Master’s thesis

The Impact of Capital Endogenization on the estimation of carbon footprint of India in the Input Output Framework (2011-23)

by

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1. Introduction

India's 2015 Nationally Determined Contributions (NDCs) towards the Paris Agreement were considered one of the most ambitious climate related commitments put forward by any developing country towards climate action. Yet, India achieved its targets ahead of time and updated its NDCs to reflect the new targets to reduce the emissions intensity of its GDP to about 45% from the 2005 level by the year 2030. India also aims to achieve the target of at least 50% of cumulative electric power generation from non-fossil energy resources by 2030.

At the 26th Conference of Parties (COP-26), India pledged to achieve the net-zero emissions target by 2070. Despite the feasibility of achieving this distant target, India’s current stage of development and population burden result in substantially high emissions. For 2022 India’s global share of CO_2 emissions from combustible fuels was 72%, and India is the third highest carbon emitting country as per International Energy Agency (IEA) data for 2022. The largest source of CO_2 emissions in India for 2022 was coal combustion to generate electric power. In 2024, India recorded blazing temperatures as high as 52.3 degrees Celsius in multiple cities. It is evident that India’s emissions levels are not in line with its expected targets and ambitious commitments. This asymmetry between the targets India aims to achieve and the ground reality of juggling the massive population burden and ecological constraints while walking on the path of economic development make India a compelling case study.

Due to its versatile nature, Input-Output (I-O) analysis has become a popular tool of analysis even in fields other than its target discipline of Economics. It is widely used in the disciplines of environmental studies, disaster management, energy, etc due to its efficiency in establishing material flow relationships among sectors of an economy and among various countries. The estimation of carbon footprints of economies using input output models is a relatively straightforward exercise. However, the traditional IO models treat capital exogenously and account mainly for the flow of goods and services. The estimation of the carbon footprints as such would not capture a realistic picture of the emissions levels and present a rather deflated estimation.

Hence, studies integrating capital usage of industries through consumption-based accounting are being widely undertaken, for instance, Södersten et al. (2018a, 2018b, 2020) and Xu et al. (2023). These studies show that accounting for capital use increases the carbon footprint of final consumption substantially. In order to endogenize capital, a capital use matrix (K) has to be estimated to add to the Intermediate Inputs matrix (A) to obtain the the total requirement matrix or the Leontief inverse matrix L^K, which explains the industry specific total requirements of capital and non-capital inputs to generate each unit of output in the economy. Most of the studies undertaking this exercise are – either focused on the Advanced Western Economies or China. There is a substantial gap of said research for developing countries like India which adds to the motivation to undertake this project for the master's thesis.

The objective to estimate the carbon footprint of India for the recent years is based on the curiosity to check if India is actually progressing towards its ambitious aims of climate action, despite its status as one of the highest carbon emitting countries (in absolute terms). Although the inclusion of capital inputs is a challenging task, it would provide a more detailed insight into the carbon intensity of capital as an input to the production structure of the Indian Economy.

With the set objective and the motivation to explore the unique case of India, this study does not engage in a comparative analysis. The aim is a narrow but deep analysis of the emissions footprint of India. The study estimates both CO_2 emissions and GreenHouse Gases (GHG) emissions for India and compares the emissions levels pre and post capital endogenization to note the effect of including capital inputs on the footprint estimation. This footprint is disaggregated into 120 industries from the Global Resource Input Output Assessment (GLORIA) framework to identify the most and least carbon intensive sectors. The analysis points out sectors which are sensitive and insensitive to capital endogenization and provides reasons for the observations. To further check for the impact of embedded emissions in the

Gross Fixed Capital Formation (GFCF) as a part of the final demand, we drop the GFCF from the final demand and then compare this with capital exogenous carbon footprint at the national and industrial levels.

This study bridges the research gap by developing capital-use matrices for subsequent studies in the much detailed GLORIA framework, providing a comprehensive analysis of the effects of capital endogenization on the emission footprint for a developing country. It further provides relevant policy inferences to shape the green transition for India.

1.1 The Problem Statement

Studies estimating the carbon footprints of developing countries with the capital endogenous input-output methodology are very limited. When present, such studies compare the emission trends of the developing countries with the advanced economies like Södersten et al (2018a, 2018b) leading to an unfair comparison. Just like the developing countries, even the advanced economies had higher rates of GHG emissions at their development stage (Vigna et al, 2024).

Only a small group of developing countries with significant population size or GDP or emission levels are included in the studies like Brazil, South Africa, India, etc and they are compared with the advanced global north economies. Studies focusing entirely on developing countries like the Latin American countries (Tausch & Magacho 2024) are very limited. This project aims to add to the capital endogenization literature by conducting a detailed analysis on one of the most compelling case studies of the developing world- India.

The datasets commonly used for such analysis have limited resolution for developing countries, inhibiting a detailed probe. Södersten et al (2018a) estimate the carbon footprint of India along with a bunch of global north countries, using EXIOBASE, which has a rather limited resolution. Therefore, there is a research gap of capital endogenization for many developing countries using more granular databases like GLORIA.

Hence the aim of this study is refined as – Capital endogenization in the Input-Output model for India for the years (2011-2023) using a detailed database to estimate its carbon footprints (CO_2 emissions and GHG emissions using consumption based accounting. The study also contributes by adding the capital-use matrix for India to the GLORIA MRIO framework. The selection of the stated period of analysis is due to the limited availability of data and a preference to focus on the recent years given the motivation of this project is to check if India's emissions levels are progressing towards its ambitious targets or not.

1.2 Research Questions

- The primary research question for this study is :

What is the effect of capital endogenization in the Input-Output models, on the carbon footprint estimation for India over the time period 2011-2023?

- Some secondary research questions that are also tackled in the project :

How does the total requirements matrix L^K (Leontief Inverse augmented to include capital inputs) compare to the total requirements matrix L (Traditional Leontief Inverse excluding capital inputs)?

How different are the CO_2 emission levels from the GHG emissions levels for India over the analysed period?

1.3 Hypotheses

- Total requirements matrix with capital endogenization L^K is higher in magnitude than the total requirements matrix L

- The inclusion of capital inputs increases the carbon footprint for India over the analysed time period.

- The trends of GHG emissions levels and CO_2 emission levels are similar over the analysed period given that CO_2 constitutes more than 70% of GHGs.

- The carbon footprint of India’s service sector is the highest when capital inputs are included in the footprint estimation.

1.4 Outline of the Thesis

The presented study is structured as follows:
The next section provides a detailed literature review of capital endogenization in I-O models including a brief section on the framework, the approaches to accounting for footprint estimation and relevant studies that help shape the argument of this thesis. Following this review, we will describe our methodology in detail including the steps of estimation of capital use matrices and estimating the CO_2 emissions and GHG emissions. This section is followed by the results of our empirical analysis which are interpreted in detail. We then elaborate on the study's contributions and note its constraining factors. Finally, we present the conclusion.

2. Literature Review

2.1 Input Output Models

Input-Output (I-O) framework is the brainchild of the Nobel laureate Wassily Leontief (1936) and is a pioneering tool developed for economics. At the most rudimentary level, I-O models have a system of linear equations that describe the allocation of an industry's product to other industries and final consumers. Despite the static nature, the input–output framework provides a detailed picture of the economy and the flexibility for incorporating various extensions to the basic model.

The fundamental aim of the input output analysis was to analyze the interdependence of industries to maintain the production processes in an economy. For this I-O models use a set of equations to register the inter-industry flows of inputs. Baumol (2000) describes it as one of the most widely used tools of economics analysis. In some ways, the I-O models were ahead of their time because of the requirements of granular data and calculation capacities for extensive applications of this model. Miller and Blair (2009) describe how the advent of technology, calculation softwares and the data availability have expanded the applications of input–output analysis at various geographic levels (regional, national, and international). Although developed for economics, the versatility of I-O models has made it a popular tool of analysis in Environmental sciences, Industrial ecology, Energy analysis, etc. This also explains the recent surge in I-O analysis in different fields. Today the basic I-O framework has bifurcated into regional & multiregional I‑O, social accounting matrices, survey estimation methods, energy & environmental I‑O, structural decomposition analysis and even dynamic & mixed models.

Traditional I-O models only capture inter-industry flow of inputs and include capital usage in the form of GFCF and Consumption of Fixed Capital (CFC), as a part of final demand and value additions respectively. They do not account for the fact that capital as inputs also gets used up during the production process. Hence, this study uses a basic I-O model for India aiming to endogenise capital inputs in the production process and check for its environmental impacts.

Despite the fact that endogenizing capital in I-O frameworks is not a novelty, there isn't extensive literature for this niche. Lenzen and Treloar (2004) compare ways to achieve capital endogenization in I-O models. The two prominent methods for capital endogenization they examine are: the augmentation method and the flow matrix method.

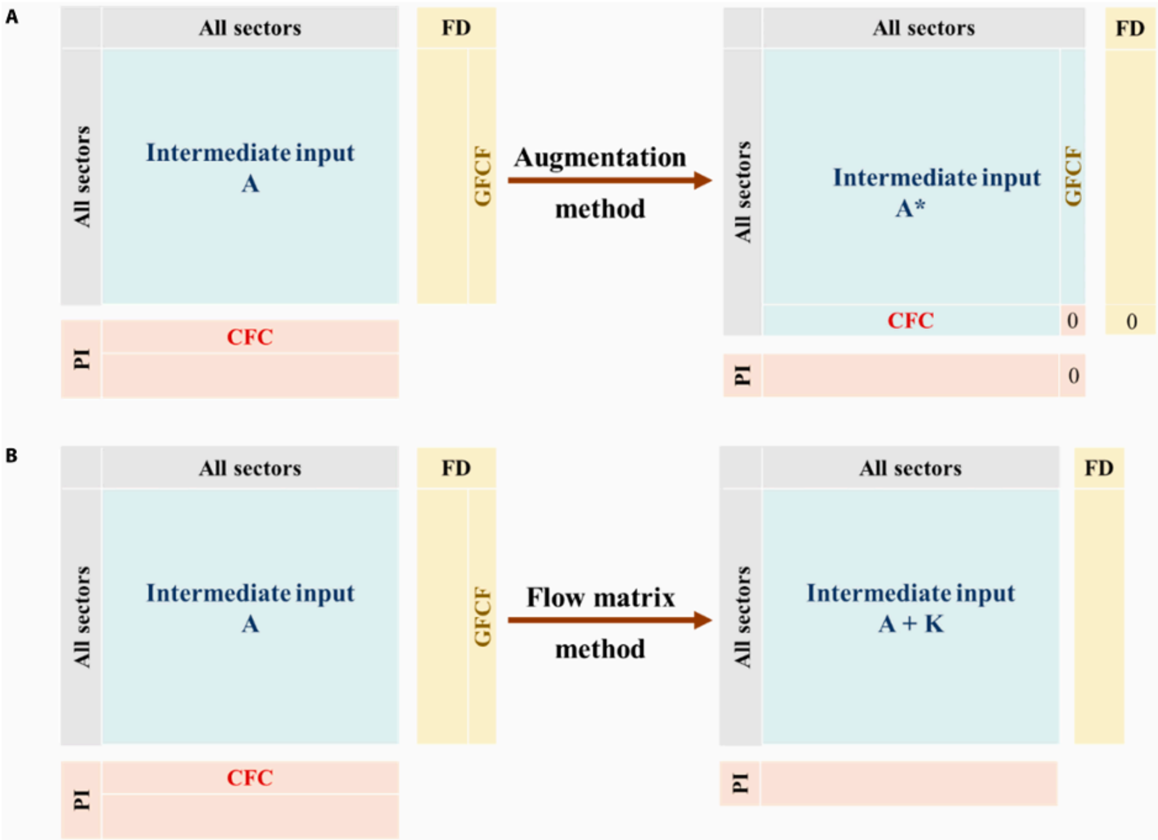

Fig. 5. Conceptual illustration of (A) augmented method and (B) flow matrix method. PI, primary inputs; FD, final demands.

Fig(1) The Augmentation method vs the Flow method of capital endogenisation

Source : Xu et al (2023)

Under the augmentation method, capital is incorporated as a homogeneous commodity provided by a fictitious 'capital' sector added to the interindustry matrix. The 'capital commodity' so incorporated is produced as per the GFCF vector and consumed as per the CFC vector of the I-O model. Although, this method is easier to implement but is not realistic as it views capital as a 'homogeneous' commodity (doesn't represent the different types of capital assets) and its estimation of multipliers is inaccurate.

The Flow matrix method disaggregates capital by different asset types and sectors and records the flow of capital within industries in a 'capital flow matrix'. This matrix combined with the regular interindustry flow matrix provides the matrix of total flows. Lenzen and Treloar (2004) recommend this method of capital endogenization as it captures the capital inputs to production in a more realistic manner.

Before reviewing the studies that endogenize capital in I-O and frameworks, it is important to discuss the approaches for emission accounting and define what a carbon footprint is!

2.2 Production Based vs Consumption Based Approaches to emissions accounting

The two ways to account for emissions represent the supply side method and the demand side method of measuring emission levels. The supply side approach is the production based accounting where the emission levels are counted from the production happening within the national territory[1] regardless of where the demand is generated from. Meaning that the emission burden from all the goods produced within national boundaries will be assigned to India even if a large share of it is due to goods exported. Even though this method is quite popular for estimating CO_2 emissions, global trade can assign an excessive burden of emissions to an export oriented country. (Peters et al 2011) show that the share of carbon emissions from global trade increased from 20% to 26% between 1990 and 2008.

The demand side approach of consumption based accounting is a more appropriate choice if the country has higher imports as it attributes all direct emissions released from production activities to the final users. In absolute terms, both India's exports (21.8% of GDP, 2023) and imports (24.1% of GDP, 2023) (based on the World Bank Data) are mammoth sized. But, over the recent years the imports are slightly higher than its exports. Hence, the consumption based accounting is a better option to estimate the carbon footprint of the final demand generated by India.

[1] Revised 1996 IPCC guidelines for national greenhouse gas inventories. Bracknell: Intergovernmental Panel on Climate Change, Meteorological Office; 1997.

2.3 Defining the term 'Carbon Footprint'

Wiedmann and Minx (2008) highlight the ambiguity surrounding the word 'carbon footprint' since 2007 when its usage became popular. They highlight that many studies use the term 'carbon footprint' interchangeably for CO_2 emissions and GHG emissions. Hence it is important to set the meaning of carbon footprint for this study.

Carbon Trust (2007) defines it as the total emission of greenhouse gases (GHG) in carbon equivalents that are generated from the production process of a product across its life cycle through the supply chain. On a similar note, ETAP (2007) defines the 'Carbon Footprint' as measuring the impact of human activities in terms of greenhouse gases produced, measured in tonnes of carbon dioxide. Wiedmann and Minx (2008) suggest the use of 'carbon footprint' for measuring CO_2 emissions only.

This study takes the approach of ETAP (2007) and defines the 'carbon footprint' as the measurement of GHG gases in carbon equivalent terms. However, the study calculates both CO_2 emissions and GHG emissions for India for the time period of the analysis and juxtaposes them.

2.5 Literature on capital endogenization in I-O models

Södersten et al (2018b) study the structure of GFCF and the embedded emissions within GFCF for a group of 22 most populated countries. They find that for countries in the earlier stages of development, the share of GFCF as part of the global carbon footprint (CF) is much higher than the share of GFCF as a share of global GDP. This means that developing countries invest in resource-intensive (and carbon intensive) assets like basic infrastructure, machinery etc, due to which their GFCF in general is more carbon intensive (dirty). The opposite is true for wealthier, advanced economies – they invest in less resource-intensive (cleaner) assets like AI, computers, software, etc. Another key takeaway from their results is the classification of India as a country with one of the ‘dirtiest’ (i.e. carbon intensive) GFCF.

Keeping this research as a foundation , It is clear that the embedded emissions of GFCF, if included in the carbon footprint of final consumption, would give a more realistic picture of the footprint estimation because parts of GFCF (as capital inputs) also get used up in the production process. To achieve this, Södersten et al (2018a) conduct an analysis of capital endogenization as a comparative study of several countries including India, for 1995-2015 by endogenising CFC with consumption based accounting to include the effects of international trade, using EXIOBASE (a narrower database compared to GLORIA). They observe a substantial rise in the carbon footprint of some countries (like Brazil) but only a narrow (close to 10% for 2015) rise in the carbon footprint of India.

Their observation of a narrow rise in carbon footprint of India can be due to following reasons – 1) They endogenise CFC in their study Södersten et al (2018a) instead of GFCF which had substantial embedded emissions as per Södersten et al (2018b). 2) India’s share of global carbon footprint was much higher than its share of GFCF owing to its labour-intensive economy.

Södersten et al (2020) show that the effects of endogenizing capital are generally larger for OECD economies than for non-OECD economies. But with a much larger population, non-OECD countries consume substantially more biomass in total than the OECD and have overtaken OECD countries in terms of the total use of fossil fuels, metals and materials.

Södersten et al (2020) also suggest that the footprint of the service sector increases substantially more than non-services when the emissions embodied in capital goods are included. As of 2025, the service sector in India contributes to about 55% (PIB.gov.in) to India’s GDP. Hence, if capital inputs are endogenous, the carbon footprint of the service sector could increase significantly!

Wu et al. (2021) developed an advanced capital-endogenous MRIO model to estimate China’s greenhouse gas (GHG) footprints from 1995 to 2015 by integrating both inter-annual and intra-annual dynamics of capital consumption by incorporating a “capital loop” to track the depreciation of newly formed capital within the same year of investment. Results show that including capital-related emissions increases China’s final consumption-based GHG footprint in 2015 by 28% compared to conventional models. The Chinese service sector accounts for nearly 77% of these emissions.

Xu et al. (2023) also agree with the established literature that capital is a major source of emissions but is often excluded from footprint calculations. They conduct the capital endogenizing exercise for China (1990-2022) by endogenizing CFC and find that the national footprint of China rises from around 7% to as high as 48% over the period of analysis. This also indicates how China became more capital-intensive in its production structure over the years.

Gao et al. (2020) investigated China's CO_2 emissions embodied in fixed capital assets from 2007 to 2017 by using both multiple input-output models and provide crucial insights into the carbon intensity of investment activities across different regions within China. The study quantifies the indirect carbon emissions embedded in the capital assets necessary for production and reveals how infrastructure and industrial investment contribute to China's overall carbon footprint beyond direct operational emissions.

Capital endogenization exercises are also conducted by researchers for applications other than footprint estimations. The work by Tausch and Magacho (2024) addresses a major gap in input–output (I-O) analysis by constructing capital-use matrices for six Latin American and Caribbean countries within the GLORIA MRIO framework. They endogenize GFCF instead of CFC to reflect the capital stock needed to sustain productive capacity as their research question revolves around the socio-economic constraints faced by developing countries during their low-carbon transitions. Their results reveal that, on an average, over 45% of every dollar invested in capital goods leaks abroad to the global north via imports of advanced technology required for the low-carbon transition.

Since the analysis by Södersten et al (2018b) reveals that India has a carbon-intensive GFCF, exploring the impact of GFCF endogenization on the footprint calculations for India would be interesting despite it being an unpopular approach for footprint estimations and complement the Södersten et al (2018a) study. Hence, this project uses the methodology of Tausch and Magacho (2024) based on Södersten et al (2018a) adapted for the Indian Case.

3. Methodology

3.1 Methods employed

Based on the above discussed literature review, we chose to apply the flow matrix method to endogenize capital in the Input-Output Framework for India. For the reasons discussed above, We endogenize GFCF in the Input-Output model to obtain capital-use matrices. Out of the supply side approach and demand side approach of emissions accounting, we chose the demand side approach, i.e., the consumption based accounting method to endogenize capital.

The Basic Leontief Framework

Based on Miller and Blair (2009), the Basic Leontief framework is as follows :

The intermediate inputs for industries are given by the multiplication of the technical coefficient matrix or the input coefficient matrix A and the column-vector of total production (x). The total production by industries for a country is given by the summation of intermediate inputs consumed in the production process and final demand (y) :-

$$\mathbf{x = Ax + y}$$

Or

$$\mathbf{x = (I - A)^{-1}y}$$

This is called the basic Input Output accounting equation. The total requirement matrix is given by :

$$\mathbf{L = (I - A)^{-1}}$$

L is the Leontief matrix or the total requirement matrix. It represents the direct and indirect inputs required to produce one unit of industry output. It must be noted that here the direct and indirect inputs requirement includes only intermediate goods.

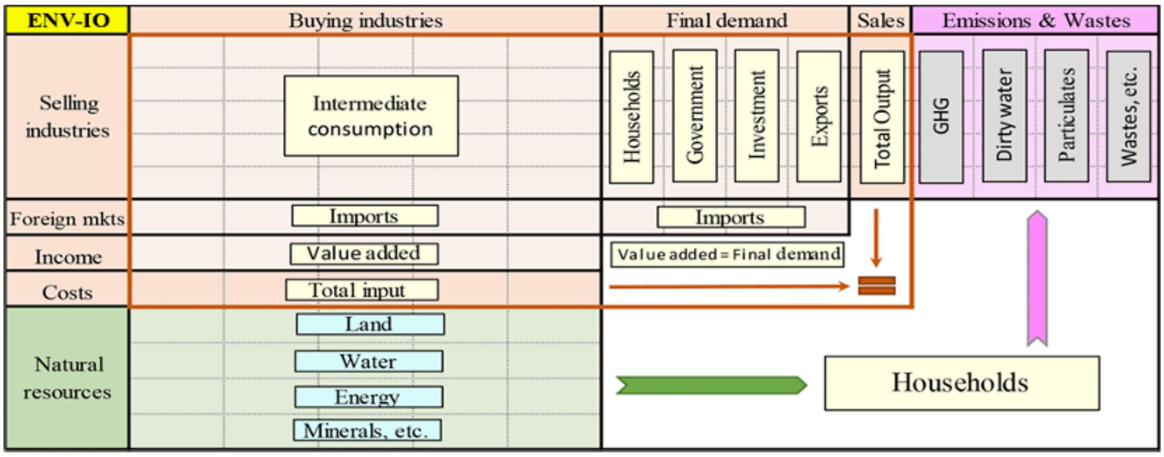

Fig (2) The environmentally extended Input Output models

Source: Guilhoto (2021)

3.2 Data

To achieve the objective of this thesis, which is to construct the Capital-Use Matrix for India for the years (2011-2023), the prime data requirement is to have data on capital stock by asset types and industries/sectors. The KLEMS data for India from the CSO Ireland provides data on the capital assets consumed by industries. The dataset has detailed the asset types and industry classifications.[2]

Observing the KLEMS dataset reveals that for the 20th and 21st Industrial classification - ‘Activities of households as employers; producing activities of households for own use’ and ‘Activities of extraterritorial organisations and bodies’ no fixed assets are consumed throughout the years of the available data. The International Standard Industrial Classification of All Economic Activities (ISIC Rev 4, 2008) explains the economic activities under these classification that provide an insight for the observation. The activities under ‘Activities of households as employers; producing activities of households for own use’ include employment of domestic personnel such as maids, cooks, gardeners, etc, (excluding provision of services like cooking, cleaning to households by service providers) and goods and services produced by households for self consumption. These activities do not enter

[2] The tables on assets and industry classification are in the appendix

the economic sphere and hence their exact value can’t be estimated and due to the nature of the activities no fixed assets are used by this KLEMS sector.

The activities under ‘Activities of extraterritorial organisations and bodies’ comprises activities of the international organisations like the UN, OECD, etc and diplomatic and consular missions when being determined by the country of their location rather than by the country they represent. These activities albeit performed in the geographical territory of the economy examined (here India) do not lie in the economic territory of the country. Hence, these activities also do not enter the economic sphere and the non-economic nature of activities does not require the consumption of fixed assets by this sector. For these reasons, the 20th and 21st Industrial sector of KLEMS can be excluded from the analysis.

The choice of Multi-regional Input-Output (MRIO) dataset is made with the following factors in mind : a) Suitability of the dataset for developing countries (mainly India for this study), b) high-sectoral resolution. Comparing with datasets like WIOD, EXIOBASE, The GLORIA MRIO database covers120 sectors for 164 countries and has been used in studies like (Tausch and Magacho, 2024)

The depreciation rates of capital assets are based on the EU KLEMS & INTANProd (Bontadini et al 2023) and the Growth rates are based on World Banks’s per capita growth rates.

3.2 Estimating the Capital Use Matrix

For estimating the GLORIA based capital use matrix for 2011-2023, the process explained in this section is repeated for each year in the time period.

Based on the above data we create a KLEMS based capital use matrix $\tilde{\mathbf{K}}$ with assets in rows and sectors in columns, meaning $\tilde{\mathbf{K}}$ has 6 asset types for rows and 19 sectors in columns. Owing to detailed sectoral classifications GLORIA[3] has a structure of 120x120. In order to be able to estimate the capital use matrix in

[3] The list of Gloria sectors can be found in the appendix.

GLORIA dimensions (which we shall call the K matrix from now on), disaggregation of sectors and assets needs to be achieved. However, before any steps of estimating the K matrix, the asset category ‘Dwellings excluding land’ needs some adjustment.

Building structures and/or Dwellings can be used for productive and non-productive activities, in the forms of residential and non-residential investment. As Södersten (2018a) many KLEMS databases clearly differentiate between residential and non-residential investments in their asset categories. However, the KLEMS (CSO Ireland)[4] database has the following categories for building structures - ‘Dwellings excluding land’ and ‘Other buildings and structures (including roads)’. The former asset category is exclusively consumed by the KLEMS sector - ‘Real estate activities’ and the latter is naturally consumed by all the industrial sectors (since all industry types classified under KLEMS[5] own/consume fixed assets in the form of building structures/roads for their operations.

This means that ‘Dwellings excluding land’ corresponds to residential investment (and is out of the productive sphere of the economy once it is consumed by the real estate sector).

It is also worth noting that the KLEMS database has only one Construction sector and GLORIA has two types of construction sectors - ‘Building Construction’ and ‘Civil Engineering Construction’. Thinking in terms of the destination GLORIAsectors (after the KLEMS matrix is expanded to achieve the K matrix), the asset type ‘Dwellings excluding land’ (i.e. residential investment) is solely produced by the ‘Building Construction’ sector and consumed by the ‘Property and real estate’ sector. Hence, to keep this particular asset type for the expansion of the KLEMS matrix in order to estimate the K matrix is redundant. Naturally, the first step towards estimating the K matrix is to separate the asset ‘Dwellings excluding land’ from the KLEMS database. Now, the modified KLEMS Capital Use matrix ($\tilde{\mathbf{K}}_{\mathbf{k,s}}$) has 19 sectors with 5 asset types.

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[4] Refer to KLEMS asset list in the appendix

[5] excluding the 2 sectors with non-economic nature.

To expand this modified KLEMS Capital Use matrix ($\tilde{\mathbf{K}}_{\mathbf{k,s}}$) to match GLORIA dimensions (120x120) the 19 sectors and 5 asset types have to be disaggregated to match their corresponding GLORIA sectors. For this, two concordance matrices G and H need to be constructed which match **k** asset types (here 5) and **s** sectors (here 19) to the GLORIA sectors.

For constructing the G matrix, we first make a basic correspondence matrix $\tilde{\mathbf{G}}$ 5x120 with KLEMS assets as rows and GLORIA sectors as columns. This matrix has ones for the corresponding assets-sectors cells and zero for all the rest such that '*All columns sum-up to one and no rules for rows summation*'. In the cases where one KLEMS asset matches multiple GLORIA sectors the values are proportioned based on the proxy vector $\mathbf{p_i}$ which is the GFCF vector (column vector) extracted from the final demand matrix (for domestic as well as imported goods) from GLORIA. The weighted concordance matrix G is calculated as:

$$\mathbf{G_{5x120} = (\hat{G}p)^{-1}\hat{G}p}$$

The concordance matrix is normalised to ensure that the sum of proportions of each KLEMS asset corresponding to the GLORIA sector adds up to one (The rows sum-up to one and column sums do not exceed one). In other words matrix normalisation ensures that there is no double counting. The so constructed G matrix **5x120** has KLEMS assets as rows and GLORIA sectors for columns.

Correspondingly, for the H matrix, we need a basic correspondence matrix $\tilde{\mathbf{H}}$ **120x19** with GLORIA sectors as rows and KLEMS sectors as columns. This matrix has ones for the corresponding sector cells and zero for all the rest such that '*All rows sum-up to one and no rules for column summation*'. Just like the proxy vector above, if KLEMS sectors correspond to more than one GLORIAsector, the the values are proportioned based on the proxy vector $\mathbf{d_j}$ which is the CFC vector (row vector) extracted from the value added matrix from GLORIA. The weighted concordance matrix H is calculated as:

$$\mathbf{H = \hat{d}\tilde{H}(d\tilde{H})^{-1}}$$

Again the concordance matrix is normalised to ensure no double counting. The resulting matrix should follow the rule: all columns sum up to one and row sums do not exceed one. The so constructed H matrix **120x19** has GLORIAsectors as rows and KLEMS sectors as columns. With the help of simple matrix algebra, the modified KLEMS Capital Use matrix **($\tilde{\mathbf{K}}_{k,s}$)** can be opened up in the GLORIA dimensions :

$\bar{K} = G' \tilde{K} H'$

Where $\bar{K}$ is the initial capital-use matrix with GLORIA dimensions

And G' and H' are the transposed concordance matrices.

Now, to account for the asset 'Dwellings excluding land' we construct the $\bar{K}_{res}$ matrix **120x120** (Capital-Use matrix of residential investment) with zeros in all cells except for the cell in the 'Building Construction' row and 'Property and real estate' column. The previously extracted value of 'Dwellings excluding land' is inserted here. This Kbarres matrix is then added to the Kbar matrix to obtain the Kbarbar capital use matrix.

$\bar{\bar{\mathbf{K}}} = \bar{\mathbf{K}} + \bar{\mathbf{K}}_{res}$

Södersten et al (2018a) mention that the $\bar{K}$ matrix constructed as above contains data obtained from national accounts and are not consistent with the CFC values from GLORIA. In order to make the $\bar{K}$ matrix consistent with CFC data from GLORIA following set of adjustments are carried out:

$\bar{\mathbf{d}} = \mathbf{\iota}'[\boldsymbol{\delta} \odot \bar{\bar{\mathbf{K}}}]$

Where $\odot$ is the element-wise multiplication

Where δ is KLEMS depreciation matrix for India and $\bar{K}$ is the capital use matrix adjusted for residential investment, **i** is the summation column vector. The element-wise multiplication of $\bar{\bar{K}}$(Capital-Use/total inputs including capital) with depreciation rates multiplied with a summation vector give us $\bar{\mathbf{d}}$ which is the hypothetical CFC based on $\bar{\bar{K}}$.

Now we perform element-wise division of **d** (CFC row vector form GLORIA) with $\bar{\mathbf{d}}$ and diagonalise the resulting row vector to obtain $\tilde{\mathbf{d}}$ **120x120** (the adjustment matrix).

$$\tilde{\mathbf{d}} = (\bar{\mathbf{d}} \oslash \hat{\mathbf{d}})\hat{}$$

Where $\oslash$ is the element-wise division

Now,

$$\mathbf{K} = \bar{\bar{\mathrm{K}}}\tilde{\mathbf{d}}$$

The final capital use **'K'** Matrix (adjusted for the CFC values in GLORIA) is obtained by multiplying $\bar{\bar{\mathbf{K}}}$ and the adjustment matrix. The **K** matrix or the Capital Use Matrix defines the relationship between capital-inputs of each sector just the the **A** matrix.
Just as the matrix of technical input coefficients $\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1}$ **.** The capital requirement matrix B, which signifies the capital requirements to produce one unit of output, is obtained through the following steps:

$$\breve{\mathbf{B}} = \mathbf{K}\hat{\mathbf{x}}^{-1}$$

Here x is the output vector (column) vector from GLORIA. $\breve{\mathbf{B}}$ represents the matrix of direct capital coefficients i.e. the direct capital required from sector I to produce one unit of total output by sector j. However, $\breve{\mathbf{B}}$ has depreciated capital-stock and doesn't account for the necessary investment to maintain the productive capital stock. To account for the fact that investment replenishes the depreciated capital stock to maintain the productive capacity, a hypothetical Investment Matrix $\bar{\mathbf{I}}$ (Investment required replace depreciation) is calculated as follows:

$$\bar{\mathbf{I}} = \delta\breve{\mathbf{B}}\mathbf{x} + \breve{\mathbf{B}}\dot{\mathbf{x}}$$

Here $\dot{x} = \mathbf{gx}$ where g is the desired growth rate (based off of the average long term logarithmic growth rate).

Now, recalling that Investment represents the gross fixed capital formation in the economy, the Investment **(I)** necessary to replace the existing capital stock (not depreciation) must equal the GFCF vector **p** from GLORIA. As defined above, $\bar{\mathbf{I}}$ represents the investment required to replace depreciation. Hence, $\boldsymbol{\beta}$ (an adjustment vector) can be defined as the capital stock needed to sustain productive capacity of the economy excluding the capital stock that replenishes depreciated capital, i.e. $\mathbf{I} = \hat{\boldsymbol{\beta}}\bar{\mathbf{I}}$. Since **I** is the same as p, $\boldsymbol{\beta}$ is calculated as :

$$\boldsymbol{\beta} = \mathbf{I} \oslash \bar{\mathbf{I}}$$

The **B** matrix that explains the capital stock needed to maintain productive capacity at the desired growth rate g can be calculated as:

$$\mathbf{B} = \hat{\boldsymbol{\beta}}\breve{\mathbf{B}}$$

Finally the sum of the technical coefficient matrix A and capital requirement matrix B gives us the total requirement of capital and non-capital goods for production. The Augmented Leontief Inverse can be calculated as:

$$\mathbf{L}^{\mathbf{K}} = (\mathbf{I} - (\mathbf{A} + \hat{\boldsymbol{\delta}}\hat{\mathbf{B}}))^{-1}$$

Here **I** is the Identity matrix and the capital requirements matrix **B** is multiplied by the matrix of annual depreciation rates.

Södersten et al. (2018a) highlight the difference between the common Leontief Matrix and this new/augmented Leontief Inverse $\mathbf{L}^{\mathbf{K}}$. The common Leontief Inverse **L** explains the total direct and indirects requirement of intermediate inputs for production and the augmented Leontief Inverse $\mathbf{L}^{\mathbf{K}}$ explains the total requirement of all direct and indirect goods (including capital inputs) for production.

3.5 Estimating the Carbon Footprint

Here we expand the augmented (capital endogenous) I-O model to an environmentally extended I-O model. The environmental extensions matrix of GLORIA(The QT matrix) provides the total direct impacts of production on extensions like Greenhouse gas (GHG) emissions, CO_2 emissions, labour use, etc. Guilhoto (2021) explains the process of estimating the carbon footprint. First, The vector of **CO_2 emissions $\mathbf{f_i}$** which contains the CO_2 emissions of industries is extracted from the QT matrix and divided by the total output $\mathbf{x_i}$. The resulting 'stressor' vector $\mathbf{s_i}$ explains the CO_2 emission intensity of industries.

$$\mathbf{s_i = f_i / s_i}$$

The above equation for matrices instead of vectors is :

$$\mathbf{s = f(\hat{x})^{-1}}$$

The consumption based CO_2 emissions **q** can be calculated as:

$\mathbf{q = sLy}$ where y is the final demand vector.

Södersten et al. (2018a) call this the 'Consumption based emissions of final demand without capital endogenization'. This estimation of the carbon footprint lacks the sectoral resolution of emissions, i.e., the consumption based CO_2 emissions of each sector due to final demand. Södersten et al. (2018a) achieve this by diagonalizing the final demand y:

$$\mathbf{q= sL\hat{y}}$$

Since the augmented Leontief Inverse $\mathbf{L^K}$ explains the requirement of direct and indirect goods (including capital inputs) for production, it would be interesting to look at a more accurate consumption based CO_2 emissions $\mathbf{q^K}$ using the $\mathbf{L^K}$.

$\mathbf{q^K = sL^K y}$

Södersten et al. (2018a) call this the 'Consumption based emissions of final demand with capital endogenization'. As above, replacing $\mathbf{y}$ with $\mathbf{\hat{y}}$gives us a vector which explains the consumption based CO_2 emissions of each sector due to final demand based on $\mathbf{L^K}$:

$\mathbf{q^K = sL^K \hat{y}}$

However, as Södersten et al. (2018a) point out, $\mathbf{L^K}$ serves the purpose of capital endogenization (by endogenizing GFCF here) in the input-output model. Hence the GFCF element should be removed from the final demand y. This can be labelled the 'adjusted final demand' represented by $\mathbf{y^*}$.

$\mathbf{q^{K*} = sL^K y^*}$

This explains the 'Consumption based emissions of final demand with capital endogenization adjusted for GFCF'. Again, diagonalizing the adjusted final demand y* gives us the sectoral resolution for the same :

$\mathbf{q^{K*} = sL^K \hat{y}^*}$

Södersten et al. (2018a) find that $\mathbf{q^K}$ is significantly larger than $\mathbf{q}$ due to the capital endogenization of GFCF. However, since the final demand at this stage of calculation of $\mathbf{q^K}$ also contains GFCF, the larger magnitude of $\mathbf{q^K}$ is due to capital endogenization of GFCF but also possibly due to the overestimation of GFCF as capital inputs and as a part of final demand. The more accurate picture is given by $\mathbf{q^{K*}}$. Södersten et al. (2018a) hypothesise that $\mathbf{q^{K*}}$ and $\mathbf{q}$ shall not match and end up finding multiple instances of $\mathbf{q^{K*}} < \mathbf{q}$ for the set of countries examined (including India). A more detailed discussion on this is included in the results section.

Since the aim of this study is to estimate the carbon footprint[6] of India, the above exercise done for CO_2 emissions is repeated step by step for GHG emissions. It will be interesting to note if the GHG emissions follow the trends of CO_2 emissions as it forms close to 70% of GHG emissions. (World Meteorological Organization).

[6] As highlighted in the Literature review, the carbon footprint refers to GHG emissions calculated in terms of CO_2.

4. Results

The results presented here are as follows:
A small section discussing the observations for the total requirements matrix with capital endogenization L^K and the total requirements matrix L
Then, the results of Consumption Based CO_2 emissions of final demand of India with capital endogenization ($\mathbf{q}^K$) and without capital endogenization ($\mathbf{q}$) are discussed at the economy level, followed by the results of Consumption Based GHG emissions of final demand (the carbon footprint) of India with and without capital endogenization.

Then, the Industry level Consumption Based CO_2 emissions of final demand with and without capital endogenization are discussed (CO_2 emissions disaggregated by industries), followed by the same for GHG emissions.

Next section of the results compare the consumption based CO_2 emissions of final demand with capital endogenization adjusted for GFCF ($\mathbf{q}^{K*}$) and the same without capital endogenization ($\mathbf{q}$) at the economy level. The same comparison for GHG emissions follows. Finally, the industrial breakdown of the CO_2 and GHG emissions adjusted for GFCF are discussed.

4.1 Observations on Leontief Inverses L and L^K

For each of the estimated Leontief Inverses (augmented for capital and traditional), the total requirement matrices L^K for the years (2011-23) had a higher multiplier than L, meaning that the direct and indirect impacts on the economy of a change in final demand for each sector as calculated for L^K were higher than that of L[7].
This result was expected as capital endogenization adds capital inputs to the requirement matrix L to form the matrix L^K. There is no better way to compare or

[7] Not every element of L^K was higher than L which is possible due from the matrix algebra methods and also due to the reallocation of direct and indirect requirements among the sectors with the inclusion of capital inputs.

present the effect of L and L^K than to compare their footprints as done in the following sections as each of them are large matrices with 120x120 elements.

4.2 Consumption Based estimations of emissions owing to final demand of India with and without capital endogenization

4.2.1 Consumption based CO_2 emissions with ($\mathbf{q}^K$) and without ($\mathbf{q}$) capital endogenization

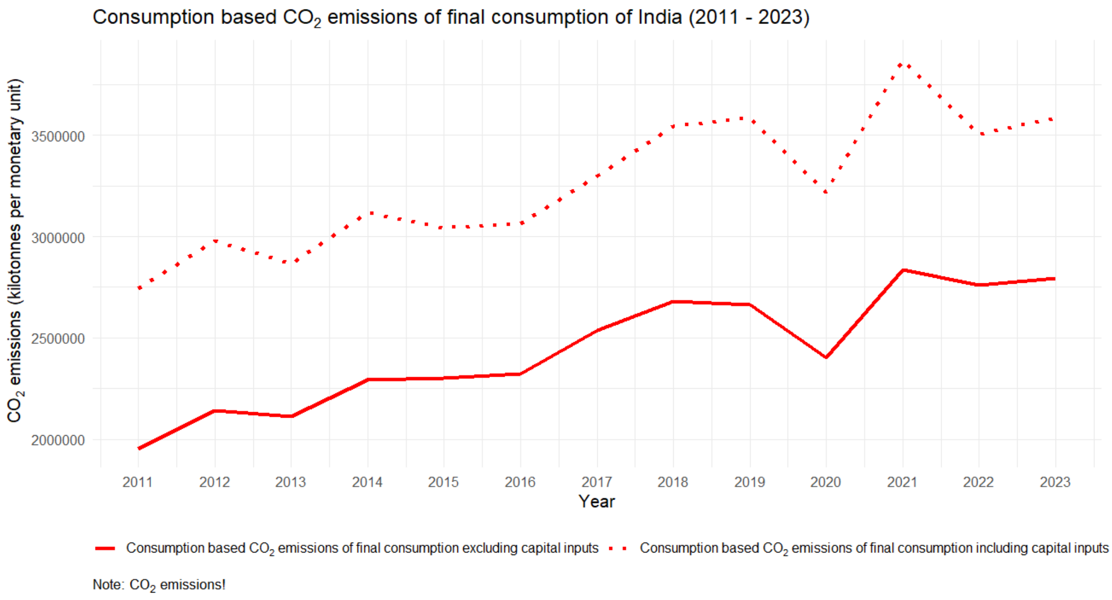


Fig (3) : Consumption Based CO_2 emissions of final demand of India with ($\mathbf{q}^K$) and without ($\mathbf{q}$) capital endogenization

The Fig (3) confirms the expectation of Consumption Based CO_2 emissions of final demand for India with capital endogenization ($\mathbf{q}^K$) being much higher than the same without capital endogenization ($\mathbf{q}$).

There is an overall increasing trend of CO_2 emissions (with and without endogenizing capital) for the observed years 2011-23 indicating that as a developing country, with the highest population, India's goal of reducing CO_2 emissions is far .

The most pronounced dip in the CO_2 emission levels is observed for the year 2020 explained by one of the world's strictest lockdown policies implemented by India due to the pandemic. However, there is a quick jump in the emission levels for 2021 owing to pent-up demand and rapid economic recovery. The percentage increase in the CO_2 emissions from capital endogenization for 2011 is 40.46% and for 2023 is 28.30%

4.2.2 Consumption based GHG emissions with and without capital endogenization

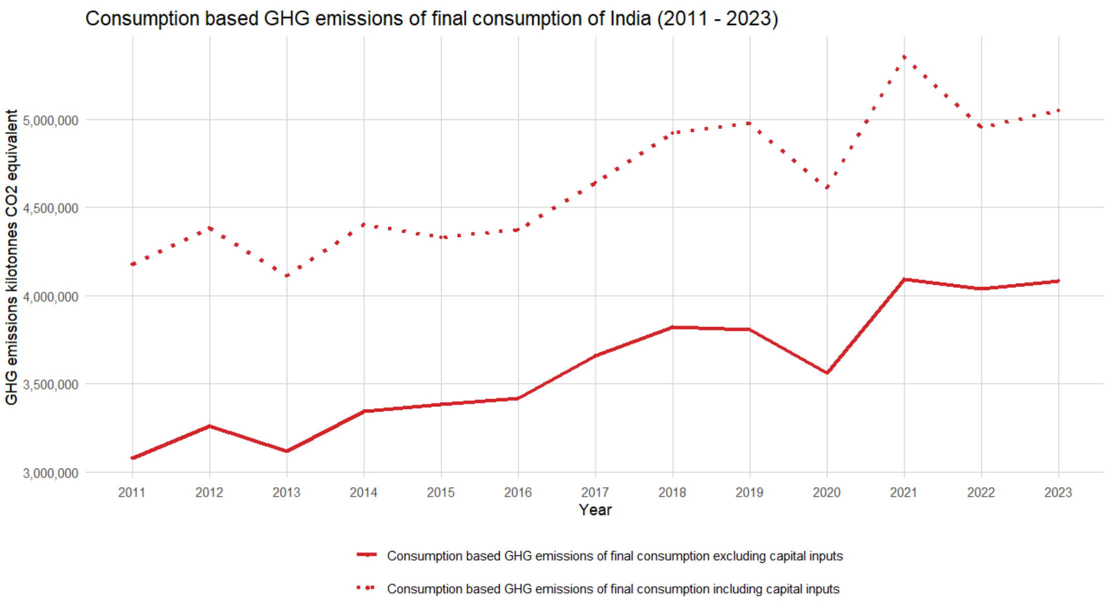


Fig (4) : Consumption Based GHG emissions of final demand of India with and without capital endogenization

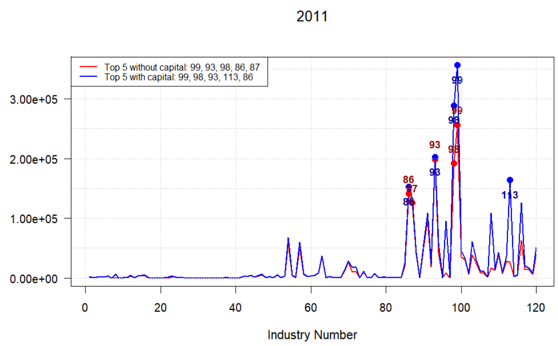
The Fig (4) showing the Carbon footprint/Consumption Based GHG emissions of final demand for India with and without capital endogenization follows the trend of the CO_2 emissions as depicted in Fig (3). This observation does not come as a surprise. Since the share of CO_2 in the GHGs is the highest, the trends of GHG emissions would be in line with those of the CO_2 emissions. Thus, there is an overall increasing trend of GHG emissions (with and without endogenizing capital) for the observed years 2011-23. The most pronounced dip in the GHG emission levels is observed for the year 2020[8] and a bounce back for 2021 due to economic recovery post pandemic, highlighting the correlation between economic activity and emission levels. The percentage increase in the carbon footprint (GHG emissions) from capital endogenization for 2011 is 35.74% and for 2023 is 23.71%.

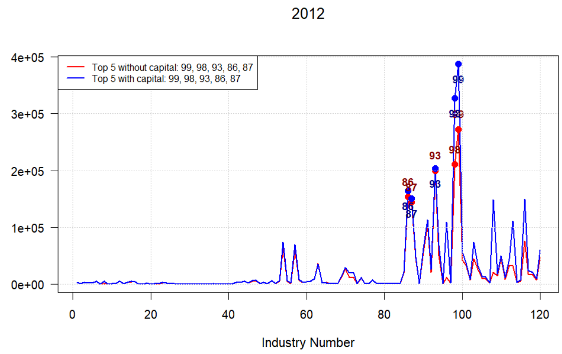
Södersten et al. (2018b) note that among the 22 analysed countries in their study, India had a substantially higher share of the global carbon footprint than its share of global GFCF. Based on which suggest that a trend of accelerated increase in emissions can be expected as less-developed countries reach higher levels of development.

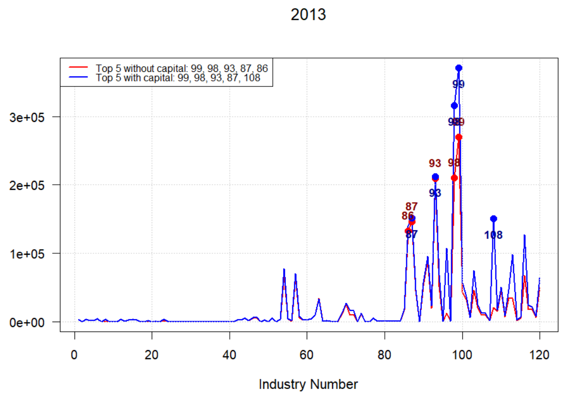
4.3 Industry level breakdown of Consumption Based estimations of emissions owing to final demand of India with and without capital endogenization

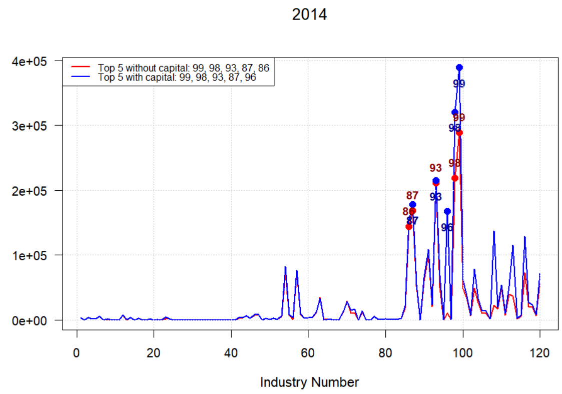
4.3.1 Industrial CO_2 emissions with ($\mathbf{q}^K$) and without ($\mathbf{q}$) capital endogenization

[8] Due to the pandemic lockdowns

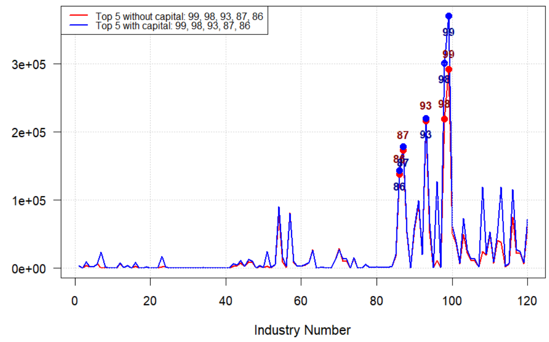

2011
Top 5 without capital: 99, 93, 98, 86, 87
Top 5 with capital: 99, 98, 93, 113, 86
3.00e+05
2.00e+05
1.00e+05
0.00e+00
0
20
40
60
80
100
120
Industry Number


2012
Top 5 without capital: 99, 98, 93, 86, 87
Top 5 with capital: 99, 98, 93, 86, 87
4e+05
3e+05
2e+05
1e+05
0e+00
0
20
40
60
80
100
120
Industry Number

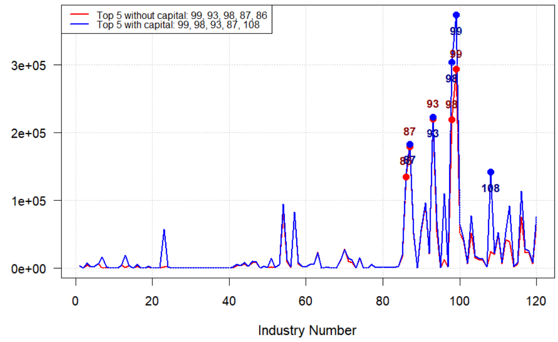

2013
Top 5 without capital: 99, 98, 93, 87, 86
Top 5 with capital: 99, 98, 93, 87, 108
3e+05
2e+05
1e+05
0e+00
0
20
40
60
80
100
120
Industry Number


2014
Top 5 without capital: 99, 98, 93, 87, 86
Top 5 with capital: 99, 98, 93, 87, 96
4e+05
3e+05
2e+05
1e+05
0e+00
0
20
40
60
80
100
120
Industry Number

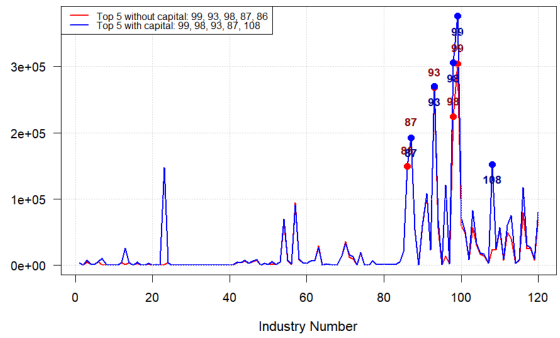
2015



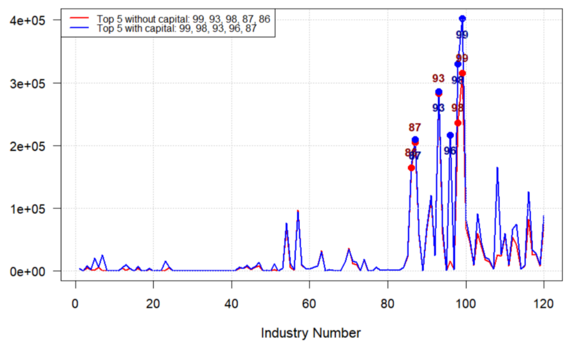
2016

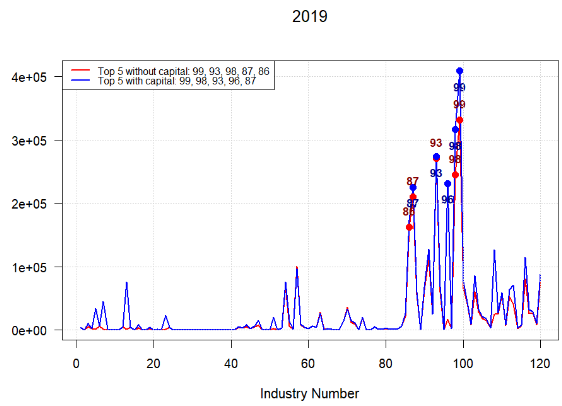


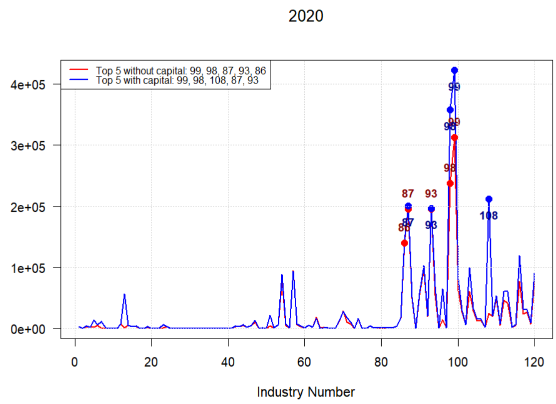
2017

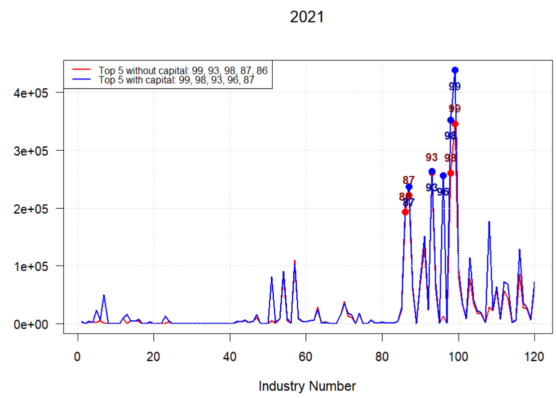


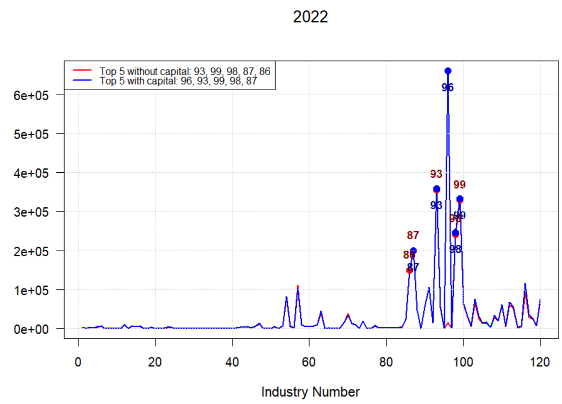
2018




2019
Top 5 without capital: 99, 93, 98, 87, 86
Top 5 with capital: 99, 98, 93, 96, 87
Industry Number


2020
Top 5 without capital: 99, 98, 87, 93, 86
Top 5 with capital: 99, 98, 108, 87, 93
Industry Number


2021
Top 5 without capital: 99, 93, 98, 87, 86
Top 5 with capital: 99, 98, 93, 96, 87
Industry Number



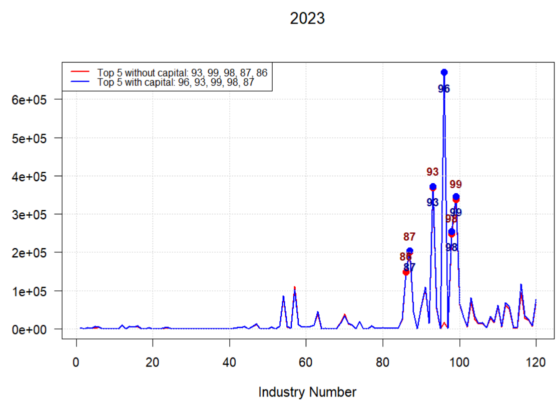


Fig (5) : Consumption Based Industrial CO_2 emissions of final demand of India with ($\mathbf{q}^K$) and without ($\mathbf{q}$) capital endogenization. The X axis with the label 'Industry Number' from 1-120 corresponds to the 120 GLORIA sectors/industries. The Y axis in all the graphs corresponds to CO_2 emissions in kilotonnes. The blue lines explain ($\mathbf{q}^K$) with sectoral resolution and red lines correspond to ($\mathbf{q}$) with sectoral resolution.

The overall sectoral resolution conveys a similar message as the economy level trend. The Consumption Based CO_2 emissions of final demand for each industrial sector is higher with capital endogenization than without it. It is worth noting that here Consumption Based CO_2 emissions of final demand with ($\mathbf{q}^K$) contains endogenous GFCF as inputs as well as GFCF as a part of final demand. The blue and red lines of the graph representing the capital endogenous emissions level and otherwise respectively, either overlap for many sectors or the blue lines overtake the red lines. This can be interpreted as follows:

In case of overlaps or very minute differences between the red and blue lines, it is clear that capital endogenization doesn't affect the overall output or emission level of the sector. A reason for this could be the labour-intensive nature of the industry/sector, i.e., the industry does not use enough capital inputs in the production process that its endogenization would register a noticeable difference.

Observations of the graphs from 2011-2023 reveal that such industries are mostly towards the left hand side of the graph, i.e., with a smaller ‘industry number’ (The ‘industry number’ from 1-120 corresponds to the 120 GLORIA sectors/industries). This mostly corresponds to the industries under the agricultural sector or the sections of the manufacturing sector dealing with the processing of agricultural produce (eg: meat/vegetable/cereal products, etc). The labour intensive agricultural sector (Gowri et al, 2025) of India explains this phenomenon for the agricultural sector. Industries manufacturing the processed agricultural produce are mostly cottage industries or the Micro, Small and Medium Enterprises (MSME). Their scale of production limits their capital requirements (low capital-output ratio) explaining the results observed. Certain segments of the manufacturing sector unrelated to the agricultural sector also register the same observation, like the mining sector, which is again due to the labour intensive nature of mining in India.

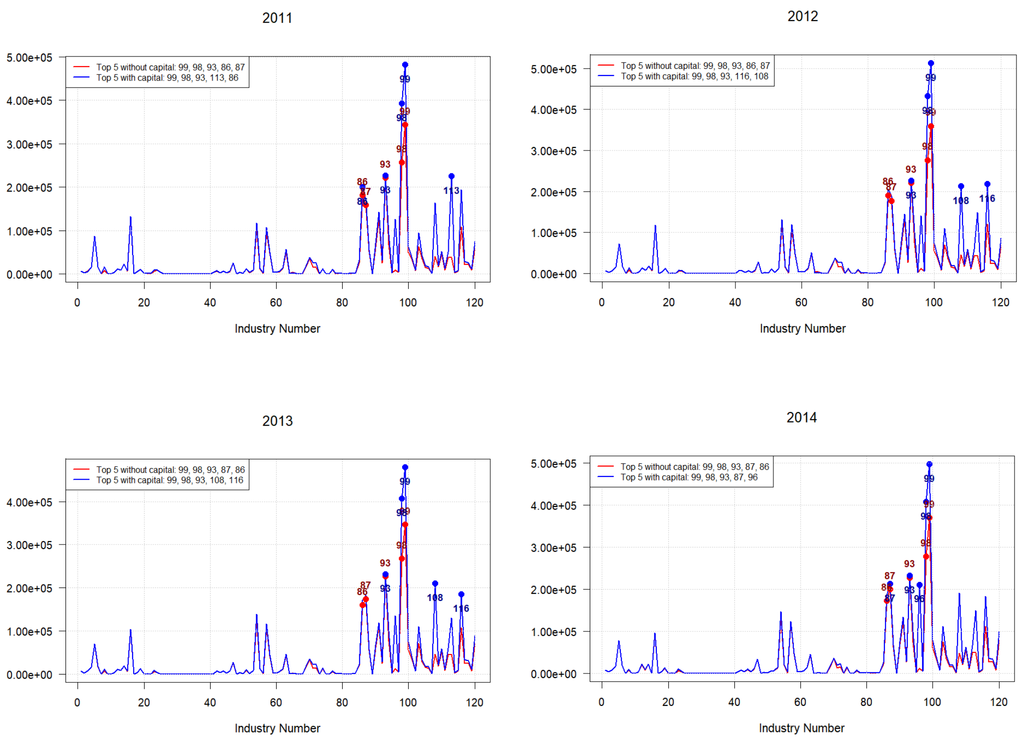
In the cases of industries capturing stark differences between CO_2 emissions with and without capital endogenization, which are – Industry 98 corresponding to ‘Building construction’ and Industry 99 corresponding to ‘Civil engineering construction’ the capital intensive mode of operation explains why capital endogenous footprint is much higher than the one without it for all the years observed. For the recent years - Industry 96 corresponding to ‘Waste collection, treatment, and disposal’ is also observing higher CO_2 emission levels with capital endogenization owing to increased capital investment due to the National Infrastructure Pipeline (NIP), Governance & Regulatory Push – 2019–2023.

In absolute terms, the industries with the highest levels of Consumption based CO_2 emissions due to final demand with and without capital endogenization over the years observed are: Industry 98 corresponding to ‘Building construction’, Industry 99 corresponding to ‘Civil engineering construction’, Industry 86 corresponding to ‘Machinery and equipment’ and Industry 87 corresponding to ‘Motor vehicles, trailers and semi-trailers’. It won’t be wrong to deduce that the Consumption based

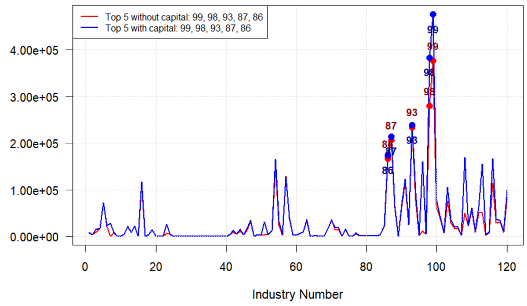
CO_2 emissions of final demand for India from the secondary sector are the highest, followed by the tertiary sector and then by the primary sector.

It must be kept in mind that an industry being labour-intensive or capital intensive doesn't indicate whether it is 'dirty' or 'clean' in terms of emissions. An example of a capital-intensive clean industry can be the 'Manufacturing of pharmaceuticals and medical products' having Industry 69. Likewise an industry can be labour intensive but have a high CO_2 emission level or a high carbon footprint. For eg : Industry 87 corresponding to 'Motor vehicles, trailers and semi-trailers' have high emission levels with and without capital endogenization indicating it is a 'dirty sector'. The results in the next sections will clarify further why the sector is 'dirty'-- due a high share of 'dirty' investments (GFCF as part of **y**) or due to a 'dirty' mode of operation.

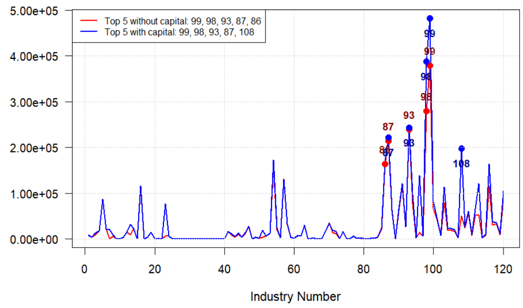
4.3.2 Industrial GHG emissions with and without capital endogenization



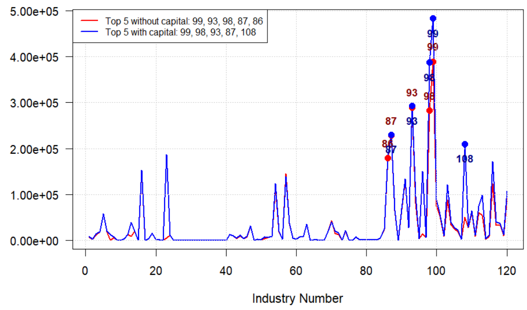
2015



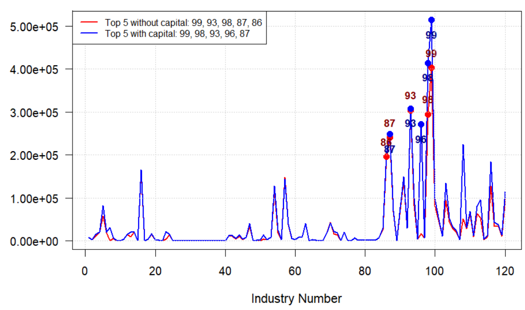
2016

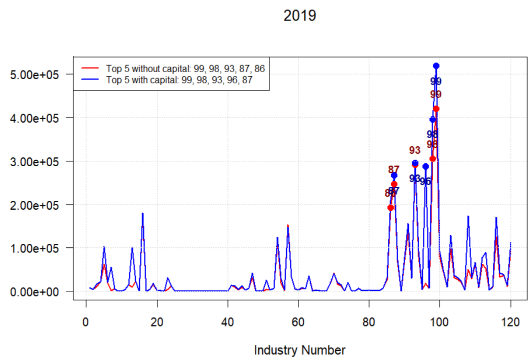


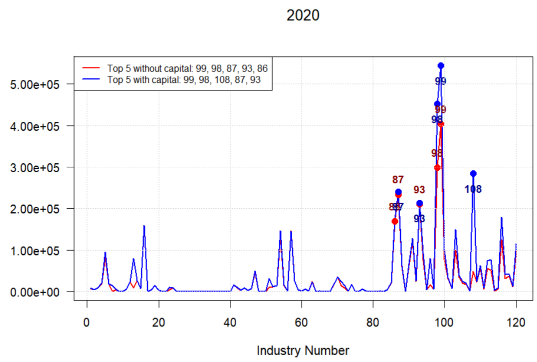
2017

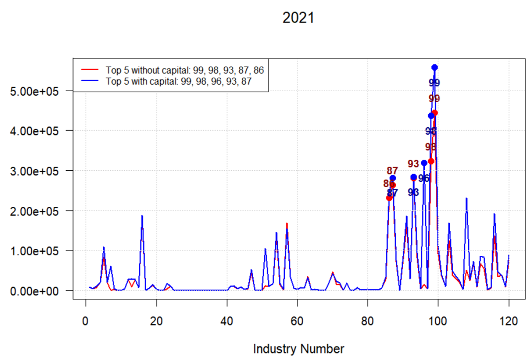


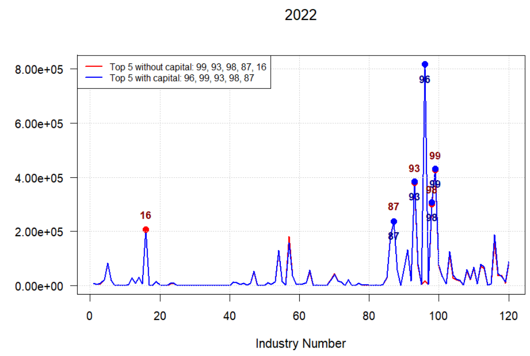
2018




2019
Top 5 without capital: 99, 98, 93, 87, 86
Top 5 with capital: 99, 98, 93, 96, 87
Industry Number


2020
Top 5 without capital: 99, 98, 87, 93, 86
Top 5 with capital: 99, 98, 108, 87, 93
Industry Number


2021
Top 5 without capital: 99, 98, 93, 87, 86
Top 5 with capital: 99, 98, 96, 93, 87
Industry Number



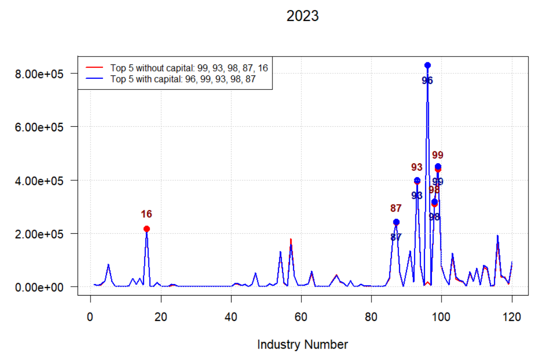


Fig (6) : Consumption Based Industrial GHG emissions of final demand of India with and without capital endogenization. The X axis with the label 'Industry Number' from 1-120 corresponds to the 120 GLORIA sectors/industries. The Y axis in all the graphs corresponds to CO_2 emissions in kilotonnes. The blue lines explain GHG emissions including capital inputs with sectoral resolution and red lines correspond to GHG emissions excluding capital inputs with sectoral resolution.

The results for this section are expectedly very similar to 4.3.1 because the trend of the Carbon footprints (GHG emissions) follows the trends of the CO_2 emissions. The most important similarity between the observations of the industry level CO_2 emissions and GHG emissions is the higher emission level with capital endogenization than without it (blue lines are higher than or equal to the red lines). The economy level policies/developments that explain these emission trends are already discussed in detail in 4.3.1 and also apply to this case.

The only difference between trends observed for GHG emissions and CO_2 emissions is that the GHG emissions for parts of agriculture sector and manufacturing sector is higher than their CO_2 emissions (higher peaks for some industries numbered between 1-60 for GHG emissions than for CO_2 emissions). The production of methane and other GHGs (except CO_2) for these sectors would drive up the carbon footprint (GHG emissions) levels but not the CO_2 emission levels. This also explains how the magnitude of GHG emission levels for the economy explained in 4.2.2 are higher than the magnitude of GHG emission levels for the economy explained in 4.2.1.

4.4 Consumption Based estimations of emissions owing to final demand of India with capital endogenization adjusted for GFCF

4.4.1 Consumption based CO_2 emissions of final demand with capital endogenization adjusted for GFCF ($\mathbf{q}^{K}*$)

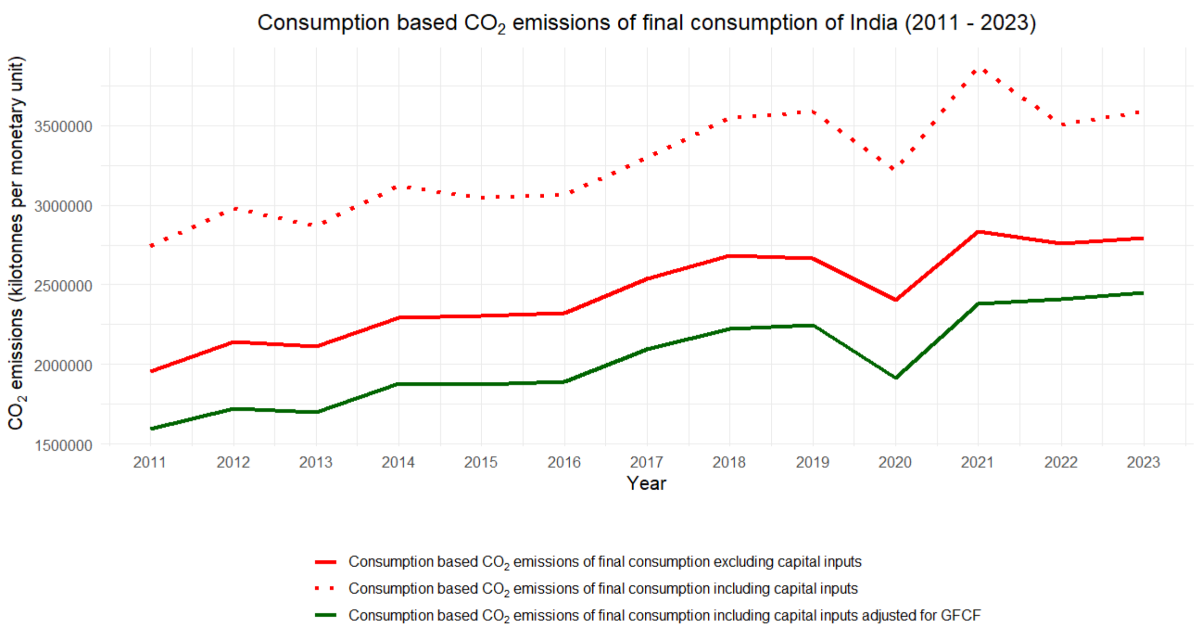


Fig (7) : Consumption Based CO_2 emissions of final demand with capital endogenization adjusted for GFCF

The more accurate picture of Consumption based CO_2 emissions with capital endogenization adjusted for GFCF is given by $\mathbf{q}^{K}*$. In line with Södersten et al. (2018a) $\mathbf{q}^{K}* < \mathbf{q}$ i.e., Consumption based CO_2 emissions of final demand with capital endogenization adjusted for GFCF ($\mathbf{q}^{K}*$) is smaller than Consumption based CO_2 emissions without capital endogenization. The only difference between $\mathbf{q}^{K}*$ and

$\mathbf{q^K}$ is that of its final demand vector (excluding GFCF $\mathbf{y^*}$ and including GFCF $\mathbf{y}$). Hence, this drop in the emission levels must account for the share of emissions of GFCF as a part of $\mathbf{y}$.

Södersten et al. (2018b) observe that countries having the lowest GDP per capita[9] (of the 22 countries analysed), have highly carbon intensive investments or GFCF. They highlight that the carbon footprint of capital goods purchased by a country is directly dependent on the way they are produced, i.e., on the electricity source of the producing country. Södersten et al. (2018b) also suggest that India falls under the group of countries with a very high share of 'dirty' assets, i.e., the share of GFCF produced by carbon intensive sources like electricity is very high.

A large share of India's electricity is produced by burning coal (IEA), which makes the domestically produced GFCF 'dirty', explaining why the carbon footprint with GFCF as a part of $\mathbf{y}$ is substantially higher than the one without it.

When we endogenise GFCF in the framework in the form of $\mathbf{q^{K*}}$ We successfully capture the capital and non-capital requirement for production of goods (with capital and non-capital nature) but we do not account for how the existing GFCF is produced.

Endogenizing a clean GFCF and a dirty GFCF might produce the the same levels of $\mathbf{q^{K*}}$ because endogenizing GFCF when calculating $\mathbf{q^{K*}}$ affects only $\mathbf{L^K}$. Dropping the entire value of GFCF from $\mathbf{y}$ to obtain $\mathbf{y^*}$ limits the possibility to account for the embedded emissions in the part of GFCF that will remain intact even after the production process is completed, because of the intertemporal nature[10] of GFCF.

Apart from the observation of $\mathbf{q^{K*}} < \mathbf{q}$, there is a general trend of increasing emissions over the years. The effect of pandemic lockdowns captured in 2020 and

[9] India is part of this group

[10] This also highlights the limitation of endogenizing GFCF discussed in the limitations section.

the subsequent economic bounce back in 2021 also hold for $\mathbf{q}^{K*}$ as in the previous graphs.

4.4.2 Consumption based GHG emissions with capital endogenization adjusted for GFCF

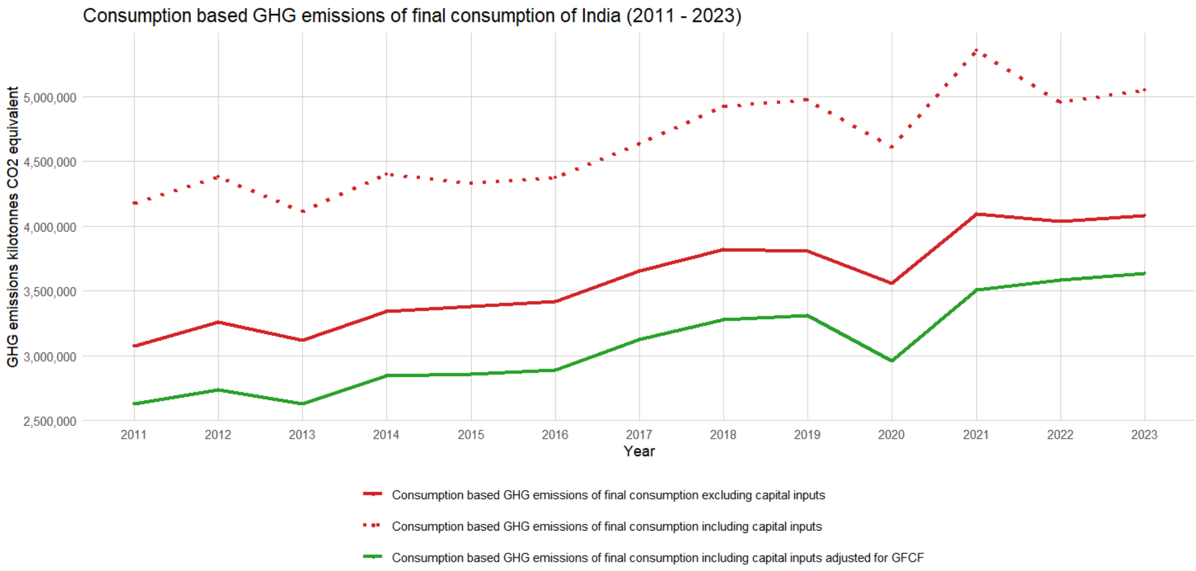


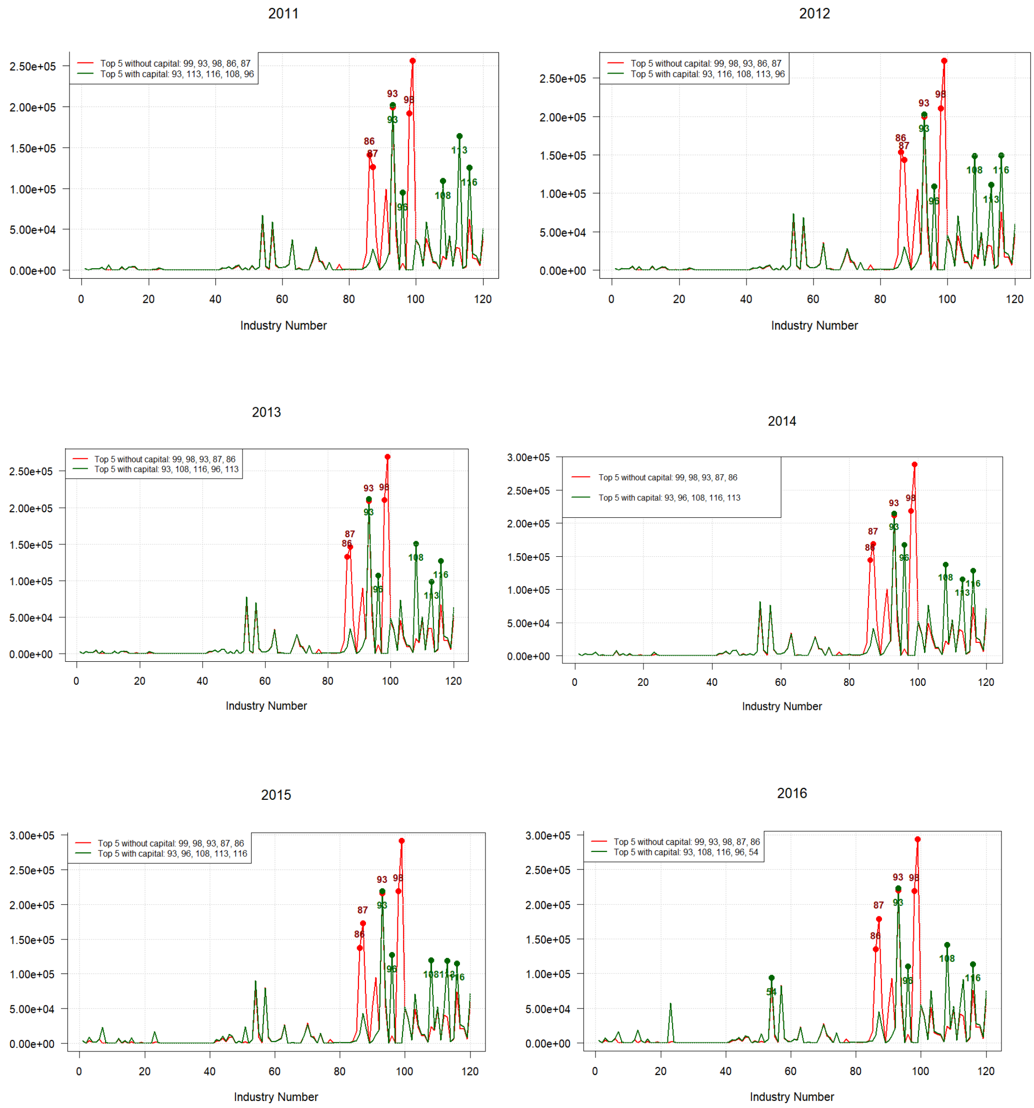
Fig (8) : Consumption Based GHG emissions of final demand with capital endogenization adjusted for GFCF

Just like the previous instances, the trend of GHG emissions is completely in line with the trend observed for CO_2 emissions. There is an overall rising trend for the carbon footprint (GHG emissions) as the economy undergoes development (Södersten et al. (2018b)). The trend for 2020 and 2021 already observed in the previous related graphs also hold for this version of the carbon footprint.

As discussed in the section above, the carbon footprint (GHG emissions) with capital endogenization adjusted for GFCF are lower than the carbon footprint (GHG emissions) without capital endogenization, due to the share of emissions of GFCF as a part of **y**. From the observations discussed above, is it clear that India's GFCF is very carbon intensive and its exclusion explains the difference.

4.5 Industry level breakdown of Consumption Based estimations of emissions owing to final demand of India with capital endogenization adjusted for GFCF.

4.5.1 Industrial CO_2 emissions with ($\mathbf{q}^{K*}$) capital endogenization adjusted for GFCF and without ($\mathbf{q}$) capital endogenization



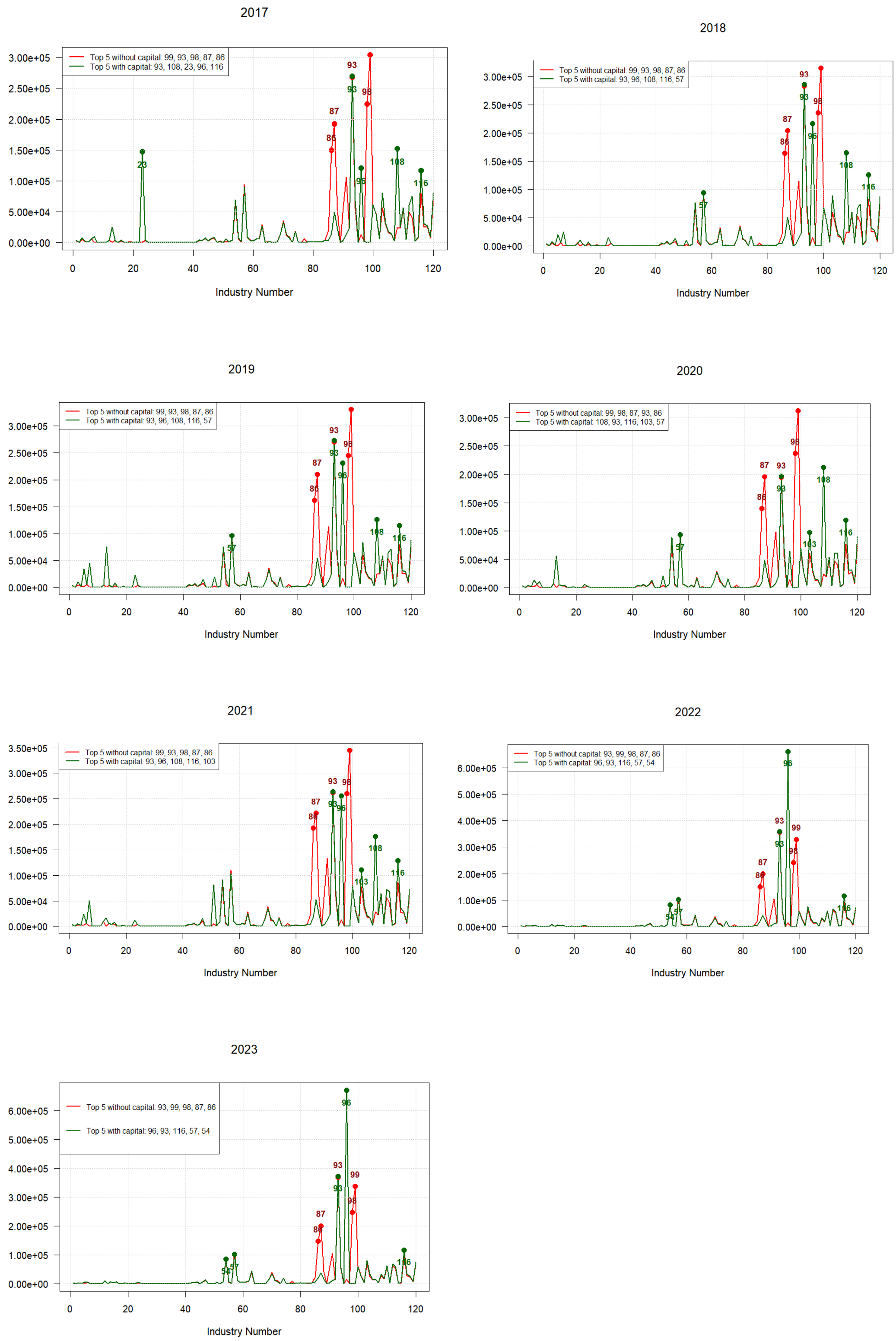


Fig (9) : Consumption Based Industrial CO_2 emissions of final demand of India with capital endogenization adjusted for GFCF ($\mathbf{q}^{K*}$) and without ($\mathbf{q}$) capital endogenization. The X axis with the label 'Industry Number' from 1-120 corresponds to the 120 GLORIA sectors/industries. The Y axis in all the graphs corresponds to CO_2 emissions in kilotonnes. The green lines explain ($\mathbf{q}^{K}$*) with sectoral resolution and red lines correspond to ($\mathbf{q}$) with sectoral resolution.

This version of CO_2 emission levels with sectoral resolution has interesting observations as it has multiple instances of overlaps between the green ($\mathbf{q}^{K}$*) and red lines ($\mathbf{q}$) and where one exceeds the other.

The overlaps between the lines indicate that for those sectors capital endogenization (endogenous GFCF as a part of L^K) does not affect its emission levels – indicating a very labour intensive mode of production. As discussed in depth in the previous sections these observations correspond mostly to the agriculture sector, cottage industries or MSME industries, etc. These industries in general have a very low level of emissions and are 'cleaner'.

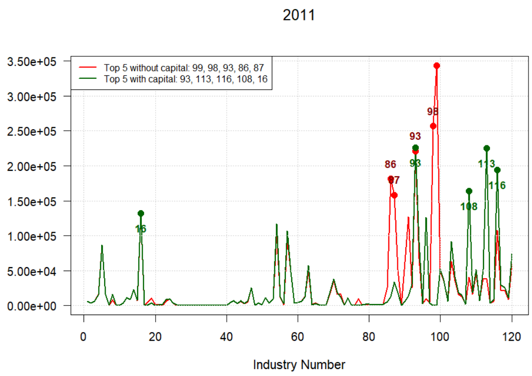
The instances in the graphs where the green lines overtake the red, i.e., the emission levels with capital endogenization are higher than without explain the capital intensive nature (endogenous GFCF in $\mathbf{L}^{K}$ embodying investment used up in production) of the industries. Dropping GFCF as a part of **y** i.e., investment as final demand doesn't affect the emission levels because the investment (GFCF) for this sector is 'clean'. The sectors with such observation over the years are – Industry 96 corresponding to 'Waste collection, treatment, and disposal', Industry 108 corresponding to 'Hospitality', Industry 113 corresponding to 'Property and real estate' and Industry 116 corresponding to 'Government; social security; defence; public order'.

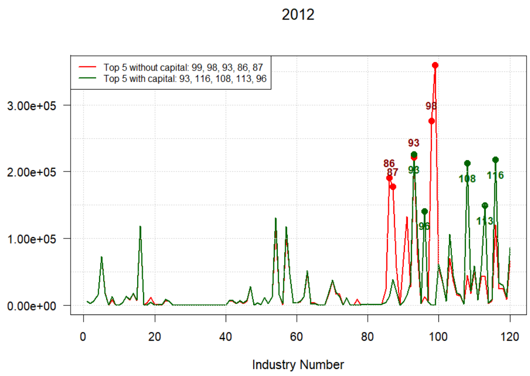
In the cases where the red graphs overtake the green ones, it means the emission levels with capital endogenization (endogenous GFCF in $\mathbf{L}^{K}$ with final demand **y***) are lower than the emissions without capital energisation (but with GFCF included in final demand **y**). This clearly indicates that GFCF as a component of final demand explains a large share of the emission levels of that industry rather than GFCF as an input in the production process. In other words, a high share of 'dirty' investments owned/purchased by the industry drives up its overall emission levels.

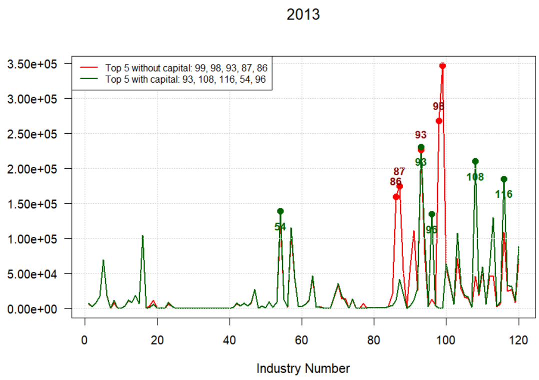
Over the years, such observations describe – Industry 86 corresponding to 'Machinery and equipment', Industry 87 corresponding to 'Motor vehicles, trailers and semi-trailers’, Industry 98 corresponding to ‘Building Construction’ and Industry 99 corresponding to ‘Civil engineering construction’.

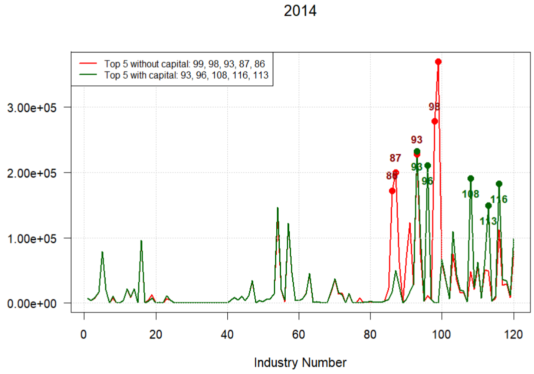
Overall, even in this instance of estimating the emission levels, the primary sector is the cleanest, followed by the tertiary sector and then the secondary sector.

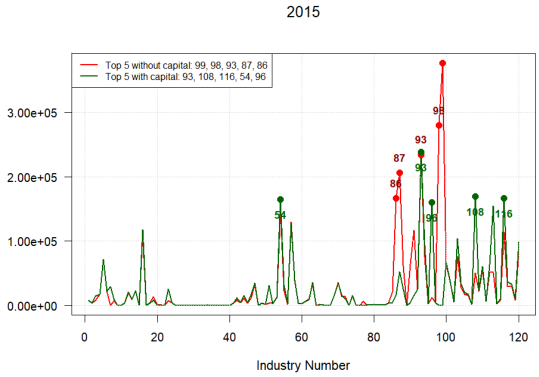
4.5.2 Industrial GHG emissions with capital endogenization adjusted for GFCF and without capital endogenization

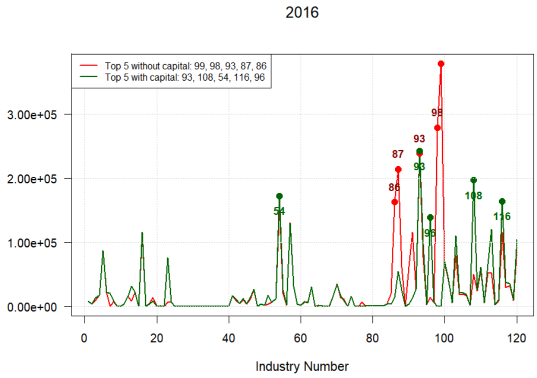


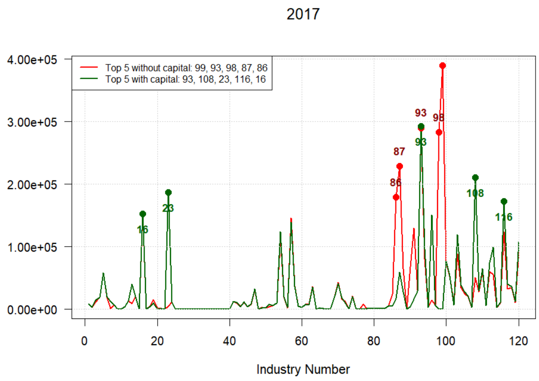




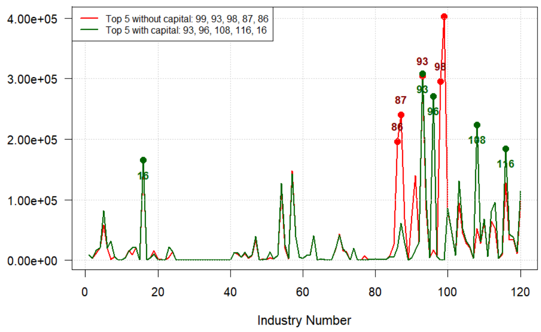

2014
Top 5 without capital: 99, 98, 93, 87, 86
Top 5 with capital: 93, 96, 108, 116, 113
Industry Number


2015
Top 5 without capital: 99, 98, 93, 87, 86
Top 5 with capital: 93, 108, 116, 54, 96
Industry Number

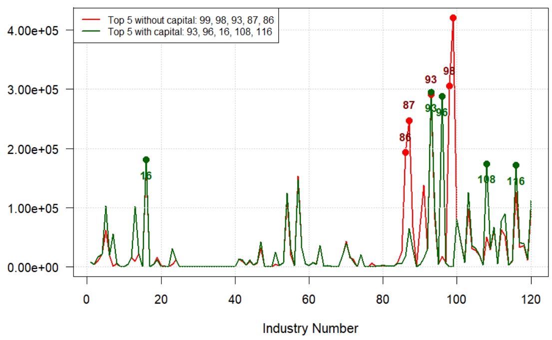

2016
Top 5 without capital: 99, 98, 93, 87, 86
Top 5 with capital: 93, 108, 54, 116, 96
Industry Number


2017
Top 5 without capital: 99, 93, 98, 87, 86
Top 5 with capital: 93, 108, 23, 116, 16
Industry Number

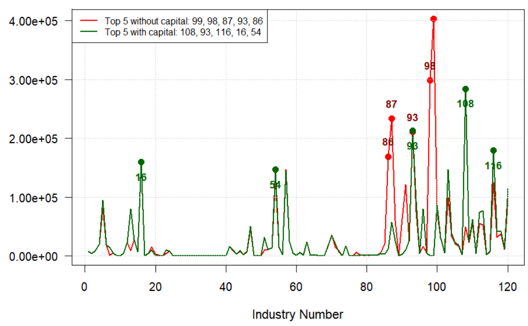
2018



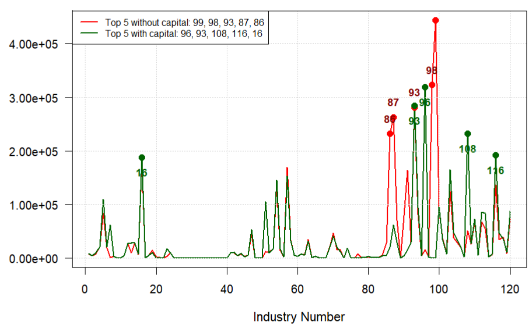
2019

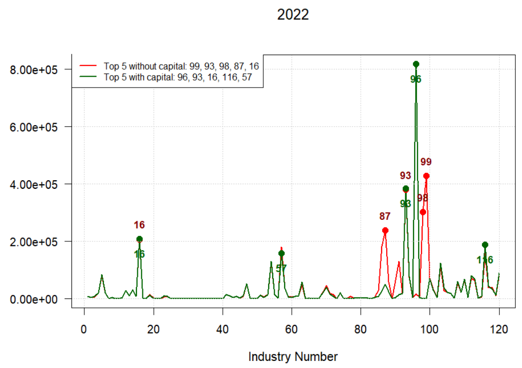


2020



2021





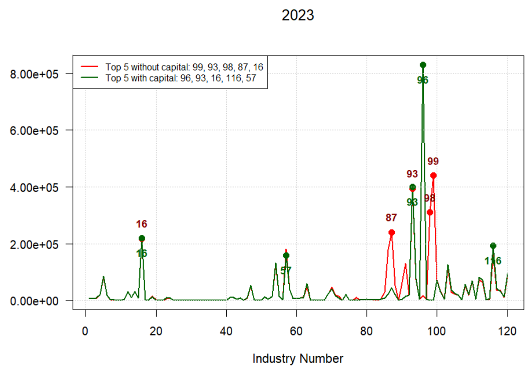


Fig (10) : Consumption Based Industrial GHG emissions of final demand of India with capital endogenization adjusted for GFCF and without capital endogenization. The X axis with the label 'Industry Number' from 1-120 corresponds to the 120 GLORIA sectors/industries. The Y axis in all the graphs corresponds to CO_2 emissions in kilotonnes. The green lines explain the emissions including capital inputs adjusted for GFCF with sectoral resolution and red lines correspond to emissions excluding capital inputs with sectoral resolution.

The results for this section can be compared with section 4.3.2 (Industry level GHG emissions for endogenous GFCF in $\mathbf{L^K}$ and as a part of final demand $\mathbf{y}$) to explain the difference in emissions pertaining to GFCF as a part of final demand, i.e., the degree of 'dirty' or 'clean' investment that constitute the GFCF of the industry. The graphs in section 4.3.2 either showcase overlaps between the blue and red lines or blue lines exceeding the red lines, it is clearly indicating Industry level GHG emissions for capital endogenization are higher than without it.
This section records instances where the red lines of the graph are significantly higher than the green lines, indicating that GFCF as a part of final demand was significant for these sectors, eg : Industry 86 corresponding to 'Machinery and

equipment', Industry 87 corresponding to 'Motor vehicles, trailers and semi-trailers', Industry 98 corresponding to 'Building Construction' and Industry 99 corresponding to 'Civil engineering construction'. The detailed reasons and comparisons are already discussed in the previous section and the economy wide policies/developments that cause these phenomenon remain the same whether we look at CO_2 emissions or GHG emissions.

The results of this section contrasted with section 4.5.1 describe the similarities in trends of CO_2 emissions and Carbon footprints (GHG emissions) which have been appropriately highlighted in the previous sections.

As it is pointed out in section 4.3.2, the only difference between trends observed for GHG and CO_2 emissions is — for parts of the agriculture sector and manufacturing sector there is a higher level of GHG emissions than CO_2 emissions. This is explicable by the production of methane and other GHGs (except CO_2) as by products from these sectors.

On an obvious note, this trend also explains how the magnitude of GHG emission levels for the economy explained in 4.4.2 are higher than the magnitude of CO_2 emission levels for the economy explained in 4.4.1.

5. Contributions

The major contributions of this project to the wider literature are listed as follows :

Academic projects undertaking the capital endogenization exercise for I-O models are not extensive and those based on developing countries are even more limited. By conducting this exercise for India, this project adds diversity to the existing literature.

The KLEMS initiative is a project aimed at providing harmonised granular data on output, capital, labour, energy and materials for the EU and the World. The database provides granular data for advanced economies (given that the initiative was initially EU based only) and for the rest of the world. The project still has a constrained dataset for the developing countries and the capital use matrices based on it (explaining the consumption of capital inputs at the interindustry level) are readily available only for some developed countries and are compatible with EXIOBASE database.

The aim of capital endogenization for India is achieved by the construction of these capital-use matrices for India compatible with the more detailed GLORIA MRIO database based on the KLEMS data. These matrices explain the usage of capital inputs by different industry types for the GLORIA MRIO database and can be used for future analysis like Tausch and Magacho (2024) for the Indian context.

As established in this manuscript early on, Södersten et al (2018b) find India's share of carbon intensive GFCF very high but chose to endogenise CFC as per the methodological norms for carbon footprint type analysis. But endogenizing CFC hardly explains how the embedded carbon emissions of GFCF add to the emissions by industry as inputs to production. This study complements the Södersten et al (2018a) analysis based on the results of Södersten et al (2018b) by estimating the same carbon footprints but by endogenizing GFCF.

The study successfully identifies the industries with the most and least carbon intensive capital assets. The industries with the most carbon intensive capital assets are – The Building Construction industry, The Civil Engineering Construction industry, Machinery and equipment sector and Motor vehicles, trailers and semi-trailers industry. The industries with the least carbon intensive capital assets are – 'Waste collection, treatment, and disposal', 'Hospitality', 'Property and real estate' and 'Government; social security, defence and public order'. The industries with the lowest carbon emissions levels are mostly from the agricultural sector, cottage industries or the Micro, Small and Medium Enterprises (MSME), their labour-intensive nature of production in India explain their emissions levels and why capital endogenization doesn't increase their footprint significantly.

6. Discussion

Apart from the above methodological contributions, the results of the project can also be used as inferences for shaping policies -

India's GDP is worth 3.57 trillion USD at current prices (2023) and witnessed a high rate of growth, around 8% in 2023-24 (World Bank Data). India has recently overtaken Japan in terms of absolute GDP to become the fourth largest economy in the world and has the highest population burden of the world. Despite the impressive numbers, India is still on its path to become a 'developed' nation and have an upper-middle income level as a country.

As the world gears for the green transition by aiming to lower the global emission levels (IPCC, 2022) India's rising trend of total CO_2 emissions and GHGs emissions gives a gloomy picture. However, the key takeaway from this study is that there is a relative decline in the estimated emissions levels : The percentage change in CO_2 emissions from capital endogenization for 2011 is +40.46% and the same for 2023 is +28.30%. This explains that despite an overall rising trend of CO_2 emissions, there is a relative decline in the rise of CO_2 emission levels. The percentage increase in the carbon footprint (GHG emissions) post capital endogenization for 2011 was 35.74% and for 2023 was 23.71%. Yet again, there is a relative decline in the increase of GHG emissions but the decline in GHG emissions is not as pronounced as it was for CO_2 emissions indicating the rise in the emissions of other GHGs.

As per Södersten et al (2018b) India's share of carbon intensive GFCF is very high (due to resource intensive investments for the development of primary infrastructure like roads, highways, etc) and as it develops further, the emission levels are expected to rise until it reaches a developmental stage where its needs of carbon-intensive GFCF drops down.

With fairer accounting systems that estimate a more realistic footprint, inclusion of capital inputs in production give us the disappointing results of an increasing carbon footprint. The results of this study also find that both CO_2 emissions and GHG emissions for India have been increasing in recent years. Another crucial finding is that India's most carbon intensive sector is the Secondary sector and the most carbon-intensive industries are – 'Machinery and equipment', 'Motor vehicles, trailers and semi-trailers', 'Building Construction' and 'Civil engineering construction'.

Given its economic prowess, India would inevitably shape the green transition directly and indirectly, for which it needs to take the path of green growth to ensure development, but in a climate sensitive manner. Although the idea of development and progress for developing countries has become synonymous with industrial expansion which results in higher emissions, this norm needs to change. This requires fundamental changes in current economic thought like redefining what 'development' means and looks like – whether development at the cost of ecological degradation can actually be considered development? Is growth really the answer to all economic problems, especially in the case of developing countries like India. It is evident that such systemic change cannot happen overnight but is a rather slow process of assimilation of critical, heterodox ideas in the current economic systems.

The advanced economies that underwent similar development stages did not experience the climatic and ecological constraints that grapple the developing world today. Tausch and Magacho (2024) highlight how the ecological transition adds to the socio-economic constraints of developing countries. Because the technological inputs necessary for the low-carbon transition are imported from advanced foreign economies, a significant share of investment spending is lost to exports from the advanced economies. Even though systemic change is a long-term undertaking, in the short term, the advanced economies need to engage in green-technological alliances with the developing world to devise climate friendly methods of advancement. This should not be viewed as a philanthropic contribution of advanced economies, but rather as partnerships for a sustainable future of our planet and the harmonious coexistence of humans in the natural environment. Such alliances can result in the form of circular economy measures, cosmolocal initiatives like the Tzoumakers (Papadimitropoulos, 2024), Solar photovoltaic installations on rooftops and research collaborations. From a more business oriented standpoint, the economic alliances can function in a way where advanced countries make investments in green businesses in the developing countries. For example a circular economy initiative from India ‘Phool.co’ collects tons of flower waste every day from rivers in India and turns it into incense sticks, funding and replicating such business models can expedite the global green transition. This would present another challenge to expand I-O models to examine the case circular economies, which is beyond the scope of discussion for this project.

On the national level, India needs to gradually pivot from carbon intensive investments to greener alternatives in a way that doesn’t trigger capital stranding cascades (Cahen-Forout et al, 2021). Meaning that the installed carbon intensive investments (GFCF) must be slowly phased out and repurposed for greener activities (like a carbon intensive building structure nearing demolition can be furnished for vertical farming or plant-based food production). At the same time, fresh investment in industries must become less carbon intensive over time.
To tackle the emissions embedded in GFCF, India must focus on harnessing the capacity to generate solar energy and move away from fossil based electricity generation that results in a ‘dirty’ GFCF.

The current carbon intensive sectors, especially the construction sectors and machinery and equipment industry, should be allocated ‘green funds’ by the government (or the technological alliances with advanced countries) for switching to greener technologies and for research and development purposes.

7. Limitations

The limitations section is divided into two major subheads focussing on the limitations of Leontief Input-Output (I-O) models and the methodology used for this research.

7.1 Limitations Based on the Leontief I-O framework

Despite the popularity and extensive functionality of Leontief Input-Output (I-O) models the framework suffers from several drawbacks :

- The assumption of Fixed Technical Coefficients (No Substitution) : The technical coefficients under the input-output model refer to – the worth of inputs from industry 'i' required to produce a dollar's worth of output by industry 'j'. This relationship between industries is fixed due to linear production function and requires fixed technical coefficients between sector 'i' and sector 'j' to remain the same, implying constant returns to scale. For analyses like (Leontief, 1936; Miller & Blair (2022).

- Requirement of highly granular datasets : For environmental extensions like carbon footprint analysis, I-O models rely on regionally aggregated emissions data leading to significant uncertainties (Peters et al., 2011). In case of an MRIO analysis, it is even more difficult to find data harmonized for cross border inconsistencies. However, with the availability of detailed databases like GLORIA, EXIOBASE, EORA, this limitation can be easily bypassed.

- Static Framework : I-O models are inherently static which means that they can describe interindustry economic relationships for a fixed point in time but not the evolutions of interindustry relationships or dynamic changes in the economy.

I-O models also suffer from the lack of behavioral realism as it does not account for consumer preferences, technological diffusion, and policy feedback (Wiedmann, 2009). Some other limitations include the assumption of linear technology, homogeneity of Outputs, exogenous final demand and lack of price mechanisms.(Madlener and Koller, 2007)

7.2 Limitations Based on the Methodology

- Steady state assumption

Like Södersten et al. (2018a) the model assumes a steady-state economy for all the years of analysis and that each component GFCF consumed in the production process is replaced in the same year by the same technology.

- The intertemporal nature of GFCF

One of the most crucial limitations of the studies like this one, aiming to endogenize GFCF as a method of endogenizing capital in input-output models, is the inability to account for the intertemporal nature of fixed capital assets (GFCF). The methodological limitations lead to this fallible assumption that the current GFCF is produced using the current technology, production structure and is valued in the present currency, despite the overwhelming evidence of a historic process of production and technology used to construct the fixed assets functioning in the present (Wu et al., 2021). Endogenizing GFCF implies that all emissions from capital formation are allocated to current final consumption disregarding that capital goods are used for a period of more than a year. (Södersten et al (2018a))

Fixed capital assets once purchased and installed, get used up in the production of other goods over a timespan of several years. Accounting for it as an input in the production process for one production cycle (say, one year) in the framework ignores the fact that owing to its intertemporal nature, a part of the same GFCF shall again contribute as an input for the next cycle, which means that for the first cycle, a part of GFCF is used as an input and a part of it remains as the final demand (investment) for that year. Hence, while estimating the carbon footprints the $\mathbf{q}^{\mathbf{K}}$ version overestimates the footprint of GFCF as it is included in both the augmented leontief inverse $\mathbf{L}^{\mathbf{K}}$ and as final demand $\mathbf{y}$. On the other hand, $\mathbf{q}^{\mathbf{K}*}$ version overestimated the footprint of GFCF as part of the augmented leontief inverse $\mathbf{L}^{\mathbf{K}}$ and completely neglects the part of GFCF that remains intact even after the current production cycle in the form of investment.

- Emissions embedded in GFCF

Another major drawback is the inability to estimate the embedded emissions in the GFCF that exists in the current production process but was produced from previous productive structures. Södersten et al. (2018a) and Gao et al (2020) mention that the consumption based emissions estimated, do not account for embedded emissions in capital goods (present in the current production structure) to the goods and service produced from this capital input, even though their share of total emissions is substantial.   Södersten et al. (2018b) highlight that India has a very high share of 'dirty' GFCF owing to the method of production of the capital goods, like electricity generated from burning coal.

The current literature on this topic has highlighted an alternative way of accounting for capital in the production process through 'capital services' (explaining the flow of productive service from capital assets to the production process) Ahmad (2004). However, there is neither academic consensus on the ways to implement this method nor availability of such granular data for many countries.

- Effect of economic fluctuations

Endogenizing GFCF may further overestimate emissions attributed to final demand during periods of rapid growth because investment allocations are more sensitive to extreme economic events. The extreme economic events in the period of analysis was the pandemic and the related lockdowns causing a slump in production and investment. This resulted in a noticeable fall in the footprint calculations for 2020.

- CFC or GFCF - the endogenisation dilemma

There are multiple studies that endogenise capital in Input-Output models by endogenizing the consumption of fixed capital CFC rather than GFCF. (Södersten et al (2018a)), (Xu et al. (2023)) Despite the drawbacks of endogenization of GFCF discussed above, CFC (depreciation) merely accounts for the loss in the value of capital assets as a result of expected obsolescence. It does not explain how the capital inputs are used in the production process.

- The depreciation rate for assets

Since the depreciation rates for each KLEMS asset type is not readily available for India, the depreciation rates used in the project are based on the EU KLEMS & INTANProd (Bontadini et al 2023). The rates are more suited to their target EU countries and might incorrectly estimate the depreciation of capital assets for India.

7.3 Scope for improvement

Following the footsteps of Södersten et al. (2018a) the matrix calculation from this method merges the capital and noncapital requirements leaving a uniform total requirement matrix $\mathbf{L}^{\mathbf{K}}$ for the calculation of the environmental footprint. They suggest that the current model can be improved by differentiating between capital and noncapital goods when applying the environmental extensions, so that it is possible to account for embedded emissions in the capital goods currently in use.

This study also suffers from this limitation, but dividing the non-capital and capital stock seems incomplete. The notion of dividing the total requirements in three units - non-capital requirements, capital stock used up in production and capital stock at the end of year for calculating the environmental footprint can be explored in future projects.

8. Conclusions

The aim of this project was to study the effect of capital endogenization within the Input-Output framework on the carbon footprint of India in recent years. The study uses the flow matrix method of capital endogenization based on Lenzen and Treloar (2004) to capture the inter-industry consumption of capital inputs in the production process. Even though India is not a capital intensive country, Södersten et al (2018b) show that its share of global carbon footprint is higher than its share of global fixed capital assets, indicating the carbon intensive nature of the production of fixed capital in India. Capital endogenization in the Input-Output framework provides the avenue to capture these embedded emissions of the fixed capital assets that produce goods for the economy and gain a realistic picture of emission levels of the country.

The research questions examined are - What is the effect of capital endogenization in the Input-Output models, on the carbon footprint estimation for India over the time period (2011-2023)? How does the total requirements matrix L^K (Leontief Inverse augmented to include capital inputs) compare to the total requirements matrix L (Traditional Leontief Inverse excluding capital inputs)? How different are the CO_2 emission levels from the GHG emissions levels for India over the analysed period?

To provide an answer to these questions, the study follows the methodology of capital endogenization by Södersten et al (2018a) and Tausch and Magacho (2024) to estimate the capital use matrices for India in the GLORIA MRIO framework based on the KLEMS capital-use tables. We end up with a matrix of total requirements that explains the direct and indirect inputs (including capital inputs) required by one sector from another sector to produce one unit of its output. Finally, to estimate the carbon footprint we expand the I-O framework to include environmental extensions and use the total requirements matrix to estimate the emission levels of CO_2 and GHG emission for the analysed period. To get a more comprehensive view of the emission levels, we break down the total emissions trends to get the industry level emissions for India. To analyse only the role of GFCF in emissions levels of various sectors, we compare the capital endogenous emissions without GFCF and non-endogenous emissions including GFCF.

The most important result from this study is the estimated increase of emissions levels : The percentage change in CO_2 emissions levels post capital endogenization for 2011 is +40.46% and the same for 2023 is +28.30%. This explains that despite an overall rising trend of CO_2 emissions, there is a relative decline in the rise of CO_2 emission levels. The percentage increase in the carbon footprint (GHG emissions) post capital endogenization for 2011 wass 35.74% and for 2023 was 23.71%. Again, there is a relative decline in the increase of GHG emissions but the decline in GHG emissions is not as pronounced as it was for CO_2 emissions.

The analysis further revealed that indeed the total requirements matrix post capital endogenization had a higher multiplier meaning – the direct and indirect impacts on the economy of a change in the final demand for each sector was higher with capital inputs than without it. We also find that overall, there is a rising trend in the CO_2 and GHG emissions for India regardless of capital endogenization. Capital endogenization simply conveys the rising trends at a higher magnitude.

At the industrial level, the agricultural sector, cottage industries or the Micro, Small and Medium Enterprises (MSME) have a very low share of carbon emissions. Due to their labour-intensive nature of production in India, capital endogenization doesn't increase their overall emission levels significantly. In absolute terms, the industries with the highest levels of Consumption based CO_2 emissions with and without capital endogenization are the construction sector and Machinery and equipment sector. Another observation for these sectors is that GFCF is the key driver of emissions for these sectors indicating the carbon-intensive nature of GFCF.

The industries that register higher emissions due to capital endogenization are mostly in the service sector - 'Waste collection, treatment, and disposal', 'Hospitality', 'Property and real estate' and 'Government; social security, defence and public order'. We also find that these sectors are capital-intensive in their requirements for production (Hospitality, Real estate services, etc can function only with the capital assets like land, property and buildings) but their share of emissions from GFCF are minimal.

Based on these results, we accept the hypotheses – that 'the total requirements matrix with capital endogenization L^K is higher in magnitude than the total requirements matrix L'; 'The inclusion of capital inputs increases the carbon footprint for India over the analysed time period'; and 'The trends of GHG emissions levels and CO_2 emission levels are similar'. We reject the hypothesis – 'The carbon footprint of India's service sector is the highest when capital inputs are included in the footprint estimation', because our findings suggest that the secondary sector has the highest carbon footprint owing to the carbon intensive nature of its GFCF.

The project contributes to the wider literature on capital endogenization in I-O models by conducting a developing country-focused analysis in the otherwise advanced country-centric research landscape. The project further adds capital-use matrices for India to the GLORIA MRIO framework. The estimated capital-use matrices can contribute to future analysis involving capital endogenization for India and comparative studies on the effects of endogenization for the developing countries. This study also complements the work of Södersten et al (2018a) by estimating the similar carbon footprints but by endogenizing GFCF.

The project successfully identifies the industries in India with the least and the most carbon intensive GFCF as well as the industries with the highest and lowest emission levels.
These results provide valuable insights that can help shape India's green transition policies and decision-making strategies for sustainable development. The paper also highlights
ways to mitigate the impacts of embedded carbon emissions in the GFCF of the country by a regulated phase out of carbon intensive GFCF especially in the Construction sector and refurnish the remains for greener economic activities. At the same time, India must harness its immense solar power potential for the production of non-fossil electricity. The use of cleaner electricity for the production of capital assets reduces the emissions assigned to GFCF based on carbon intensity.

The study also suffers from some major limitations based on methodology and the I-O framework. The most important limitation of this study is the choice of GFCF endogenization which leads to the assumption that all the capital assets are consumed by the industries in the current cycle of production which completely disregards the intertemporal nature of capital assets. This leads to an overestimation of the carbon footprint. The analysis is sensitive to economic shocks that can affect the investment levels of the economy.

Finally, the study suggests a more accurate way of capital endogenization by dividing the total requirements in non-capital requirements, capital inputs used up in production process and capital stock at the end of year for calculating a more realistic environmental footprint.

Word Count : 12704

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Appendix

List of KLEMS Assets :

- Dwellings, excluding land
- Cultivable assets
- Other buildings and structures including roads
- Transport equipment
- Other machinery and equipment including office machinery and hardware
- Intangible fixed assets including computer software and research and development

List of KLEMS Industries :

- Agriculture, forestry and fishing (A)
- Mining and quarrying (B)
- Manufacturing (C)
- Electricity, gas, steam and air conditioning supply (D)
- Water supply, sewerage, waste management and remediation activities (E)
- Construction (F)
- Wholesale and retail trade: repair of motor vehicles and motorcycles (G)
- Transportation and storage (H)
- Accommodation and food service activities (I)
- Information and communication (J)
- Financial and insurance activities (K)
- Real estate activities (L)
- Professional, scientific and technical activities (M)
- Administrative and support service activities (N)
- Public administration and defence; compulsory social security (O)
- Education (P)
- Human health and social work activities (Q)
- Arts, entertainment and recreation (R)
- Other service activities (S)
- Activities of households as employers; producing activities of households for own use (T)
- Activities of extraterritorial organisations and bodies (U)

List of GLORIA Industries:

1. Growing wheat
2. Growing maize
3. Growing cereals n.e.c
4. Growing leguminous crops and oil seeds
5. Growing rice
6. Growing vegetables, roots, tubers
7. Growing sugar beet and cane
8. Growing tobacco
9. Growing fibre crops
10. Growing crops n.e.c.
11. Growing grapes
12. Growing fruits and nuts
13. Growing beverage crops (coffee, tea etc)
14. Growing spices, aromatic, drug and pharmaceutical crops
15. Seeds and plant propagation
16. Raising of cattle
17. Raising of sheep
18. Raising of swine/pigs
19. Raising of poultry
20. Raising of animals n.e.c.; services to agriculture
21. Forestry and logging
22. Fishing
23. Crustaceans and molluscs
24. Hard coal
25. Lignite and peat
26. Petroleum extraction
27. Gas extraction
28. Iron ores
29. Uranium ores
30. Aluminium ore
31. Copper ores
32. Gold ores
33. Lead/zinc/silver ores
34. Nickel ores
35. Tin ores
36. Other non-ferrous ores
37. Quarrying of stone, sand and clay
38. Chemical and fertilizer minerals
39. Extraction of salt
40. Mining and quarrying n.e.c.; services to mining
41. Beef meat
42. Sheep meat

43. Pork
44. Poultry meat
45. Other meat products
46. Fish products
47. Cereal products
48. Vegetable products
49. Fruit products
50. Food products and feeds n.e.c.
51. Sugar refining; cocoa, chocolate and confectionery
52. Animal oils and fats
53. Vegetable oils and fats
54. Dairy products
55. Alcoholic and other beverages
56. Tobacco products
57. Textiles and clothing
58. Leather and footwear
59. Sawmill products
60. Pulp and paper
61. Printing
62. Coke oven products
63. Refined petroleum products
64. Nitrogenous fertilizers
65. Non-nitrogenous and mixed fertilizers
66. Basic petrochemical products
67. Basic inorganic chemicals
68. Basic organic chemicals
69. Pharmaceuticals and medicinal products
70. Dyes, paints, glues, detergents and other chemical products
71. Rubber products
72. Plastic products
73. Clay building materials
74. Other ceramics n.e.c.
75. Cement, lime and plaster products
76. Other non-metallic mineral products n.e.c.
77. Basic iron and steel
78. Basic aluminium
79. Basic Copper
80. Basic Gold
81. Basic lead/zinc/silver
82. Basic nickel
83. Basic tin
84. Basic non-ferrous metals n.e.c.
85. Fabricated metal products
86. Machinery and equipment

87. Motor vehicles, trailers and semi-trailers
88. Other transport equipment
89. Repair and installation of machinery and equipment
90. Computers; electronic products; optical and precision instruments
91. Electrical equipment
92. Furniture and other manufacturing n.e.c
93. Electric power generation, transmission and distribution
94. Distribution of gaseous fuels through mains
95. Water collection, treatment and supply; sewerage
96. Waste collection, treatment, and disposal
97. Materials recovery
98. Building construction
99. Civil engineering construction
100. Wholesale and retail trade; repair of motor vehicles and motorcycles
101. Road transport
102. Rail transport
103. Transport via pipeline
104. Water transport
105. Air transport
106. Services to transport
107. Postal and courier services
108. Hospitality
109. Publishing
110. Telecommunications
111. Information services
112. Finance and insurance
113. Property and real estate
114. Professional, scientific and technical services
115. Administrative services
116. Government; social security; defence; public order
117. Education
118. Human health and social work activities
119. Arts, entertainment and recreation
120. Other services

Plagiarism declaration

The following statutory declaration is a part of the thesis, and should be included in the bound work.

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