., 2013)	Terrestrial and aquatic ecotoxicity assessment of chromium	Yes	No	P-LCA + RECIPE midpoint
(Dong & Ng, 2014)	Construction	Yes	Yes	P-LCA + RECIPE
(Samani et al., 2015)	Sustainability Assessment of Advanced Materials for Novel Housing Solutions	No	Yes	P-LCA + RECIPE
(Repele & Bazbauers, 2015)	Building material (bricks)	Yes	No	P-LCA + RECIPE
(Park et al., 2016)	U.S. mamufacturing, eco-system level, single region, impact assessment	Yes	Yes	ECO-LCA + RECIPE

From the Table 2-1, it can be seen that RECIPE and EIO-LCA had been used in a recent work done by Park et al., (2016), whose focus was the U.S. economy and the model was single region (U.S. only) EIO LCA. The other limitation of this study is that the data is currently outdated and it is a single year study, which was based on 2005 ECO-LCA model. In addition, keeping a single region scope (U.S. economy only) lacks the estimation of potential impacts occurred at the global trade level (outside of the U.S.). To the best knowledge of the authors, no work in the literature addresses the comparative midpoint and endpoint impact assessment of the U.S. and China's manufacturing as a time-series investigation. Thus, this thesis focuses on the midpoint and endpoint impact of U.S. and China's manufacturing, and the

implemented methodologies are discussed in the next chapter. To do so, MRIO framework is used to model and quantify the life cycle inventory (LCI), ReCiPe is used to conduct the life cycle impact assessment and quantify the mid-point and end-point impacts.

CHAPTER 3: METHODOLOGY

The proposed hierarchical methodology is summarized in Figure 4-1. There are 4 phases, namely: data collection, developing MRIO models for the study period between 1995-2014, conducting mid-point and end-point impact assessment with ReCiPe, and lastly, conducting structural decomposition analysis (SDA). The Input-Output and final demand data of 40 major countries and the Rest of the World (RoW) were collected by using World Input-Output Database (WIOD) (Timmer et al., 2015). In the second phase, multi-regional input-output (MRIO) models were developed to be used to quantify the total economic output and the three GHG emissions-types.

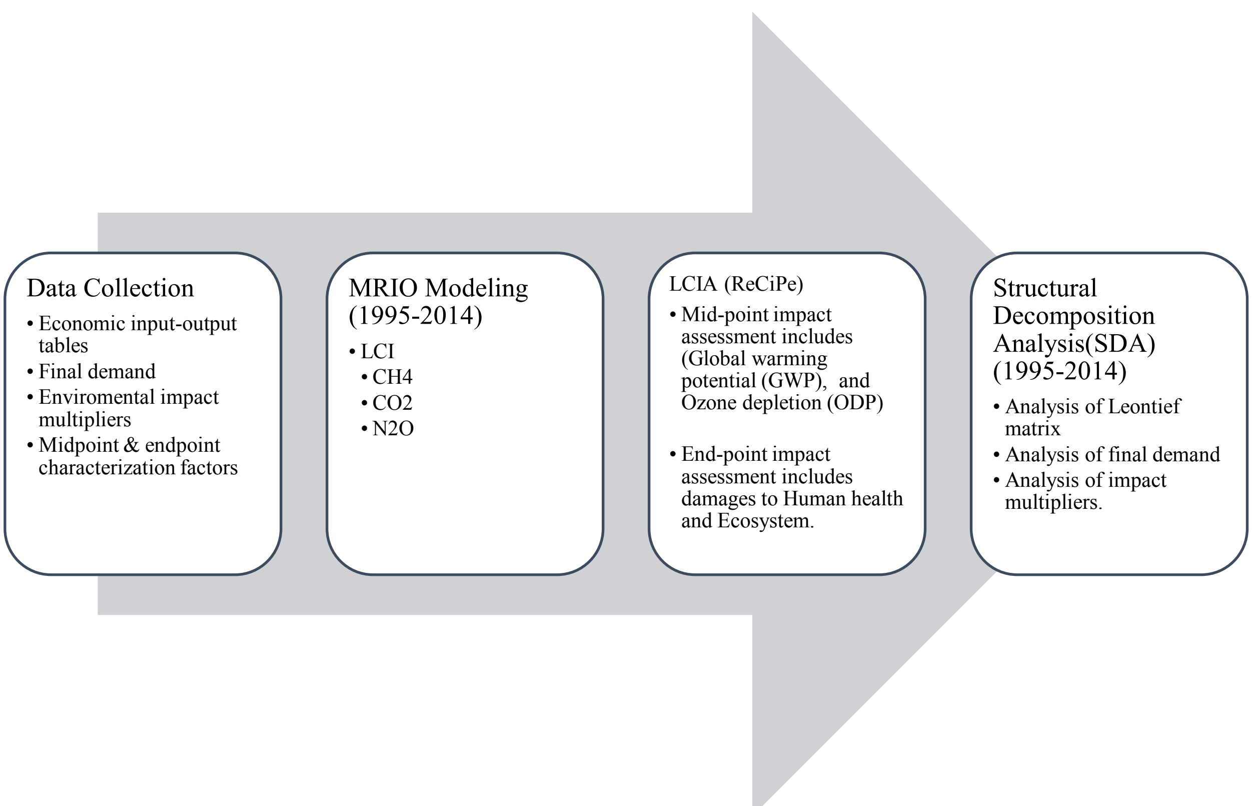

Figure 3-1: Summary of the Methods

MRIO models were designed to cover the period between 1995 and 2014. The third step was using ReCiPe framework, (Huijbregts et al., 2017), which primarily uses the MRIO life cycle inventory results as input parameters to estimate the mid-point and end-point impacts, termed as the LCIA. Finally, structural decomposition analysis (SDA) was employed to investigate the effect of the changes in economic output, GHG emissions multipliers, and the final demand.

3.1 Data Collection

Data used to build MRIO models were obtained from the World Input-Output Database (WIOD). The data consists of economic input-output tables (flow matrix), final demand, and environmental impact (GHG emissions) multipliers for all countries, and all industries (41x35=1435rows). WIOD provides economic input-output data for 40 major countries and the rest of the world (RoW). The list of countries and industries are shown in Tables 3-1 and 3-2, respectively. In Table 3-2, sectors that are on row #1 through #16 are manufacturing sectors and remaining industries are energy, construction, service, etc. type.

Table 3-1:Regions included in MRIO model

Euro-Zone	**Non-Euro EU**	**NAFTA**	**China**	**East Asia**	**BRIIAT**	**Rest of World**
Austria	Bulgaria	Canada	China	Japan	Brazil	RoW
Belgium	Czech Rep.	Mexico		Korea	Russia	
Cyprus	Denmark	USA		Taiwan	India	
Estonia	Hungary				Indonesia	
Finland	Latvia				Australia	
France	Lithuania				Turkey	
Germany	Poland					
Greece	Romania					
Ireland	Sweden					
Italy	UK					
Luxembourg						
Malta						
Netherlands						
Portugal						
Slovakia						
Slovenia						

Spain						

Table 3-2: Sectors included in MRIO model for each region

#	**Manufacturing (1-16) and Service Sectors**
1	Agriculture, Hunting, Forestry and Fishing
2	Mining and Quarrying
3	Food, Beverages and Tobacco
4	Textiles and Textile Products
5	Leather, Leather and Footwear
6	Wood and Products of Wood and Cork
7	Pulp, Paper, Paper, Printing and Publishing
8	Coke, Refined Petroleum and Nuclear Fuel
9	Chemicals and Chemical Products
10	Rubber and Plastics
11	Other Non-Metallic Mineral
12	Basic Metals and Fabricated Metal
13	Machinery, Nec
14	Electrical and Optical Equipment
15	Transport Equipment
16	Manufacturing, Nec; Recycling
17	Electricity, Gas and Water Supply
18	Construction
19	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
20	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
21	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
22	Hotels and Restaurants
23	Inland Transport
24	Water Transport
25	Air Transport
26	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
27	Post and Telecommunications
28	Financial Intermediation
29	Real Estate Activities
30	Renting of M&Eq and Other Business Activities
31	Public Admin and Defence; Compulsory Social Security
32	Education
33	Health and Social Work
34	Other Community, Social and Personal Services
35	Private Households with Employed Persons

The latest release of WIOD was in 2016. The 2016 version consists of a time series from 2000 until 2014. However, in this thesis, the 2013 version was used since the data of GHG emissions multipliers was available from 1995 until 2009 and the 2016 release of WIOD does not provide data for the years 1995 to 1999 and uses a slightly different country-industry structure. In 2013 release, WIOD provides time series input data for economic and environmental impact categories from 1995 to 2011. For the years 2012 to 2014, a modification was implemented based on 2011-year data by using 2016 release, since data for these years are not available in 2013 release.

To assess the midpoint and the endpoint impacts of GHG emissions the results of LCI are used to characterize the midpoint and endpoint impacts. The characterization factors were obtained from Huijbregts et al., (2017). The characterization factors have three different cultural perspectives.

i) Individualist (20 years),

ii) Hierarchist (100 years),

iii) and Egalitarian (1,000 years)

Issues like time perspective or appropriate management, or future innovation and improvements could be represented by the 3 aforementioned perspectives. Repele & Bazbauers, (2015) suggests the use of hierarchist perspective since the impact, with proper management, could be avoided due to its balanced time perspective. Thus, the hierarchist aspect is chosen in this thesis.

3.2 Developing MRIO Models: *Cradle-to-gate Life Cycle Assessment (LCA)*

After the data are collected and prepared, MRIO model for the 2014 year was established, and initial findings that are related to U.S. manufacturing were presented at the Annual Conference of Industrial and Systems Engineers Saber et al, (2018). Then, MRIO models were developed for the period between 1995-2013. Once MRIO models were developed, the final demand of U.S. and Chinese manufacturing industries were entered in the models to quantify their national and global GHG emissions inventory as

well as total economic output. The economic output ($M) and GHG emissions were characterized as national-onsite, national-supply chains, and global supply chains.

MRIO models developed in this study comprised of the flow matrices for all the 41 countries (this covers national and international economic flows). In contrast to a single region input-output model, MRIO models enable researchers to trace the economic and environmental impacts both at the national and global scale, which can uncover the links between various sectors, as well as the economic relationship between different regions of the global economy (Miller & Blair, 2009); Guo et al., 2012; Wiedmann et al., (2011).

Equation 3-1 shows the quantification of the GHG emissions inventory:

$$E_{GHG} = C_{GHG}(I - A^{CR_{ij}})^{-1} f_i \qquad \text{Eq. 3-1}$$

where E_{GHG} is GHG emissions vector for each production sector and C_{GHG} is carbon emissions per million dollar economic activity for each sector of 41 regions as a diagonal matrix. **I** is identity matrix, and all the elements of I matrix are zeros except the diagonal elements which are equal to 1. A^{CR}_{ij} matrix is technical coeffect matrix. A^{CR}_{ij} contains inter-industry requirements for all the 35 sectors of all the 41 regions. A^{CR}_{ij} present the sales (input) of sector i from country C to industry j in country R. For the model used in this thesis, R=1,2, 3….41, i=1,2,3….35, j=1,2,3….35, C=1,2,3….41. The term $(I - A^{CR_{ij}})^{-1}$ is called Leontief inverse (Leontief, 1970) which is also termed with **L** in the literature.

In equation 3-1, f_i is a vector output from the economic sectors; the focus of this thesis is the manufacturing industries of U.S. and China, thus, in the U.S. model, U.S. manufacturing industries have output vector f_i and zero for all the rest of sectors and all the countries. Similarly, for the China model, only China manufacturing industries have output vector with setting the rest of sectors of all the countries to zero. As discussed before, in 2016, 97% of U.S. GHG emissions came from CO_2, N_2O, and CH_4 (United States Environmental Protection Agency, 2018). Thus, these three GHG were focused in this thesis.

3.3 Mid and End-point Impact Assessment: MRIO+ReCipe

LCIA could be performed by multiplying the results of LCI by the midpoint and endpoint characterization factors (CF). Thus, the midpoint impacts of GHG emissions inventory is calculated using equation 3-2

$$GWP = \sum E_{GHG_m} * CF_{E,GWP_m} \qquad \text{Eq 3-2}$$

where GWP is global warming potential from GHG and its unit is kg CO2 equivalents ; E_{GHG_m} is total emissions of GHG_m; CF_{E,GWP_m} is the characterization factors obtained from Huijbregts et al., (2017) and it converts emissions of GHG_m to global warming potential (GWP) , where m represents the GHG emission type investigated (m =1,2, and 3, CO_2, N_2O, and CH_4, accordingly).

Equation 3-3 illustrates the calculation of ozone depletion protentional.

$$ODP = \sum E_{GHG_n} * CF_{E,ODP_n} \qquad \text{Eq 3-3}$$

where ODP is ozone depletion potential from GHG in kg CFC-11 equivalents; E_{GHG_n} is total emissions of GHG_n; CF_{E,ODP_n} is the characterization factor that converts emissions of GHG_n to ozone depletion potential, where m represents the number of GHG investigated; for ozone depletion, n = 1 since only N_2O has ozone depletion midpoint impact, thus CO_2 and CH_4 were not considered.

The two type of end point impacts that are studied in this thesis are damage to human health and damage to the ecosystem. Damage to human health is premature death and sickness disability including irrigation that is caused by the emissions of GHG by the manufacturing industries. Damage to human health is measured as disability-adjusted life years (DALY) and it's unit could be understood as one lost year of healthy life. Damage to human health in this study comes from GWP and ODP mid-point impacts. The second type of damage is damage to the ecosystem. Damage to the ecosystem is defined as the loss of species due to environmental load and its measured by species per year (Species.year). Species.year's unit indicates that there is roughly one extinction per million species each year. Damage to the ecosystem is

assumed to be the sum of the damage of GWP to terrestrial species and the damage of GWP to freshwater fish.

The endpoint impact is calculated by multiplying midpoint impact by endpoint characterization factors, as illustrated in the equation 3-4 below.

$$HH = GWP \ * CF_{GWP,HH} + ODP \ * CF_{ODP,HH} \qquad \text{Eq 3-4}$$

HH is the damage to human health in DALY; $CF_{GWP,HH}$ is GWP to HH characterization factor; $CF_{ODP,HH}$ is ODP to HH characterization factor. Finally, the mathematical formulation for damage to ecosystem is presented in equation 3-5.

$$ES = GWP \ * CF_{GWP,ES} \qquad \text{Eq 3-5}$$

where ES is damage to the ecosystem and it is measured as species.year and $CF_{GWP,ES}$ is GWP to ES characterization factor.

The flow chart below, figure 3-2, shows the midpoint and endpoint impact of the three investigated GHG.

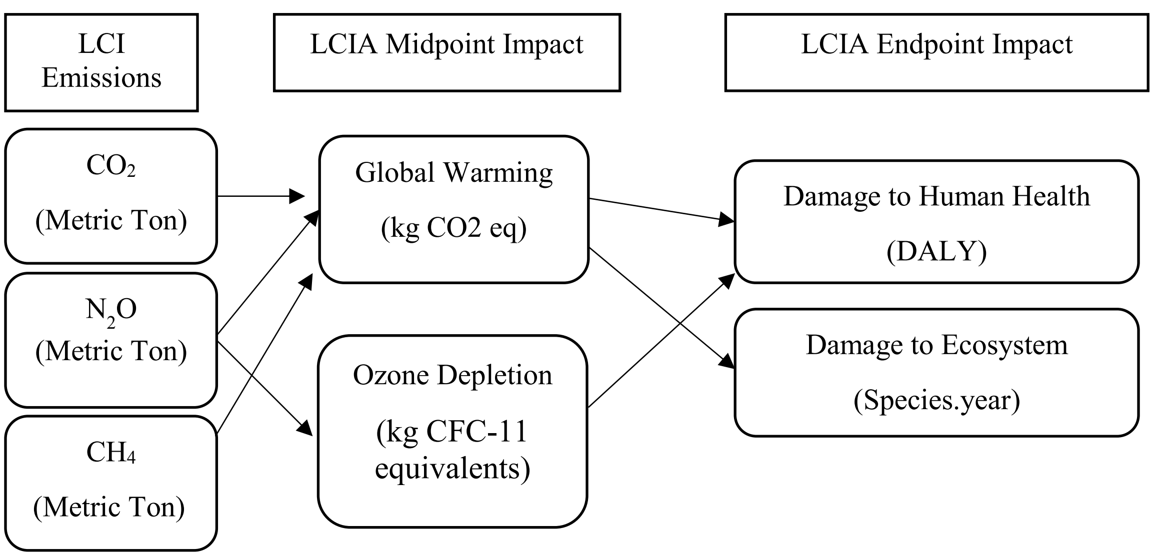

Figure 3-2: LCI and LCIA flowchart (Huijbregts et al., 2017)

Figures 3-3 illustrates the calculation of midpoint impact from the multiplication of LCI results with the characterization factors as well as the estimation of endpoint impacts from the multiplication of midpoint impacts by the endpoint characterization factors.

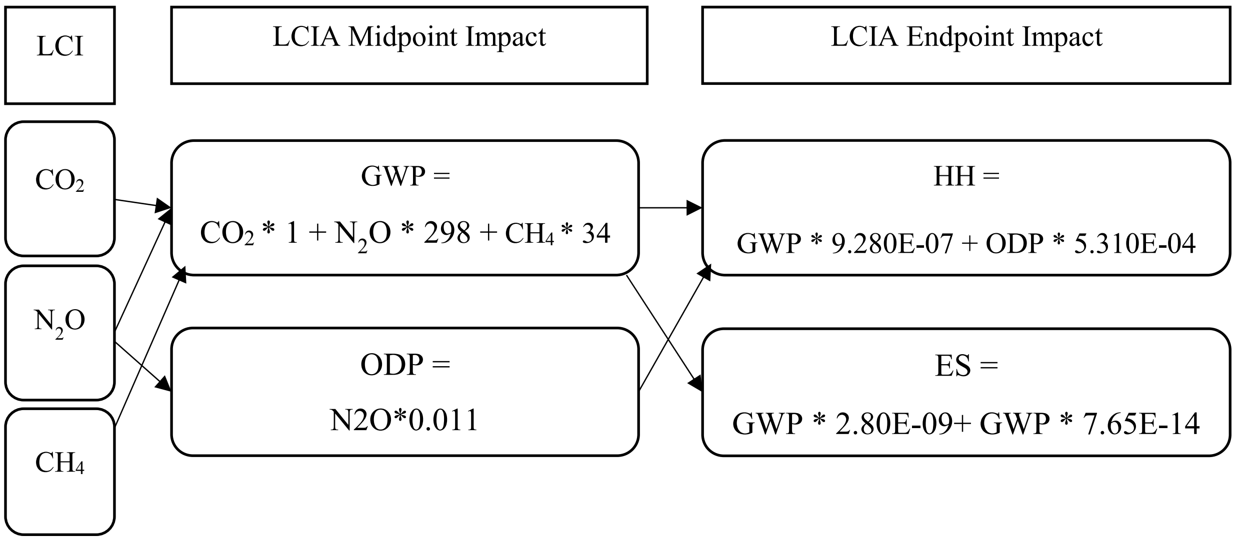

Figure 3-3 Mid and end-point Impact characterization factors (Huijbregts et al., 2017)

3.4 Structural Decomposition Analysis (SDA)

Rose & Chen (1991) defines structural decomposition analysis (SDA) as an "analysis of economic change utilizing a set of comparative static changes in key parameters in an input-output table." SDA investigates the driving factor that over time changes the total output. For example, if SDA is applied to equations 3-1, it can examine how the change in C_{GHG}, $A^{CR_{ij}}$, and f_i will drive the change in GHG emissions. To formulate the equations of SDA on equation 3-1, for simplicity E_{GHG} is set as **X,** $(I - A^{CR_{ij}})^{-1}$ as **L**, C_{GHG} as **c**, and f_i as f, thus equation 3-1 is modified to:

$$X = cLf \qquad \text{Eq 3-6}$$

There are three terms in equation 3-6, and considering two different years, y_{i+1} and y_i , i=1995, 1996,..., 2013. The number of decomposition equations describing the change in output are determined by taking the factorial of the number of terms in equation 3-6, which is equal to 3!=6. Therefore, six

decomposing equations that represent the change in **X** are derived. Equations 3-7 to 3-12 illustrate the decomposition equations of change in GHG emissions.

$$\Delta X = c_{yi+1}\Delta L f_{yi+1} + c_{yi+1} L_i \Delta f + \Delta c L_i f_{yi} \quad \text{Eq 3-7}$$

$$\Delta X = c_{yi+1}\Delta L f_{yi+1} + c_{yi} L_i \Delta f + \Delta c L_i f_{yi+1} \quad \text{Eq 3-8}$$

$$\Delta X = c_{yi+1}\Delta L f_{yi} + c_{yi+1} L_{i+1} \Delta f + \Delta c L_i f_{yi} \quad \text{Eq 3-9}$$

$$\Delta X = c_{yi}\Delta L f_{yi} + c_{yi+1} L_{i+1} \Delta f + \Delta c L_{i+1} f_{yi} \quad \text{Eq 3-10}$$

$$\Delta X = c_{yi}\Delta L f_{yi+1} + c_{yi} L_i \Delta f + \Delta c Li +_1 f_{yi+1} \quad \text{Eq 3-11}$$

$$\Delta X = c_{yi}\Delta L f_{yi} + c_{yi} L_{i+1} \Delta f + \Delta c L_{i+1} f_{yi+1} \quad \text{Eq 3-12}$$

The effect of the change in the Leontief matrix can be calculated by taking the mean for the six first terms in the six decomposing equations. However, Dietzenbacher & Los, (1998) state that maximum, minimums and standard deviations of each term could also be considered. In this study, the change in emissions for each term is calculated by taking the mean for the terms. Next section describes the results.

CHAPTER 4: RESULTS

In this section, the results of the model will be explained. First, 2014 results are explained regarding LCI and LCIA of U.S. and China. Second, the LCI and LCIA results for the time series analysis are presented for U.S. and China. Finally, the U.S. and China's SDA results are illustrated.

4.1 Comparison of the Manufacturing Industries of U.S. and China for the year 2014

4.1.1 LCI Results

4.1.1.1 Total Economic Output by Sector

Figure 4-1 shows the total economic output of U.S. manufacturing by top 10 industries. As shown the figure, Food, Beverages, and Tobacco industry had the highest economic output of 716 billion dollars while Mining and Quarrying came in the second place, and Chemicals and Chemical Products industry was ranked as the third with the total economic output of 562 billion dollars and 559 billion dollars respectively.

On the other hand, the total economic output of the top 10 industries in China is shown in Figure 4-2. Based on Figure 4-2, Electrical and Optical Equipment had the highest total economic output of 1,517 billion dollars while Agriculture, Hunting, Forestry, and Fishing was ranked as the second and Food, Beverages and Tobacco industry was ranked as the third with the total economic output of 1,255 billion dollars and 1,187 billion dollars, srespectively.

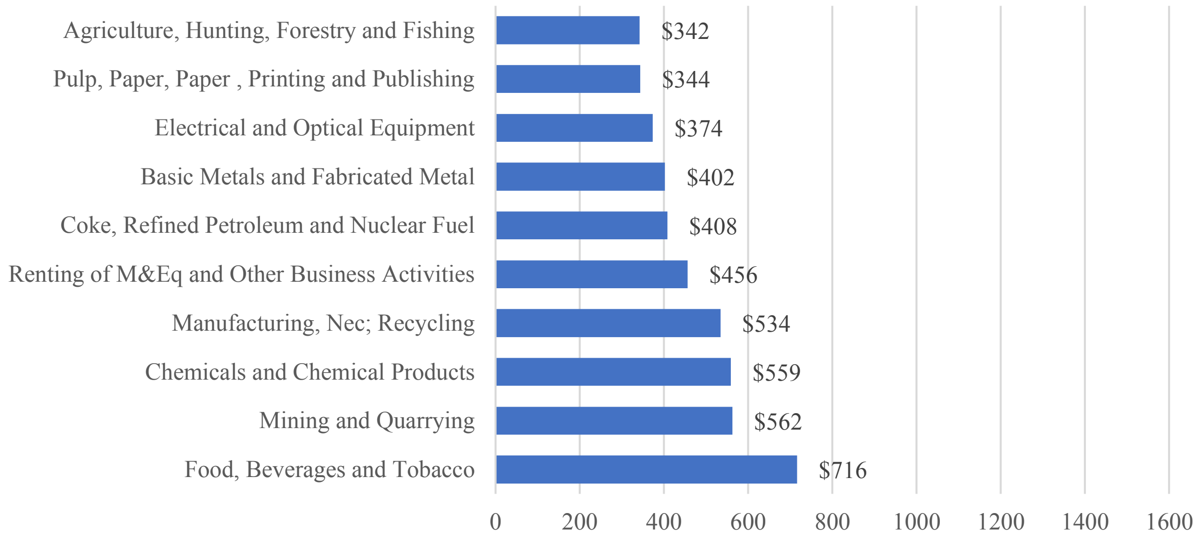

Figure 4-1: Top 10 U.S. mfg. industries in terms of economic output in $B in 2014

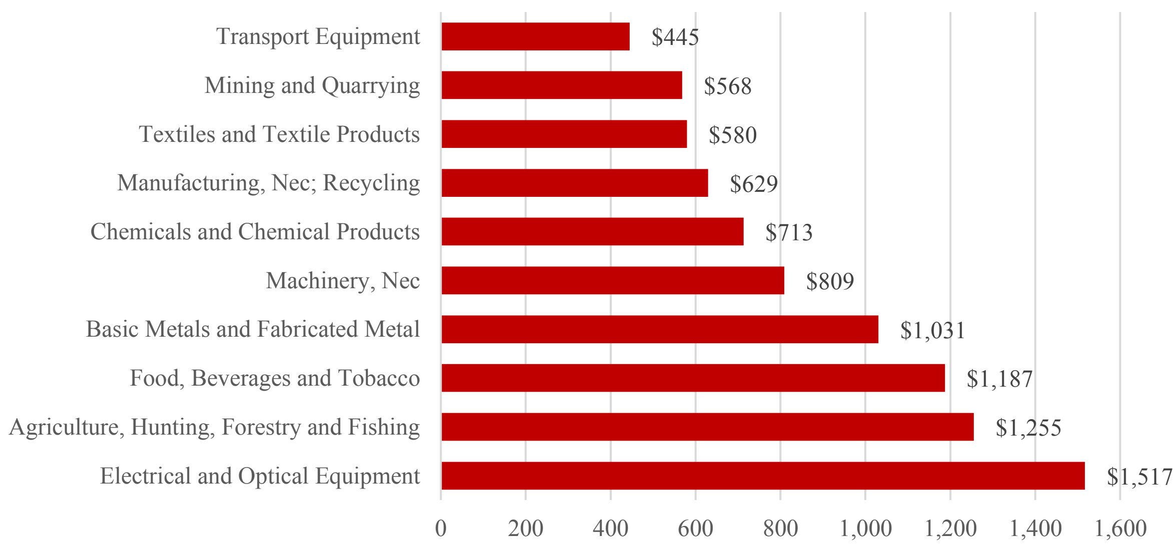

Figure 4-2: Top 10 China mfg. industries in terms of economic output in $B in 2014

4.1.1.2 CO_2 Emissions by Sector

In terms of CO_2 emissions, the analysis showed that China is superior to the U.S. in this category. Figure 4-3 and Figure 4-4 illustrate the top 10 industries with the highest share of CO_2 emissions for the U.S. and China respectively. In both countries, Electricity, Gas, and Water Supply had the top CO_2 emissions with 329 million tons for the U.S. and 1870 million tons for China. The second largest CO_2 emissions for the U.S. comes from Coke, Refined Petroleum and Nuclear Fuel with a total of 148 million tons while the second largest for China comes from Basic Metals and Fabricated Metal. Mining and Quarrying of the U.S. was ranked as the third with total CO_2 emissions of 138 million tons. In contrast, the third largest CO_2 emissions' inventory share in China was found to be from Chemicals and Chemical Products with total CO_2 emissions of 219 million tons.

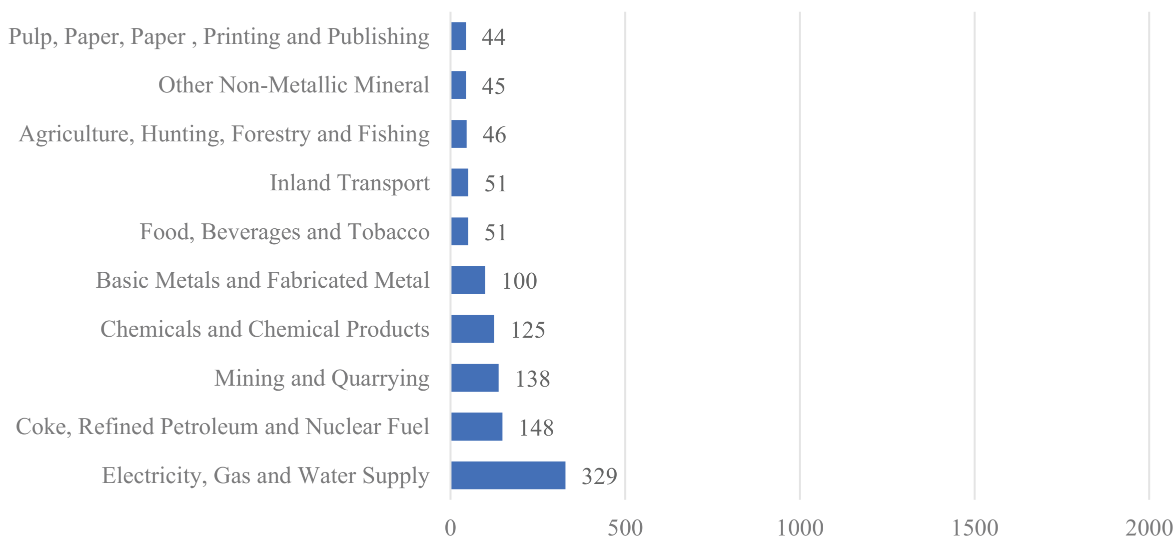

Figure 4-3: CO_2 emis. of 10 top U.S. industries due to activities of U.S. mfg. in MMT

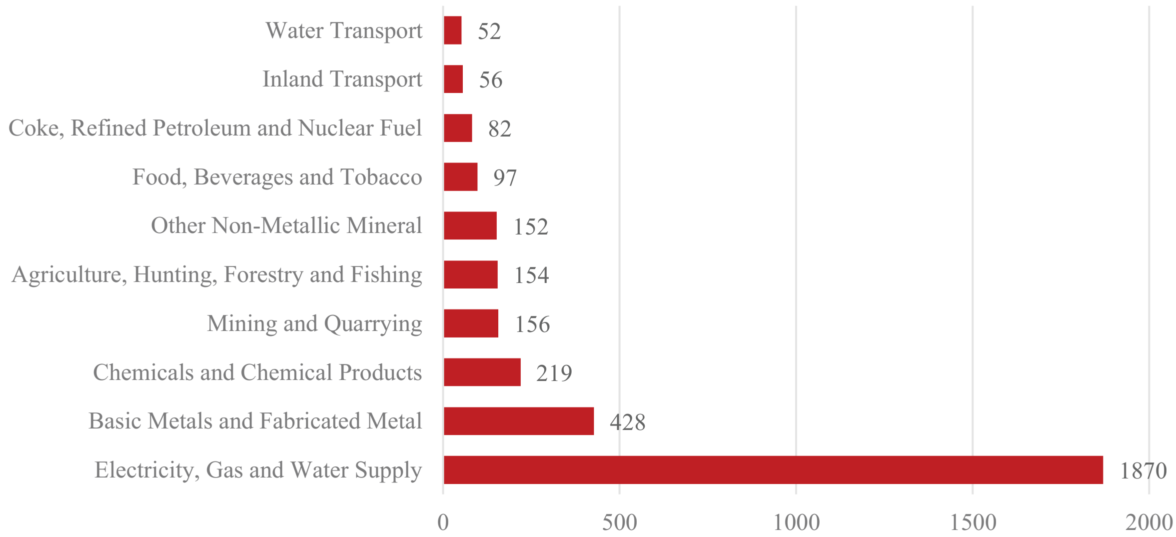

Figure 4-4: CO_2 emis. of 10 top China industries due to activities of China mfg. in MMT

4.1.1.3 CH_4 Emissions by Sector

The top 5 industries regarding CH_4 emissions for the U.S. and China were shown in Figures 4-5 and 4-6 respectively. The primary two industries regarding CH_4 emissions were Agriculture, Hunting, Forestry and Fishing and Mining and Quarrying, which was the same for both countries. In the U.S., the highest CH_4 emitting industry was Mining and Quarrying with total of CH_4 emissions of 11.7 million metric tons while Mining and Quarrying in China had the second highest CH_4 emissions of 18.9 million metric tons. Moreover, Agriculture, Hunting, Forestry and Fishing of U.S. had the second highest CH_4 emissions of 9.1 million metric tons while in China, Agriculture, Hunting, Forestry and Fishing had the highest CH_4 emissions with 34.5 million metric tons.

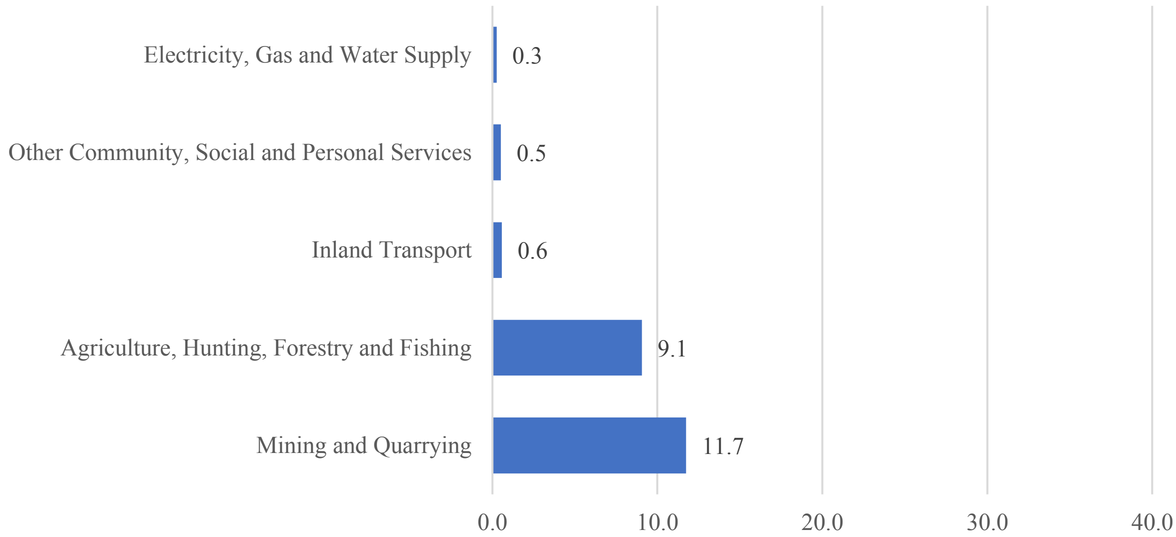

Figure 4-5: CH_4 emis. of 5 top U.S. industries due to activities of U.S. mfg. in MMT

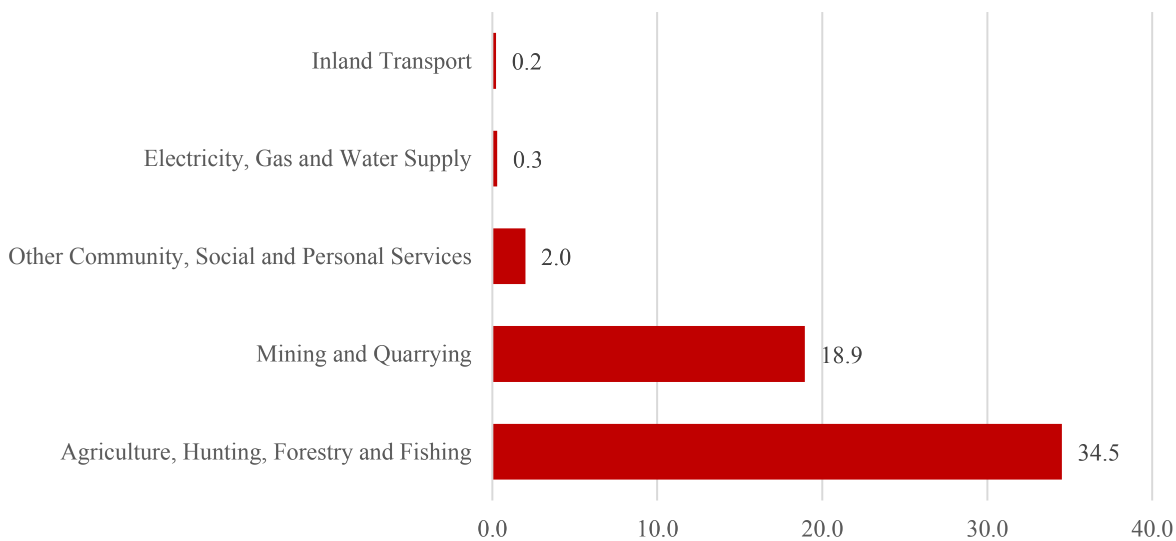

Figure 4-6: CH_4 emis. of 5 top China industries due to activities of China mfg. in MMT

4.1.1.4 N_2O Emissions by Sector

For N_2O emissions, the top 3 industries for both the U.S. and China were found to be:

i) Agriculture, Hunting, Forestry, and Fishing with 0.68 million metric tons for the U.S. and 2.41 million metric tons for China.

ii) Chemicals and Chemical Products with 0.06 million metric tons for the U.S. and 0.1 million metric tons for China.

iii) Electricity, Gas and Water Supply with 0.01 million metric tons for the U.S. and 0.04 million metric tons for China.

The N_2O emissions results for both the U.S. and China were shown in Figures 4-7 and 4-8, respectively.

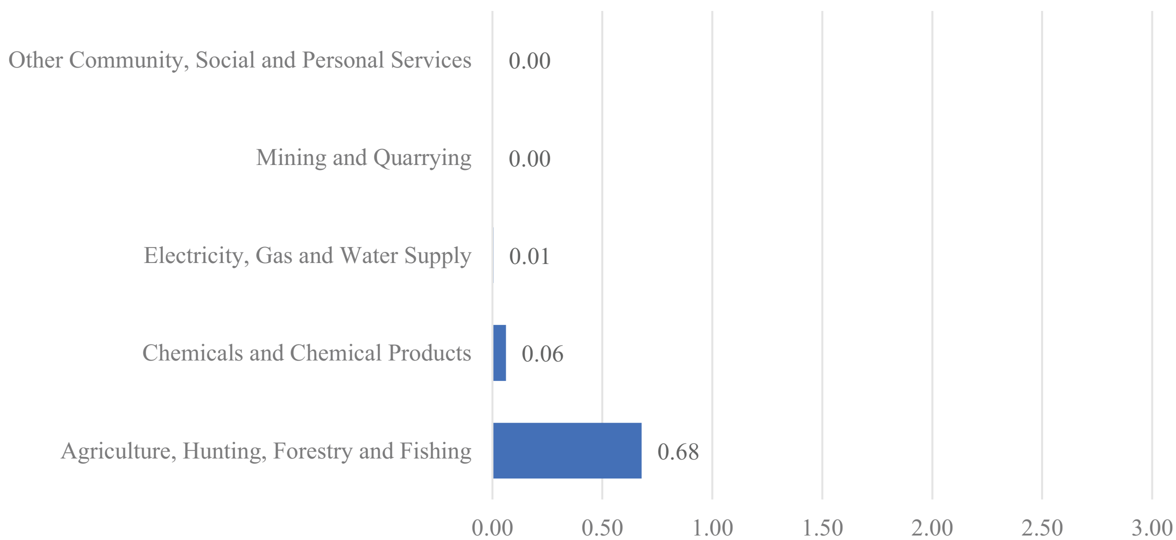

Figure 4-7: N_2O emis. of 5 Top U.S. industries due to activities of U.S. mfg. in MMT

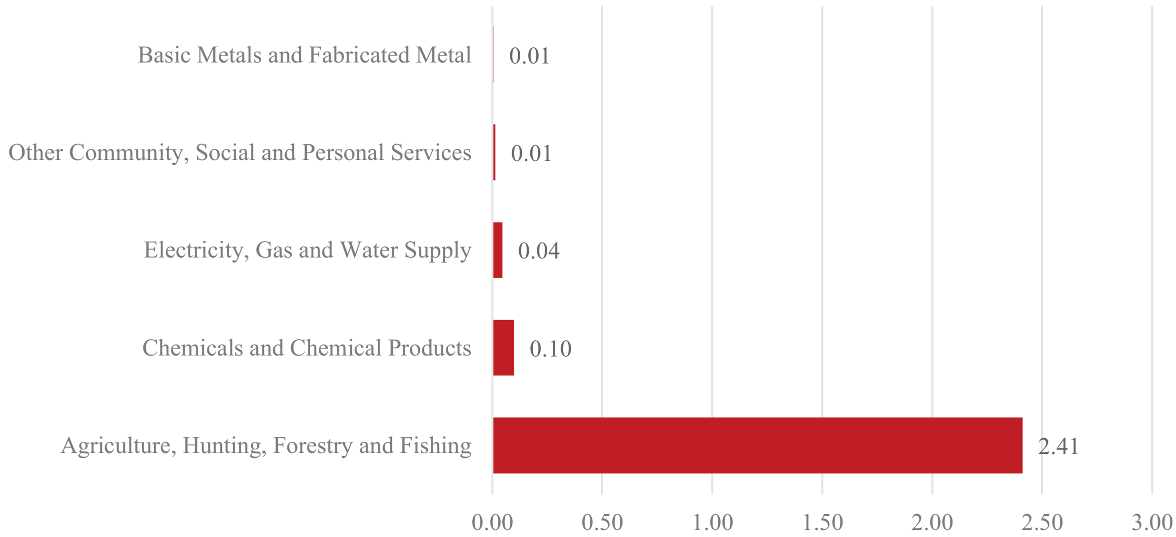

Figure 4-8: N_2O emis. of 5 top China industries due to activities of China mfg. in MMT

4.1.2 LCIA Results

4.1.2.1 Midpoint Impact

4.1.2.1.1 Global Warming Potential (GWP) by Country

The global warming potential of U.S. manufacturing, Figure 4-9, in the United States was around 1681 million kg CO_2 equivalent. Furthermore, the GWP impact of the U.S. manufacturing on the RoW (rest of the world) was ranked as the second highest, and China was the third highest with total GWP of 172 and 111 million kg CO_2 equivalent respectively. These ROW and China results need to be considered as the top global supply chain emittant countries due to the U.S. manufacturing activities.

On the other hand, the global warming potential of China manufacturing, Figure 4-10, was around 5614 million kg CO_2 equivalent. Similar to the U.S., second highest region regarding GWP by China manufacturing was RoW with total GWP of 265 million kg CO_2 equivalent, and Russia was the third highest impacted country with GWP of 77 million kg CO_2 equivalent. Thus, the U.S. was not found to be among the top three global supply chain emittant countries for the China manufacturing.

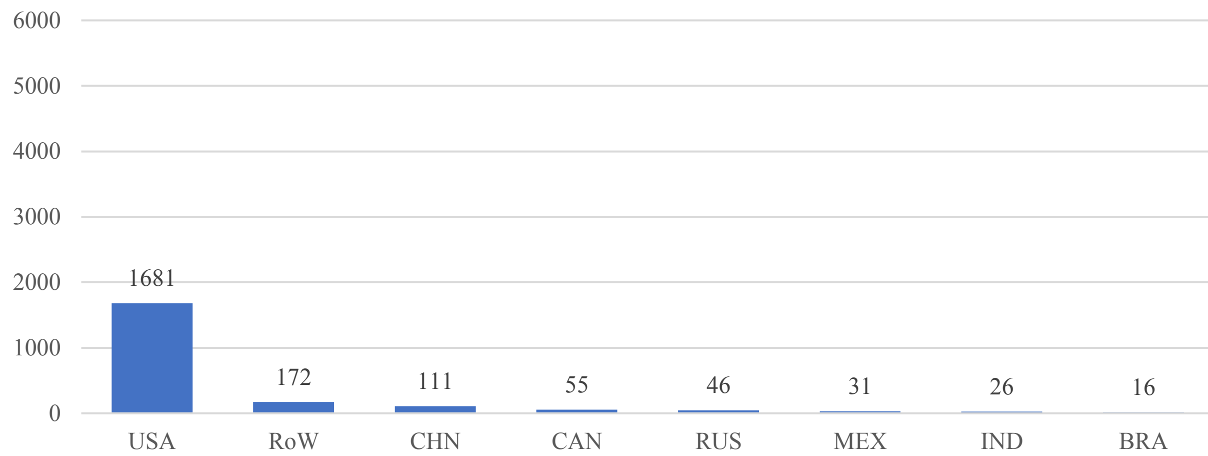

Figure 4-9: GWP of U.S. mfg. on the U.S. and top 7 countries in million kg CO_2 eq

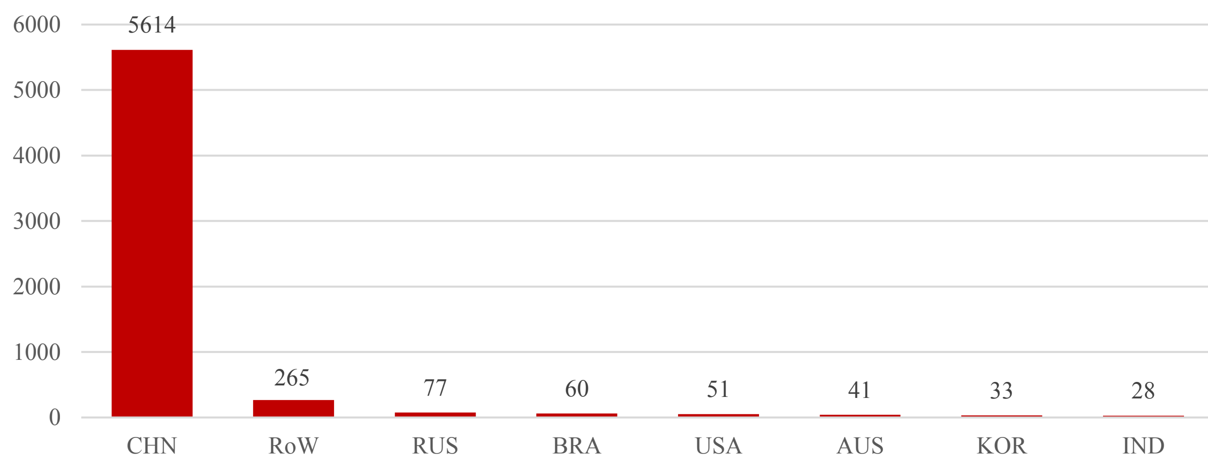

Figure 4-10: GWP of China mfg. on China and top 7 countries in million kg CO_2 eq

4.1.2.1.2 Ozone Depletion Potential (ODP)

The ozone depletion potential of the U.S. manufacturing and the top 7 countries in the global supply chains were shown in Figure 4-11. The impact of U.S. manufacturing on the United States (domestic supply chain) was around 69 hundred kg CFC-11 eq. The U.S. manufacturing impacts on the RoW and China weere found to be the the second and third highest with total ODP of 7 hundred kg CFC-11 eq and 2 hundred kg CFC-11 eq., respectively.

On the other hand, the impact of China's manufacturing (See Figure 4-12), on China regarding OPD is around 258 hundred kg CFC-11 eq. Similar to the U.S. the second highest impact is on RoW with total OPD of 14 hundred kg CFC-11 eq. However, the third highest impacted coutnry due to China's manufacturing was found to be Brazil with total OPD of 6 hundred kg CFC-11 eq.

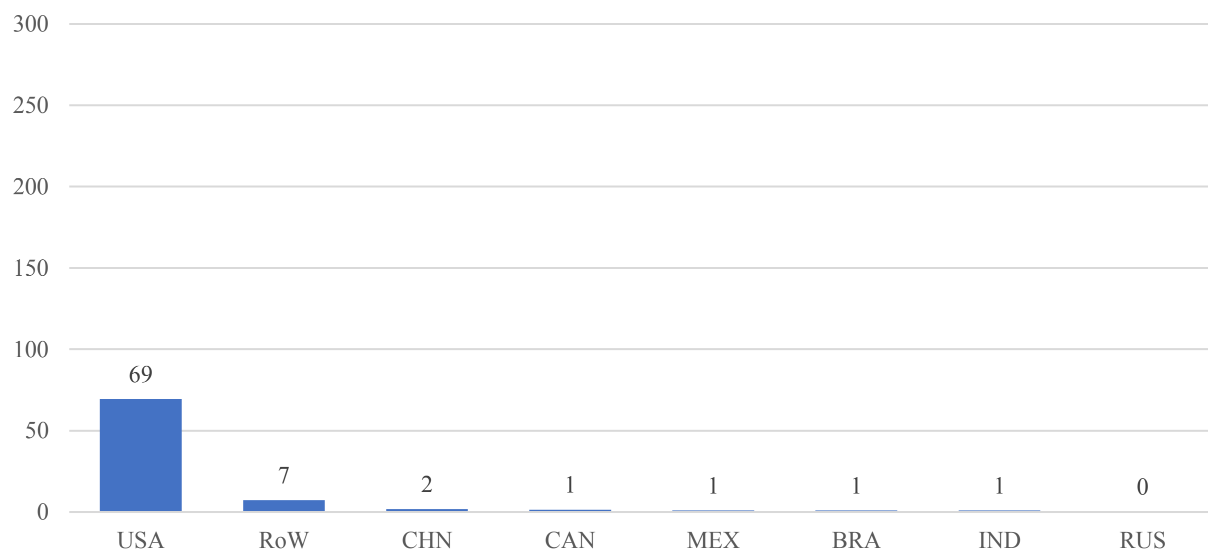

Figure 4-11: ODP of U.S. mfg. on the U.S. and top 7 countries in HND kg CFC-11 eq.

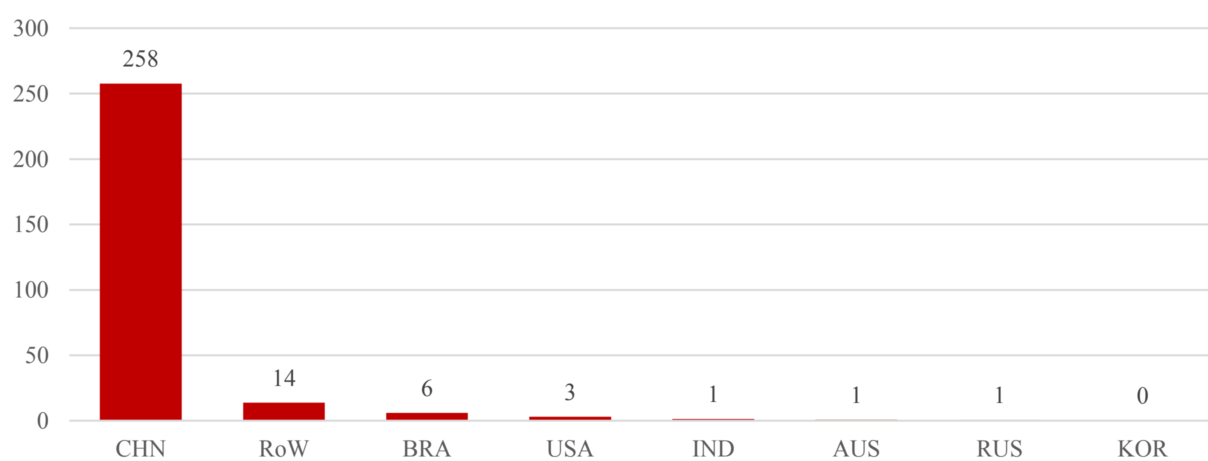

Figure 4-12: ODP of China mfg. on China and top 7 countries in HND kg CFC-11 eq.

4.1.2.2 Endpoint Impacts

4.1.2.2.1 Damage to Human Health by Country

The result of damage to human health analysis for the U.S. manufacturing was shown in Figure 4-13. The impact of U.S. manufacturing on human health in the U.S. was around 72293 disability-adjusted life year (DALY). While the impact on the RoW is 7303 DALY and the third highest impact is on China with 2099 DALY.

Similarly, the DALY impact of the China manufacturing were shown in Figure 4-14. According to the figure, the damage by the China manufacturing on human health in China was 249496 DALY. While manufacturing industries of China had the second most significant impact on the RoW with 13162 DALY. Furthermore, Brazil was ranked as the third most significant impacted country with 5622 DALY, and the U.S. was ranekd as the fourth most substantial impact with 2847 DALY.

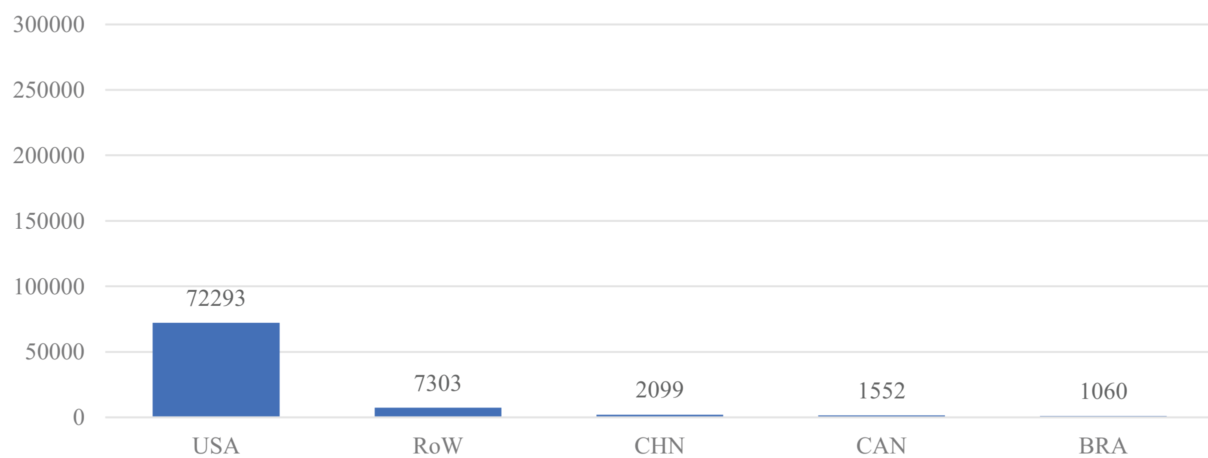

Figure 4-13: Impact of U.S. mfg. on human health for top 5 countries in DALY

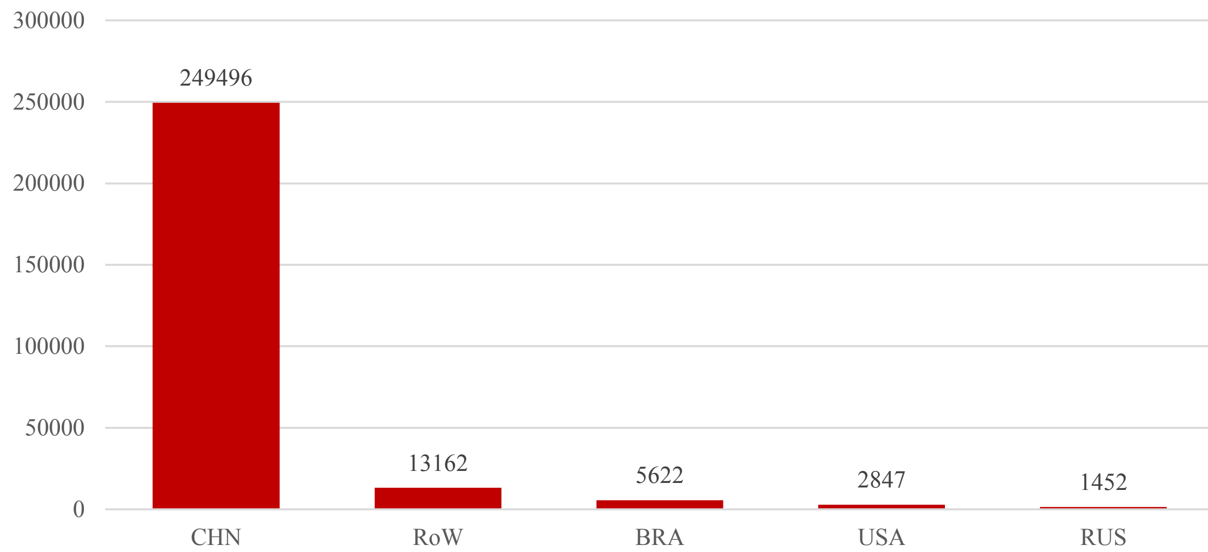

Figure 4-14: Impact of China mfg. on human health for top 5 countries in DALY

4.1.2.2.2 Damage to Ecosystem by Country

Damage to the ecosystem in the U.S. (domestic impact) by the U.S. manufacturing was estimated as 218 species.year. While the damage of U.S. manufacturing to the ecosystem of the RoW was 22 species.year and the ripple impact of damage to China's ecosystem was estimated as 6 species.year, as shown in Figure 4-15.

While the damage of China's manufacturing to the domestic ecosystem was 753 species.year and the damage to the RoW was 40 species.year. And, Brazil and the U.S. were ranked in the third and fourth places with 17 species.year and 9 species.year respectively as shown in Figure 4-16.

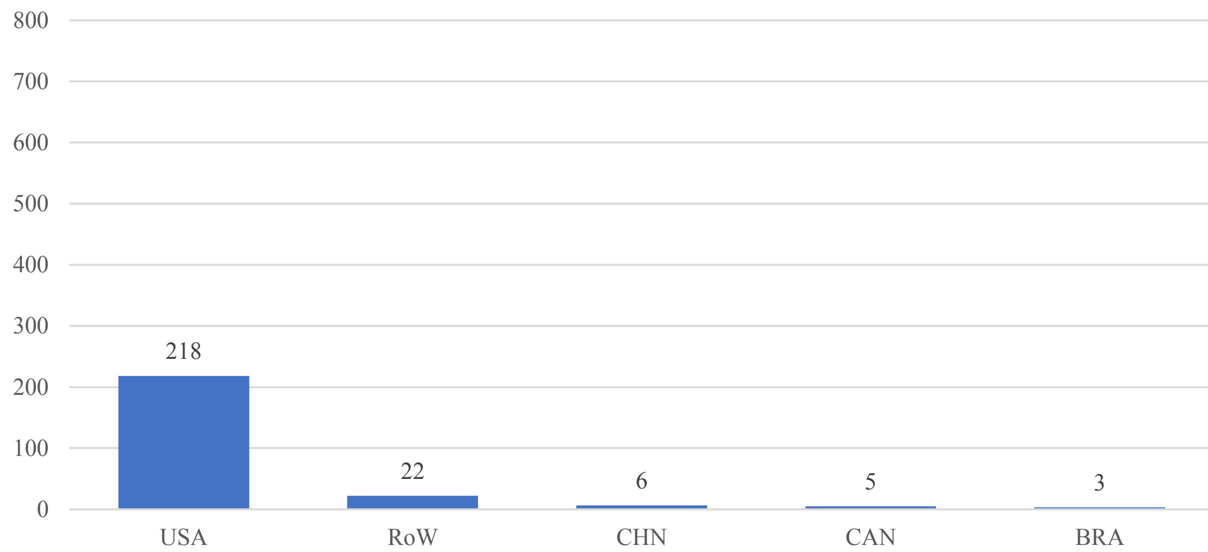

Figure 4-15: Impact of U.S. mfg. on ecosystem for top 5 countries in species.year

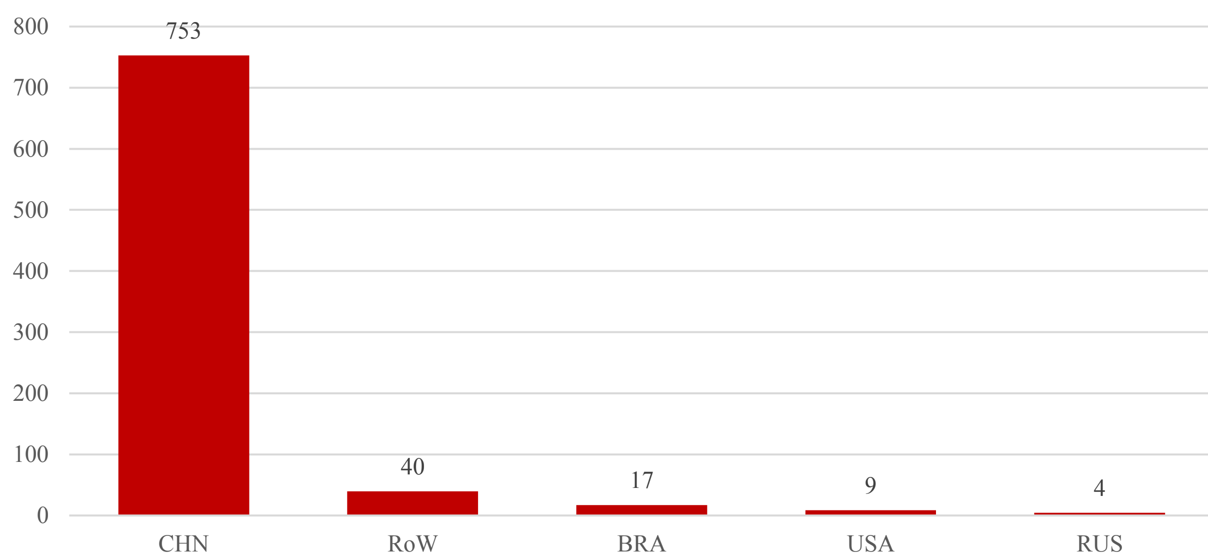

Figure 4-16: Impact of China mfg. on ecosystem for top 5 countries in species.year

4.2 Times Series Analysis

4.2.1 LCI Results

4.2.1.1 Total Global, Domestic, and Manufacturing Domestic Economic Output

The results of time series analysis of U.S. manufacturing economic output is shown in Figure 4-17. From the figure, U.S. economic output has an increasing trend up until the financial crisis in 2008. Due to the crisis, U.S. total economic output has dropped by approximately one billion dollars due to the U.S. manufacturing economic output decline in 2008. The economic output fell from 5,485 billion dollars to 4,590 billion dollars. From 2010 to 2011 U.S. economic output yielded the highest increase of around one billion. The U.S. had the highest economic output of 6,560 billion dollars in 2014. U.S. manufacturing domestic on-site economic output remains proportionate to the total global economic output. The percent share of the U.S. manufacturing domestic (on-site) output ranges between 64% and 69% of total global economic output. Early years have higher percent share in comparison to recent years.

Moreover, the domestic economic output of the U.S. manufacturing ranges from 81% to 89%, based on Figure 4-17, the early years had a higher percentage share of economic output, and the recent ones have lower. Based on these findings, it could be concluded that the increase of total global economic output resulted in a higher percentage of global supply chains' economic output in recent years rather than the domestic (onsite + domestic supply chains) economic output.

Similarly, China's economic output results from years 1995 through 2014 are shown in Figure 4-18. China's total economic output increased throughout the 19 years. However, similar to the U.S., the highest increase in total economic output was between years 2010-2011. The overall increase in China's economic output between the years 2010-2011 was 1.78 billion dollars. China had the highest economic output of 11,892 billion dollars in 2014. China's manufacturing domestic on-site percent share ranged 71% to 79% of total economic output between the years 1995 to 2014. While in comparison to early years, China's domestic percent share decrease in recent years while its global output increased.

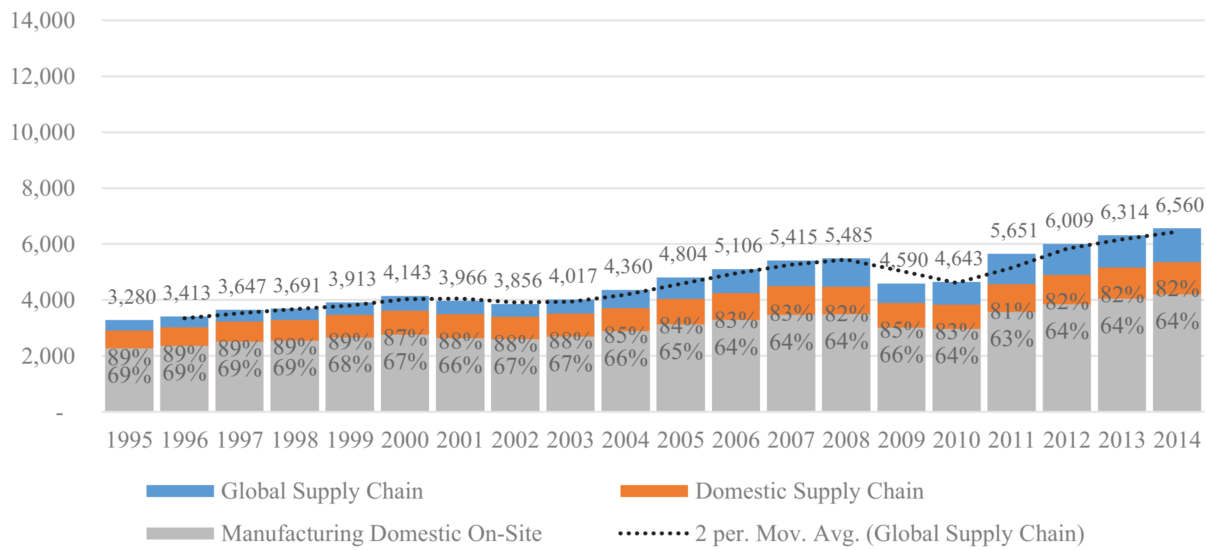

Figure 4-17: U.S. mfg. economic output (global ($B), domestic and mfg. domestic on-site (% share))

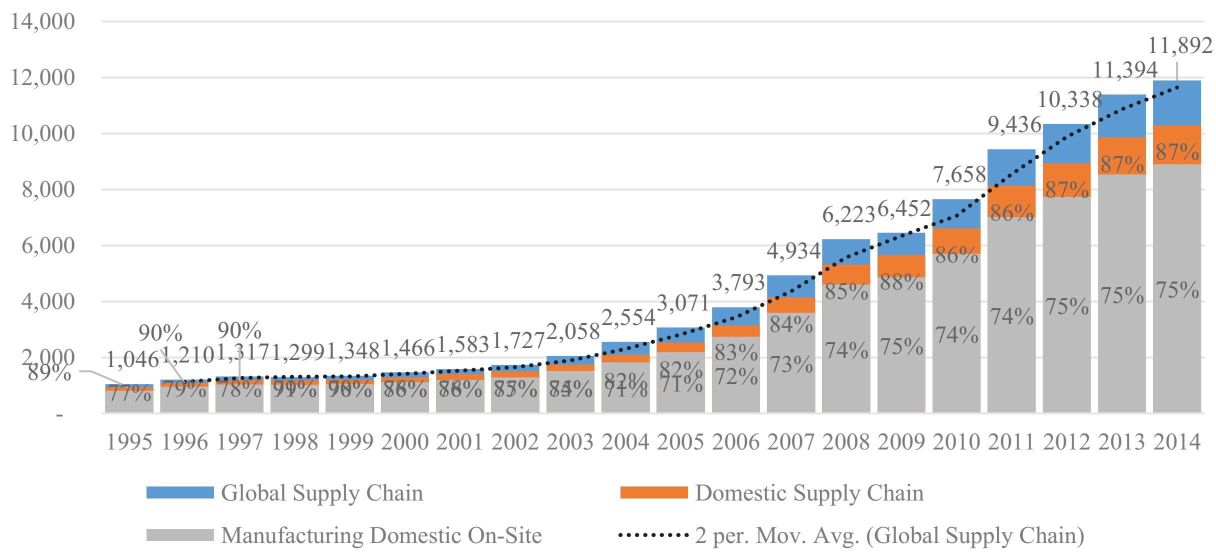

Figure 4-18: China mfg. economic output (global ($B), domestic and mfg. domestic on-site (% share))

4.2.1.2 Total Global, Domestic, and Manufacturing Domestic Greenhouse Gas Emissions

Figure 4-19 shows the total GHG emissions for U.S. manufacturing between the years 1995-2014. The GHG emissions seemed to be increasing from year to year except during the financial crisis in 2009. In comparison to 2008, in 2009 the GHG emissions dropped by 163 million metric tons of CO_2 equivalent.

From Figure 4-19, it can be noticed that the GHG emissions in 2010 are relatively high in comparison to the total global economic output of 2010. U.S. manufacturing domestic on-site GHG emissions range from 41% to 54% of the total GHG emissions (onsite+domestic supply chain+global supply chain). While the domestic GHG emissions ranged from 71% to 84%.

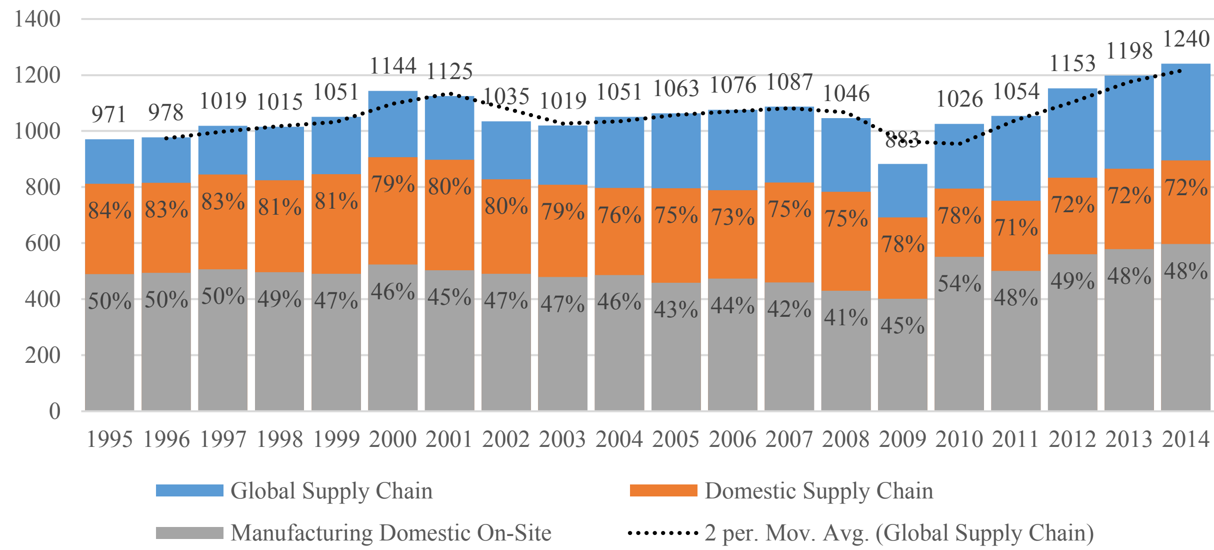

Figure 4-19: U.S. Mfg. GHG emis. (global (MMT CO_2 eq.), domestic supply chain & on-site (% share))

In comparison, China's total GHG emissions are illustrated in Figure 4-20. From the figure, China's GHG emissions had a slight drop in GHG emissions in the years 1997, 1998, 1999, and 2000. However, starting in 2001, the GHG emissions of China's manufacturing had experienced a continuous increase. Moreover, manufacturing domestic on-site percent share along with the domestic supply chains' percent shares decreased towards the recent years, however, the global supply chain-linked emissions increased.

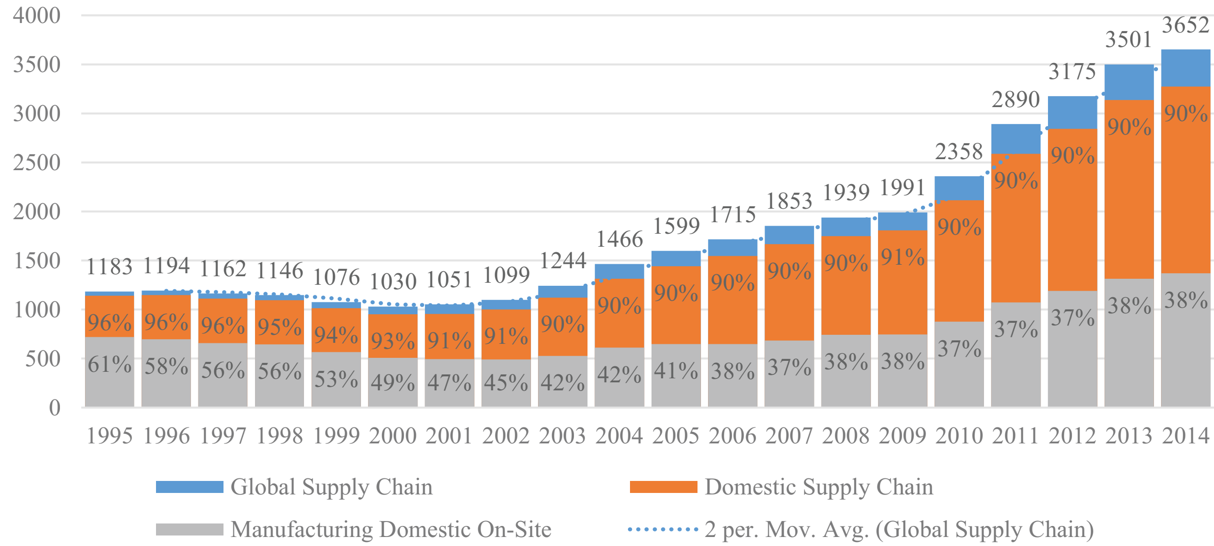

Figure 4-20: China mfg. GHG emis. (global (MMT CO_2 eq), domestic and mfg. domestic on-site (% share))

4.2.1.3 Contribution of CO_2, CH_4, and N_2O to total GHG emissions

Figures 4-21 and 4-22 show the contribution of CO_2, CH_4, and N_2O to total GHG emissions of the U.S. and China, respectively. For both countries, the main contributor to GHG emissions was found to be CO_2 with at least 97.5% for all the years in the U.S., and 97.91% for China. The second highest contributor was found to be CH_4 for both countries.

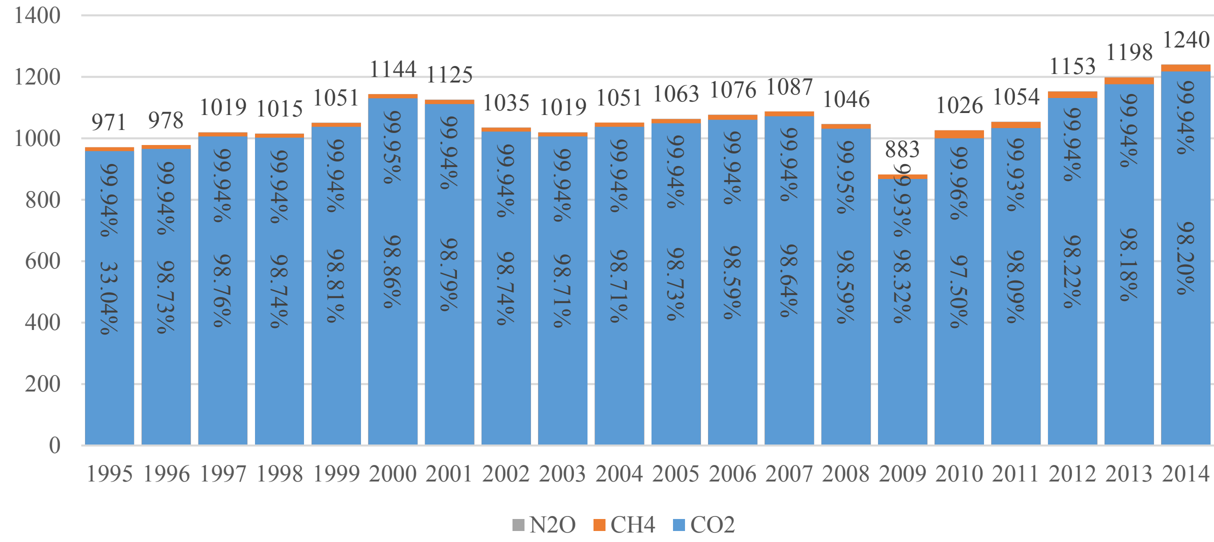

Figure 4-21: Contribution of CO_2 (% cum), CH_4 (% cum), and N_2O (cum GHG emis.) to GHG emissions of U.S mfg..

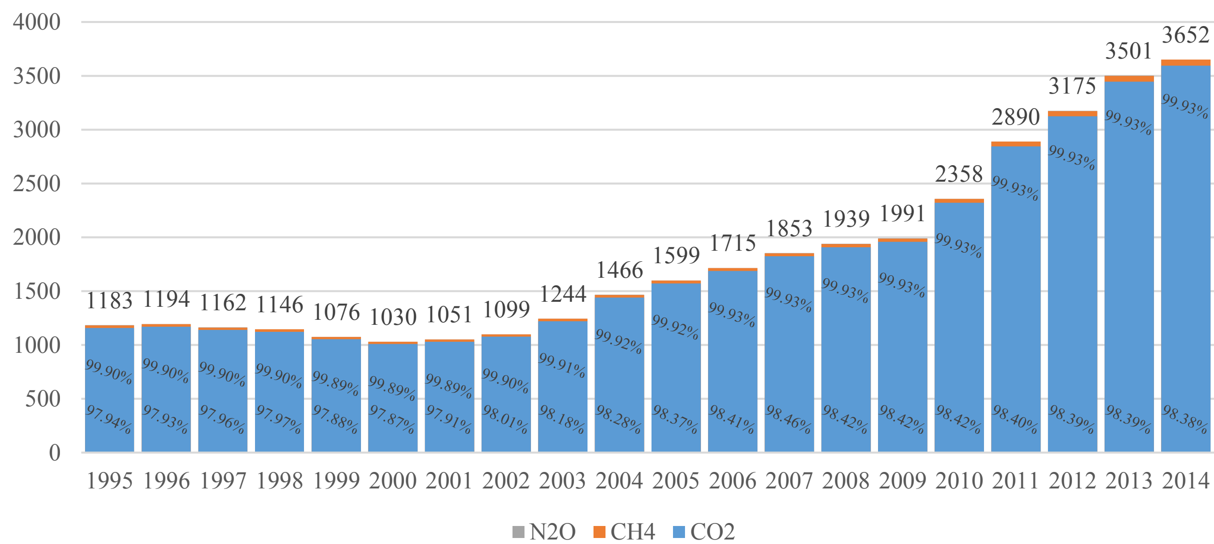

Figure 4-22: Contribution of CO2 (% cum), CH4 (% cum), and N2O (cum GHG emis.) to total GHG emis. of China mfg..

4.2.2 LCIA Results

4.2.2.1 Midpoint Impacts

4.2.2.1.1 GWP

The impacts of the U.S. manufacturing on global warming is shown in Figure 4-23. The GWP for the years before the U.S. economic crisis does not have too many fluctuations across the years. However, an increasing trend is clearly for the years after the economic crisis in 2008. Although the GHG emissions of 2010 were lower than the ones in in 2011, the GWP of 2010 was higher than in 2011. This is because the amount of CH_4 emissions of 2010 was found to be higher than the CO_2 and CH_4 GWP characterization factor is 34 times larger than CO_2 characterization factor. Similarly, the GWP results of China manufacturing on global warming are depicted in Figure 4-24. Since 2002, it is evident that China's manufacturing industries' GWP impact is on a continuous rise, compared to a less steep rise observed in the U.S. manufacturing grapgh in figure 4-23.

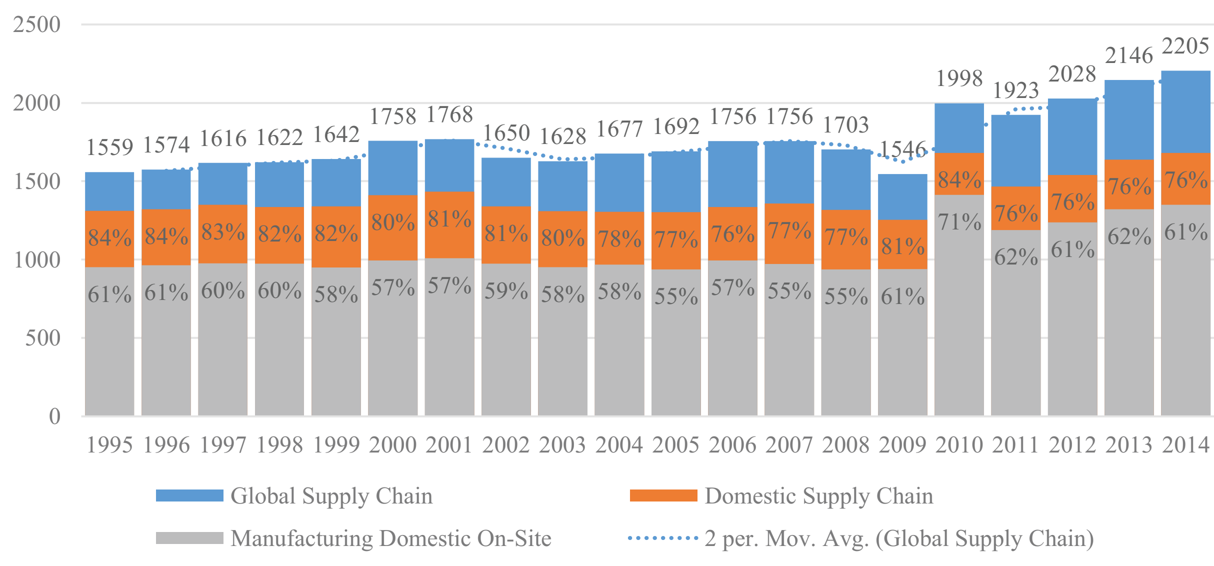

Figure 4-23: U.S. mfg. GWP (global (M kg CO2 eq.), domestic and mfg. domestic on-site (% share))

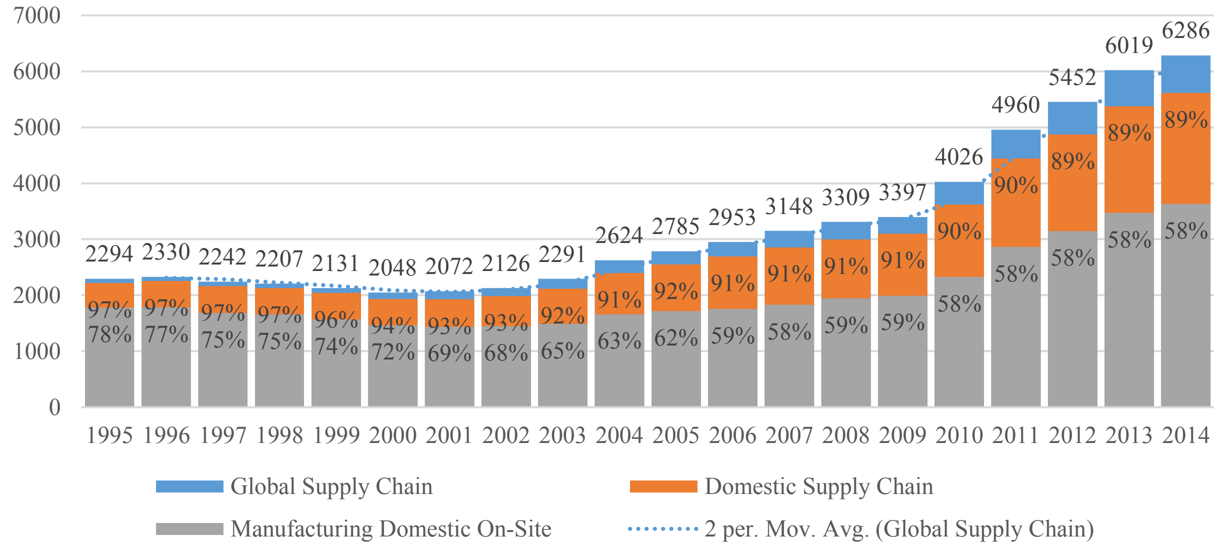

Figure 4-24: China mfg. GWP (global (M kg CO2 eq), domestic and mfg. domestic on-site (% share))

4.2.2.1.2 ODP

Figure 4-25 shows the trend of ozone depletion impacts of U.S. manufacturing. There is an inherent fluctuation continues until 2009, which seems to have a relatively small range. However, in 2010, crucial amount of drop observed in the ozone depletion potential, and after 2010, the ozone depletion potential was found to be on an increasing trend. The GHG emissions of 2012 were found to be more substaintial than 2011. However, the ODP of 2012 was found to be relatively lower than 2011. This could be attributed to the share of N_2O emissions in 2011 to be higher than its in in 2012.

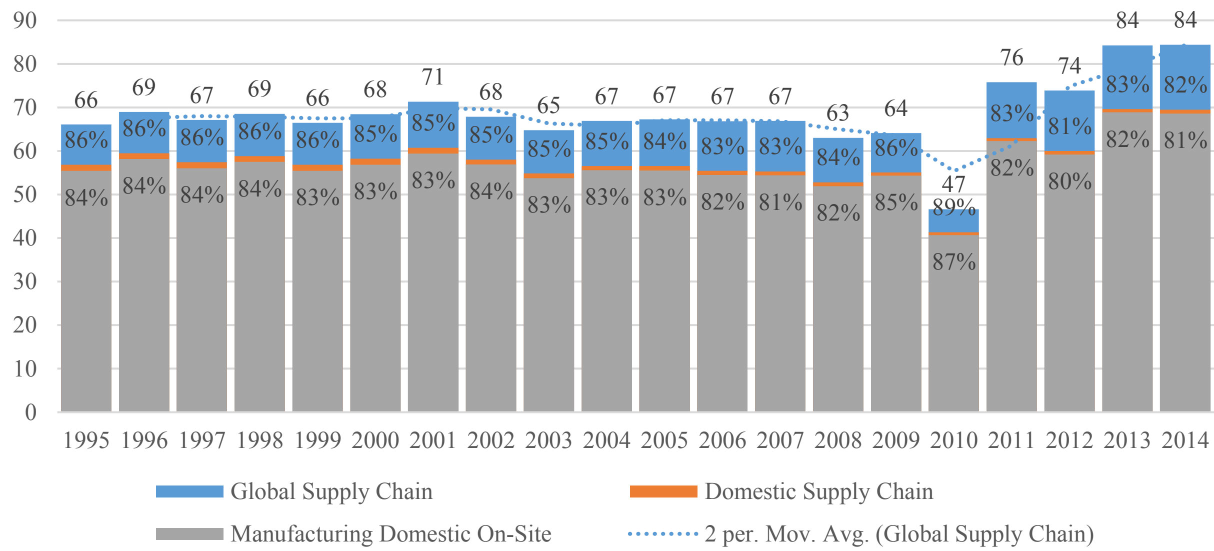

Figure 4-25: U.S. mfg. ODP (global (HND kg CFC-11 eq), domestic and mfg. domestic on-site (% share))

Similarly, the ODP impact of China's manufacturing industry was shown in Figure 4-26. The ODP results of China seems to be relatively aligned with the GWP results of China. The ODP of China manufacturing was found to be on a continuously increasing trend starting from 2003 until 2014.

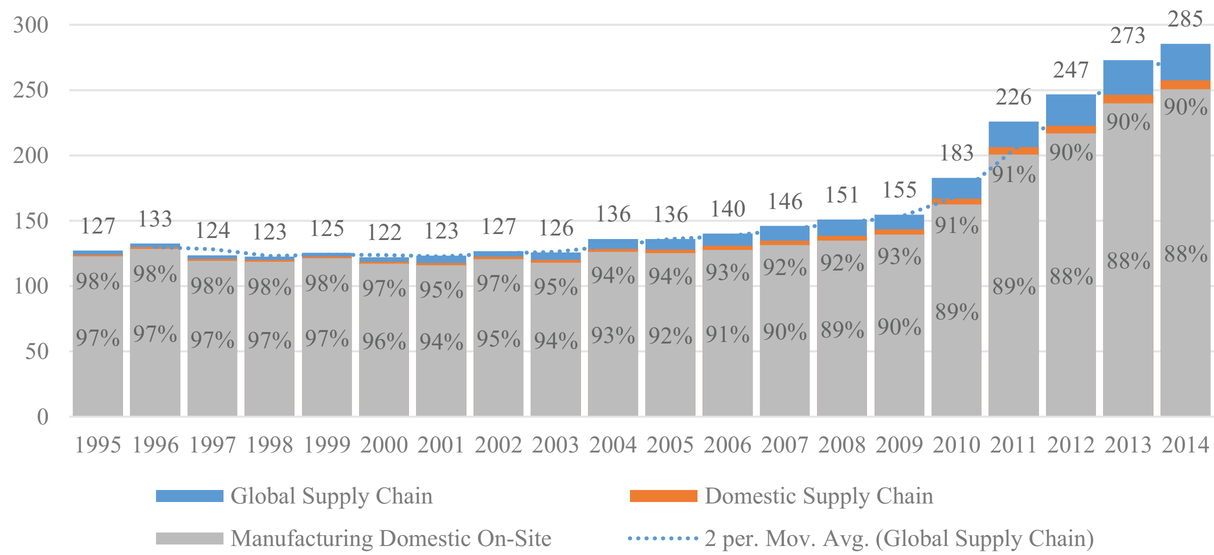

Figure 4-26: China mfg. ODP (global (HND kg CFC-11 eq), domestic and mfg. domestic on-site (% share))

4.2.2.2 Endpoint Impact

4.2.2.2.1 Damage to Human Health

The U.S. manufacturing damage to human health results were shown in Figure 4-27. It can be concluded that damage to human health increased drastically after 2010. However, for China (See Figure 4-28), the damage has been on the rise since 2003.

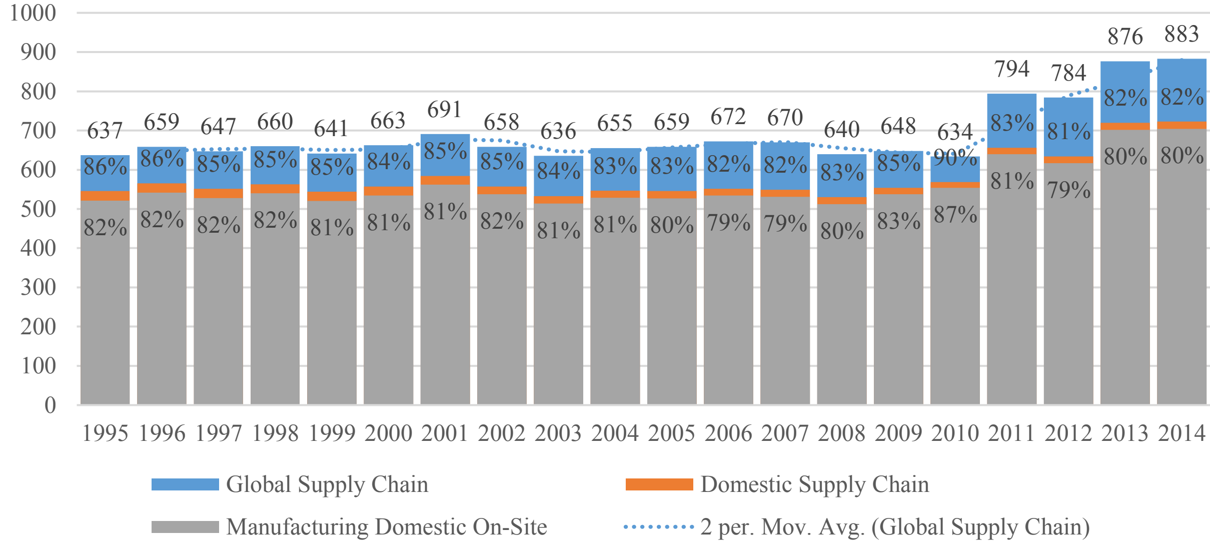

Figure 4-27: U.S. mfg. damage to human health (global (HND DALY), domestic and mfg. domestic on-site (% share))

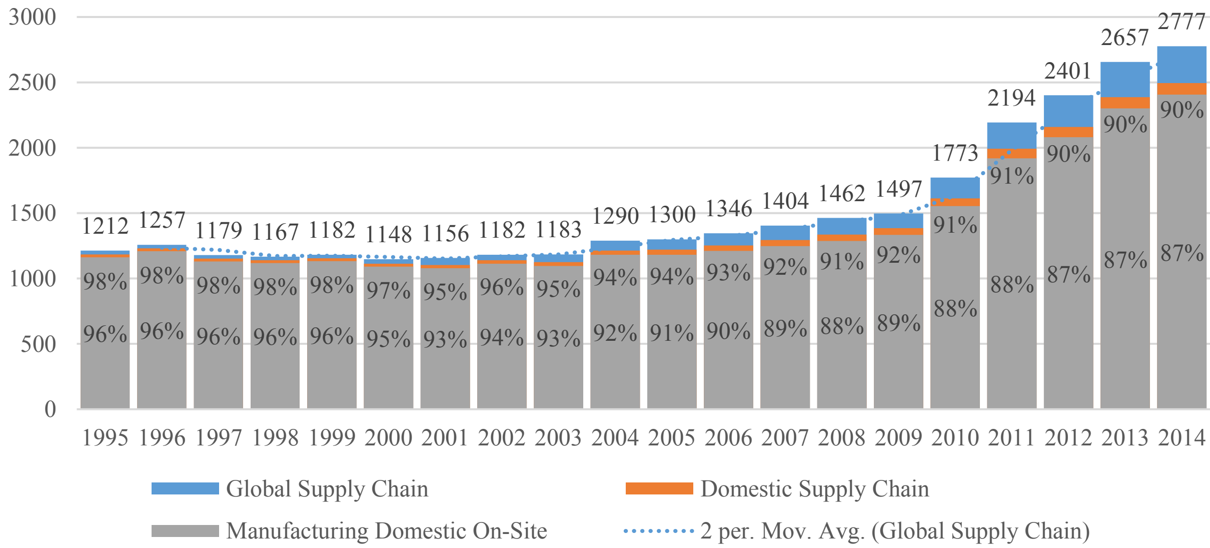

Figure 4-28: China mfg. damage to human health (global (HND DALY), domestic and mfg. domestic on-site (% share))

4.2.2.2.2 Damage to Ecosystem

The results of the U.S. and China manufacturing industries' impacts on the ecosystem weres shown in Figure 4-29 and 5-30 respectively. Similar to the results of human health impact, the impact of U.S. manufacturing increases after 2010. While the for China, the impact is on a continuous rise since 2003.

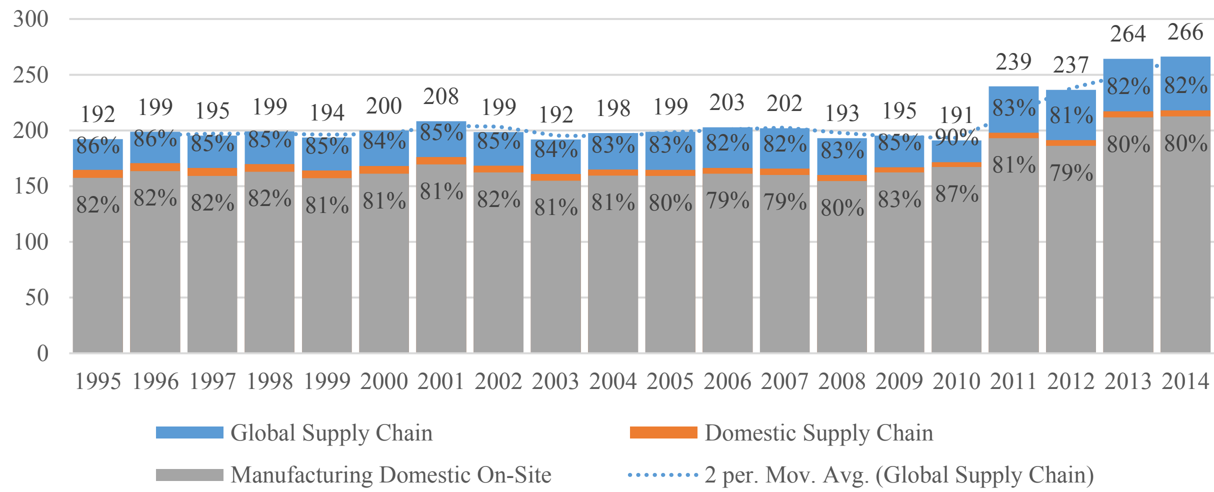

Figure 4-29: U.S. mfg. damage to ecosystem (global (species.year), domestic and mfg. domestic on-site (% share))

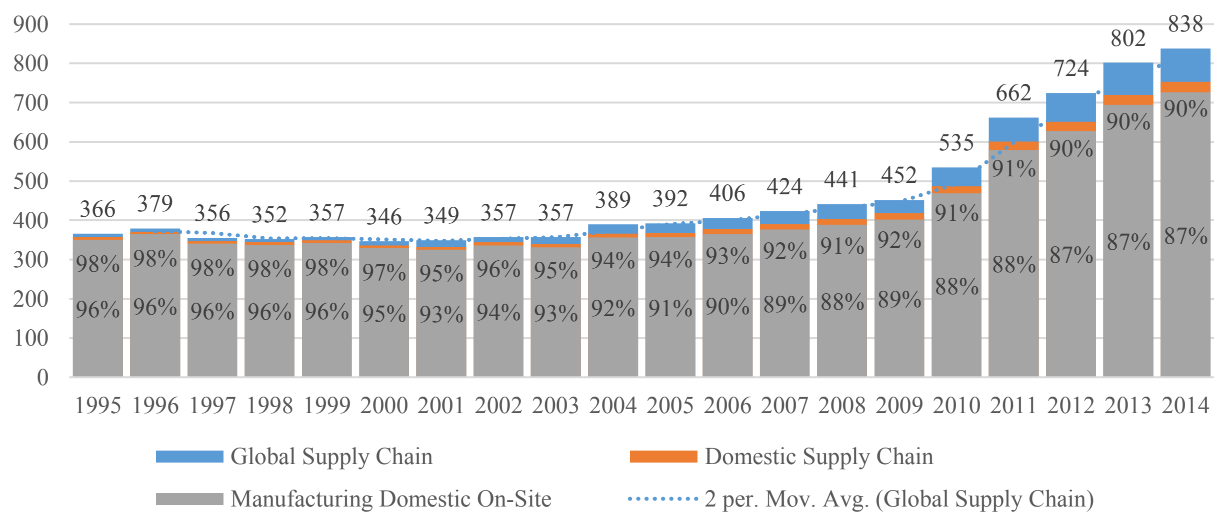

Figure 4-30: China mfg. damage to ecosystem (global (species.year), domestic and mfg. domestic on-site (% share))

4.2.3 Time Series Comparison between U.S. and China Manufacturing

4.2.3.1 LCI Results

4.2.3.1.1 Total Economic Output

Figure 4-31 shows the global economic output of China and the United States manufacturing industries. From the figure, China's global economic output surpasses the U.S. after 2008.These economic output results should be interpreted as the total economic output occurs as a result of the U.S. and China manufacturing industries economic activities during the study period.

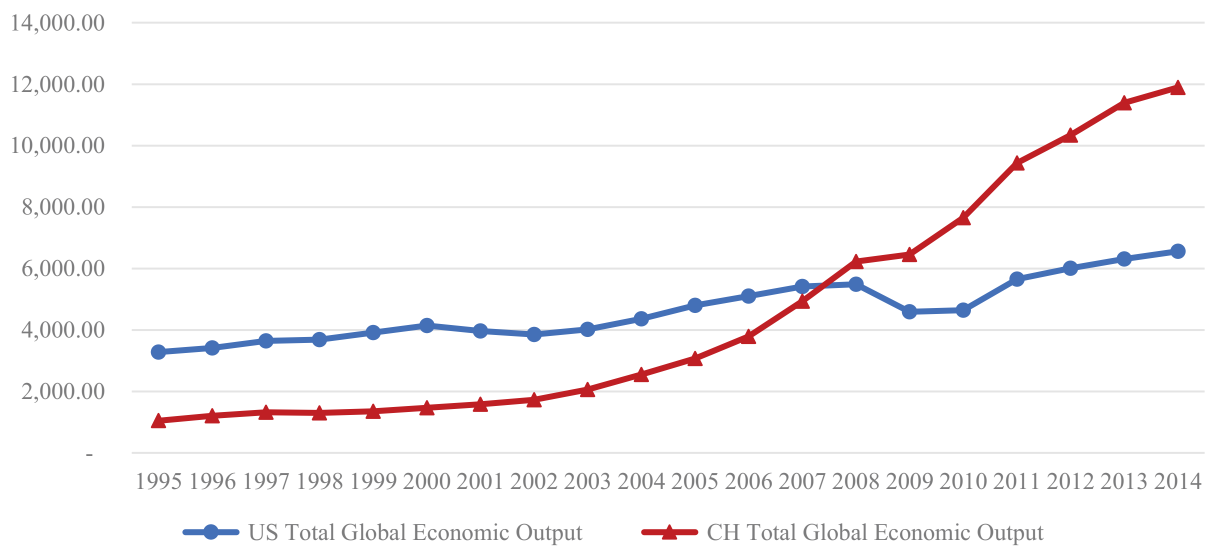

Figure 4-31: U.S. and China mfg. industries global economic output ($B)

4.2.3.1.2 GHG Emissions

The total CO_2, CH_4, and N_2O emissions of U.S. and China manufacturing are shown in Figure 4-32. As shown in the figure, China's manufacturing GHG emissions exceeded the GHG emissions of U.S. since 1995 except for 2000 and 2001. The total GHG emissions were found to be increasing for both the U.S. and China.

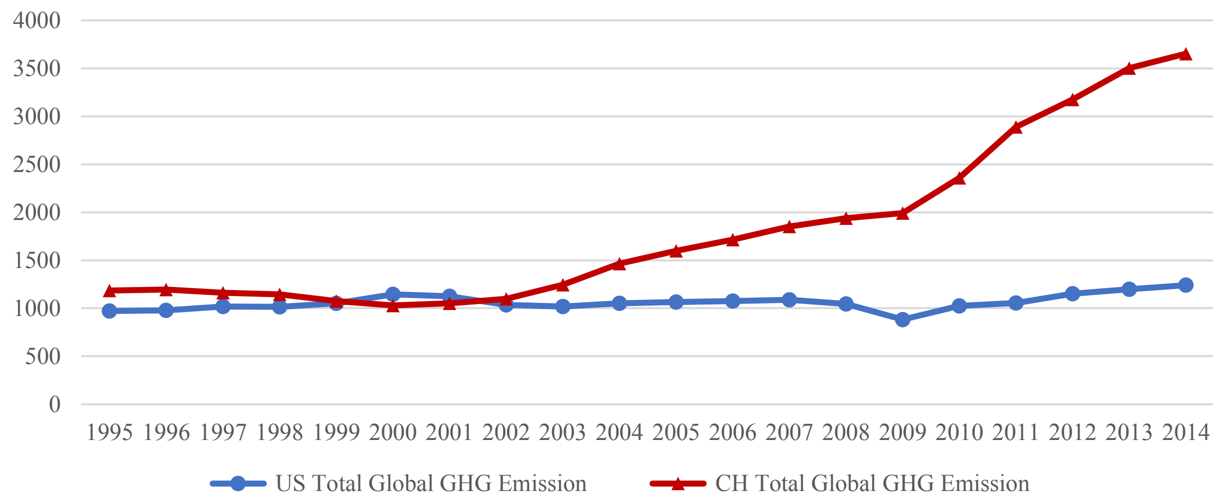

Figure 4-32: U.S. and China mfg.s GHG emissions (MMT CO2 eq)

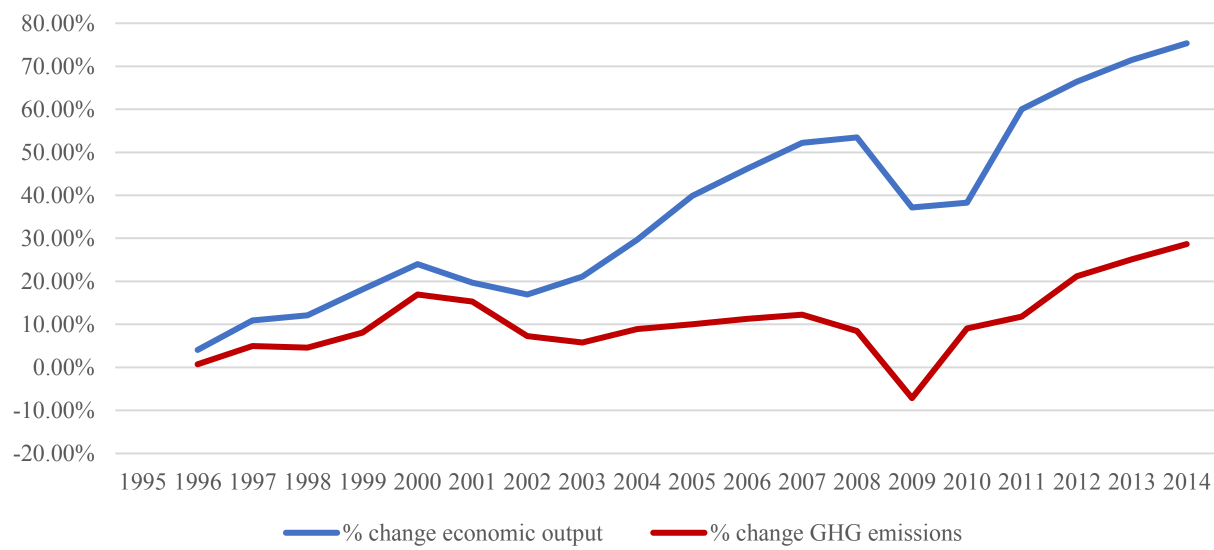

Figure 4-33: U.S. mfg. industries' cumulative growth in global economic output versus cumulative growth in global GHG emissions

Figure 4-33 illustrates the economic growth of U.S. versus the growth in GHG emissions. From the figure, the gap between the economic growth and the GHG emissions is a narrow gap up until 2002. After 2002, the gap is getting wider and wider which may be an indication to the fact that the environmental policies and regulations that are in place in the U.S. are effective. The cumulative growth in U.S. economic output in 2014 is 75.3% while the cumulative growth in GHG emissions in 2014 is 28.7%. On the other

hand, Figure 4-34 shows the cumulative growth of China manufacturing industries in economic output and GHG emissions. Similar to the U.S., the economic output of China's manufacturing grew faster than its GHG emissions. However, the cumulative growth of China in 2014 is 266%. The growth is about 3.5 times higher than U.S. growth. While China's GHG emissions are 121%, and the growth of GHG emissions in China is 4.25 times higher the GHG emissions by U.S. manufacturing.

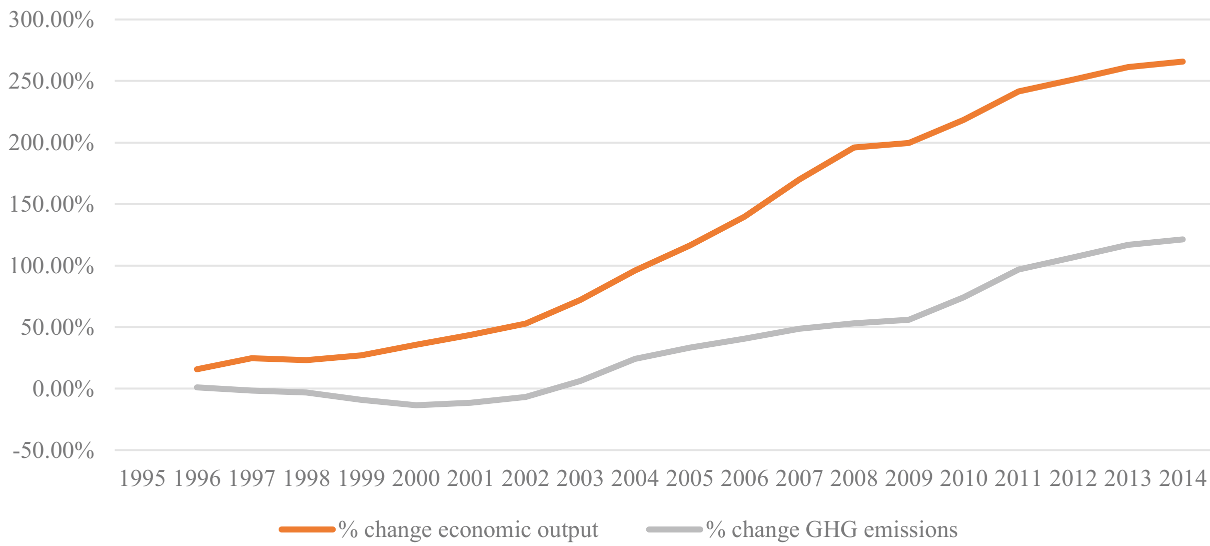

Figure 4-34: China mfg. cumulative growth in global economic output versus cumulative growth in global GHG emis.

4.2.3.2 LCIA Results

4.2.3.2.1 Midpoint Results

The midpoint time series analysis, GWP and ODP, for U.S. and China manufacturing are shown in Figures 4-35 and 4-36 respectively. China's manufacturing industries, over the course of the 19 years, had a higher damage impact on the GWP and ODP.

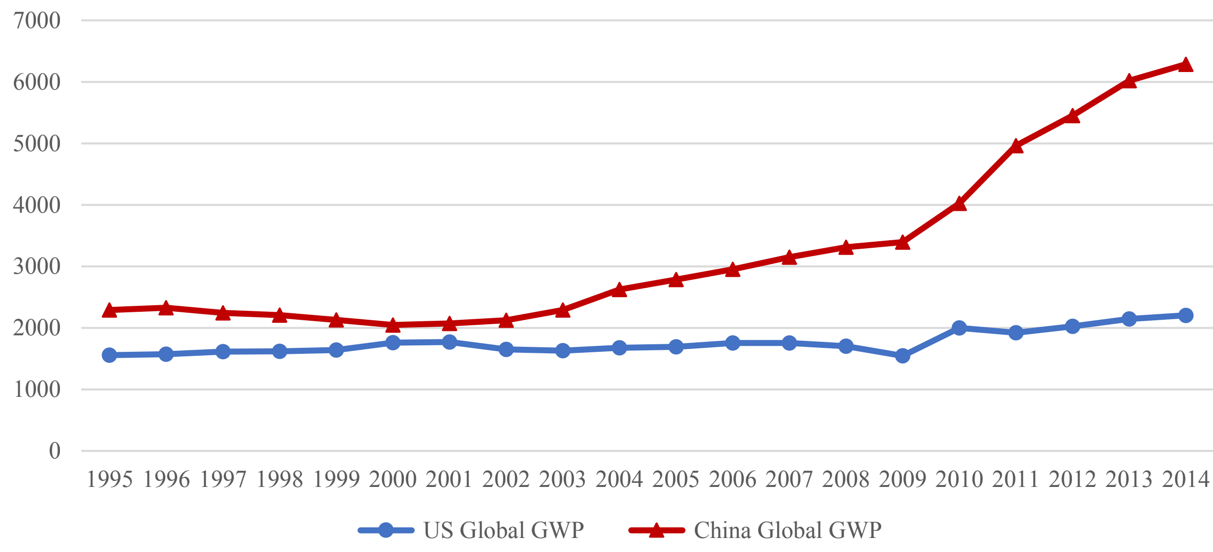

Figure 4-35: U.S. and China mfg. GWP (M kg CO2 eq)

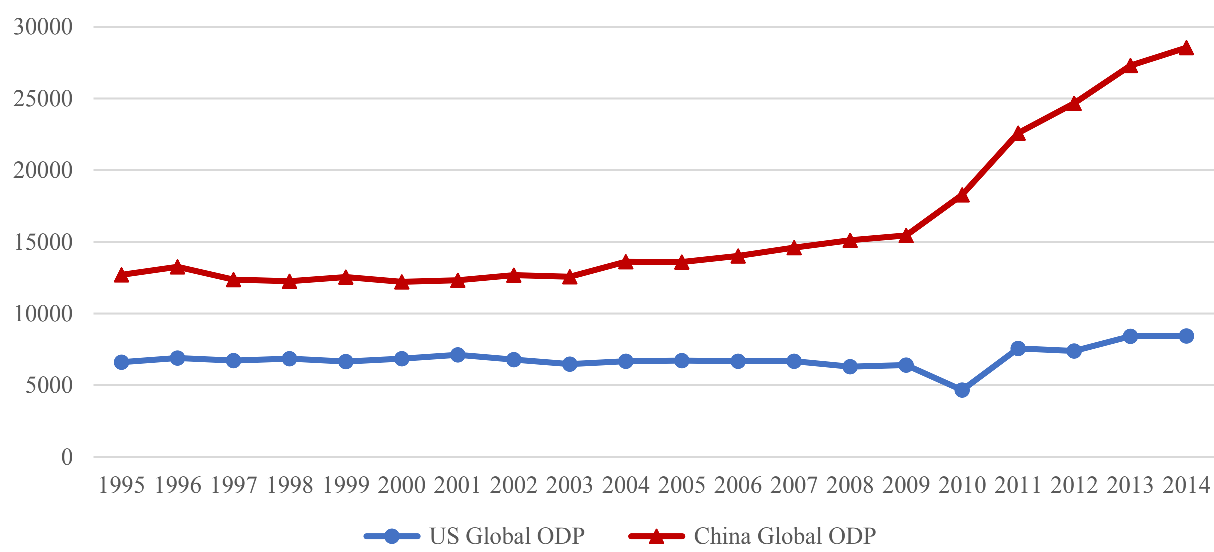

Figure 4-36: U.S. and China mfg. ODP (hundreds kg CFC-11 equivalents)

4.2.3.2.2 Endpoint Results

Figures 4-37 and 4-38 show the endpoint impact, damage to human health and damage to the ecosystem, for U.S. and China respectively. Similar to the midpoint impact, China's manufacturing industries are superior to the U.S. manufacturing industries regarding endpoint impacts.

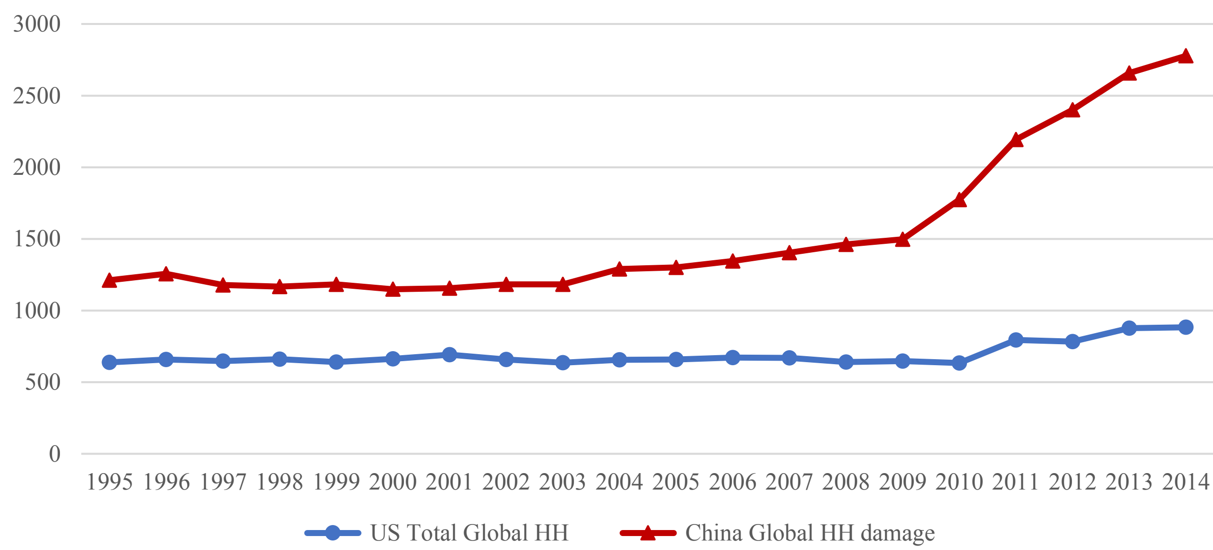

Figure 4-37: U.S. and China mfg.s damage to human health (hundreds DALY)

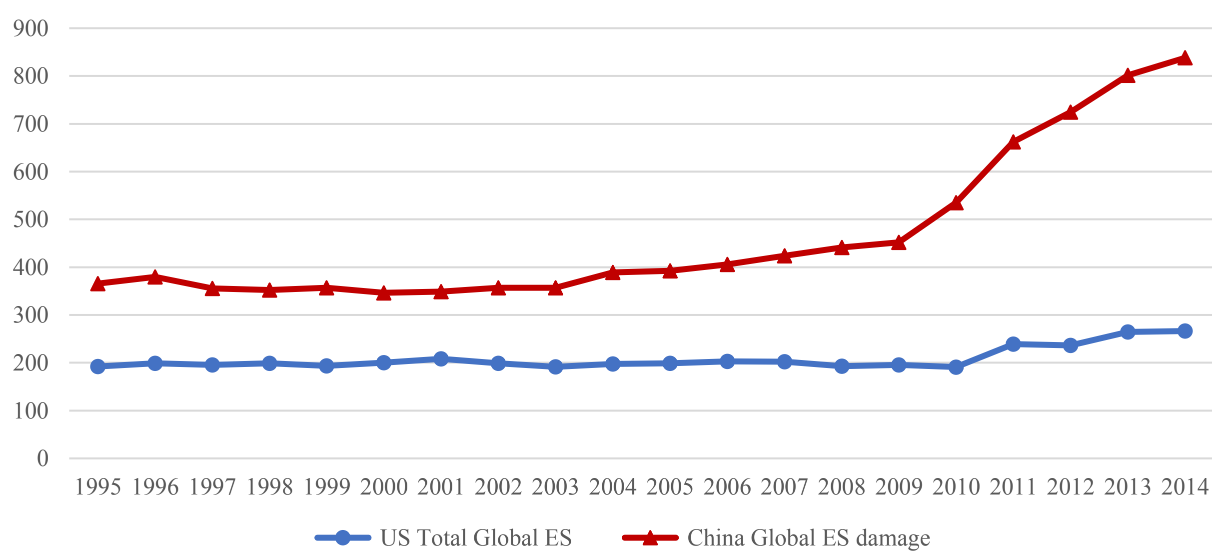

Figure 4-38: U.S. and China mfg.s damage to ecosystem (species.year)

4.3 SDA Results

SDA results are summarized based on the change in Leontief Inverse, final demand, and GHG emissions multipliers as follows.

4.3.1 Leontief inverse *($L=(I-A)^{-1}$)*

In Figure 4-39, the effect of change of interindustry demand in the U.S. on the total GHG emissins is depicted. In the figure, blue color code represents an increase and orange color code indicates a decrease. The chart depicts that the total economic output drops down significantly in 2001-2002 and 2008-2009 periods. Similarly, Figure 4-40 shows the effect of change of interindustry demand in China on the total GHG emissions. Overall all, the effect of China's interindustry demand is increasing across the years, except in 2005-2006, the effect of inter industries demand is decreasing.

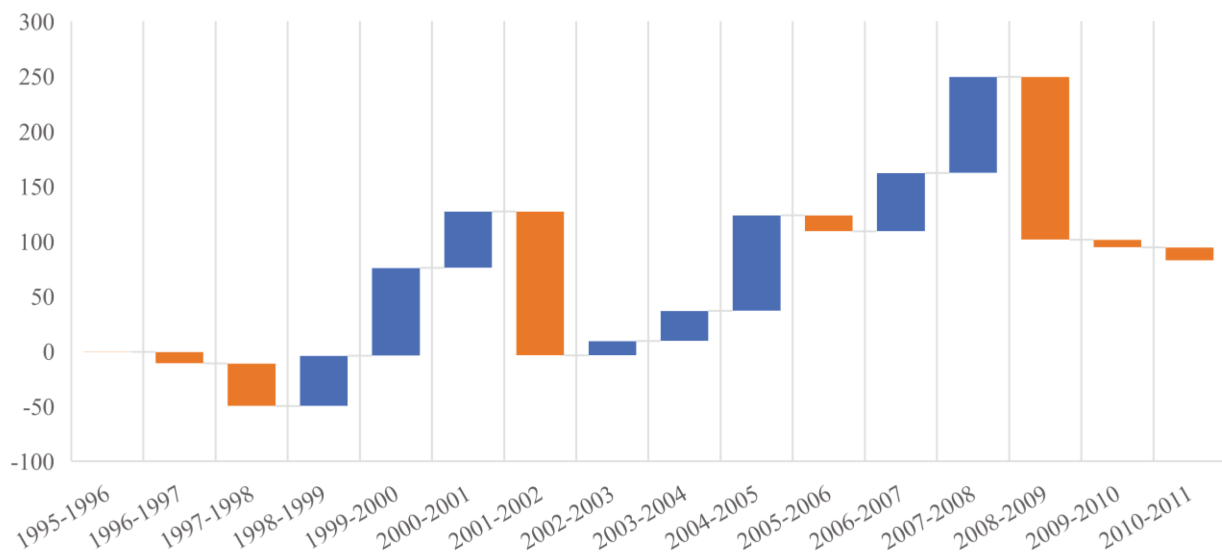

Figure 4-39: Effect of change in Leontief's inverse ($L=(I-A)^{-1}$) *on the total emis. of U.S. mfg. (MMT)*

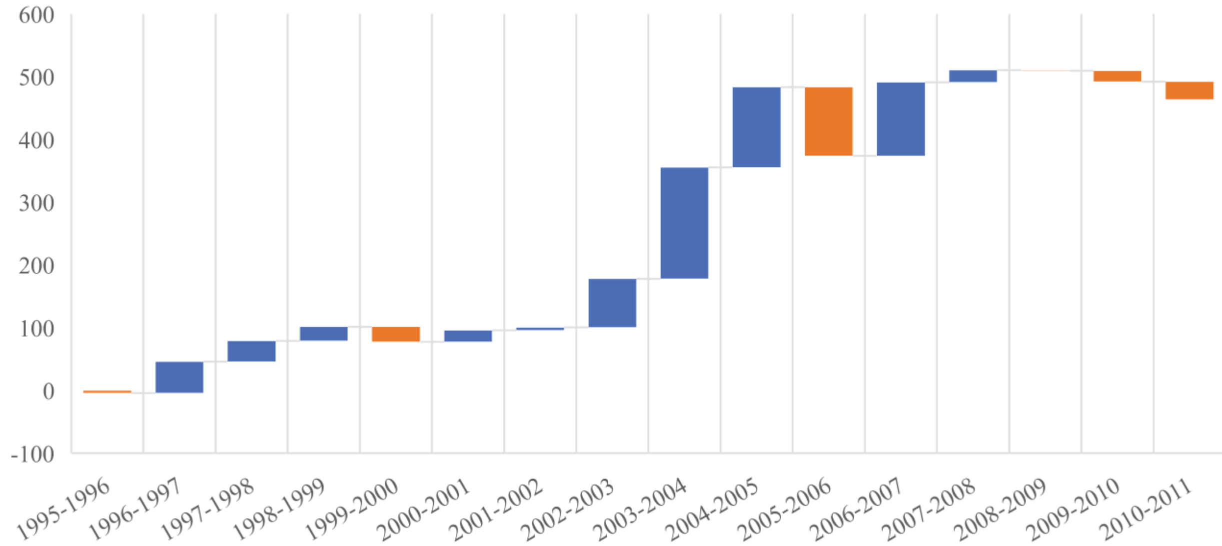

Figure 4-40: Effect of change in Leontief's inverse ($L=(I-A)^{-1}$) *on the total output of China mfg. (MMT)*

4.3.2 Final Demand

The effect of the change in final demand on total GHG emissions of U.S. and China are shown in Figures 4-41 and 4-42, respectively. In the U.S., the effect of final demand on the GHG emissions is on a continuous rise, apart from some slight drops in 2000-2001, 2001-2002 and substantial decline in 2008-2009 which could be mainly attributed to the stock market crash impact. A similar effect is observed in China as well. In Figure 4-40, the impact of the change in final demand on the GHG emissions of China increases rapidly between 1995 and 2014.

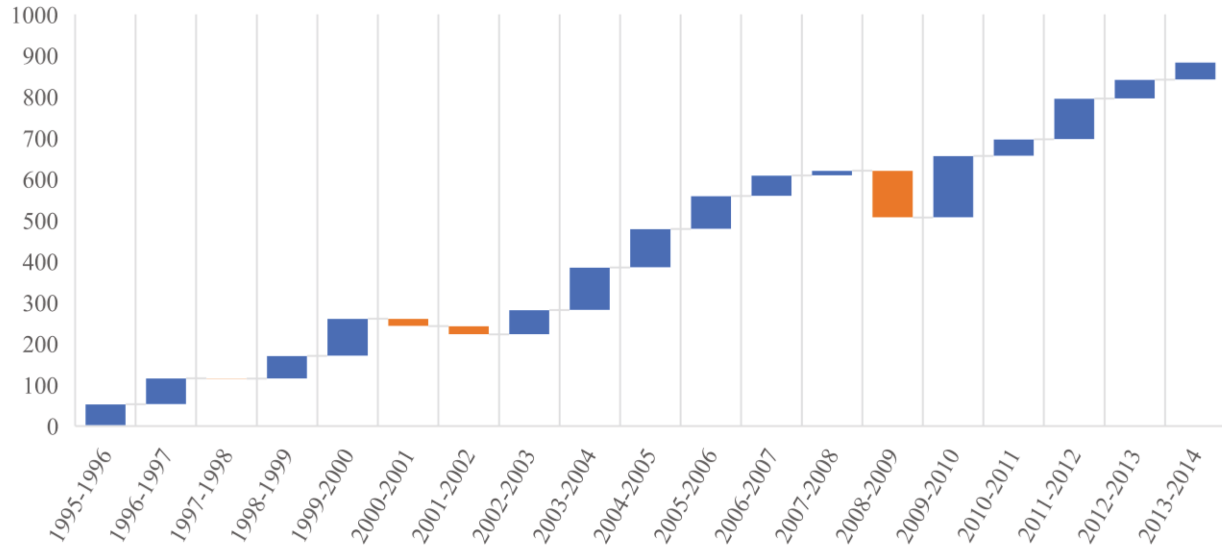

Figure 4-41: Effect of change in final demand (f) on GHG emis. of U.S. mfg. (MMT)

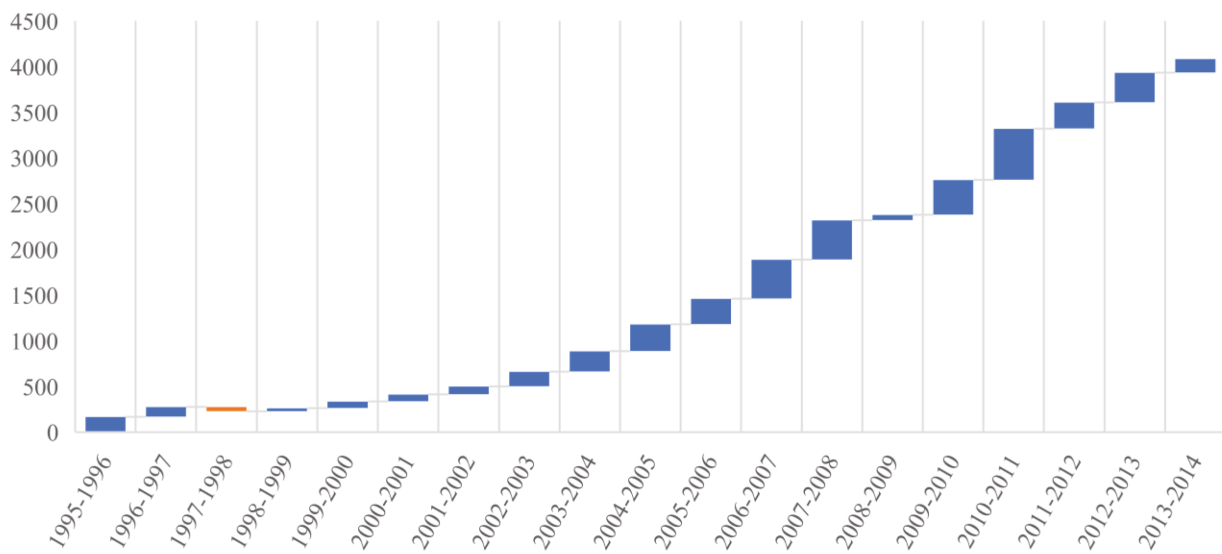

Figure 4-42: Effect of change in final demand (f) on GHG emis. of China mfg. (MMT)

4.3.3 GHG Emissions Coefficients

The Figure 4-43 shows the SDA results of GHG emissions' coefficients for the U.S. Unlike the final demand, the GHG emissions coefficients decreased across the years. Similarly, Figure 4-44 shows the

effect of the change in China's GHG emissions coefficient on GHG emissions. According to the figure, the change in the multipliers has an adverse impact on total GHG emissions

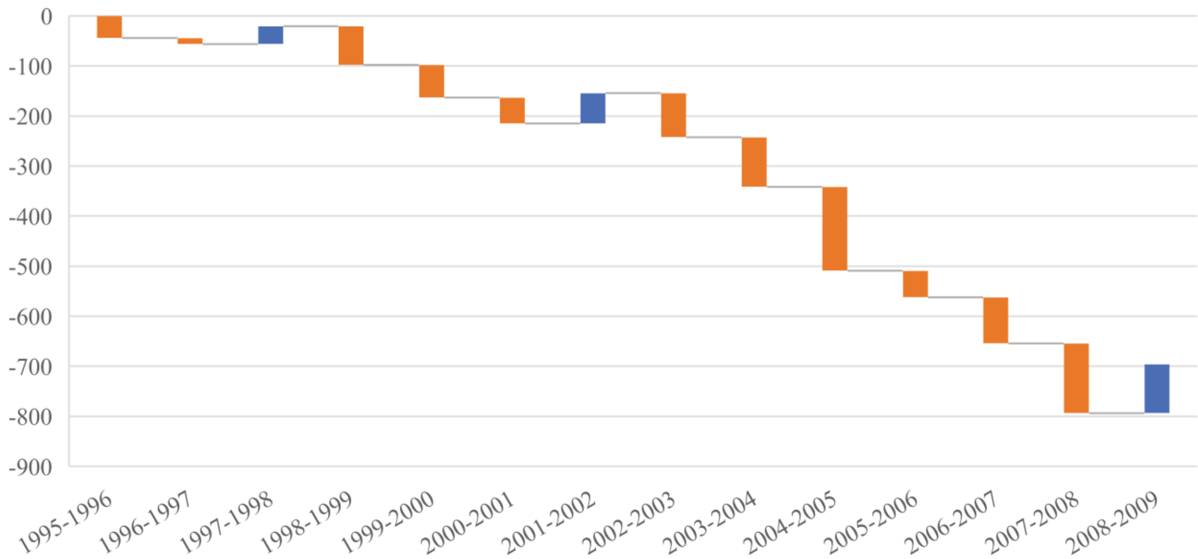

Figure 4-43: Effect of change in emis. coefficients (c) on GHG emis. of U.S. mfg. (MMT)

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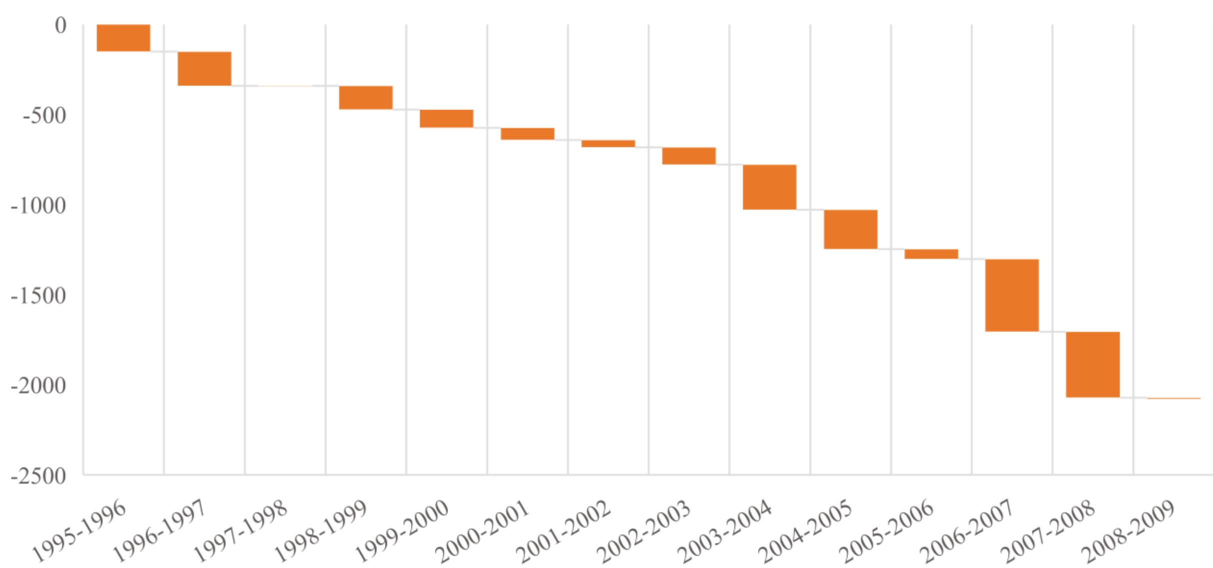

Figure 4-44: Effect of change in emis. coefficients (c) on GHG emis. of China mfg. (MMT)

CHAPTER 5: DISCUSSION, CONCLUSIONS, AND FUTURE WORK

Manufacturing industries play an essential role in any economy. They contribute to the economy in various ways including through creating direct economic output ($), indirect economic output ($), and service and manufacturing emloyment. On the other hand, manufacturing industries are also primarily responsible for the rising GHG emissions and global warming. Therefore, it is important to investigate the manufacturing industries in today's global economic system from both economic and environmental impacts. In this regard, economic output of manufacturing industries in the U.S. and China have been a central discussion of economic, environmental, and political debates.

This thesis aimed to investigate the life cycle inventory, mid-point, and end-point impacts of the selected GHG emissions caused by U.S. and China manufacturing industries in the last two decades from global trade perspective. To reach this overarching goal, an integrated methodology that consists of MRIO and ReCipe approaches was proposed, and implemented. The analysis focused on 40 major countries and considered rest of the world as the 41st country. Each country was represented with 35 major service, construction, energy, manufacturing, etc. industries based on the WIOD database notation and classification. The selected GHG emissions were CO_2, N_2O, and CH_4. A total of 20 MRIO models were developed, which was used to estimate the GHG emissions inventory (LCI). Then, LCI was merged with the ReCiPe so as to estiamate the midpoint and endpoint impact of the manufacturing industries of the U.S. and China. The study period was between 1995 and 2014. In the final phase of the methodology, structural decomposition analysis (SDA) was implemented to assess the change in the selected components of the MRIO model such as emissions to air (E2A) multipliers, final demand, and Leontief's inverse, on the total GHG emissions. The results are discussed below.

5.1 LCI results of the manufacturing industries of U.S. and China for 2014

a) Top 3 sectors in terms of economic output in 2014 for the U.S. were Food, Beverages, and Tobacco, Mining and Quarrying, and Chemicals and Chemical Products respectively. While for China, the top 3 economic contributors were Electrical and Optical Equipment, Agriculture, Hunting, Forestry, and Fishing, and Beverages and Tobacco.

b) Regarding greenhouse gas emissions:

   i) Top 3 industries contributing to the CO_2 emissions in the U.S. in 2014 were Electricity, Gas, and Water Supply, Coke, Refined Petroleum and Nuclear Fuel, and Mining and Quarrying. While for China, Electricity, Gas, and Water Supply, Basic Metals and Fabricated Metal, and Chemicals and Chemical Products. The CO_2 emissions for Electricity, Gas, and Water Supply for the U.S. was 222% larger than the emissions by Coke, Refined Petroleum and Nuclear Fuel. In China, Electricity, Gas, and Water Supply emissions was 437% larger than Basic Metals and Fabricated Metal. This highlights the importance of using clean energy in this sector since the amount of CO_2 share is substaintially high compared to the other industries.

   ii) Top two industries regarding CH_4 emissions in the U.S. were found to be Mining and Quarrying, and Agriculture, Hunting, Forestry and Fishing. For China, Agriculture, Hunting, Forestry, and Fishing was the top industry contributing to CH_4 emissions while Mining and Quarrying was the second highest.

   iii) Finally, the industry that contributes to N_2O emissions the most in the U.S. and China was Agriculture, Hunting, Forestry, and Fishing

5.2 Time series analysis of LCI

a) The recession severely affected the developed countries in early 2000, which resulted in ripple negative impacts on the U.S. economy in 2002. Due to the recession, U.S. economic output was decreased. After that, the U.S. economy recovered from the recession until 2008-2009, during which, another market crash occurred. The 2008 crisis caused significant decrease in total economic output, which followed a

positive trend starting from 2011. China's economic output has seen tremendous growth throughout the years, and it has seen a substantial increase especially after the economic crisis in the U.S.

b) U.S. GHG emissions followed the same pattern discussed above. However, it should be noted that although years 2010 and 2011 had a difference of $101 ten thousand million dollars, the total GHG emissions of those two years were quite close to each other with a total difference of 28 million tons only. This indicates that not only the economic output but the supply chain influences the GHG emissions. China's GHG emissions have seen a slight decrease in the early 2000s, however, the GHG emissions started increasing after 2002, and it followed the same pattern of total economic output.

c) The majority of U.S. and China's GHG emissions were attributed to CO_2, and a few percentages were attributed to CH_4, and N_2O.

5.3 Time series analysis of LCIA

a) For the global warming potential, the economic crisis had a negative impact in global warming in 2009. However, it increased by near 452 million kgs of CO_2 equivalent by the end of 2010. While the ozone depletion potential in 2010 was the lowest. This is because ozone depletion is based on the emissions of N_2O while global warming is based on CO_2, CH_4, and N_2O together. China manufacturing industries' impact on global warming and ozone depletion underwent a slight decrease in the early 2000s, and then ramped up again.

b) U.S. manufacturing industries' damage to human health and ecosystem had slowly increased until 2011 and steeply increased starting from 2011, while for China, the rise of damage was more like a linear trend that started in 2004.

5.4 Time series comparison between U.S. and China manufacturing

a) In terms of economic output, U.S. manufacturing economic output used to exceed China. However, after 2007, China's manufacturing surpassed the U.S. manufacturing in economic output. The financial crisis dropped U.S. economic output, but China's manufacturing economic output grew larger after the economic crisis in the U.S.

b) Although China's manufacturing had lesser total economic output than the U.S. in 1995 -2007, but China's GHG emissions for that period was higher than, U.S. manufacturing GHG emissions. The U.S. and China's GHG emissions were increasing in recent years, but China's increase trend is clearly steeper.

c) In terms of GWP and ODP impact, China's manufacturing has a larger on GWP and ODP impacts than the U.S. The GWP and ODP of both countries are on an increasing trend.

d) Similar to midpoint impacts, China's damage to human health and ecosystem was found to be higher than the U.S., but the overall trend of both countries was found to be increasing.

5.5 SDA results

a) In terms of the U.S., across the years, there seemed to be many positive and negative fluctuations in GHG emissions due to the change in Leontief's inverse. However, for China, the change in Leontief's inverse, mostly, had a positive effect on the GHG emissions.

b) The change in final demand of U.S. across the years had a positive effect on the GHG emissions, except for the recession and financial crisis years. For China, the effect of the change in final demand on GHG emissions was increasing for the entire study period.

c) Overall, the emissions coefficients were decreasing across the years for U.S. and China.

Based on the results of SDA, it should be noted that although the amount of GHG emissions per million-dollar output decreases, the total GHG emissions increases. The main influencer on GHG emissions output were found to be the final demand.

In conclusion, final demand was found to be increasing in both U.S. and China economies, which was a key factor to the non-decreasing GHG emission stock worldwide. However, the rising human consumption pattern has still been an important and primary driver of the rises in environmental impacts at the mid and end point. Both U.S. and China manufacturing economic output's causes the vast majority of the environmental impacts at the house country, while rest of the world (ROW) stands out as significantly

impacted. GHG emissions per million-dollar economic output has been decreasing, which could be attributed to the technological advancement in manufacturing processes. However, this reduction in the emissions intensity was not found to be facilitating a decrease even in the increase rate of total global emissions.

Electricity, Gas, and Water Supply; Coke, Refined Petroleum and Nuclear Fuel; Mining and Quarrying; Basic Metals and Fabricated Metal; and Chemicals and Chemical Products industries were still the major drivers of environmental impacts investigated, while contributing to the host country's economy substantially. This clearly indicates that the both of the economies are not circular, which means the mid and end point environmental impacts of production processes are steadily increasing.

This research could have the following extensions and they are left as future work. This thesis investigated the manufacturing industries of U.S. and China. Similar approach could be used for service or other industries. Additionally, this study examined U.S. and China manufacturing; however, similar approach could be used to include the manufacturing industries of other countries. This thesis investigated the U.S. and China manufacturing separately for fair comparison. However, it would be important to study the U.S. and China manufacturing impacts together in the same model, which could be further compared with the findings of this thesis. Finally, eco-efficiency analysis on the results of midpoint and endpoint impacts could be carried out by considering the economic output. To do so, methods such as Principal Component Analysis and Data Envelopment Analysis (DEA) could be employed over a longtitudional study period.

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