

Supply Chain Analyses of Environmental Loads in India

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<https://hdl.handle.net/2324/7182284>

出版情報 : Kyushu University, 2023, 博士 (経済学), 課程博士
バージョン :
権利関係 :



Supply Chain Analyses of Environmental Loads in India

A Dissertation Submitted in Partial Fulfillment of the Requirement for the Degree of

Ph.D. in Economics

Department of Economic Systems

Graduate School of Economics

Kyushu University

by

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Chapter 1. Introduction

1.1. India's remarkable economic growth and its pollution issues

In 2023, India became the country with the largest population, surpassing China (UNFPA, 2023). India has experienced remarkable economic growth; its constant GDP has increased fourfold from 2000 to 2022 (World Bank, 2023) and further economic growth is expected. Although India's current exports are only approximately one-tenth of China's (UNCOMTRADE, 2023), recent moves in supply chain restructuring in response to supply chain disruptions and political uncertainty may boost India's importance in global supply chains as an alternative manufacturing site.

However, rapid industrialization and urbanization have caused pollution issues in India. People in India have been suffering from air pollution-related diseases, leading to 1 million premature deaths annually (HEI, 2020). This accounts for one-quarter of the global number of premature deaths caused by air pollution. The health effects of air pollution on pregnant women and their children are of great concern. Exposure to air pollution during pregnancy increases the risk of premature birth and infant mortality (HEI, 2022), and children exposed to it have been linked to asthma and lower respiratory diseases (Siddique *et al.*, 2011; Lee and Kim, 2018; HEI, 2022). Some studies have also reported its effect on children's brain development (Rees, 2017). In this situation, schools are forced to close, and children find it challenging to play outdoors safely.

Air pollution also affects economic activity and leads to profit losses in India. Flights to and from New Delhi International Airports are often canceled because of the

poor visibility caused by air pollution (Manisalidis *et al.*, 2020). Studies have reported that serious air pollution results in a high incidence of workers' sick leave (Holub *et al.*, 2021), a decrease in labor productivity (Chang *et al.*, 2019), and a drain of highly-skilled labor from cities (Wang and Wu, 2021). In terms of consumer behavior, air pollution decreased consumer footfall, leading to losses of USD 22 billion in 2019 (Clean Air Fund, 2021).

In response to the significant demand from its citizens to address serious air pollution, the Indian government launched the National Clean Air Programme (NCAP), which is a time-bound national-level strategy to reduce PM_{2.5} pollution by 20%–30% by 2024 as compared to 2017 in 122 cities (Government of India, 2019). This program encourages cities to develop clean action plans to achieve their targets and enhance the capacity of their air quality monitoring stations (Ganguly *et al.*, 2020). In particular, the Indian Supreme Court notified the implementation of Delhi's clean air action plan. However, because this program lacks binding obligations to implement plans in other cities, the effectiveness of the plan depends on the efforts of each individual city.

Another pollution issue is greenhouse gas (GHG) emissions, which are the primary causes of global warming. India is under pressure from the international community to mitigate significant CO₂ emissions as the third-largest CO₂ emitting country. Frameworks to mitigate global GHG emissions have been gradually formulated by the international community since the late 1980s. The Intergovernmental Panel on Climate Change (IPCC), which comprises representatives from national governments and leading climate scientists worldwide, was established in 1988 to determine the state of knowledge on

climate change agreed upon by the scientific community (IPCC, 2023). Its assessment reports have been influential in international diplomacy. In a recent report, the IPCC stated that human activities have “unequivocally” caused global warming (IPCC, 2021). The United Nations Framework Convention on Climate Change (UNFCCC), which came into effect in 1994 and has been ratified by 197 countries, is a mechanism for negotiating international rules among national governments to address climate change (UNFCCC, 2023). The Kyoto Protocol was the first international rule designed based on the UNFCCC, which legally required developed countries (i.e., Annex B countries) to reduce GHG emissions by an average of 5% below the 1990 levels. Although the Kyoto Protocol has contributed to decreasing GHG emissions from developed countries, it has played a minor role in binding global GHG emissions because it did not involve developing countries, including the large emitters, China and India, as well as the US, which retreated from the protocol.

With the recognition of shortcomings in the Kyoto Protocol, the Paris agreement adopted in 2015 requires all countries to submit GHG mitigation targets and implement climate actions to hold the increase in the global average temperature to well below 2 °C above pre-industrial levels and pursue efforts to limit the temperature increase to 1.5 °C above pre-industrial levels (UNFCCC, 2023). In the context of the Paris Agreement, India, along with other developing countries, is facing international obligations for CO₂ emissions reduction for the first time. Addressing how to achieve significant emissions reductions while sustaining economic growth is an important focus for many developing countries.

1.2. Emission transfer from developed countries to developing countries

When discussing responsibility for a country's emissions, the production-based accounting method is currently employed, which attributes responsibility for the emissions involved during the production of goods and services to producers. Based on this accounting method, two-thirds of global CO₂ emissions are attributed to emerging developing countries (IEA, 2021). However, as the world has become more globalized, scholars have questioned whether this method should be employed from the perspective of the fairness and effectiveness of environmental policy (Kanemoto *et al.*, 2014; Afionis *et al.*, 2017). For example, Peters *et al.* (2011) highlighted that the increase in net emission transfers between developed and developing countries from 1990 to 2008 exceeded the emission reduction achieved by the Kyoto Protocol. They argued that ignoring emission transfers via international trade undermines territorial climate policies such as the Kyoto Protocol. Davis and Caldeira (2010) pointed out that 22% of China's CO₂ emissions were produced to satisfy the final demands of their foreign consumers. They argued that the responsibility for emissions from developing countries, including China, should be shared with developed countries that have already benefited from emissions and have greater paying power.

The consumption-based accounting method is the most supported counterpart to the production-based method (Munksgaard and Pedersen, 2001). It attributes the responsibility for emissions to the final consumers of goods and services. The instrumental role of the consumption-based methods is expected to provide evidence for policy discussions on sharing responsibility between producers and consumers (Davis

and Caldeira, 2010; Afionis *et al.*, 2017).

The Environmentally-Extended Input-Output (EEIO) model has contributed to quantifying the responsibilities of countries using the consumption-based method. It serves as a useful tool for measuring all emissions that occurred to satisfy the demands of final consumers by tracking a series of domestic and international intermediate transactions among countries (i.e., the global supply chain). Additionally, EEIO studies have identified hotspots in which a significant share of emissions is concentrated, allowing for more efficient mitigation of consumption-based emissions. The number of studies on EEIO has grown significantly in recent years, and a significant number of these studies have highlighted the gap between production- and consumption-based emissions in China (e.g., Peters and Hertwich, 2008; Davis and Caldeira, 2010; Peters *et al.*, 2011; Fischer, 2011; Jakob and Marschinski, 2013; Kanemoto *et al.*, 2014), with the aim of discussing the equitable allocation of responsibility for emissions within the global supply chain. However, despite the high expectations of its important role in the global supply chain, few EEIO studies have centered around India.

1.3. Pollution concerns attributed to the large presence of the “Informal sector”

In any allocation of responsibility, when addressing emissions from developing countries that directly emit large amounts of pollutants, understanding the structure of their economic systems is essential. The large presence of unofficial economic activities, often referred to as the “informal sector,” is a representative characteristic of the economic systems of developing countries. The informal sector encompasses various industries,

with popular examples including small-scale farmers in agriculture, small family-based factories in manufacturing, street vendors, and informal taxi drivers in service industry. While the informal sector purchases intermediate inputs, including energy, to produce goods and services, as in the formal sector, these economic activities are not accounted for in the official statistics. Although the informal sector's activities are not directly observable, their economic size has been indirectly estimated by econometric models (e.g., Schneider *et al.*, 2010; Elgin and Oztunali, 2012) with broad coverage of countries and time series. According to Ohnsorge and Yu (2021), the average share of informal output in GDP among developing countries declined between 1990 and 2018; however, the informal sector still accounted for 31% of GDP in 2018, whereas it accounted for 17% in developed countries. Survey-based estimations have also compensated for the exclusion of informal activities from the national account statistics of each country. For example, the size of India's informal sector as a percentage of GDP was estimated to be 50% using this methodology (Government of India, 2021).

The large presence of informal sectors in developing countries is associated with pollution issues caused by undermining environmental policies. The unavailability of statistical information on individual informal activities, such as energy input and production capacity, makes controlling polluting activities in the informal sector challenging. Several studies have reported the environmental hazards of the informal sector's polluting activities, such as the discharge of dangerous chemicals into rivers and the air (Blackman, 2000; Dondeyne *et al.*, 2009). Furthermore, the effect of environmental regulations is weakened by pollution leakage between the formal and informal sectors. The presence of a large informal sector undermines environmental

regulations, allowing it to circumvent them by outsourcing pollution-intensive activities to the informal sector (Biswas *et al.*, 2012; Baksi and Bose, 2016; Chen *et al.*, 2018). Therefore, effective environmental policies in developing countries cannot be implemented without considering the role of the informal sector in pollution.

Previous studies attempted to explore the contribution of the informal sector to pollution issues; however, they treated the activities of the informal sector as a “single sector” to be a counterpart of the “single formal sector” for an economy; in other words, they aggregated all activities from various industries into single sectors (e.g., the two-sector model in Baksi and Bose, 2016). The informal sector’s contribution to pollutant emissions and its linkage structure with the formal sector vary significantly among industries and the industrial variations are essential for developing environmental policies. The EEIO model can contribute to investigating the industrial variations in the role of the informal sector in mitigating pollution, addressing the shortcomings of previous studies.

1.4. Outline of this dissertation

Given the background of pollution issues in developing countries, including India, this dissertation conducts two supply chain analyses using the EEIO model to investigate how environmental loads in India are induced by domestic and global economic systems, respectively. The first analysis aims to quantify domestic and foreign consumer responsibility for PM_{2.5}-emission-related premature deaths in India by integrating a global Multiregional Input-Output Table (MRIOT) and a PM_{2.5}-emission-related health impact inventory. The second analysis examines the contribution of the informal sector in 25

manufacturing industries to the carbon footprint (i.e., CO₂ emissions embodied in supply chains) by constructing an Environmentally-Extended Input-Output Table (EEIOT) that distinguishes between the formal and informal sectors. Based on the results of the analyses, this dissertation discusses the key factors required for India to mitigate its environmental loads equally and efficiently.

1.5. Structure of this dissertation

This thesis comprises five chapters (Figure 1.1). Chapter 2 presents a comprehensive review of important articles that contributed to the development of the EEIO model and Input-Output Tables (IOTs), which are fundamental to the EEIO model. I also review important papers discussing the reliability of IO analysis, with a focus on the aggregation bias. This chapter also identifies the contributions and problems of the existing research and describes the significance and objectives of this thesis. Chapter 3 describes the first supply chain analysis, where I estimate consumption-based PM_{2.5}-emission-related deaths in India induced by both domestic and global supply chains. Specifically, this study employs a structural path analysis combined with a health impact inventory database analysis to estimate the number of consumption-based PM_{2.5}-emission-related deaths attributed to India's electricity generation sector. I identified the critical supply chain paths for both direct (production) electricity uses and indirect (consumption) uses. I also consider both domestic and foreign final demands and their effect on PM_{2.5}-emission-related deaths. Chapter 4 describes the second analysis, where I investigate the informal sector's contribution to the national carbon footprint (i.e., CO₂ emissions embodied in supply chains) by estimating an IOT for India that distinguishes

between the formal and informal sectors in 25 manufacturing industries. The proposed table reflects the differences in terms of input structure and carbon emission intensity between each industry's formal and informal sectors. I also examine the bias of the EEIO analysis caused by aggregating the formal and informal sectors based on the direct and embodied CO₂ emission intensities of industries. Chapter 5 summarizes the empirical results obtained in Chapters 3 and 4 and presents the conclusions of this thesis.

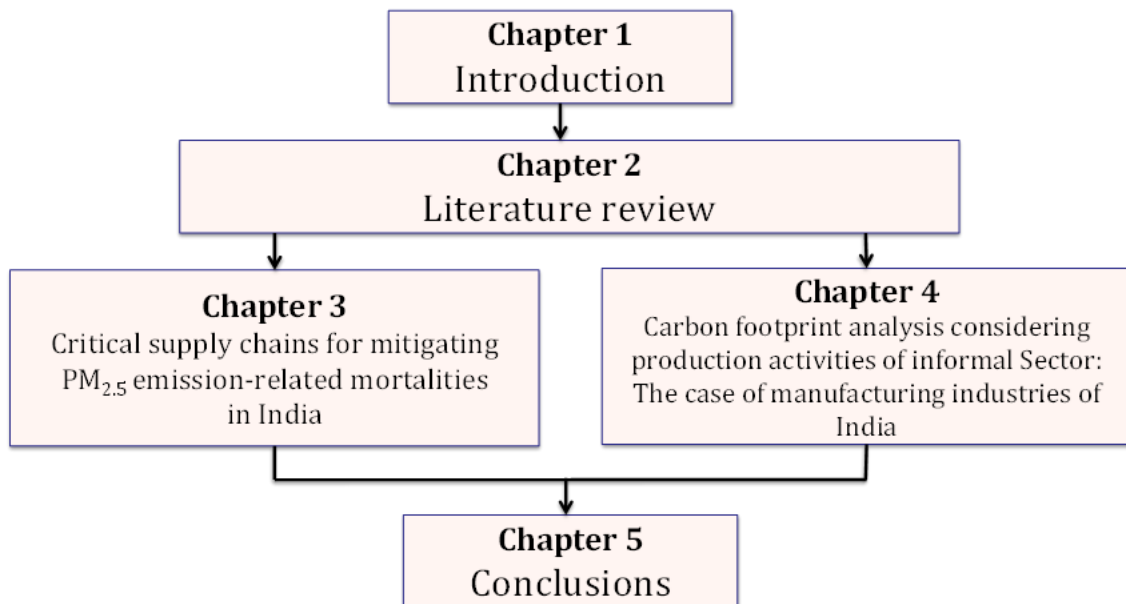


Figure 1.1. Structure of this thesis

Chapter 2. Literature Review

2.1. Development of Environmentally-Extended Input-Output (EEIO) model

First, I review important early works that contributed significantly to the development of the EEIO model. Daly (1968) and Isard *et al.* (1968) were the first to link flows between the economy and the environment using an IO framework. Daly (1968) proposed a simple IOT composed of the human sector and the non-human (i.e., ecology) sector. He stated that the human sector's economic activities are based on input from the environment (e.g., energy, water, and air) and that economic activities result in output to the environment (e.g., pollutant emissions), referring to the entropy law. Although his model conceptually succeeded in incorporating economic activities and the environment, its application was problematic. In his model, the units of economic and environmental activities are not comparable because the activities of the non-human sector are hardly accounted for in the monetary base.

On the contrary, Isard *et al.* (1968) proposed an EEIOT for application. The model solves the non-comparable unit problem by using a commodity-by-industry table rather than an industry-by-industry table (e.g., Forssell and Polenske, 1998). To include the ecological system in the IO framework, they made tremendous efforts to collect statistical information on marine ecology and conducted an empirical analysis of a hypothetical new town in the Plymouth Bay region using the extended IOT.

Unlike the extended IOTs proposed by Daly (1968) and Isard *et al.* (1968), in which pollutant emission accounts were set as columns in the tables, Leontief (1970) set

pollutant emission accounts in the rows of the IOT, which is the ordinary form of today's EEIOT. Inversing the treatment of pollutant emissions in the IOT, Leontief (1970) overcame the problem of the non-comparable unit problem of the industry-by-industry table. Additionally, his model includes anti-pollution activities as columns of the IOT. Leontief and Ford (1972) demonstrated the empirical implementation of an extended IOT with 90 industries and five types of air pollutants. Based on the EEIO model established in early studies, the application of the EEIO model has flourished since 1995 (Hoekstra, 2010), with extensive attention to climate change. Today, the EEIO model stands as a superior analysis tool for measuring the environmental impacts embedded in supply chains and has contributed significantly to policy discussions on environmental issues. In the next section, I present a review of the development of IOTs, which is fundamental to the EEIO model.

2.2. Development of Input-Output Tables (IOTs)

2.2.1. Introduction of IOTs and the first IOT constructed by Wassily Leontief

Today, IOTs are constructed by governments in 74 countries (Lenzen *et al.* 2013) and various research projects and they have been used in a wide range of research to solve the issues of each era. Several decades after the birth of the IOT, unemployment due to the postwar recession was a significant issue, especially in the US (Rose and Miernyk, 1989). The IO analysis at the time was focused on economic development, and economists in this field were interested in how employment and national income were generated by the economic system. Due to economic development, concerns about environmental issues, such as air pollution and waste, have grown, and the EEIOT has

contributed to linking the amount of pollution with economic activities. Especially around the 1970s, when oil shocks occurred, IO analysis of resources and energy gained societal attention. Since the 1990s, when the international community introduced the issue of global warming, IO analysis of greenhouse gas (GHG) emissions has become a mainstream environmental study in this field. China joined the World Trade Organization (WTO) in 2001. Alongside the significant increase in international trade since the 2000s, the internationalization of IO analysis has rapidly advanced. Recently, IO analysis has contributed to the impact assessment of COVID-19. In the next section, I will explain how IO analysis has developed over time.

The first IOT was published by Professor Wassily Leontief in 1936, which was a table of 40 US industry sectors created for the year 1919 (Leontief, 1936). In this article, he criticized modern economists who relied on numerical examples that were not based on actual statistical information to analyze the structure of the national economy. He also stressed the necessity of empirical analysis and made significant contributions to applied economics. The roots of IOT are Quesnay's "Tablau Economique," which depicts the circular flow of the economic system and interdependency among different economic activities. His motivation for constructing an IOT was to construct it based on real statistical data to "open the black boxes of economic theory" (Polenske, 2004). The theory of IOT was also influenced by Walras' general equilibrium theory, which made use of "coefficients of production" (Miernyk, 1965).

The system of an IOT is composed of intermediate transaction sector, value-added

sector, including the cost of labor and capital, as well as tax and final demand sector, which includes exports. The rows of an IOT present the sales structure of each industry; they show how goods and services produced by a certain industry are distributed to other industries and households. Its column presents the cost structure of each industry, which outlines the expenditure of certain industries to acquire the goods, services, and factor inputs (i.e., capital and labor) necessary for its production activities from other industries and households. The sales of certain industries recorded on its “credit side” are recorded on the “debit side” of other industries as intermediate input (Leontief, 1936). Therefore, in the system of an IOT, the sums of the rows and columns are equal. Leontief stated that an IOT covers the entire “balance of trade” of the individual enterprise (or household) (Leontief, 1936).

2.2.2. Regionalization of IOT

With the increasing attention paid to regional analysis, the regionalization of IOT has progressed. Scholars have attempted to reveal the contribution of each region to national economy and the interdependency among subnational regions using regional or interregional IOTs. The development of the regional IOTs was derived by Leontief (1953) and Isard (1951). Leontief’s model, often referred to as the balanced model, was constructed by disaggregating national IOT into subnational regions. Conversely, Isard’s model, often referred to as the pure interregional model, is constructed by aggregating several sub-national IOTs. Analysts do not view these models as alternatives but can choose which model to adopt depending on their research objectives. Chenery (1953) and Moses (1955) modified Isard’s interregional model for application by improving

computability, which is commonly used in interregional analysis today. Moore and Petersen (1955) constructed a single-region IOT for Utah, which closely resembles Leontief's model. However, their significant contributions to the development of regional and interregional IOTs include specifying regional production technology (i.e., regional input coefficients) without solely relying on national coefficients.

Many studies, including those described above, have faced a serious scarcity of regional input and output data when constructing regional and interregional IOTs. Some studies conducted surveys to collect regional data from enterprises to estimate purely regional coefficients for constructing regional and interregional IOTs (e.g., Hirsch, 1959; Isard and Langford, 1971). Hirsch (1959) pioneered the construction of a survey-based regional IOT. Hirsch constructed the IOT of the St. Louis metropolitan area in the US, where the input and output data were directly obtained from companies operating in the area (Miernyk, 1965). The Washington IOT is the survey-based table with the longest history (Roberts and Beyers, 2021). It was constructed by the Washington State Government between 1963 and 2012. Although survey-based IOTs provides valuable information on the regional economic system, it is significantly expensive and time-consuming.

Non-survey methods have been employed to estimate regional coefficients using limited data. Commonly used approaches in the literature include the “rows only” or RPC approach (Hansen and Tiebout, 1963), RAS methods (Stone and Brown, 1962), the Local Quotient (LQ) method (e.g., Flegg *et al.*, 1995), and the Gravity model (Leontief and Strout, 1963). However, as emphasized by Michael L. Lahr, regional analysts can choose

from a wide range of construction methods for regional or inter-regional IOT. This not only includes a full survey-based method or truly non-survey methods but also combined or hybrid methods (Lahr, 1993)

2.2.3 Internationalization of IOT

It is natural that scholars had an interest in revealing the structure of the world economy using the IO model. Based on the techniques developed in regional and interregional IO models, the construction of an MRIO model that treats each individual country as a region has advanced to provide insights into the global economy. The MRIO model enables us to comprehensively understand how intermediate and final commodities are produced and traded by component countries. Early environmental analysis studies attempted to analyze the pollution intensity of traded goods using a single national IOTs (e.g., Walter, 1973; Robinson, 1988). For example, Walter (1973) estimated the pollution intensity of US trade by multiplying the unit pollution abatement cost of US industries by the value of the US's exports and imports obtained from the US national IOT. Wyckoff and Roop (1994) extended the analysis of pollution embodied in trade to multiple regions using several national IOTs and bilateral trade data, as well as data on energy intensity, to identify trade patterns or trade partners that involve large amounts of pollution. However, in this study, the pollution intensity of imported goods was evaluated using domestic goods production technology. Some studies (Ahmad and Wyckoff, 2003; Lenzen *et al.*, 2004b; Nijdam *et al.*, 2005; Peters and Hertwich, 2006a, 2006b, 2006c) modified the multi-regional IO model to differentiate production technology between domestic and imported goods. Peters and Hertwich (2006c) demonstrated that assuming imported

goods with domestic technology leads to a substantial underestimation of their environmental impacts. They also indicated that gaps in pollution intensity were significantly higher in the electricity sector across countries. In particular, the pollution intensity of the electricity sector in China was 231 times higher for CO₂ and 1078 times higher for SO₂ than in Norway (Wiedmann *et al.*, 2007).

Their MRIO model successfully included the difference in production technologies for imported goods along with international trade flows in previous IO models by exogenously combining national IOTs and bilateral trade data. However, the model captures only imports of final goods; that is, the trade structure of intermediate goods is missing. For example, the model assumes that all parts of an automobile (i.e., final goods) imported from Japan to the US are produced in Japan. However, in the 21st century, the production process is fragmented worldwide due to the second wave of globalization (Baldwin, 2012), which has led to the assumption that intermediate goods (e.g., parts of automobiles) necessary to produce final goods (e.g., automobiles) are significantly dependent on imports from other countries. Therefore, a more sophisticated MRIO model that endogenously combines national IOTs with trade data is necessary to estimate pollution embodied in the trade involved in the entire supply chain stage (i.e., intermediate and final trades).

Leontief (1974) outlined a framework similar to MRIOT; however, it took several decades to realize the actual construction of an MRIOT. Builders of MRIOT face the problem of inconsistencies in accounts compiled by different national statistical agencies. For example, even within EU countries, substantial variations exist in the accounting

methodologies of national IOTs (Eurostat, 2019). In particular, variations in industry and commodity classifications make it difficult to match the value of exports from certain countries to the imports of others. Therefore, they must spare substantial resources to build a set of compatible national IOTs and adjust the combined matrix to ensure that the sums of the rows and columns are equal.

To address the problem of inconsistency, international organizations have improved their standardization processes. For example, the UN has published manuals on constructing national IOTs (UN, 1999, 2018); in particular, it provided the International Standard Industrial Classification of All Economic Activities (ISIC) (UN, 2008), and the OECD provided harmonized national IOTs (Yamano and Ahmad, 2006). The rapid development of computers has also been an important factor in MRIO construction because it requires mass matrix calculations. Morgenstern reported that it took 48 hours to calculate the inverse of the 38-sector matrix; this time was shortened to 5 minutes in 1953 (Morgenstern, 1954). Now it takes only 0.05 seconds using an ordinary PC. In addition to this methodological progress, international society's demand for tools to quantify the environmental impact of consumption, as described in the introduction, has also pushed the development of MRIO (Tukker and Dietzenbacher, 2013).

Several initiatives have been launched for sophisticated MRIOTs, as listed in Table 2.1, and most of the constructed MRIOTs are open to researchers. The MRIOT, constructed by different initiatives, has different purposes, which are reflected in the level of disaggregation of sectors, coverage of countries, and satellite accounts (Lenzen *et al.*, 2013). For example, the Eora, constructed by the University of Sydney, has the highest

resolution in sectors and countries, providing more than 15000 sectors (including 500 sectors including industry sectors and commodity sectors of 187 countries), while other MRIOTs provided 3760 to 7353 sectors at the time of publication (Lenzen *et al.*, 2012). EXIOBASE (EXIOPOL) has a detailed sector aggregation for environmentally relevant sectors, such as agriculture, mining, and energy. The World Input-Output Database (WIOD), constructed by the University of Groningen, provides rich time-series data and also provides MRIOT in constant monetary as well as nominal values. Recently, the University of Sydney has been working on a project called IE-Lab, a virtual laboratory where researchers can share relevant datasets and technologies to reduce labor-intensive processes to build MRIOTs. This also allowed us to flexibly select the number of sectors and countries to construct the MRIOTs. GLORIA is the MRIOT constructed in the IE-Lab and has the latest annual coverage and higher sector resolution, similar to Eora. In a review paper, Wiedmann *et al.* (2007) stated that there were few sophisticated MRIO models at that time. However, today, the MRIO model has gained momentum in this field and is widely used to investigate the structure of the global value chain and the environmental impact embodied in trade.

Table 2.1. Overview of the MRIOT

Database name	Number of Countries/ Industries	Time series	References
AIIOT (Asian International Input- Output Table)	10/76	1975-2005	Meng <i>et al.</i> (2013)
Eora	190/25-500	1990-2022	Lenzen <i>et al.</i> (2012, 2013)
EXIOBASE3	44+RoW/163	1995-2022	Stadler <i>et al.</i> (2018)
GRAM	62+RoW/48	1995-2010	Wiebe <i>et al.</i> (2012a, 2012b)
GTAP (Global Trade Analysis Project)	141+RoW/65	1993-2017	Aguiar <i>et al.</i> (2022)
WIOD (World Input-Output Database)	43+RoW/56	2000-2014	Timmer <i>et al.</i> (2015, 2016)
ICIO (Inter-Country Input-Output table)	67/45	1998-2018	OECD (2021)
GLORIA (Global Resource Input-Output Assessment)	164/120	1990-2027	Lenzen <i>et al.</i> (2017, 2022)

Note: This table represents the latest information available from the MRIOT publishers.

2.3. Discussions of aggregation bias and attempts to disaggregate IOTs

2.3.1 Discussions of aggregation bias

To enhance the resolution of the IO analysis, a more detailed sector disaggregation is desirable for the IOT. For example, when conducting an IO analysis of the automobile industry, using the “automobile sector” is preferable to the “transport equipment sector,” which includes trains, vessels, and aircraft. However, IOT developers often need to aggregate sectors to some extent owing to data and resource constraints. The aggregation of sectors with different production structures leads to a loss of information, which would bias the results of the IO analysis. In this section, I review the studies discussing aggregation issues. Discussions on aggregation issues have a long history, and have been mentioned in Leontief’s first paper on IOT (Leontief, 1936), and remain an actively investigated research topic today. Aggregation was defined by the mathematical formula to demonstrate the errors associated with aggregating sectors as “aggregation bias” (e.g., Fei, 1956; Theil, 1957; Morishima and Seton, 1961; Fisher, 1958; Morimoto, 1970; Kymn, 1990). According to Morimoto (1970), the “aggregation bias” is the difference between the sectoral total output calculated by the aggregated IO model and those calculated by the original IO model. In these theoretical studies (e.g., Malinvaud, 1954; Hatanaka, 1952; McManus, 1956; Theil, 1957), the conditions under which the aggregation bias was equal to zero were explored; however, these conditions were not practical (Guccione and Gillen, 1985).

The discussion of aggregation bias has shifted to the calculation of bias and methodologies for minimizing it (e.g., Blin and Cohen, 1977; Cabrer *et al.*, 1991;

Okasanen and Williams, 1992; Roy *et al.*, 1982; Murray, 1998). Recently, Lenzen (2019) suggested Structural Path Analysis (SPA) as a computationally inexpensive methodology for aggregation with minimal bias. He compared existing aggregation methodologies suggested by previous studies and revealed that the optimal aggregation methodology depended on the research question at hand.

The aggregation bias was evaluated in the context of various applications of IOT. For example, from the perspective of regional IO analysis, Lahr and Stevens (2002) evaluated the blended effect of rough regionalization, which significantly depends on national coefficients and a high aggregation level of sectors (i.e., aggregation bias), on the results of regional IO analysis. Their simulation indicated that blended bias was not acceptable and unnecessary sector aggregation should not be performed, especially for regional analysis. From the perspective of MRIO analysis, Steen-Olsen *et al.* (2014) evaluated the effect of high levels of aggregation in the sectors and regions of various MRIOT (Eora, EXIOBASE, GTAP, and WIOD) on environmental analysis. They demonstrated that a high level of aggregation in sectors and regions significantly affected the findings of the analysis across MRIOTs and concluded that the additional costs to improve the sector detail may be justified.

From the perspective of EEIO analysis, Lenzen (2011) evaluated the bias driven by aggregation to resolve inconsistencies in sector classifications between environmental accounts and the IOTs. As environmental accounts typically provide more detailed sector classifications for environmentally relevant sectors than IOT, which is primarily designed for environmental analysis, IO practitioners must choose to aggregate environmental

accounts or disaggregate IOT to resolve this inconsistency. They revealed that for a more reliable EEIO analysis, IO practitioners should disaggregate the IOT because aggregation causes larger errors in the EEIO analysis, even if the disaggregation is performed in a random manner.

2.3.2. Attempts to disaggregate IOTs

Lenzen's (2011) simulation was the most general and robust in the literature, and its implications provided critical insights into later studies addressing the issue of aggregation bias. This finding supported the motivation for studies attempting to disaggregate IOT sectors with large heterogeneity in their production technologies. For example, Lindner *et al.* (2012, 2013) presented versatile algorithms for disaggregating sectors in the IOT, with a focus on disaggregating the electricity sector in China. The electricity sector was disaggregated into different processes (e.g., generation, distribution, and transmission) and energy sources (e.g., coal, hydro, and solar). Some studies (Lau *et al.*, 2007, 2010; Duan *et al.*, 2021) have disaggregated processing exports, which rely more on imported intermediate inputs than ordinary exports. Analyses based on the distinguished table revealed that aggregating processing exports with ordinary exports may lead to a misunderstanding of China's consumption-based environmental impact in its exports (Dietzenbacher *et al.*, 2012) and extent of China's vertical specialization (Yang *et al.*, 2015). In Japan's IOT, Ogawa *et al.* (2012) partitioned sectors according to enterprise size to investigate the propagation mechanism of financial distress in the Japanese economy. In the context of development economics, Rada (2010) distinguished between the formal and informal sectors from the existing IOTs of China and India

because the informal sector depends significantly on traditional technologies with smaller intermediate inputs and lower efficiency and operates under different legal regulations.

2.4. Summary and contribution of the thesis

At the beginning of this chapter, I reviewed how the concept of the Environmentally-Extended Input-Output (EEIO) model was established. The EEIO model successfully integrated the interaction between economic activities and the environment into the classical IO model, which captures the circulation of production and consumption activities in economies. Today, the EEIO model stands as a superior analysis tool for comprehensively measuring the environmental impacts of production and consumption activities within individual countries, subnational regions, and the world. Next, I presented important papers that significantly contributed to the development of IOTs, with a focus on regional extensions. With extensive attention paid to the environmental impacts of international trade, the MRIOT has been compiled and contributes to policy discussions on environmental issues at the global scale. Finally, I reviewed papers on the reliability issues of IO analysis with a focus on aggregation bias. Many studies have confirmed that the aggregation of IOT sectors significantly affects the findings of IO analyses and provides motivation to disaggregate sectors with large heterogeneity.

As explained in the previous chapter, this dissertation comprises two supply chain analyses using the EEIO model. The first analysis, described in Chapter 3, is an EEIO analysis that combines the MRIOT and a PM_{2.5}-related health impact inventory to

estimate the consumption-based PM_{2.5}-related health impacts in India induced via the global supply chain. The contribution of this study lies in the extended PM_{2.5}-related health impact database, which includes the impact of secondary particulate matter and a detailed supply chain analysis centered around India. While previous EEIO studies have evaluated the impacts of air pollution based on emissions (as reviewed in Chapter 3), some studies have focused on health impacts, but they often only included the impact of primary particulate matter. Furthermore, many past EEIO studies have concentrated on the impact of air pollution in China, with fewer addressing the impact in India.

The second analysis, detailed in Chapter 4, aims to disaggregate IOT sectors with significant heterogeneity to address the issue of aggregation bias. This study constructed an EEIOT that distinguishes between the formal and informal sectors in India, revealing the contribution of the informal sector to the carbon footprint. While Rada (2010) previously constructed an IOT that disaggregated the informal sector, prior studies only considered the economic size of the informal sector for disaggregation. In contrast, our study takes into account both the difference in production structure and the size of the informal sector to disaggregate the IOT sectors. Moreover, this study introduces the environmental accounts of the formal and informal sectors to conduct a comprehensive carbon footprint analysis.

Chapter 3. Critical Supply Chains for Mitigating PM_{2.5} Emission-related Mortalities in India

3.1. Introduction

Air pollution is the fifth highest risk factor for mortality worldwide and the leading environmental risk factor; air pollution is responsible for 4.2 million deaths annually (HEI, 2017, 2019). Among various air pollutants, fine particulate matter measuring 2.5 micrometers or less in aerodynamic diameter (PM_{2.5}) is sufficiently small to penetrate the lungs deeply and pass into the blood stream. This may cause cardiovascular and respiratory diseases, such as lower respiratory infection (LRI), ischemic heart disease, cerebrovascular disease, chronic obstructive pulmonary disease (COPD), and lung cancer (Pope *et al.*, 2004; HEI, 2017, 2019).

During the period 2000–2015, when the annual GDP growth rate in India exceeded 8% (World Bank, 2019), the number of premature deaths attributable to PM_{2.5} exposure increased from 857,300 to 1,090,400 people (HEI, 2017). In 2015, PM_{2.5}-related premature deaths in India accounted for a quarter of global deaths attributed to PM_{2.5}, a level that was comparable to that of China, which has some of the world's highest air pollution levels (HEI, 2017).

India's rapid economic growth between 1995 and 2009 was mainly due to increasing fixed capital formation (i.e., final demand), and the additional capital formation (i.e., investment) was attributed to a marked increase in coal consumption in

India during the same period; coal consumption is one of the major sources of PM_{2.5} emissions (Wang and Song, 2019). Thus, to reduce premature deaths related to PM_{2.5} emissions in India, it is considered important for Indian policymakers to develop effective demand- and supply-side policy with a focus on higher priority sectors.

In 2019, the Indian government launched the National Clean Air Programme (NCAP) to achieve its sustainable development goals; the proposed national target was a 20–30% reduction in PM_{2.5} and PM₁₀ levels by 2024 (Government of India, 2019). This is the first time-bound commitment concerning air pollution that has been promulgated in India. Although the NCAP mentioned the importance of adopting a multi-sectoral and collaborative approach (Government of India, 2019), concrete collaborative policies have not yet been developed. To develop effective demand- and supply-side policies, it is important to obtain a deeper understanding of the supply chain structure centered around a critical sector that has contributed to PM_{2.5} emissions —and therefore, premature deaths— in India.

According to the Regional Emission Inventory in Asia (REAS) database for emissions from 2000 to 2008 (Kurokawa *et al.*, 2013), the power generation sector is one of the largest contributors of PM_{2.5} emissions in India, accounting for 822,000 tons of PM_{2.5} in 2008. In addition, the emissions from the power generation sector increased consistently from 2000 to 2008. Considering energy sources for electrical power generation in India, coal-fired thermal power accounted for 68% of the total 462 TWh generated in 2007 (Government of India, 2017). However, coal-fired thermal power plants were responsible for more than 90% of PM_{2.5} emissions in the power generation

sector in 2007 (Kurokawa *et al.*, 2013), which means that coal-fired thermal power is the most emission-intensive sector and that it plays a critical role in the emissions-related health impact on the people of India. This study examined power generation sector including the coal-fired thermal power and oil-fired thermal power generation, biomass power generation, which account for the remaining 10% of PM_{2.5} emissions as a critical emission source sector.

PM_{2.5} emissions from the electric power sector have been increasing due to the increases in electric power consumption that is *directly* necessary for households, and for industries that produce “final” goods and services. In addition to direct electric power use, it is also important to note that both consumers, i.e., households and industry, also *indirectly* consume electric power through the production of “intermediate” goods and services (including electric power) that are required to produce the final goods and services. It is also important to note that both direct and indirect electric power consumption generate PM_{2.5} emissions.

The electric power generation sector plays an important role in the supply chain (Kagawa *et al.*, 2013). To effectively mitigate the health impacts related to PM_{2.5} emissions in India, the PM_{2.5} emissions associated with the indirect use of electricity (i.e., Scope 3 emissions from the electricity sector in line with the greenhouse gas [GHG] protocol) (WRI and WBCSD, 2009), as well as emissions associated with the direct use of electricity (i.e., Scope 2 emissions from the electricity sector in line with the GHG protocol) (WRI, 2015) need to be reduced. In other words, it is necessary to identify environmentally important supply chain paths that have the greatest mitigation potential

for health impacts in India.

A highly relevant study by Guttikunda and Jawahar (2014) focused on coal-fired power plants located in Indian states in 2010 and estimated the total annual PM_{2.5} emissions in India at around 580,000 tons. These authors also estimated that the annual PM_{2.5}-induced mortalities in India were between 80,000 and 115,000. However, because the study of Guttikunda and Jawahar (2014) only examined “production-based” PM_{2.5} emissions and production-based mortality risks, these results provide a relatively limited understanding of how the final demand of countries such as India affects PM_{2.5}-induced mortality risks.

Nansai *et al.* (2020) quantified the mortality-based economic losses (i.e., income loss) attributed to primary and secondary PM_{2.5} emissions in individual Asian countries that were induced by the final demand of the world’s five largest consuming countries. Their findings showed that in 2010, consumption in the USA, China, Japan, Germany, and the United Kingdom caused approximately 2,000, 7,700, 2,700, 3,300, and 3,400 deaths in India, respectively. These deaths resulted in economic losses in India of 0.14, 0.26, 0.087, 0.11, and 0.11 billion US dollars in purchasing power parity, respectively. In India, particularly, the export of goods and services from India to these developed countries contributed considerably to PM_{2.5} emissions, and therefore the high number of premature deaths in India. This situation calls for an analysis of how the global supply chain is impacting health in India in terms of emission responsibility (Davis and Caldeira, 2010). In addition, domestic policies need to be introduced to mitigate air pollution inside India, and demand-side policies that consider the role of consumers outside India need to

be developed.

Structural path analysis (SPA) is a well-known and effective method that was first introduced by Defourny and Thorbecke (1984) to trace important supply chain paths from complex input-output structures by decomposing matrix products into elements (paths). Previous studies addressing PM_{2.5} emissions have applied this method. For example, Meng *et al.* (2015) identified PM_{2.5} emission-intensive supply chain paths in China using SPA. However, they only considered PM_{2.5} emissions and did not consider the reduction potential of health impacts. Nagashima *et al.* (2017) identified critical supply chain paths that contribute toward premature deaths in East Asian countries; however, they did not include secondary PM_{2.5} generation, which has a marked influence on health, and they did not consider India in their analysis.

This study used EXIOBASE 3 data for 2010 and applied an SPA (Toreloar, 1997; Lenzen, 2003; Peters and Hertwich, 2006b; Lenzen, 2007) to identify important supply chain paths driven by domestic and international demands that contribute to primary and secondary PM_{2.5} emissions from the power sector, which is an environmentally critical sector in India. This study introduced an atmospheric transport model to fully link final demand via supply chains to the primary emitter that is the power sector in India. Finally, the atmospheric transport of emissions from the emitter was linked to the impact on health in India. To the best of our knowledge, this study is the first attempt to estimate consumption-based PM_{2.5} emissions as well as the consumption-based mortality risk in India by using a combined approach that is based on an environmentally extended multi-regional input-output (EE-MRIO) analysis and an atmospheric transport model.

The remainder of this chapter is structured as follows: Section 3.2 explains our methodology, Section 3.2 describes the data, Section 3.4 presents and discusses the results, and finally, Section 3.5 contains the discussion and conclusions.

3.2. Methodology

To estimate consumption-based $PM_{2.5}$ emissions, this study employed the consumption-based health impact accounting method developed by Takahashi *et al.* (2014) and Nagashima *et al.* (2017).

3.2.1. Consumption-based $PM_{2.5}$ emissions

The output vector, $\mathbf{x} = (x_i^r)$ ($r = 1, \dots, R, i = 1, \dots, N$) in a MRIO analysis with N industries and R countries can be obtained using the equation $\mathbf{x} = \mathbf{Ax} + \mathbf{f}$; where $\mathbf{f}^g = (f_i^{rg})$ is the global final demand vector that shows the final demand for goods and services flowing from industry i in country r to the final consumers of R countries; $\mathbf{A} = (Z_{ij}^{rs}/x_j^s) = (a_{ij}^{rs})$ is an input coefficient matrix showing the intermediate input of industry i in country r that is necessary for producing one unit of the product from industry j in country s , for which Z_{ij}^{rs} represents the intermediate input into industry j of country s from industry i of country r .

The global final demand vector, $\mathbf{f}^g$, can be expressed as the sum of the final demand vectors of each demand country: $\mathbf{f}^g = \mathbf{f}^1 + \mathbf{f}^2 + \dots + \mathbf{f}^R = \sum_{s=1}^R \mathbf{f}^s$; where, $\mathbf{f}^s$ is the domestic final demand vector for country s . Solving the above equation for the

output vector $\mathbf{x}$ yields the following:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{L}\mathbf{f}^g \quad (3.1)$$

where $\mathbf{I}$ is the identity matrix and $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} = (L_{ij}^{rs})$ is the Leontief inverse matrix with elements L_{ij}^{rs} expressing the outputs of industry i in country r that are directly and indirectly required to satisfy one unit of final demand from industry j in country s .

The electricity output in India triggered by the final demand in country s can be estimated as follows:

$$e^s = \mathbf{w}'(\mathbf{I} - \mathbf{A})^{-1}\mathbf{f}^s = \mathbf{w}'\mathbf{L}\mathbf{f}^s \quad (3.2)$$

where $\mathbf{w}'$ is the transpose of the vector $\mathbf{w}$ whose elements for the electricity sector in India are unity and are 0 for other sectors.

3.2.2. Consumption-based health impacts

Referring to the work of Nagashima *et al.* (2017), the number of premature deaths in India due to PM_{2.5} emissions from the power generation sector associated with final demand in country s can be estimated using the following equation:

$$m^s = \alpha\mathbf{w}'\mathbf{L}\mathbf{f}^s = \alpha e^s \quad (3.3)$$

where α represents the number of PM_{2.5}-induced premature deaths in India per unit output from the power generation sector.

3.2.2. Identifying critical supply chain paths

Next, this study identify the environmentally important supply chain paths by evaluating the contribution made by the supply chain paths that link consumption and production to the consumption-based PM_{2.5} emissions obtained above. If we perform a series expansion of the Leontief inverse matrix in Eq. (3.1), we obtain $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} = \mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \dots$. Then, from Eq. (3.3), we can estimate the health impacts in India induced by consumption in country s as follows:

$$m^s = \alpha \mathbf{w}' \mathbf{f}^s + \alpha \mathbf{w}' \mathbf{A} \mathbf{f}^s + \alpha \mathbf{w}' \mathbf{A}^2 \mathbf{f}^s + \alpha \mathbf{w}' \mathbf{A}^3 \mathbf{f}^s + \dots \quad (3.4)$$

Next, let us define $\alpha \mathbf{w}'$ as $\mathbf{q}'$, which represents premature deaths attributable to the emissions of primary and secondary particulate matter per unit output of the power generation sector of India, and the other vector elements as zeros. In this case, we can rewrite Eq. (3.4) as follows:

$$m^s = \mathbf{q}' \mathbf{f}^s + \mathbf{q}' \mathbf{A} \mathbf{f}^s + \mathbf{q}' \mathbf{A}^2 \mathbf{f}^s + \mathbf{q}' \mathbf{A}^3 \mathbf{f}^s + \dots \quad (3.5)$$

If we focus on India (*IND*) as the final demand country, then Eq. (3.5) can be expressed as $m^{IND} = \mathbf{q}' \mathbf{f}^{IND} + \mathbf{q}' \mathbf{A} \mathbf{f}^{IND} + \mathbf{q}' \mathbf{A}^2 \mathbf{f}^{IND} + \mathbf{q}' \mathbf{A}^3 \mathbf{f}^{IND} + \dots$, where the first term on the right-hand side denotes premature deaths in India associated with electricity directly consumed by final consumers in India, the second term denotes the premature deaths in India associated with the electricity that is directly required to meet final demand of goods and services in India, and the other terms represent premature deaths in India that are associated with electricity that is indirectly required to meet final demand of goods and services in India. Using this equation, we can estimate the consumption-based health impacts associated with the final demand of other countries.

The consumption-based health impacts in India can also be estimated by the following supply chain equation:

$$\begin{aligned}
m^s &= \sum_{v=1}^R \sum_{j=1}^N q_{Elec}^{IND} (\mathbf{I}_{Elec,j}^{IND,v} + \mathbf{A}_{Elec,j}^{IND,v} + (\mathbf{A}^2)_{Elec,j}^{IND,v} + (\mathbf{A}^3)_{Elec,j}^{IND,v} \dots) f_j^{vs} \\
&= \sum_{v=1}^R \sum_{j=1}^N q_{Elec}^{IND} (I_{Elec,j}^{IND,v} + a_{Elec,j}^{IND,v} \\
&\quad + \sum_{t=1}^R \sum_{k=1}^N a_{Elec,k}^{IND,t} a_{kj}^{tv} + \sum_{u=1}^R \sum_{t=1}^R \sum_{l=1}^N \sum_{k=1}^N a_{Elec,l}^{IND,u} a_{lk}^{ut} a_{kj}^{tv} + \dots) f_j^{vs} \\
&= q_{Elec}^{IND} f_{Elec}^{IND,s} + \sum_{v=1}^R \sum_{k=1}^N q_{Elec}^{IND} a_{Elec,j}^{IND,v} f_j^{vs} \\
&\quad + \sum_{t=1}^R \sum_{k=1}^N \sum_{v=1}^R \sum_{j=1}^N q_{Elec}^{IND} a_{Elec,k}^{IND,t} a_{kj}^{tv} f_j^{vs} + \dots
\end{aligned}$$

(3.6)

where q_{Elec}^{IND} represents the premature deaths attributable to the emission of primary and secondary particulate matter per unit output of the power generation sector of India, while $a_{Elec,j}^{IND,v}$ is the intermediate input for the power generation sector of India that is necessary per unit of production of the product of industry j in country v . The second term on the right-hand side of Eq. (3.6), $q_{Elec}^{IND} a_{Elec,j}^{IND,v} f_j^{vs}$, expresses the health impacts in India due to PM_{2.5} emissions induced by the production of electricity in India that is required by industry j to produce the products in country v to satisfy final demand in country s . From the second term on the right-hand side of Eq. (3.6), we can identify the supply chain paths, such as “health impacts on India (impact receptor country)” → “electricity of India (emission source country)” → “industry j of country v (transmission country)” → “final demand in country s (i.e., consumption driver country).”

3.3. Data and computation

This study used EXIOBASE 3 data for 2010 (Stadler *et al.*, 2018). The EXIOBASE is a MRIOT that includes 44 countries, five international regions (Middle East, Other Asia, Other America, Other Europe, and Other Africa), and 163 industrial sectors. In this study, I constructed a “new electricity sector of India” by aggregating three power generation sectors in EXIOBASE 3 (i.e., production of electricity by coal, production of electricity by petroleum and other oil derivatives, and production of electricity by biomass and waste) whose activities emit PM_{2.5} (Kurokawa *et al.*, 2013) to ensure that the IOT corresponds to the emission inventory data.

This study considered 7,985 sectors (48 countries and regions $\times$ 163 industrial sectors, and 161 industries in India) in our MRIO framework. Consequently, the number of supply chain paths in the 0th tier expressed by the first term on the right-hand side of Eq. (3.6) (i.e., $q_{Elec}^{IND} f_{Elec}^{IND,s}$) is 49, the number of paths in the first tier (i.e., $\sum_{v=1}^R \sum_{j=1}^N q_{Elec}^{IND} a_{Elec,j}^{IND,v} f_j^{vs}$) is $163 \times 48 + 161 = 7985$, the number of paths in the second tier is 7985^2 , and the number in the n^{th} tier is 7985^n . However, there is a computation problem, as the number of computations for the total emissions in a given tier increased rapidly as the tier number increased. Therefore, for the purposes of this study, I set a threshold to disregard supply chain paths that (1) accounted for less than 0.001% of the total consumption-based health impacts for the paths triggered by Indian final demand, and (2) induced less than one premature death in the paths triggered by international final demand. As a result, this study only considered paths up to the fourth tier, which includes more than 95% of consumption-based health impacts derived from the final demand in India. Considering international demand, this study focused on the paths driven by final demand in the top three driver countries or regions, i.e., the Middle East, the USA, and China. In terms of consumption-based health impacts, our estimates covered more than 90% (Middle East), 85% (USA), and 60% (China) of the deaths induced in India. The Middle East region includes the following 14 countries: Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, the United Arab Emirates, and Yemen.

This study also used data on PM_{2.5} emissions by power sector and Source Receptor Relationship (SRR) matrix estimated in a previous study (Nagashima *et al.*, 2018). In that study, the SRR matrix was estimated using an atmospheric transport model with a focus

on Asian countries, including India. Modeling simulations were performed using the Community Multiscale Air Quality modeling system (Byun and Schere, 2006), and the Weather Research and Forecasting (WRF) modeling technique (Skamarock *et al.*, 2008) was used to calculate meteorological field conditions. Further, the Emission Database for Global Atmospheric Research (EDGAR) inventory map (Crippa *et al.*, 2018) was used to generate a 0.1° resolution map of sectoral emissions. The simulations were used to estimate the yearly averaged regional concentrations of primary PM_{2.5} (black carbon and organic carbon) and secondary precursors (NO_x, SO₂, NH₃, CO, and NMVOC) emitted from all sectors and each individual sector in India, respectively. The grid consisted of $0.5^\circ \times 0.5^\circ$ (about 45 km $\times$ 45 km) squares, with Papua New Guinea in the east, Iran to the west, Australia to the south, and Russia to the north. First, the human health effects (i.e., premature deaths) for each age group in each grid induced by the pollution concentrations from *all sectors* in India were estimated using the PM_{2.5} concentration map, an integrated exposure-response model (Burnett *et al.*, 2014; Apte *et al.*, 2015), and population distribution data by sex and age (CIESIN, 2017). The relative risks of five diseases (ischemic heart disease, COPD, cerebrovascular disease, lung cancer, and LRI) were calculated for each age group using the integrated exposure-response model. The number of premature deaths in each grid was estimated using the same method as Apte *et al.* (2015). To calculate the contribution of PM_{2.5} emissions to the total premature deaths for each sector associated with PM_{2.5} emissions in India, this study adopted a proportional attribution assumption, in which the health impacts were proportional to the PM_{2.5} concentration generated by each sector. This study also employed the proportional assumption of PM_{2.5} concentration to both primary PM_{2.5} emissions and secondary precursors emissions to obtain α in Eqs. (3.3) and (4.3).

3.4. Results

3.4.1. Consumption-based health impact analysis

I first calculated the direct and indirect impacts of the power sector in India on the total number of PM_{2.5}-related premature deaths. A direct health impact was defined as when electricity is consumed as a final product, mainly by households. An indirect impact was defined as when electricity is consumed as an intermediate product, mainly by industries that engage in production activities. The former can be calculated using $q_{Elec}^{IND} f_{Elec}^{IND,S}$, while the latter can be calculated by subtracting the direct health impact from the total of the consumption-based health impacts triggered by the final demand of countries, $\sum_{S=1}^R m^S$. The findings showed that the indirect impact was approximately four times larger than the direct impact. The findings also showed that it is important to further investigate the indirect impacts in order to better understand the mechanisms underlying mortality generation and to identify the stakeholders responsible, despite the complexity of the global supply chain.

Figure 3.1 shows the consumption-based health impacts (i.e., number of deaths) in India that are attributable to PM_{2.5} emissions induced by power generation in India for domestic and foreign final demand. The consumption-based mortality in India estimated in this study is 113,000 people in 2010. It is important to note that the consumption-based health impacts in India induced by the final demand of countries ($\sum_{S=1}^R m^S$) is the same as the production-based health impacts. Guttikunda and Jawahar (2014) reported that the production-based mortality induced by coal-fired power generation in India in the same

year was between 80,000 and 115,000 people. Although the estimation methodology is different, the results of this study are consistent with those of Guttikunda and Jawahar (2014).

Importantly, 87% of air pollution-related deaths in India were due to the domestic final demand of India, whereas 13% was due to the final demand of other countries (Figure 3.1). The Middle East was the largest contributor to these health impacts, accounting for 19% of the total impact, followed by the USA, China, and the United Kingdom, which contributed 15%, 6%, and 5%, respectively. I note that both domestic and foreign drivers account for health impacts in India via direct and indirect electricity use.

Next, this study applied the SPA to 163 domestic sectors and the three largest contributors to final demand (i.e., the Middle East, the USA, and China), as well as India, to identify critical supply chain paths and to understand how these final demands are linked to the health impact of PM_{2.5} emissions from the power generation sector in India.

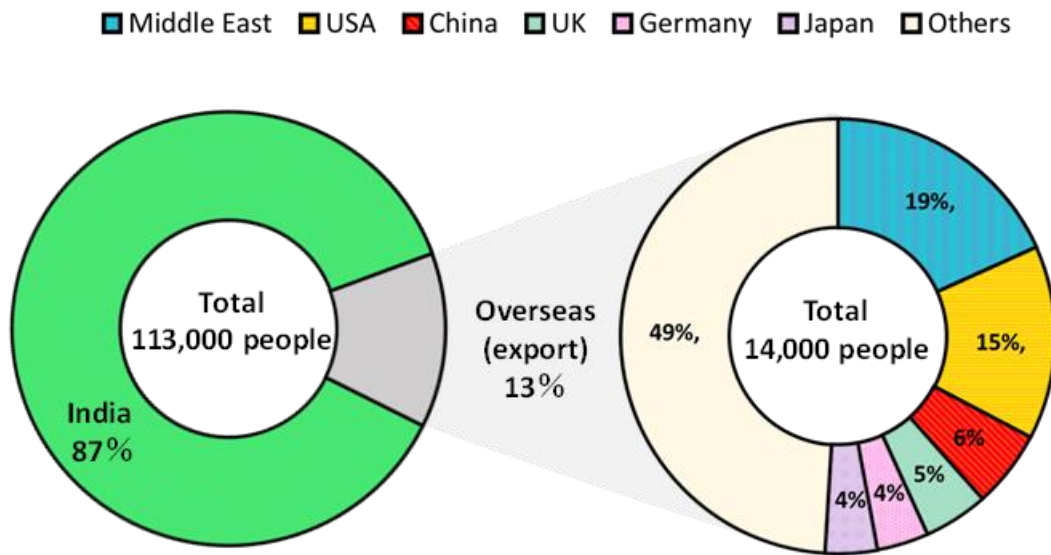


Figure 3.1. Consumption-based health impact in India triggered by domestic and international final demand.

3.4.2. Health impact analysis based on India's final demand

Figure 3.2 shows the contribution of final demand sectors in India to PM_{2.5} emission-related mortality in India. The rectangular areas in Figure 3.2, calculated by multiplying the size of a certain final demand sector's final demand (x -axis: along the bottom) by the number of premature deaths per unit of that sector's final demand (y -axis: height), represents the number of premature deaths caused by that sector through direct and indirect electricity consumption. The x - and y -axes can also be thought of as “market scale” and “intensity of electricity consumption”, respectively.

According to Figure 3.2, the construction sector is responsible for 17,500 PM_{2.5} emission-related premature deaths, the greatest number of all final sectors (Table 3.1). As the construction sector's rectangular area is characterized by having a considerably wider

base compared to its height, we can see that the market scale of the construction sector—which reflects India’s active domestic infrastructural development—contributes greatly to the number of premature deaths. In contrast, the paddy rice sector is responsible for 5,500 premature deaths and is the second largest contributor in the country (Table 3.1). While the construction sector’s rectangle has a base that is wider than its height, the paddy rice sector’s rectangle is taller than it is wide; therefore, it is the intensity of its electricity consumption that contributes greatly to premature deaths. Consequently, reducing the premature deaths ascribed to the paddy rice sector will require a considerable reduction of its electricity consumption through basic policies, such as capital investment and re-examining systems. This is a characteristic shared with other agricultural sectors, such as the wheat and processed rice sectors.

The textile sector is the third-largest contributor to premature deaths in India, being responsible for 4,370 deaths (Table 3.1). Unlike the rectangles of the construction and rice paddy sectors mentioned above, the rectangle of the textile sector is close to a perfect square and, as such, is a sector in which market scale and intensity of electricity consumption both contribute equally to premature deaths.

Considering the proportions of the upper and lower rectangles shown in Figure 3.2, we can infer the proportion of (1) premature deaths associated with the electricity required to satisfy each sector’s final demand (*direct electricity consumption*) in relation to (2) premature deaths associated with the electricity required to produce the intermediate goods necessary to satisfy each sector’s final demand (*indirect electricity consumption*). The former tends to be greater than the latter in the case of paddy rice, wheat, and cereal

grains in the agricultural sector, and electrical machinery and communication equipment in the manufacturing sector. These sectors have a large number of premature deaths and the supply chain paths that involve them are: (1) electrical machinery (IND) → communication equipment (IND) → electricity (IND) (50 premature deaths); (2) electrical machinery (IND) → fabricated metal products (IND) → electricity (IND) (29 premature deaths); (3) communication equipment (IND) → electrical machinery (IND) → electricity (IND) (211 premature deaths); and (4) communication equipment (IND) → post and telecommunications → electricity (IND) (70 premature deaths).

In contrast, in the service sector — such as hotels and restaurants and other land transport — more premature deaths are due to indirect than direct electricity consumption. The key paths for hotels and restaurants were: hotels and restaurants (IND) → paddy rice (IND) → electricity (IND) (89 premature deaths) and hotels and restaurants (IND) → wheat (IND) → electricity (IND) (70 premature deaths). In the case of other land transport, the key paths were: other land transport (IND) → rubber and plastic products (IND) → electricity (IND) (74 premature deaths) and other land transport (IND) → textiles (IND) → electricity (IND) (45 premature deaths).

As mentioned above, the construction sector was the final demand sector with the highest number of PM_{2.5} emission-related premature deaths, and the number of premature deaths induced by *direct electricity consumption* was roughly the same as those by *indirect electricity consumption* (Figure 3.2). The key paths involving these sectors were: construction (IND) → cement, lime, and plaster (IND) → electricity (IND) (1,634 premature deaths); construction (IND) → ceramic goods (IND) → electricity (IND)

(1,016 premature deaths). From these results, it is clear that even if a particular final demand sector's electricity demand (the height in Figure 3.2) is low, that sector still has an indirect, but marked impact on the number of premature deaths. This impact occurs through Scope 3 PM_{2.5} emissions, which are caused by investing the goods produced in these sectors with intense electricity demand into intermediate goods. To efficiently reduce the health impact of PM_{2.5} emissions caused by the power sector, policies to reduce electricity consumption should focus on the intermediate goods sectors that provide a given final demand sector with intermediate goods, as well as the final demand sector itself.

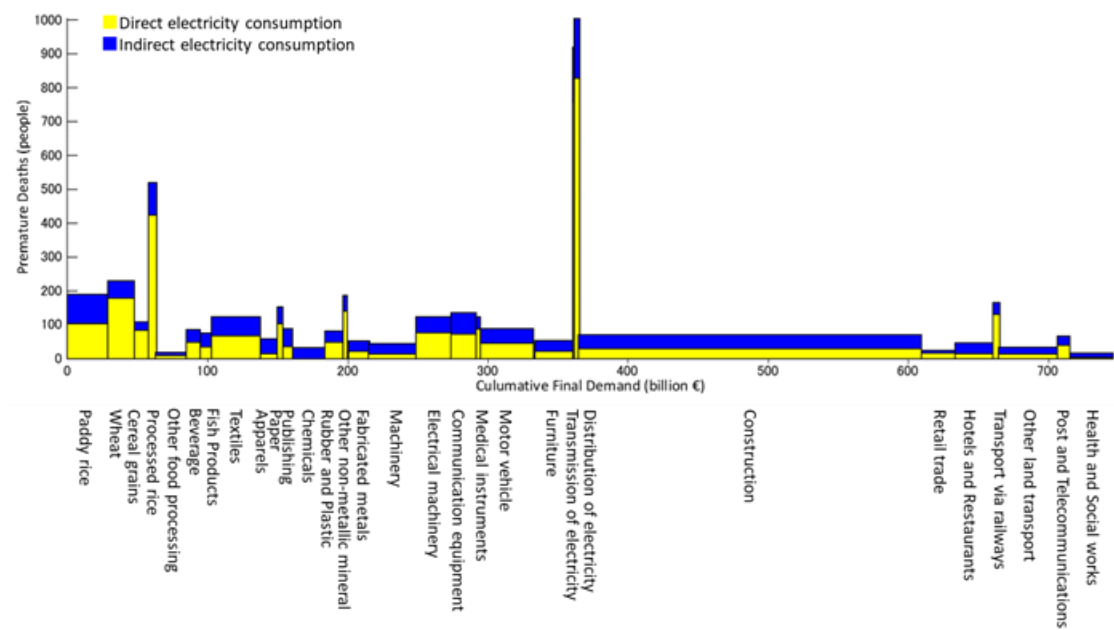


Figure 3.2. Contribution of electricity consumption by India's domestic sectors to health impacts.

Table 3.1. Highest PM_{2.5}-related health impacts induced by electricity consumption in domestic final demand sectors in India

Final Demand Sector	Premature Deaths (<i>n</i>)
Construction	17,500
Paddy rice	5,500
Textiles	4,370
Wheat	4,360
Distribution and Trade of Electricity	3,800
Motor Vehicle	3,400
Electrical Machinery	3,050
Processed rice	3,000
Communication Equipment	2,500

3.4.3. Analysis of health impacts triggered by foreign final demand

Next, I present the results of the SPA to break down the consumption-based health impacts triggered by foreign final demand for different global supply chain paths extending from final demand to producers. Figure 3.3 shows a Sankey Diagram composed of the top 10 supply chain paths in tier 1 driven by final demands in the Middle East, the USA, and China (i.e., a total of 30 paths). The path with the largest health impact was: Middle East → processed rice (IND) → electricity (IND), which induced 433 premature deaths. Middle Eastern countries import processed rice produced in India; consequently,

rice processing induces a high health impact through PM_{2.5} emissions from power plants. Based on imports of processed rice, Middle Eastern countries have a large responsibility concerning India's premature death rate. Figure 3.4 also shows the path USA → textiles (IND) → electricity (IND), which also has a high health impact, inducing 110 premature deaths. The USA imports textiles produced in India, and the textiles sector in India induces a health impact in India via electricity consumption. I therefore posit that the USA should also be involved in mitigation measures related to imports of Indian textiles.

Figure 3.4 is a Sankey Diagram showing the top 10 supply chain paths in tiers 2 to 4 that are driven by final demand sectors in the Middle East, the USA, and China (Total 30 paths). The figure shows that there are high-ranking paths centered on imports of processed rice in India via food processing and service sectors in the Middle East: Middle East → hotels and restaurants (Middle East) → processed rice (IND) → electricity (IND) (80 premature deaths); Middle East → processing of food (Middle East) → processed rice (IND) → electricity (IND) (38 premature deaths); and Middle East → health and social works (Middle East) → electricity (IND) (35 premature deaths). The textile supply chains linking India with the USA also have a high health impact: USA → apparel (USA) → textiles (IND) → electricity (IND) (28 premature deaths); USA → textiles (USA) → textiles (IND) → electricity (IND) (15 premature deaths); and USA → textiles (IND) → plant-based fiber (IND) → electricity (IND) (13 premature deaths).

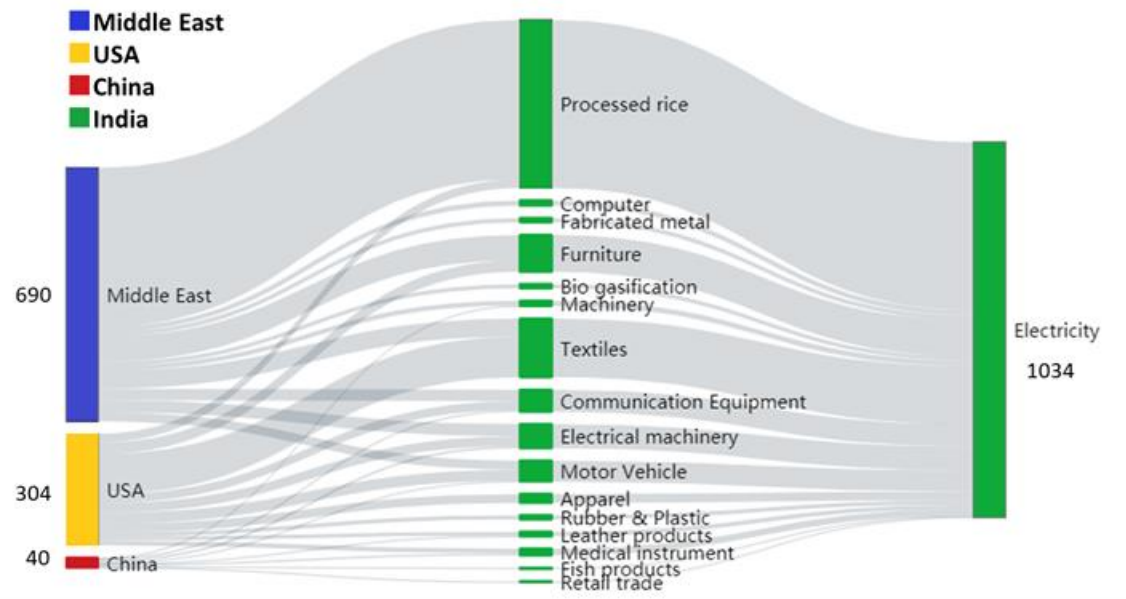


Figure 3.3. Top 10 supply chain paths ranked in terms of health impact driven by the Middle East, USA, China in the first tier

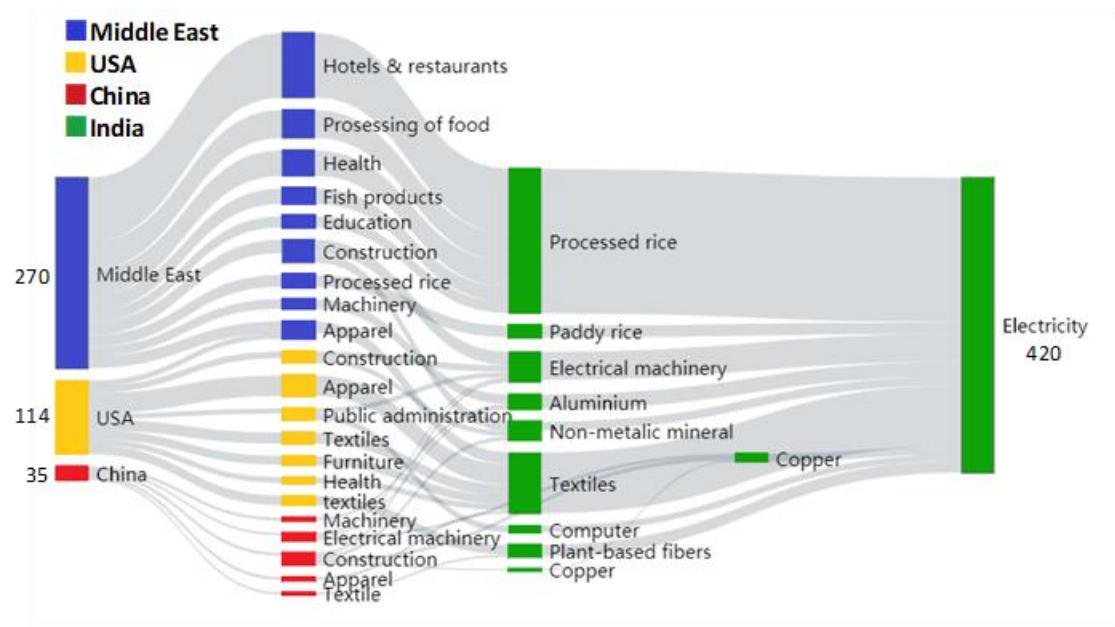


Figure 3.4. Top 10 supply chain paths ranked in terms of health impact driven by the Middle East, USA, China in the second to fourth tiers

3.5. Discussion and Conclusion

I first calculated the consumption-based health impact associated with PM_{2.5} emissions from the domestic power sector in India by combining a health impact database with a global MRIOT. Then an SPA was used to reveal how the PM_{2.5} emitter (the power generation sector in India) is linked to domestic Indian final demand and international demand in a global supply chain. The results showed that the total number of premature deaths attributable to PM_{2.5} emissions from the power generation sector was 113,000 and that 87% of those deaths was induced by Indian final demand and 13% was induced by international final demand (i.e., exports from India). Construction was the largest domestic contributor to PM_{2.5} emission-related mortality in India as it consumed the most electricity, either directly or indirectly.

A key finding of this study was that supply chain paths centered around agriculture, e.g., paddy rice (IND) → electricity (IND), processed rice (IND) → electricity (IND), Middle East (Final demand) → processed rice (IND) → electricity (IND), played a major role in premature deaths associated with PM_{2.5} emissions from the power sector in India. Although it is well-known that agricultural sectors in India, such as paddy rice cultivation, directly emit considerable quantities of PM_{2.5} by burning fields (Venkataraman *et al.*, 2018), I found that indirect emissions via its electricity consumption also considerably affected human health in India.

This finding also showed that electricity consumption at the cultivation stage of paddy rice and wheat was responsible for approximately 5,500 and 4,360 PM_{2.5} emission-

related premature deaths, respectively (Table 3.1). One of the primary causes of electricity consumption in the paddy rice and wheat sector is electric pumps for irrigation (Garg *et al.*, 2011; Jadhav *et al.*, 2020). Rice and wheat are also both highly water-intensive crops and it has been shown that irrigation agriculture in India is structured in a way that consumes more electricity than is necessary (Shah *et al.*, 2012). The Indian government has set a low fixed price for electricity for agricultural use through subsidies, and under this system, irrigation farmers have no incentive to conserve electricity. Thus, the Indian government should raise the price of electricity for the agricultural sector to a reasonable level by reevaluating the subsidies provided to the agricultural industry. Instead, the government should subsidize capital investment for irrigation farmers, e.g., by investing in energy-saving irrigation pumps, to move the agricultural sector in a more energy-saving direction.

As India is a vast country, there is considerable regional variation in economic activities such as agriculture. Although MRIO analysis of sub-regions in India can provide detailed information on the spatial heterogeneity in production and consumption (e.g., Nagashima, 2018), there is, at present, no MRIO database available for Indian sub-regions. As a result, I used the following simplified sub-regional analysis (Moran *et al.*, 2018) to spatially break down the domestic supply chain paths in India. I calculated the contributions of states and union territories of India to the PM_{2.5} emission-related premature deaths along the supply-chains of rice (wheat) by distributing the total number of premature deaths induced by electricity consumption required for rice (wheat) cultivation according to the share of rice (wheat) production in each state and union territory (Table A1).

Figures 3.5A and 3.5B show the spatial distributions of the PM_{2.5} emission-related premature deaths in the rice and wheat supply chains, respectively. The results show that the three states of West Bengal, Uttar Pradesh, and Punjab accounted for approximately 40% of the premature deaths that are attributable to rice supply, while the three states of Uttar Pradesh, Punjab, and Haryana accounted for 66% of the premature deaths attributable to wheat supply. We suggest that the local governments of West Bengal, Uttar Pradesh, Punjab, and Haryana should implement aggressive electricity-saving policies in the areas of rice and wheat production in order to mitigate against PM_{2.5} emissions from the power sector in India.

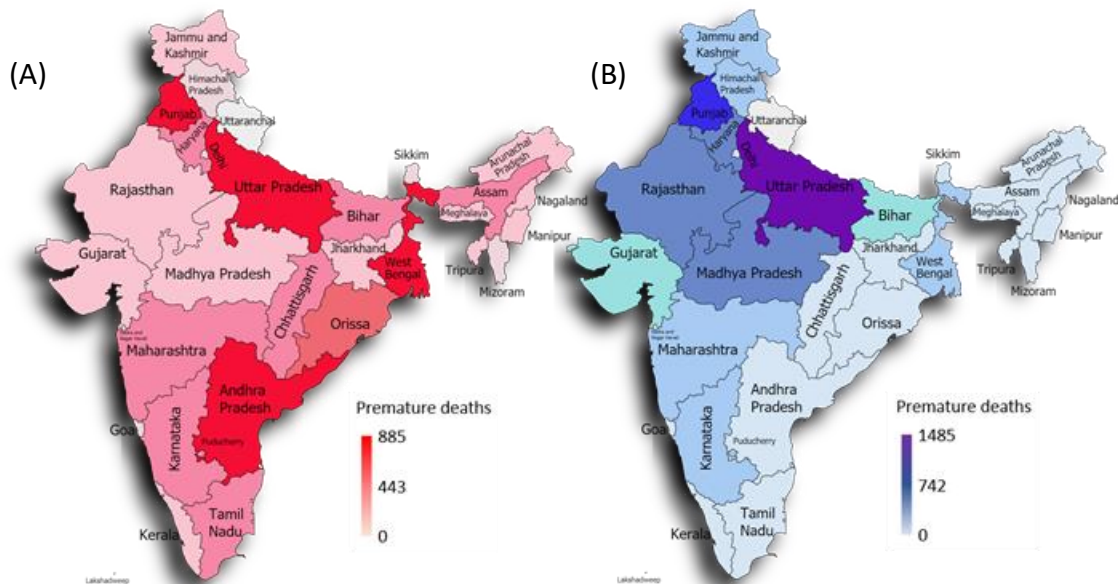


Figure 3.5. Spatial distributions of the PM_{2.5} emission-related premature deaths via rice (A) and wheat (B) supply chains. Maps generated in Paintmaps.com (<https://paintmaps.com/>).

The processed rice sector was responsible for approximately 3,000 premature deaths due to the electricity required for production to meet domestic demand, and

approximately 600 premature deaths for production to meet the export demand of the Middle East. Rice processing can be broadly divided into four processes—parboiling to remove pesticides and insects, de-husking, selection, and preservation—and this sector requires large amounts of electricity due to the increasing mechanization required to polish such large quantities of rice (Goyal *et al.*, 2014). In addition, the rice processing equipment in India is old, and while the Indian government is supporting the introduction of newer and more energy-efficient equipment, its penetration is only 50% (Shweta *et al.*, 2011). One reason for this low penetration is the high installation costs associated with this equipment. The second reason is that, even if the government were to encourage technical improvements in the rice processing sector through subsidies and regulations, ensuring technical improvements and maintaining efficiency would incur high monitoring costs for the government in a developing country such as India. To avoid this, it is crucial to motivate the rice processing sector itself to take the initiative for conducting technical improvements. Considering the key supply chain paths described in this study that involve India's rice processing sector, “environmental labeling” is very important; that is, communicating the number of premature deaths (environmental data) caused by the production of rice when that rice is sold to consumers in India and the Middle East. This environmental labeling policy would allow India's rice processing sector to introduce and use efficient technologies of its own initiative to improve environmental data.

The results of this study showed that, at the consumption stage of rice, a significant proportion of electricity-induced premature deaths are caused by the importation of rice by the Middle East. In 2017, India was the world's largest rice exporter (USDA, 2020)

and countries in the Middle East (Iran, Saudi Arabia, and Iraq) were the top three destinations for its rice (Government of India, 2020). While Middle Eastern countries import a large amount of rice from India, Saudi Arabia ranked first in the world for food wastage per capita in 2017, including rice (EIU, 2016). Purchasing more Indian rice than is necessary only to waste it is a consumption pattern that results in additional and unnecessary domestic electricity consumption in India, which, in turn, leads to an increase in health risks due to the increase in PM_{2.5} emissions during electricity generation. Suppressing this wasteful consumption pattern will require measures such as levying a pollution tax on imports of rice produced in India and educating consumers about the effects of indirect pollution beyond their borders.

As India's population is expected to increase further in the future, rice and other food sectors are industries that not only generate value added but are also essential for feeding one of the largest populations in the world. With increasing the food demand, higher mechanization of agriculture will increase electricity consumption in India. To mitigate health burden triggered by the agricultural production, improving energy efficiency in these sectors is crucial for sustainable agricultural production. It is important to reduce the electricity consumption through introducing equipment with higher energy efficiency as well as strengthening monitoring system of measuring potential energy savings associated with pumping water for irrigation (USDA, 2021). Ensuring the sustainable production in these sectors is a pressing challenge and an issue that must be prioritized by all stakeholders.

The limitations of this study are the following.

- (1) It should be noted that our sub-regional results described in Figure 3.5 are based on the simplified spatial attribution analysis. Multi-regional input-output analysis with a focus of the Indian economy could elaborate the sub-regional results. This elaboration is an important follow-up study.
- (2) This study focused only on PM_{2.5} emissions, therefore we did not consider health burdens triggered by other pollutants. The analysis scope should be expanded in a future study.
- (3) The share of unorganized sector (i.e., informal sector) in net domestic product in India was 57% in 2002 (Rada, 2010), and thus the informal sector played a crucial role in the Indian economy. It is important to note that a social accounting matrix for India was estimated by Rada (2010) using the shares of net domestic product or factor incomes for the unorganized and organized enterprises. The net domestic product for the informal sector was estimated based on detailed employment surveys by the Indian government (Rada, 2010). As a result, the IOT for India included in the EXIOBASE3 captures economic activities in both formal and informal sectors. Therefore, I implicitly considered the PM_{2.5} emissions from the informal sector, however; the detailed disaggregation analysis with a focus of the informal sector is also a future study.

Chapter 4. Carbon Footprint Analysis Considering Production Activities of Informal Sector: The Case of Manufacturing Industries of India

4.1. Introduction

According to a special Intergovernmental Panel on Climate Change (IPCC) report (IPCC, 2018) global warming is likely to reach 1.5° C between 2030 and 2052, and by 2030, a 45% reduction in carbon dioxide (CO₂) emissions (from the 2010 level) is necessary for limiting global warming to 1.5 ° C. To achieve this urgent target, each enterprise faces the responsibility of reporting and reducing ‘indirect’ CO₂ emissions from their supply chains as well as ‘direct’ CO₂ emissions from its own production activity (WRI and WBCSD, 2009).

Consumption-based emission accounting contributes to the comprehensive calculation of the carbon footprint (i.e., CO₂ emissions embodied in supply chains) (Wiedmann, 2009; Heinonen *et al.*, 2020). Based on this framework, many studies have investigated the carbon footprint of individual countries (e.g., Peters *et al.*, 2007; Weber and Mathews., 2007; Minx *et al.*, 2008) and multiple countries (e.g., Peters *et al.*, 2011; Kagawa *et al.*, 2015; Kanemoto *et al.*, 2014; Wiedmann and Lenzen, 2018; Maeno *et al.*, 2022) to identify CO₂ emission hotspots in supply chains, and these studies have emphasized the importance of suppliers’ collaborative efforts to mitigate CO₂ emission hotspots.

In emerging and developing countries, which emit two-thirds of the global CO₂ emissions (IEA, 2021), it is difficult to accurately determine the CO₂ emission hotspots because unofficial economic activities occurring in the *informal* sector are an important part of supply chains. Although the output of an individual production activity belonging to the informal sector is very small, it is estimated that the informal economy generates one-third of the total gross domestic product (GDP) of emerging and developing regions (Ohnsorge and Yu, 2021).

Though definitions of the *informal sector* vary among countries and institutions, low productivity and insufficient regulation are the key characteristics shared with those definitions (Elgin and Oztunali, 2014). It should be noted that the goods or services themselves produced by the informal sector are not illegal in most cases (Schneider and Enste, 2013). Given that production activities of the informal sector are not recorded in official statistics, it is difficult for authorities to design appropriate policies (e.g., emissions regulations) based on statistical information (e.g., CO₂ emissions from production activities).

We should also note emission leakage between the formal and informal sectors when discussing policies in emerging and developing countries. Chen (2012) reported that few production activities of informal sector are isolated from the formal sector. Specifically, the informal sector is likely to trade with the formal sector as a subsector or subcontractor. Baksi and Bose (2016) demonstrated that the informal sector could be a source of pollution leakage. They showed that when the formal sector can avoid costly regulations by outsourcing pollution-intensive intermediate goods from the informal

sector, stricter regulations in the formal sector can increase total pollution.

Previous studies have used econometric analysis to demonstrate a relationship between the size of a country's informal sector and its CO₂ emissions per capita (Biswas *et al.*, 2012; Chen *et al.*, 2018; Swain *et al.*, 2020). These scholars concluded that an increase in the size of the informal sector could increase CO₂ emissions per capita (Biswas *et al.* 2012; Chen *et al.*, 2018; Swain *et al.*, 2020).

Although concerns regarding CO₂ emissions from the informal sector are well recognized (Zhou, 2019; Shao *et al.*, 2020; Ortiz *et al.*, 2022), previous studies did not reveal the contribution of the informal sector in the carbon footprint of nations because of the lack of an IOT that distinguishes between the formal and informal sectors (e.g., Hertwich and Peters, 2009). To the best of our knowledge, this study is the first attempt to estimate an EEIOT that distinguishes between formal and informal sectors to demonstrates the informal sector's contribution to the national carbon footprint. Given that most emerging and developing countries lack an environmental policy targeting the informal sector, this study provides essential information to support policymakers' development and implementation of such policies.

This study focuses on India's economy as a case study because it is the third largest CO₂ emitter (IEA, 2021) and has the largest informal economy among emerging and developing countries (Ohnsorge and Yu, 2021). Half of India's GDP is derived from the informal sector (Government of India, 2021). To compensate for the exclusion of the informal sector from existing official statistics, the Indian statistical office has conducted

several surveys specific to the informal sector (Government of India, 2012). Based on the results of these surveys, India's IOT *implicitly* includes informal production activities in the sense that formal and informal production activities belonging to a specific industry are not distinguished *explicitly*, and these activities are aggregated into a specific sector (Government of India, 2015). Therefore, it is necessary to distinguish between these two.

For a relevant study, Rada (2010) proposed a methodology to estimate an IOT that distinguishes between the formal and informal sectors. Rada (2010) implicitly assumed the same production technology for formal and informal production activities belonging to each industry sector because the proposed methodology only considers the size (i.e., net domestic products) of each activity. However, it is important to note that the informal sector (i.e., informal production activities belonging to a specific industry sector) tends to be more labor intensive than the formal sector (i.e., formal production activities belonging to a specific industry sector) and that there is a significant difference in the sectors' labor productivity (Sahoo and Ten Raa, 2009; La Porta and Shleifer, 2014). In contrast, this study considers the gross value added (GVA) ratio to reflect the informal sector's higher labor intensity and its smaller intermediate input, in addition to the size of the informal sector's production activities. Furthermore, this study considered the difference in carbon emission intensity between the formal and informal sectors.

Another key difference is that Rada (2010) focuses on macroeconomic analysis, which integrates the IOT to social accounting matrices and applies CGE analysis to investigate the multiplier effect of the informal sector in relation to GDP and income. In contrast, this study focuses on carbon footprint analysis, in which the extended IOT is

integrated with emissions accounts and EEIO analysis is applied.

The remainder of this chapter is organized as follows. Section 4.2 describes the input–output tables of India constructed in this study. Section 4.3 presents the study methodology. Section 4.4 presents the empirical results. Section 4.5 discusses the major findings and concludes the paper.

4.2. Methodology and Data

4.2.1. IOTs of India constructed in this study

In this study, the industry-by-industry IOT is constructed based on a 2015 supply-use table of 66 sectors provided by the Indian government (Government of India, 2021) (Table A2 in Appendix). The supply-use table for India was converted to a supply-use table based on producer prices using vectors of commercial and transportation margins and tax-less subsidy of each sector (UN, 2018). This study also excluded imports from the intermediate input matrix and final demand vector using the import coefficients of goods and services.

Subsequently, the use table is transformed from commodity-by-industry matrix $\mathbf{U}$ to an industry-by-industry matrix $\mathbf{Z}$ based on the industry technology assumption (Miller and Blair, 2009). Specifically, the industry-by-industry use matrix $\mathbf{Z}$ is estimated as $\mathbf{Z} = \mathbf{D}\mathbf{U}$ where $\mathbf{D} = (d_{ij})$ represents the market share of industry i for commodity j . Note that the market share matrix $\mathbf{D}$ can be easily obtained from the supply table (i.e., industry-by-commodity matrix $\mathbf{V}$). Similarly, the commodity final demand vector $\mathbf{g} =$

(g_i) representing the final demand for each commodity i is also transformed into the industrial final demand vector $\mathbf{f} = (f_i)$ representing the final demand for each industry i using the industry technology assumption equation of $\mathbf{f} = \mathbf{Dg}$. Figure 4.1 shows the structure of the IOT estimated in this study.

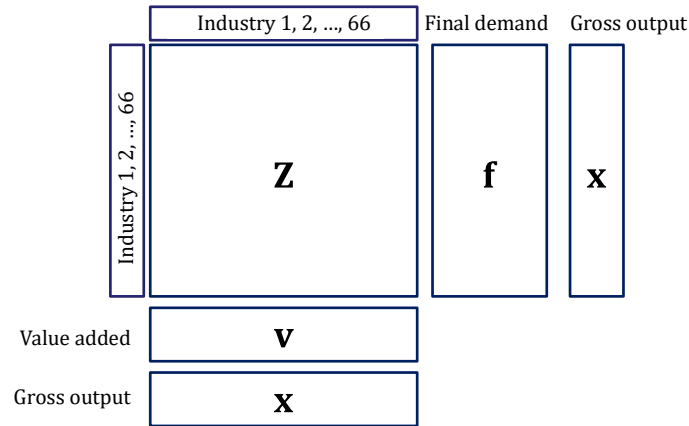


Figure 4.1. The structure of the IOT

This study further estimates an IOT for India in 2015 that distinguishes the formal and informal sectors using the Indian National Accounts Statistics (NAS) version 2021 (Government of India, 2021). It should be noted that this study focuses on the informal sector in 25 manufacturing industries,¹ highlighted in Table A2, because of the lack of data for other industries.

National Accounts Statistics (NAS) version 2021 (Government of India, 2021) of

¹ This study excludes informal sector in 3 industries (i.e., ‘Textiles + cotton ginning’, ‘Computer and peripheral equipment’, ‘Printing and reproduction of recorded media’) where CO₂ emission of informal sector are estimated to be larger than CO₂ emissions in WIOD and ‘Other manufacturing’ where GVA are estimated larger than its output.

India provides gross outputs and value-added from the ‘corporate sector’ and ‘household sector’ in manufacturing. This study employed the corporate and household sectors as proxies for the formal and informal sectors, respectively. In India’s national accounts, all enterprises are allocated following institutional sectors (EC, IMF, OECD, UN, World Bank, 2009).

- 1) The general government sector
- 2) The corporate sector, including public corporations and quasi-corporations
- 3) Household sector or unorganized sector: enterprises not covered above, including non-profit institutions serving households (e.g., charities, religious societies)

The new series of national accounts (from 2011–2012) regards unincorporated enterprises that maintain their accounts as the corporate sector. Therefore, all unincorporated enterprises that do not provide statistical information on their production activities for the government are classified as the household sector. In India and many developing countries, the term ‘unorganized sector’ is used interchangeably with the informal sector (Kulshreshtha, 2011).

If the gross output vector and the value-added vector of the *informal* manufacturing sectors are defined as $\mathbf{x}^I = (x_j^I)$ and $\mathbf{v}^I = (v_j^I)$, respectively, the gross output and value-added of the formal sector belonging to a specific manufacturing sector (M) highlighted in Table A2 can be easily calculated by the two equations of $x_{j \in M}^F = x_{j \in M} - x_{j \in M}^I$ and $v_{j \in M}^F = v_{j \in M} - v_{j \in M}^I$, respectively, where the superscripts F and I indicate the formal and informal sectors, respectively.

The output shares of the informal and formal sectors belonging to a specific manufacturing sector can be obtained as $\theta_{j \in M}^I = \frac{x_{j \in M}^I}{x_{j \in M}}$ and $\theta_{j \in M}^F = \frac{x_{j \in M}^F}{x_{j \in M}} = \frac{x_{j \in M} - x_{j \in M}^I}{x_{j \in M}} = 1 - \theta_{j \in M}^I$, respectively. It should be noted that we have the equation: $\theta_{j \in M}^F + \theta_{j \in M}^I = 1$.

The total intermediate inputs required by a specific manufacturing sector j ($z_{j \in M}$) is computed by the equation $z_{j \in M} = x_{j \in M} - v_{j \in M}$. In addition, the total intermediate inputs required by an *informal* sector belonging to the specific manufacturing sector j ($z_{j \in M}^I$) is also computed by the equation $z_{j \in M}^I = x_{j \in M}^I - v_{j \in M}^I$. Hence, the total intermediate inputs required by a *formal* sector belonging to the specific manufacturing sector j ($z_{j \in M}^F$) is estimated by the equation $z_{j \in M}^F = z_{j \in M} - z_{j \in M}^I$.

The proportions of intermediate inputs required by the informal and formal sectors belonging to a specific manufacturing sector can be obtained as $\varphi_{j \in M}^I = \frac{z_{j \in M}^I}{z_{j \in M}}$ and $\varphi_{j \in M}^F = \frac{z_{j \in M}^F}{z_{j \in M}} = \frac{z_{j \in M} - z_{j \in M}^I}{z_{j \in M}} = 1 - \varphi_{j \in M}^I$, respectively. It should be noted that we have the equation: $\varphi_{j \in M}^F + \varphi_{j \in M}^I = 1$.

In this study, sectors in the IOT shown in Figure 4.1 were further disaggregated into formal and informal sectors. Figure 4.2 shows the structure of the disaggregated IOT developed in this study.

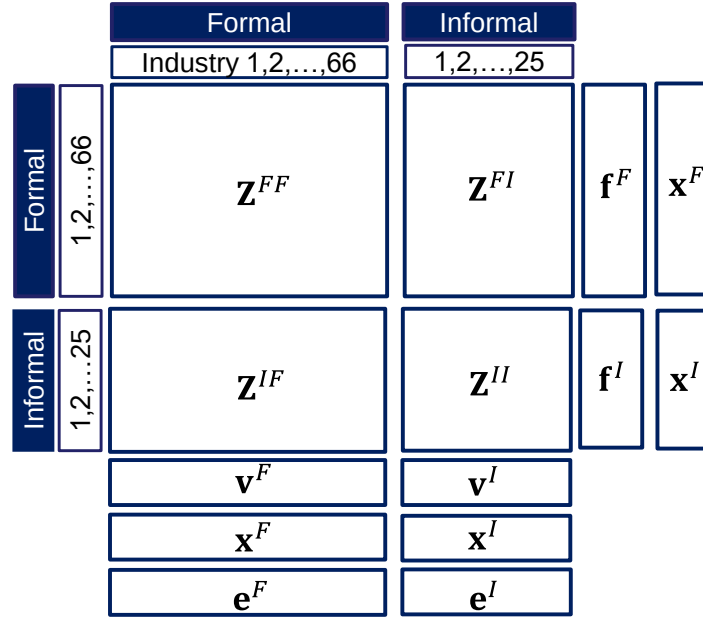


Figure 4.2. The structure of the extended IOT distinguishing the formal sector and the informal sector

In Figure 4.2, an original intermediate transaction matrix $\mathbf{Z}$ is divided into four blocks of intermediate interindustry transactions (i.e., $\mathbf{Z}^{FF}$, $\mathbf{Z}^{FI}$, $\mathbf{Z}^{IF}$, $\mathbf{Z}^{II}$) and two blocks of the final demand (i.e., $\mathbf{f}^F$ and $\mathbf{f}^I$). Note that the 66 industries listed in Table A2 were finally disaggregated into 25 formal sectors (F) belonging to the 25 manufacturing industries, as highlighted in Table A2, 25 informal sectors (I) belonging to the 25 manufacturing industries are highlighted in Table A2, and the other 31 industries (R). For the other 31 industries (R), there were no available data on gross output and value-added in the informal sectors in India. Therefore, I assumed that all production activities in the other 31 sectors were formal. This is a limitation of this study. Based on this assumption, I set the gross output shares of the formal and informal sectors belonging to other sectors as $\theta_{j \in R}^F = 1$ and $\theta_{j \in R}^I = 0$, respectively. I also have intermediate input shares of $\varphi_{j \in R}^F = 1$ and $\varphi_{j \in R}^I = 0$, respectively.

This study estimated the four blocks of the intermediate interindustry transactions as follows.

$$z_{ij}^{FF} = \theta_i^F z_{ij} \varphi_j^F \quad (4.1)$$

$$z_{ij}^{FI} = \theta_i^F z_{ij} \varphi_j^I \quad (4.2)$$

$$z_{ij}^{IF} = \theta_i^I z_{ij} \varphi_j^F \quad (4.3)$$

$$z_{ij}^{II} = \theta_i^I z_{ij} \varphi_j^I \quad (4.4)$$

In Eqs. (4.1), (4.2), (4.3), and (4.4), goods produced by formal and informal production activities belonging to a specific industry i are sold in proportion to their gross output shares of θ_i^F and θ_i^I , whereas intermediate goods required by formal and informal production activities belonging to a specific industry j are purchased in proportion to their intermediate input shares of φ_j^F and φ_j^I .

Furthermore, the final blocks of the final demand were estimated as

$$f_i^F = \theta_i^F f_i \quad (4.5)$$

$$f_i^I = \theta_i^I f_i \quad (4.6)$$

, respectively. The detailed estimation procedure of the disaggregated IOT is provided in Appendix B.

For direct CO₂ emissions from formal and informal sectors, this study used the satellite account in the World Input-Output Database (WIOD) (Timmer *et al.*, 2015) and Biswas *et al.* (2018), which is a peer-reviewed report published by the Council on Energy, Environment and Water in India. Biswas *et al.* (2018) focused on six types of fuels (i.e., coal and lignite, natural gas, diesel, furnace oil, liquefied petroleum gas [LPG], other fuels/biomass, and other petroleum fuels) and estimated greenhouse gas (GHG) emissions from the informal manufacturing sectors. Specifically, Biswas *et al.* (2018) calculated the physical fuel consumption of each fuel type by dividing the consumption expenditure of each fuel type paid by a specific informal manufacturing industry by the average fuel price. This study used the physical fuel consumption provided by Biswas *et al.* (2018) and calculated direct CO₂ emissions from informal manufacturing sectors following IPCC guidelines (IPCC, 2006).

The industry classification used by Biswas *et al.* (2018) was not consistent with that of the WIOD. I converted the industry classification of Biswas *et al.* (2018) into that of the WIOD in accordance with the International Standard Industrial Classification (ISIC) code (UN, 2008) (Table A3 in Appendix). Then, for each manufacturing industry, direct CO₂ emissions from the formal sector were obtained by subtracting the direct CO₂ emissions of the informal sector from the direct CO₂ emissions reported in the WIOD.

4.2.2. Carbon footprint calculation

From Figure 4.1, the gross output vector is expressed as:

$$\mathbf{x} = \mathbf{Ax} + \mathbf{f} \quad (4.7)$$

where $\mathbf{A} = (a_{ij})$ represents the intermediate input coefficient matrix obtained by the equation $\mathbf{Z}\hat{\mathbf{x}}^{-1} = (\mathbf{z}_{ij}/x_j)$ where the symbol $\hat{}$ represents the diagonalization of the vector. Therefore, the element a_{ij} represents the direct intermediate delivery of industry i to industry j required for one unit of production in industry j . From Eq. (4.1), we obtain the following:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{Lf} \quad (4.8)$$

where $\mathbf{I}$ is the identity matrix, and $(\mathbf{I} - \mathbf{A})^{-1} = \mathbf{L}$ is the Leontief inverse matrix. The element of the Leontief inverse matrix l_{ij} shows the *direct and indirect* intermediate delivery of industry i to industry j required for one unit of final demand in industry j .

The national carbon footprint (i.e., direct and indirect CO₂ emissions triggered by the final demand of a country) is estimated based on the EEIO model as (e.g., Tukker, 2006; Minx *et al.*, 2009):

$$q = \mathbf{eLf} \quad (4.9)$$

where $\mathbf{e} = (e_j)$ is the direct CO₂ emissions coefficient vector showing the volume of direct CO₂ emissions generated by one unit of production in industry j .

The carbon footprint calculation formulated in Eq. (4.9) is easily applicable to the

extended IOT in Figure 4.2. In Figure 4.2, the extended gross output vector can be obtained as follows:

$$\underbrace{\begin{bmatrix} \mathbf{x}^F \\ \mathbf{x}^I \end{bmatrix}}_{\bar{\mathbf{x}}} = \underbrace{\begin{bmatrix} \mathbf{A}^{FF} & \mathbf{A}^{FI} \\ \mathbf{A}^{IF} & \mathbf{A}^{II} \end{bmatrix}}_{\bar{\mathbf{A}}} \underbrace{\begin{bmatrix} \mathbf{x}^F \\ \mathbf{x}^I \end{bmatrix}}_{\bar{\mathbf{x}}} + \underbrace{\begin{bmatrix} \mathbf{f}^F \\ \mathbf{f}^I \end{bmatrix}}_{\bar{\mathbf{f}}} \quad (4.10)$$

where $\mathbf{A}^{FF} = (a_{ij}^{FF}) = (z_{ij}^{FF}/x_j^F)$ represents the intermediate input coefficient sub-matrix showing the inter-industry deliveries between formal sectors, $\mathbf{A}^{FI} = (a_{ij}^{FI}) = (z_{ij}^{FI}/x_j^I)$ is the intermediate input coefficient sub-matrix showing inter-industry deliveries from the formal sector to the informal sector, $\mathbf{A}^{IF} = (a_{ij}^{IF}) = (z_{ij}^{IF}/x_j^F)$ is the intermediate input coefficient sub-matrix showing the inter-industry deliveries from the informal sector to the formal sector, and $\mathbf{A}^{II} = (a_{ij}^{II}) = (z_{ij}^{II}/x_j^I)$ is the intermediate input coefficient sub-matrix showing the inter-industry deliveries between the informal sector. From Eq. (4.10), the extended input-output model can be formulated as

$$\bar{\mathbf{x}} = (\mathbf{I} - \bar{\mathbf{A}})^{-1} \bar{\mathbf{f}} = \bar{\mathbf{L}} \bar{\mathbf{f}} \quad (4.11)$$

where $\bar{\mathbf{L}}$ is the extended Leontief inverse matrix, including the formal and informal sectors. We can estimate the gross outputs of the formal and informal industries induced by the final demand for goods and services using Eq. (4.11).

The extended IO model also provides the following new extended carbon footprint calculation method:

$$\bar{q} = \bar{\mathbf{e}}\bar{\mathbf{L}}\bar{\mathbf{f}} = [\mathbf{e}^F \quad \mathbf{e}^I] \begin{bmatrix} \mathbf{L}^{FF} & \mathbf{L}^{FI} \\ \mathbf{L}^{IF} & \mathbf{L}^{II} \end{bmatrix} \begin{bmatrix} \mathbf{f}^F \\ \mathbf{f}^I \end{bmatrix} \quad (4.12)$$

where $\bar{\mathbf{e}} = [\mathbf{e}^F \quad \mathbf{e}^I]$ represents the direct CO₂ emissions coefficient vector showing the volume of direct CO₂ emissions generated by one unit of production in formal or informal industry j . Eq. (4.12) can be used to estimate the environmental impact of each industry's final demand (i.e., a downstream sector) as a driver of the national carbon footprint.

It is important to note that the informal sector in manufacturing industries tends to be positioned upstream of supply chains (Chen, 2012). Therefore, although CO₂ emissions triggered by the final demand for the informal sector may be relatively small, the informal sector can indirectly contribute significantly to the supply chain emissions of goods and services. To visualize the contribution of the informal sector in supply chain emissions of goods and services, this study formulated an environmentally extended unit structure model (Kagawa *et al.*, 2015) that distinguishes between formal and informal sectors.

$$\bar{\mathbf{Q}}_s = \bar{\mathbf{e}}\bar{\mathbf{A}}\widehat{\mathbf{L}}\bar{\mathbf{f}}_s \quad (4.13)$$

where $\bar{\mathbf{f}}_s$ is the extended final demand vector that has a figure in a specific formal or informal industry s , and otherwise, zeros and $\widehat{\mathbf{L}}\bar{\mathbf{f}}_s$ represent the diagonal matrix whose diagonal elements are intermediate goods or service deliveries to satisfy the final demand for industry s . $\bar{\mathbf{Q}}_s$ is the unit structure matrix comprising elements $\bar{Q}_{ij,s}$ representing the CO₂ emissions associated with the intermediate goods or service delivery of industry i to industry j to satisfy the final demand to industry s .

4.3. Results

4.3.1. Basic indicators for estimating the extended IOT of India

Table 4.1 shows the basic indicators used to estimate the extended IOT of India in 2015. Several observations follow from the results in Table 4.1. First, when we examine the contribution of the informal sector to the gross output of each industry from the first column of Table 4.1, the size of the informal sector differs among industries. The informal sector's gross output is less than 10% in most industries; however, there are some industries in which it is larger, namely leather and related products, tobacco products, and fabricated metal products, where the informal sector's output accounts for 20%–30% of each industry's gross output. In the case of furniture and wood and products of wood, the informal sector's contribution to the gross output of the industrial sector exceeds that of the formal sector, with the informal sector accounting for 64% and 77% of total sectoral output, respectively.

Second, the informal sector's value-added ratio is higher than that of the formal sector in 21 out of the 25 industries (see the third column of Table 4.1). This trend is especially strong in grain mill products, etc., and animal feeds, fabricated metal products, and electrical equipment, where the informal sector's value-added ratio is almost twice as high as that of the formal sector.

Third, the informal sector's production activities tend to be more CO₂ emission-intensive than those of the formal sector within the same industry. In 20 out of 25 industries, CO₂ emission intensity was higher in the informal sector than in the formal

sector, with basic iron and steel, coke and refined petroleum products, and other non-metallic mineral products showing extremely high emission intensities (10.9 t-CO₂, 8.7 t-CO₂, and 8.1 t-CO₂, respectively) for the informal sector. These high values are comparable with the emission intensities of mining of coal and lignite and electricity, which are the major emission sources in India. This result indicates that while the size of the informal sector in manufacturing in India is not large, and despite the lower intermediate input, production activities in the informal sector are very CO₂ emission-intensive.

The reasons for the significant differences in CO₂ emission intensities between the formal and the informal sector would be technology and type of fuel used in each enterprise. Informal enterprises tend to employ traditional technologies with poor energy efficiency (Pandey *et al.*, 2014). Joshi *et al.* (2011) reported that 74.2% of the about 150,000 informal enterprises surveyed had plant and machinery valued at less than 10,000 rupees, roughly US\$200. In addition, the small size of informal enterprises' production activities makes it difficult to be benefited from economies of scale.

Regarding fuel type, a higher dependency on energy generated by coal was observed in the informal sector. The share of coal in energy consumption in manufacturing (excluding electricity) was 63% for the formal sector (Timmer *et al.*, 2015) and 78% (Biswas *et al.*, 2018) for the informal sector. By contrast, in the industries where the formal sector has higher CO₂ emission intensity (i.e., wood and products of wood and cork, and fabricated metal products), said sector's dependency on coal energy was higher than that of the informal sector.

Table 4.1. Basic indicators for estimating the extended IOT distinguishing formal and informal sectors

Industry name	Contribution to gross output (%)		Contribution to intermediate input (%)		Value added ratio to gross output (%)		Direct CO ₂ emission coefficient (kg-CO ₂ per lakhs)		Direct CO ₂ emission coefficient calculated by the WIOD (kg-CO ₂ per lakhs)
	Formal	Informal	Formal	Informal	Formal	Informal	Formal	Informal	Average
	θ_i^F	θ_i^I	φ_i^F	φ_i^I	v_i^F/x_i^F	v_i^I/x_i^I	e_i^F	e_i^I	$\frac{(E_i^F + E_i^I)}{(x_i^F + x_i^I)}$
Meat, fish, fruit, vegetables, oils, and fats	93	7	93	7	11	17	2	305	25
Dairy products	96	4	97	3	10	19	0.1	21	1
Grain mill products, etc., and animal feeds	87	13	89	11	9	25	22	1531	218
Other food products	84	16	85	15	21	26	4	188	34
Beverages	95	5	97	3	37	49	361	938	389
Tobacco products	78	22	82	18	51	55	391	68	319
Apparel	86	14	92	8	31	51	32	456	91
Leather and related products	70	30	79	21	25	44	47	56	50
Basic iron and steel and casting of iron and steel	97	3	97	3	14	14	2327	10898	2617
Basic precious and non-ferrous metals and casting of non-ferrous metals	99.5	0.5	99.6	0.4	19	24	62	2243	71
Fabricated metal products	79	21	91	9	24	41	1814	683	1572
Electronic components, consumer electronics, magnetic and optical media	92	8	95	5	30	43	79	499	112
Communication equipment	98	2	99.9	0.1	22	43	0.03	499	9
Optical and electronics products n.e.c.	98	2	98	2	46	32	113	499	120
Electrical equipment	95	5	99	1	22	43	79	73	79
Machinery and equipment n.e.c.	96	4	97	3	33	43	130	784	154
Transport equipment	98	2	98	2	29	29	78	87	78
Coke and refined petroleum products	99	1	99.98	0.02	22	28	269	8707	272
Chemicals and chemical products	99	1	99	1	20	20	382	483	383
Medicinal chemicals and botanical products	99	1	98	2	43	20	3	0.003	3
Rubber and plastic products	95	5	95	5	28	28	96	512	116
Other non-metallic mineral products	84	16	85	15	35	37	2378	8118	3292
Wood and products of wood and cork	36	64	43	57	32	43	3641	81	1374
Paper and paper products	95	5	97	3	25	35	525	1204	558
Furniture	23	77	24	76	36	37	53	113	99

Note: E_i^F and E_i^I represent the direct CO₂ emissions of formal and informal sectors, respectively.

4.3.2. Comparisons with direct and embodied CO₂ emission coefficients based on the aggregated EEIOT

Comparing the average direct CO₂ emission coefficients calculated by the environmental account of the WIOD with the those of the formal and the informal sectors estimated in this study, it was observed that the average coefficients deviated from both the formal sector's and the informal sector's coefficient in many industry sectors shown in the Table 4.1. The gap between the direct coefficient of the formal sector and the average direct coefficient ranged from 0.1% (transport equipment) to 165% (wood), with a mean value of 37%. The gap between the coefficient of the informal sector and the average coefficient was extremely high in the following five industries: communication equipment (5440%), coke and refined petroleum (3100%), basic iron and steel (3060%), dairy products (2000%), production of meat, fish, vegetable oils, and fats (1120%). The gap in other industries ranged from 8% (electrical equipment) to 604% (grain mill products), and the calculated mean value excluding the five industries mentioned above was approximately 200%.

Further, this study compared the embodied (i.e., direct and indirect) CO₂ emission coefficients of the formal and the informal sectors with the average embodied coefficients calculated using the aggregated EEIOT (represented as 0% in Figure 4.4). As shown in Figure 4.4, informal sector of coke and refined petroleum industry exhibited extremely large gap (1100%) between the embodied CO₂ emission coefficient of the formal sector and the average embodied CO₂ emission coefficient. Except for the coke and refined petroleum industry, the gap between the coefficient of the formal sector and the average

coefficient ranged from 0.04% (transport equipment) to 117% (wood), with a mean value of 9%. The gap between the informal sector's coefficient and the average coefficient ranged from 0.4% (furniture) to 166% (basic iron and steel) and the mean value of was 46%. It indicated that the aggregated EEIOT bias the findings on the direct and embodied CO₂ emission intensities of industries by aggregating the formal and informal sectors into single industry sector. Researchers should pay attention to the bias when conducting a carbon footprint analysis for developing countries with large informal economy such as India.

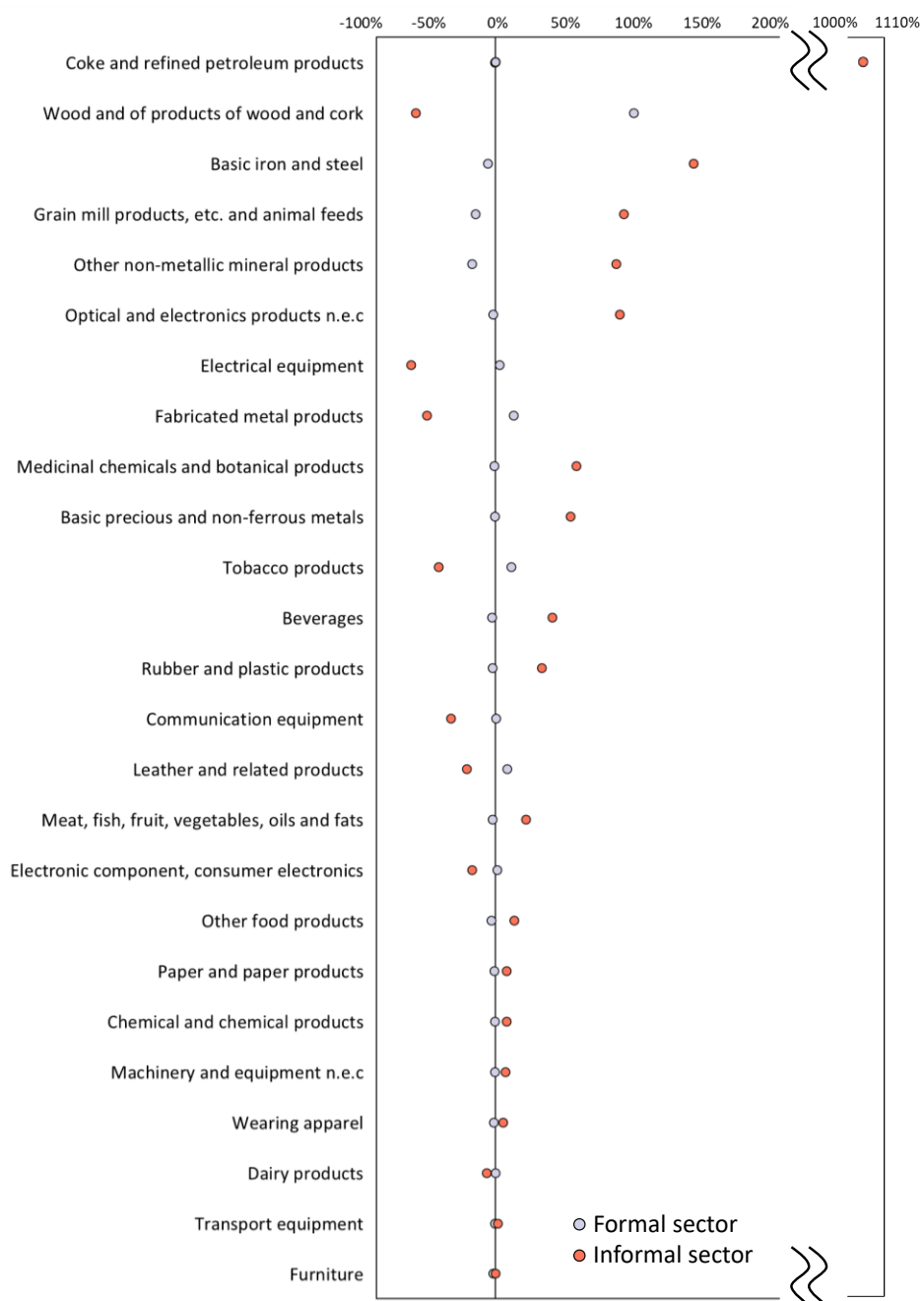


Figure 4.4. Percentage deviation of the embodied CO₂ emission intensity of a specific manufacturing sector of the formal or the informal sector based on the “disaggregated” Indian EEIOT covering 91 sectors from that based on the “aggregated” Indian EEIOT covering 66 sectors

4.4.3. Production-based emissions

The total production-based CO₂ emissions (PBE) (i.e., direct CO₂ emissions) of the 25 India's manufacturing industries in 2015 highlighted in Table A2, calculated with reference to the WIOD database, is 508 Mt-CO₂, accounting for 27% of the total national PBE. The sum of the informal sector's PBE considered in this study is 96 Mt-CO₂, accounting for approximately 20% of the total PBE of manufacturing.

Figure 4.3 shows the top ten manufacturing industries with higher PBE values, among which there are several industries where the bulk of their PBE is emitted by the informal sector. Looking at the top two, basic iron and steel and other non-metallic mineral products, the informal sector's share of PBE is about 15% and as high as 40%, respectively. Further, for grain mill products, etc., and animal feeds, which is ranked seventh, the informal sector's share of PBE exceeds 90%.

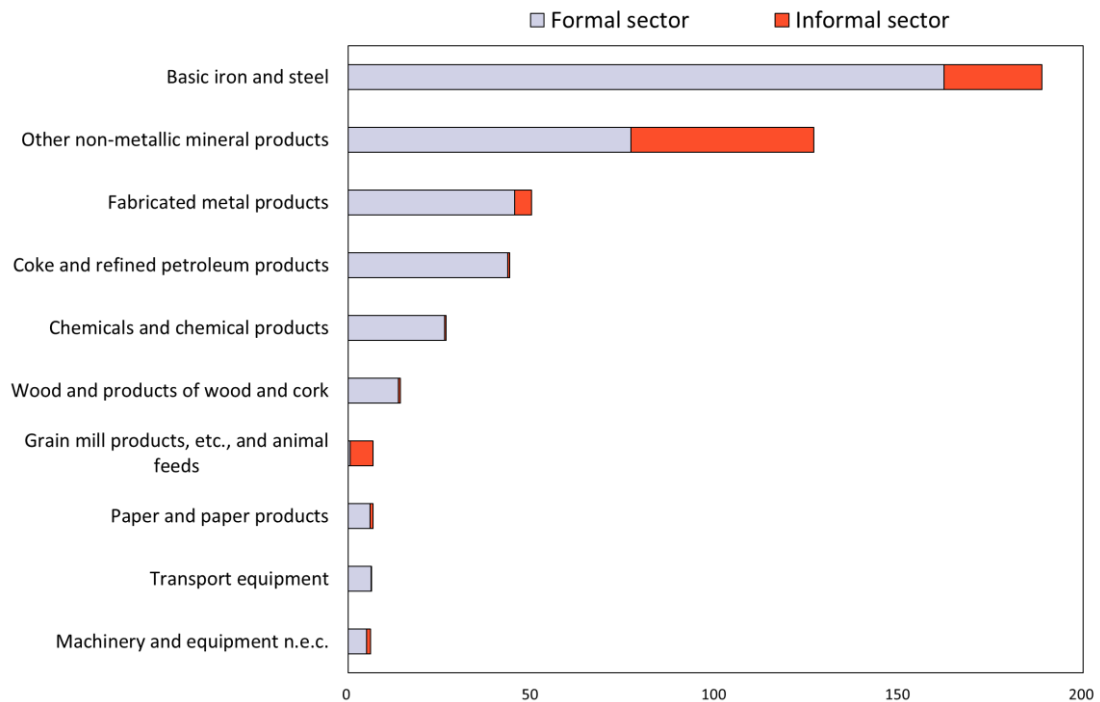


Figure 4.3. Production-based CO₂ emissions from the formal sector and the informal sector for each industry in 2015

Given the higher CO₂ emissions intensity and the larger volume of direct CO₂ emissions, the informal sector's CO₂ emissions are not negligible. It should be noted that the informal sector's production activities are induced by supply chains of various goods and services. An important issue is that supply chain emissions centered around the informal sector are not regulated by the government (Schneider *et al.*, 2010; Elgin and Oztunali, 2014).

The next section sheds light on how the informal sector's CO₂ emissions contribute to supply chain emissions. Specifically, this study explores the informal sector's contribution to the supply chain emissions induced by the final demand of construction,

transport equipment, and machinery and equipment n.e.c., which are the top three supply chains that account for approximately 40% of the total CO₂ emissions attributable to the production of intermediate goods and services.

4.3.4. The informal sector's contribution to the supply chain emissions

Figures 4.5–4.7 illustrate supply chain networks showing major industry-to-industry deliveries induced by the final demand of construction, transport equipment, and machinery and equipment n.e.c., machinery and equipment n. e. c., respectively. In the figures, each delivery is weighted according to the CO₂ emissions generated to meet each final demand; the top 30 deliveries with the highest emissions are shown in Figures 4.5–4.7. Note that the industries in the source nodes in the supply chain network are CO₂ emitters, while those in the destination nodes are CO₂ emission drivers.

The top 30 deliveries generate nearly 80% of supply chain CO₂ emissions for each final demand (76% for construction, 78% for transport equipment, and 77% for machinery and equipment, n.e.c.). The informal sector is marked with an asterisk, and deliveries that include the informal sector are highlighted in orange. Notably, deliveries that included the informal sector were ranked among the top 30 deliveries across the top three final demands.

Figure 4.5 shows the major supply chains network induced by the final demand for construction. The total CO₂ emissions derived by the top 30 deliveries is 290 Mt-CO₂, with 45 Mt-CO₂ (15%) attributable to deliveries that include the informal sector. Four

deliveries that include the informal sector are listed among the top 30, namely *other non-metallic mineral products → construction; *basic iron and steel → construction; coal and lignite → *other non-metallic mineral products; and *other non-metallic mineral products → other non-metallic mineral products, to which 33 Mt-CO₂, 6 Mt-CO₂, 2 Mt-CO₂, and 2 Mt-CO₂ can be attributed, respectively. The informal sector in other non-metallic mineral products plays a significant role in mitigating CO₂ emissions associated with the construction supply chain.

Figures 4.6 and 4.7 show the major supply chain networks induced by the final demand for transport equipment and machinery and equipment n.e.c. For transport equipment, the top 30 deliveries generated 108 Mt-CO₂, with 4 Mt-CO₂ (4%) attributable to deliveries that include the informal sector. Regarding deliveries induced by machinery and equipment n.e.c., the top 30 deliveries generated 49 Mt-CO₂, with 2 Mt-CO₂ (4%) attributable to deliveries in the informal sector. The informal sector in basic iron and steel forms part of both supply chains as follows: * basic iron and steel → transport equipment; * basic iron and steel → machinery and equipment n.e.c.; and * basic iron and steel → basic iron and steel.

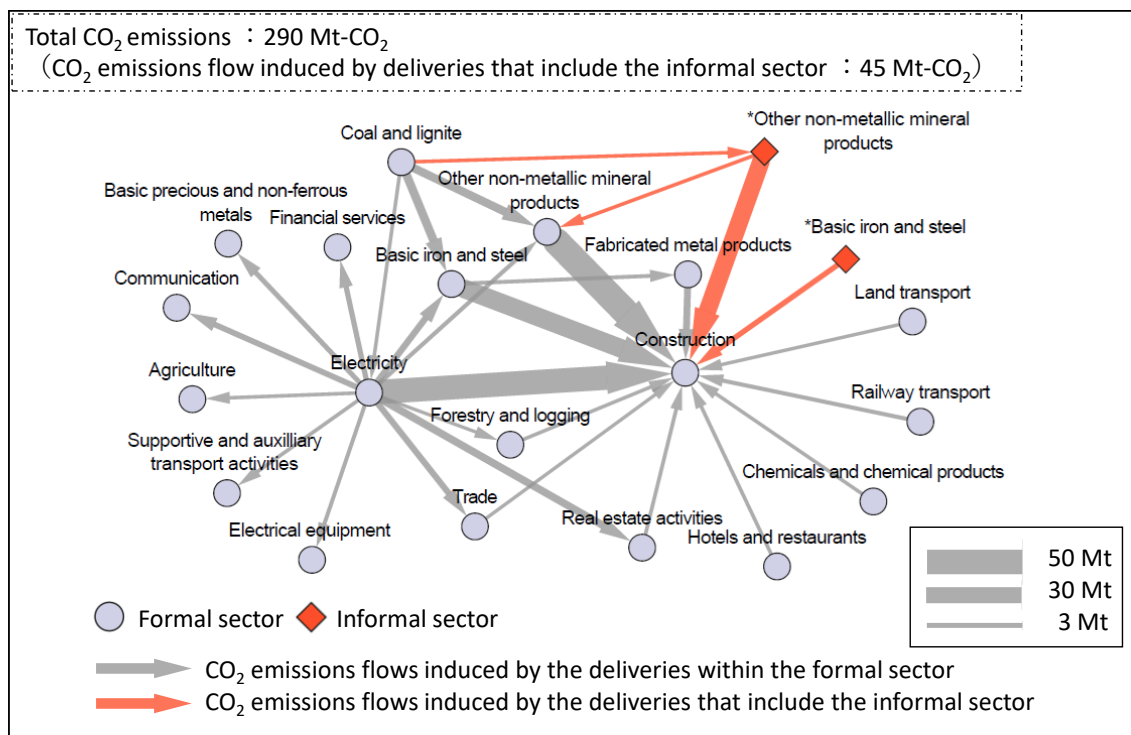


Figure 4.5. Top 30 CO₂ emissions deliveries induced by the final demand of construction

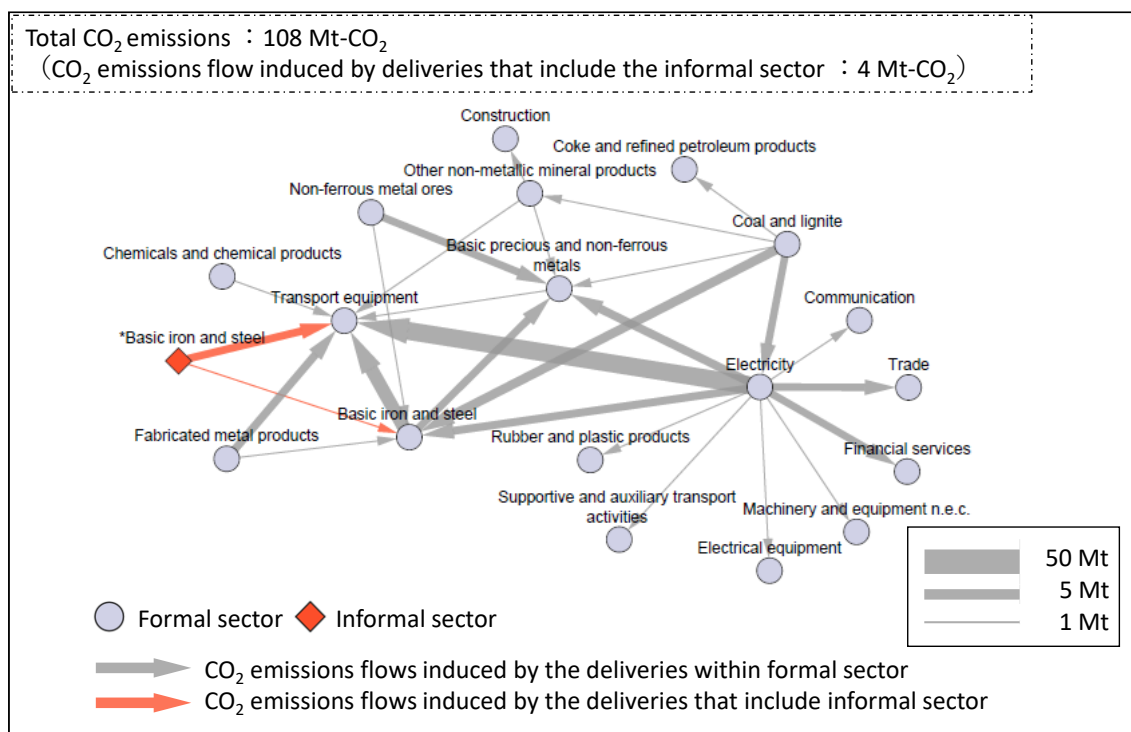


Figure 4.6. Top 30 CO₂ emissions deliveries induced by the final demand of transport equipment

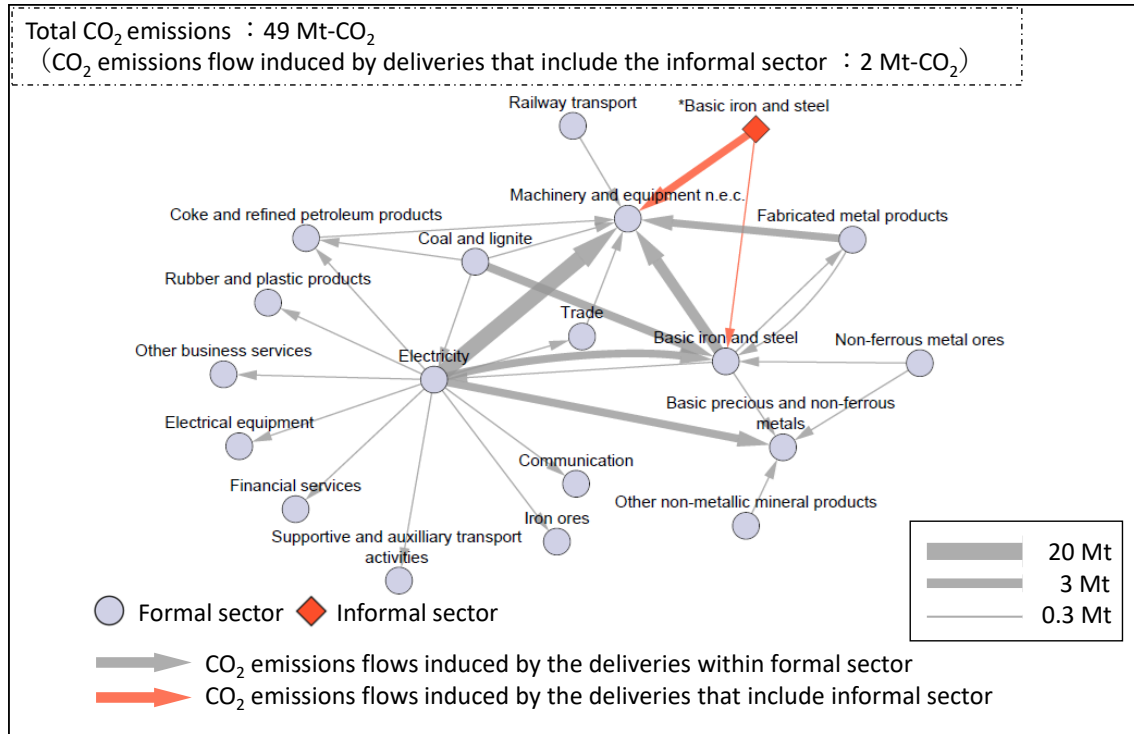


Figure 4.7. Top 30 CO₂ emissions deliveries induced by final demand of machinery and equipment n.e.c.

4.4. Discussion

As described in Section 4.3.4, the informal sector producing other non-metallic mineral products contributed significantly to the carbon footprint of construction supply chain. According to Biswas *et al.* (2018), among the activities classified under other non-metallic mineral products, brick production is the largest contributor to CO₂ emissions because it requires a large amount of energy input (i.e., coal) in India. In addition, looking at basic iron and steel, micro-enterprises, including the informal sector, supply major steel enterprises, and some participate in the supply chain as producers that make iron and steel products using scrap iron (FICC, 2016). To mitigate the informal sector's CO₂ emissions in these CO₂ emission-intensive industries, transitioning to a more energy-efficient fuel

(i.e., higher-quality coal or another type of fuel) and promoting overall energy efficiency are necessary.

However, considering that most owners and workers in the informal sector are in a dire situation (Chen, 2012), it is assumed that they cannot afford to purchase energy-efficient fuel or install new equipment to improve energy efficiency. Therefore, to mitigate CO₂ emissions in the informal sector, it is necessary to involve various stakeholders, such as enterprises positioned downstream of the informal sector. Based on the results of this study, the following industries are important stakeholders in the formal sector: basic iron and steel, other non-metallic mineral products, construction, transport equipment, and machinery and equipment. The implication of these findings for policymakers is that the aforementioned CO₂-intensive industries in the informal sector should be prioritized for formalization. Simultaneously, it is important for the Indian government to strengthen CO₂ mitigation through greener supply chain engagement between the formal and informal sectors, as shown in Figures 4.5 to 4.7.

There are two types of policies involving formal and informal sectors. The first is encouraging the formal sector to improve the formality in their supply chains. This policy aims to accelerate formalization to address the informal sector's CO₂ emissions using the existing approach of the government (e.g., regulations and financial support). For example, the government can evaluate a supply chain's formality when determining subsidies for formal enterprises. If the formal sector chooses to trade with formal suppliers, informal enterprises are motivated to formalize. This type of policy should be applied to the construction industry, which is identified as an important stakeholder. The

final demand for construction has been stimulated by “The Housing for All Program” of the Indian government to address housing shortages among low-income groups (De la Maisonneuve and Dek, 2020). As a first step, the government should call related housing producers to improve their supply chain’s formality. The other is encouraging formal enterprises to engage in cooperative efforts toward CO₂ emission reduction in the informal sector. Studies exploring triggers and barriers to small and medium-sized enterprises (SMEs) implementing environmental management practices (e.g., Dasanayaka *et al.*, 2022) would provide tips for cooperative efforts between the formal and informal sectors. First, it has been pointed out that forming a collaborative network to achieve environmental performance with similar businesses, such as belonging to the same industry or location, is a substantial trigger (Halila and Tell, 2013).

Conversely, lack of owners and employees' knowledge and skills, as well as support from the government and limited availability of technology, were identified as barriers for SMEs (Ferenhof *et al.*, 2014), which are common problems in the informal sector (Elgin and Oztunali, 2014). Hence, it is important to build networks for sharing resources between the formal and informal sectors, especially knowledge and skills, to eliminate the informal sector’s barriers to environmental management. For the basic iron and steel industry and the other non-metallic mineral products, which have large CO₂ emissions flows between the formal and informal sectors of the same industry (Figures 4.5 to 4.7), their cooperative efforts toward CO₂ emissions reduction are important.

4.5. Conclusion

This study focuses on CO₂ emissions from the informal sector, which forms an important component of supply chains in emerging and developing countries. To quantify the impact of the informal sector on the national carbon footprint, an IOT for India that distinguishes between the formal and informal sectors was estimated using the national accounts of India. The results demonstrate that the informal sector contributed significantly to the carbon footprint in the top three supply chains with larger CO₂ emissions in India.

The implications of this study are helpful to policymakers because the research identifies the industries that should be prioritized for the introduction of an environmental policy targeting the informal sector, namely other non-metallic mineral products and basic iron and steel.

Users of the IOT presented in this article should note that the table only considers the informal sector in the manufacturing industry. According to the CO₂ emissions accounts in the WIOD, each industrial contribution to India's total CO₂ emissions in 2015 was 47% (976 Mt-CO₂) for power generation, 25% (508 Mt-CO₂) for manufacturing, 10% (213 Mt-CO₂) for services including construction and transport, 10% (203 Mt-CO₂) for agriculture and mining, and 8% (172 Mt-CO₂) for household fuel consumption. Given that the power generation industry operates in the formal sector, the table focuses on the largest CO₂-emitting industry among those in the informal sector. However, the coverage of the informal sector in the IOT should be extended in future research. Nevertheless, the

extended IOT of India presented in this study provides opportunities to investigate the informal sector's role through various perspectives via integration with other emissions or resource accounts, such as air pollution and water consumption, both of which are urgent problems in India (Mitoma *et al.*, 2021).

Given that all the data used to estimate the table and the CO₂ emissions coefficients are published, the extended IO analysis framework proposed in this study can be applied to other emerging and developing countries. The proposed framework is a useful tool for investigating the carbon footprint of countries with large informal economies. For example, investigating the carbon footprints of major CO₂ emitters, such as Indonesia, which is ranked tenth globally, and Mexico, which is ranked twelfth, as well as African regions, where remarkable CO₂ emission growth is predicted, is crucial for achieving carbon neutrality on a global scale.

Chapter 5. Conclusions

India is one of the most rapidly growing countries, and the international community expects it to play an important role in global supply chains in the near future. However, the country faces serious pollution issues associated with rapid industrialization and urbanization. This dissertation aims to reveal how environmental loads in India are induced via a supply chain, with a focus on India's domestic and global economic systems, and to identify key factors in domestic or global supply chains to mitigate the environmental loads in India. This study conducted two supply chain analyses using the EEIO model.

The first analysis, described in Chapter 3, focuses on the role of the global supply chain, along with the domestic supply chain, in mitigating serious air pollution-related health impacts in India. The analysis revealed that the impact of foreign demand on the number of PM_{2.5}-related premature deaths in India was significant and identified supply chain paths that indirectly contributed to a large number of premature deaths in India. Specifically, I found that India's rice supply chain has high energy intensity, which contributed to a large number of premature deaths, and foreign consumers in the Middle East regions indirectly contributed to the large health impact of India through the consumption of exported rice. The results of the analysis indicated that responsibility for air pollutant emissions should be shared among producers (i.e., the electricity generation sector in India), foreign consumers, and domestic consumers.

The second supply chain analysis, described in the Chapter 4 focused on the

contribution of the informal sector to the carbon footprint (CO₂ emissions embodied in the supply chain). The large presence of the informal sector is a representative characteristic of economic systems in developing countries, including India. This study constructed an EEIOT that distinguishes between the formal and informal sectors in Indian manufacturing industries. The results revealed that the informal sector contributes significantly to India's carbon footprint. In particular, CO₂ emissions involved in industrial transactions, including the informal sector, accounted for 15% of the total emissions involved in the supply chain of India's construction industry, which emits approximately 300 Mt-CO₂ annually. This study indicated that the large presence of the informal sector would undermine the effect of existing environmental policies that do not cover the informal sector and that the Indian government should launch an environmental policy to address CO₂ emissions from the informal sector.

An important future development remaining in this dissertation is to integrate the impact of domestic and global economic systems on environmental loads in India, which are currently analyzed separately. Environmental loads are induced by interactions between domestic and global economic systems. The interaction can be observed by integrating the structure of IOT estimated in Chapter 4, which distinguishes between the formal and informal sectors in the MRIOT, which was used in Chapter 3. Furthermore, the environmental impact of the production shift to India from other countries that may occur in line with the recent trend of supply chain restructuring can be observed by applying the scenario-based hypothetical extraction method (HEM) (Dietzenbacher and Lahr, 2013; Dietzenbacher *et al.*, 2019; Maeno *et al.*, 2022; Maeno, 2023) to integrated IOT.

Acknowledgements

First, I would like to express my deepest gratitude to my supervisor, Prof. Shigemi Kagawa of Kyushu University. He is a person with immense talent and affection. He guided me with his deep knowledge and years of research experience. As my research progressed, he understood and praised my efforts. When my research was not going well, he encouraged me and gave me confidence. I have tried to change my research topic several times when I strayed from my research direction. He taught me that sometimes research goes well, but sometimes it takes a long time to make progress; however, we should keep track of our research topic. I remember his phrase, “Treat your research topic as your lover.” Now I am proud of my research, mainly because of his support and motivation.

I would also like to express my gratitude to Prof. Fumiya Nagashima of Kindai University. He has supported my research since I was an undergraduate student, as has Prof. Shigemi Kagawa. His support helped me in every process of my research, such as formulating programming codes, making presentations, writing academic papers, etc. Without his continuous support, I would not have completed my Ph.D. thesis.

I am very thankful to Prof. Hidemichi Fujii and Prof. Toshiyuki Fujita of the Faculty of Economics, Kyushu University, for numerous helpful and constructive observations on my Ph.D. thesis. Their knowledgeable and insightful suggestions for my presentations really helped me examine my research and improve my thesis. Professor Fujii has supported me with insightful suggestions from my undergraduate days.

I am also grateful to Dr. Keisuke Nansai of the National Institute for Environmental Studies. He is one of the authors of the study described in Chapter 3. He made several critical observations on my research, and I was influenced by his passionate attitude toward research aimed at solving environmental issues. I appreciate the support of Dr. Shunichi Hienuki of the Central Research Institute of the Electric Power Industry. He gave me the opportunity to learn the basic knowledge and techniques of IO analysis through joint research with him.

I also appreciate the feedback from the research workshops and academic conferences offered by Prof. Seiji Hashimoto of Ritsumeikan University, Prof. Hiroki Tanikawa of Nagoya University, Prof. Yosuke Shigetomi of Nagasaki University, Dr. Keiichiro Kanemoto of the Research Institute for Humanity and Nature, Dr. Satoru

Chatani of the National Institute for Environmental Studies, and Dr. Norihiko Yamano of the Organisation for Economic Cooperation and Development. Their scientific expertise has continuously advanced my research.

My research was highly motivated by students, room members, and senior and younger researchers in the Kagawa Laboratory and the Q-Energy Fellowship at Kyushu University. I am especially grateful to my colleague Keitaro Maeno, who has worked hard together and encouraged me. We have always discussed how to improve our research and become good researchers. He was my rival and friend. I am also grateful to Sora Matsushima, who provided me with emotional support when I was disappointed. I hope that we will continue working together in the future. I also thank my younger colleagues, Daigo Ushijima, Waka Nishifuji, and Marina Uematsu. They gave me the opportunity to grow together while working on our research. I appreciate all the fellows of the Kagawa Laboratory family for giving me precious time over the past six years.

I am grateful to my family for their support and understanding. I cannot thank you enough.

Appendix

Appendix A.

Table A1. State-wise production of rice and wheat in 2010

State/Union territory	production(Thousand Tonnes)	
	rice	wheat
Andhra Pradesh	10538	10
Arunachal Pradesh	216	5
Assam	4336	64
Bihar	3599	4571
Chhattisgarh	4110	122
NCT of Delhi	19	93
Goa	101	-
Gujarat	1292	2352
Haryana	3625	10500
Himachal Pradesh	106	327
Jammu and Kashmir	497	290
Jharkhand	1538	173
Karnataka	3691	251
Kerala	598	-
Madhya Pradesh	1261	8410
Maharashtra	2183	1740
Manipur	320	-
Meghalaya	207	1
Mizoram	44	-
Nagaland	240	2
Odisha	6918	6
Puducherry	52	-
Punjab	11236	15169
Rajasthan	228	7501
Sikkim	24	6
Tamil Nadu	5665	-
Telangana	-	-
Tripura	640	1
Uttar Pradesh	10807	27518
Uttarakhand	608	845
West Bengal	14341	847
ALL INDIA	89093	80804

-: Not Available.

Source: Reserve Bank of India (2021) Handbook of Statistics on Indian States, webpage
<https://rbi.org.in/Scripts/AnnualPublications.aspx%3Fhead%3DHandbook%20of%20Statistics%20on%20Indian%20States> (accessed March 28, 2021)

Table A2. 66 industry sectors

No.	Industry name	No.	Industry name
1	Agriculture	34	Manufacture of other non-metallic mineral products
2	Livestock	35	Manufacture of wood and of products of wood and cork, except furniture, manufacture of articles of straw and plaiting material
3	Forestry and logging	36	Manufacture of paper and paper products
4	Fishing and aquaculture	37	Printing and reproduction of recorded media except publishing
5	Coal and lignite	38	Manufacture of furniture
6	Crude petroleum	39	Other manufacturing
7	Natural gas	40	Repair and installation of machinery and equipment
8	Iron ore	41	Construction
9	Non-ferrous metal ores	42	Electricity
10	Other mining	43	Gas
11	Production, processing and preservation of meat, fish, fruit, vegetables, oils and fats	44	Water supply
12	Manufacture of dairy products	45	Railway transport
13	Manufacture of grain mill products, etc., and animal feeds	46	Land transport
14	Manufacture of other food products	47	Water transport
15	Manufacture of beverages	48	Air transport
16	Manufacture of tobacco products	49	Supportive and auxiliary transport activities
17	Manufacture of textiles and cotton ginning	50	Storage and warehousing
18	Manufacture of wearing apparel, except custom tailoring	51	Communication
19	Manufacture of leather and related products	52	Trade
20	Manufacture of basic iron and steel and casting of iron and steel	53	Hotels and restaurants
21	Manufacture of basic precious and non-ferrous metals and casting of non-ferrous metals	54	Financial services
22	Manufacture of fabricated metal products, except machinery and equipment	55	Insurance services
23	Manufacture of electronic components, consumer electronics, magnetic and optical media	56	Ownership of dwellings

24	Manufacture of computer and peripheral equipment	57	Education and research
25	Manufacture of communication equipment	58	Medical and health
26	Manufacture of optical and electronics products n.e.c.	59	Legal services
27	Manufacture of electrical equipment	60	Computer related services
28	Manufacture of machinery and equipment n.e.c.	61	Other business services
29	Manufacture of transport equipment	62	Real estate activities
30	Manufacture of coke and refined petroleum products	63	Renting of machinery and equipment
31	Manufacture of chemicals and chemical products except pharmaceuticals, medicinal and botanical products	64	Community, social and personal services
32	Manufacture of pharmaceutical, medicinal chemicals and botanical products	65	Other services
33	Manufacture of rubber and plastic products	66	Public administration and defense

Table A3. Sector classification table in this study

Code	Industry classification in World Input-Output Database	Code	Industry classification in SUT of India
1	Crop and animal production, hunting and related service activities	1	Agriculture
		2	Livestock
2	Forestry and logging	3	Forestry and Logging
3	Fishing and aquaculture	4	Fishing and aquaculture
4	Mining and quarrying	5	Coal and lignite
		6	Crude petroleum
		7	Natural gas
		8	Iron ores
		9	Non ferrous metal ores
		10	Other Mining
5	Manufacture of food products, beverages and tobacco products	11	Production, processing and preservation of meat, fish, fruit, vegetables, oils and fats
		12	Manufacture of dairy products
		13	Manufacture of grain mill products, etc., and animal feeds
		14	Manufacture of other food products
		15	Manufacture of beverages
		16	Manufacture of tobacco products
6	Manufacture of textiles, wearing apparel and leather products	17	Manufacture of textiles and cotton ginning
		18	Manufacture of wearing apparel, except custom tailoring
		19	Manufacture of leather and related products
7	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	35	Manufacture of wood and of products of wood and cork, except furniture, manufacture of articles of straw and plaiting material
8	Manufacture of paper and paper products	36	Manufacture of paper and paper products
9	Printing and reproduction of recorded media	37	Printing and reproduction of recorded media except publishing
10	Manufacture of coke and refined petroleum products	30	Manufacture of coke and refined petroleum products

11	Manufacture of chemicals and chemical products	31	Manufacture of chemical and chemical products except pharmaceuticals, medicinal and botanical products
12	Manufacture of basic pharmaceutical products and pharmaceutical preparations	32	Manufacture of pharmaceutical, medicinal chemicals and botanical products
13	Manufacture of rubber and plastic products	33	Manufacture of rubber and plastic products
14	Manufacture of other non-metallic mineral products	34	Manufacture of other non-metallic mineral products
15	Manufacture of basic metals	20	Manufacture of basic Iron and steel and casting of iron and steel
		21	Manufacture of basic precious and non-ferrous metals and casting of non-ferrous metals
16	Manufacture of fabricated metal products, except machinery and equipment	22	Manufacture of fabricated metal products, except machinery and equipment
17	Manufacture of computer, electronic and optical products	23	Manufacture of electronic component, consumer electronics, magnetic and optical media
		24	Manufacture of computer and peripheral equipment
		25	Manufacture of communication equipment
		26	Manufacture of optical and electronics products n.e.c
18	Manufacture of electrical equipment	27	Manufacture of electrical equipment
19	Manufacture of machinery and equipment n.e.c.	28	Manufacture of machinery and equipment n.e.c
20	Manufacture of motor vehicles, trailers and semi-trailers	29	Manufacture of transport equipment
21	Manufacture of other transport equipment	29	Manufacture of transport equipment
22	Manufacture of furniture; other manufacturing	38	Manufacture of furniture
		39	Other manufacturing
23	Repair and installation of machinery and equipment	40	Repair and installation of machinery and equipment
24	Electricity, gas, steam and air conditioning supply	42	Electricity
		43	Gas
25	Water collection, treatment and supply	44	Water supply

26	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services	44	Water supply
27	Construction	41	Construction
28	Wholesale and retail trade and repair of motor vehicles and motorcycles	52	Trade
29	Wholesale trade, except of motor vehicles and motorcycles	52	Trade
30	Retail trade, except of motor vehicles and motorcycles	52	Trade
31	Land transport and transport via pipelines	45	Railway transport
		46	Land transport
32	Water transport	47	Water transport
33	Air transport	48	Air transport
34	Warehousing and support activities for transportation	49	Supportive and auxiliary transport activities
		50	Storage and warehousing
35	Postal and courier activities	51	Communication
36	Accommodation and food service activities	53	Hotels and restaurants
37	Publishing activities	51	Communication
38	Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities	51	Communication
39	Telecommunications	51	Communication
40	Computer programming, consultancy and related activities; information service activities	60	Computer related services
41	Financial service activities, except insurance and pension funding	54	Financial services
42	Insurance, reinsurance and pension funding, except compulsory social security	55	Insurance services
43	Activities auxiliary to financial services and insurance activities	54	Financial services
		55	Insurance services
44	Real estate activities	62	Real estate activities
45	Legal and accounting activities; activities of head offices; management consultancy activities	59	Legal services
46	Architectural and engineering activities; technical testing and analysis	57	Education and research

47	Scientific research and development	57	Education and research
48	Advertising and market research	57	Education and research
49	Other professional, scientific and technical activities; veterinary activities	57	Education and research
50	Administrative and support service activities	61	Other business services
51	Public administration and defence; compulsory social security	66	Public administration and defense
52	Education	57	Education and research
53	Human health and social work activities	58	Medical and health
54	Other service activities	65	Other services
55	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	65	Other services
56	Activities of extraterritorial organizations and bodies	65	Other services

Note: When sectors (e.g., crop and animal production, hunting, and related service activities) in the Indian SUT are aggregated into a specific sector (e.g., Agriculture and Livestock) in the WIOD, CO₂ emissions from the sectors in the Indian SUT are estimated by multiplying the CO₂ emissions from the aggregated sector in the WIOD by the gross output shares of the disaggregated sectors in the Indian SUT by the gross output of the aggregated sector in the WIOD.

Appendix B.

The detailed estimation procedure of the disaggregated IOT is explained below. In Figure 4.2, the total supply of intermediate goods produced by formal and informal production activities belonging to a specific industry i can be easily calculated as:

$$TS_i^F = \sum_j z_{ij}^{FF} + \sum_j z_{ij}^{FI} = \sum_j \theta_i^F z_{ij} \varphi_j^F + \sum_j \theta_i^F z_{ij} \varphi_j^I = \theta_i^F \sum_j z_{ij} \quad (B1)$$

and

$$TS_i^I = \sum_j z_{ij}^{IF} + \sum_j z_{ij}^{II} = \sum_j \theta_i^I z_{ij} \varphi_j^F + \sum_j \theta_i^I z_{ij} \varphi_j^I = \theta_i^I \sum_j z_{ij} \quad (B2)$$

where $\varphi_j^F + \varphi_j^I = 1$. Eqs. (B1) and (B2) imply that the total supply of intermediate goods described in Figure 4.1 is divided into those of the formal and informal sectors based on their gross output shares. In Figure 4.2, the total demand for the intermediate goods required by formal and informal production activities belonging to a specific industry j can also be easily calculated as

$$TD_j^F = \sum_i z_{ij}^{FF} + \sum_i z_{ij}^{IF} = \sum_i \theta_i^F z_{ij} \varphi_j^F + \sum_i \theta_i^I z_{ij} \varphi_j^F = \varphi_j^F \sum_i z_{ij} \quad (B3)$$

and

$$TD_j^I = \sum_i z_{ij}^{FI} + \sum_i z_{ij}^{II} = \sum_i \theta_i^F z_{ij} \varphi_j^I + \sum_i \theta_i^I z_{ij} \varphi_j^I = \varphi_j^I \sum_i z_{ij} \quad (B4)$$

where $\theta_i^F + \theta_i^I = 1$. Eqs. (B3) and (B4) imply that the total demand for the intermediate goods described in Figure 4.1 is divided into those of the formal and informal sectors based on their intermediate input shares.

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