Energy and Emissions Accounting: The case of Intra-Regional Industrial Shifts in SE Asia

Dimitrios Pappas

A Thesis submitted to

Norwich Business School

University of East Anglia

For the Degree of Doctor of Philosophy

September 2019

Supervisors:

Prof. Konstantinos Chalvatzis

Prof. Dabo Guan

ID: 100141524

To my mother and father, Eleni and Konstantinos

To Melanie, my love

To my daughter, Eleni Rose.

"I ain't no good
And I live by the woods,
They say I ain't bad
I'm the best that I've had,
And I know it ain't right
But I'll fight my whole life
to prove that I was right…"

- *Mastodon - "The Jaguar God"*

Publications Adapted from Thesis

2018 D. Pappas, K. J. Chalvatzis, D. Guan, A. Ioannidis. Energy and carbon intensity: A study on the cross-country industrial shift from China to India and SE Asia, *Applied Energy*, Vol. 225, 2018, pp. 183-194.

2018 D. Pappas, K. J. Chalvatzis, D. Guan, X. Li. Industrial Relocation and CO2 Emission Intensity: Focus on the Potential Cross-Country Shift from China to India and SE Asia, *Energy Procedia*, Vol. 142, 2018, pp. 2898-2904.

2017 D. Pappas, K. J. Chalvatzis. Energy and Industrial Growth in India: The Next Emissions Superpower?, *Energy Procedia*, Vol. 105, 2017, pp. 3656-3662.

Abstract

The potential relocation of various industrial sectors from China to India and countries of the SE Asian region presents low cost opportunities for manufacturers, but also risks are rising for energy demand and CO_2 emissions. A cross-country shift of industrial output presents challenges in accounting, controlling, and defining energy and emissions requirements. This is pronounced for the case of India and SE Asian countries as they experience high economic growth rates, by global standards, and strong coupling between economic growth and energy demand.

This thesis locates the existing emissions accounting gaps of India, which acts as a potential host of the Chinese manufacturing activities. It concludes that significant differences are present in the majority of the industrial sectors studied. Indian emissions intensity is double that of China in the iron and steel and triple for the cement industry. The decomposition of selected CO_2 drivers exemplifies the added significance of labour productivity and industrial scale in driving industrial emissions. Fuel mix concentration in industrial activities is found to be a requirement for every potential host country, highlighting an urgency for diversification if production is to be sustainable.

The results demonstrated by this thesis, show that reporting authorities must reach a methodological consensus for increased efficiency in carbon emissions future policy. Carbon emissions are driven by higher carbon fuel mix intensity in the host countries and higher energy intensity in their industrial activities. This thesis effectively concludes that while industrial relocation could further benefit the host countries in financial terms, it would impose considerable threats to their energy supply security and compliance capacity, with the environmental commitments set by the Paris Agreement.

Acknowledgments

I would like to express my sincerest gratitude to my primary supervisor, Professor Konstantinos Chalvatzis. Konstantinos has proven himself as an invaluable mentor and a dear friend. Through his support and advice, I secured my admission to the Norwich Business School, for conducting my PhD studies. His guidance, encouragement, insightfulness, and extreme amount of patience during these four years have been the solid foundation for completing this thesis. I thank him for providing me the opportunity to publish my work in well-respected journals of the field. For allowing me to teach in modules that are relevant to my research. For enabling me to attend international conferences and assemblies, networking and communicating my research. For allowing me to hold research roles as part of the TILOS Horizon 2020 project. Through his invaluable guidance and trust, Konstantinos reshaped my mindset and character for the better. He taught me that everything is only achievable through hard work and credibility. For his support on a personal and academic level, his inexhaustible faith and positivity in me, I will always be thankful.

I would also like to express my gratitude to my second supervisor, Professor Dabo Guan. Dabo enabled me to see the big picture of hot topics in the environmental agenda, identifying cutting-edge themes. The chosen research subjects that Dabo suggested that I follow, will continue to produce results in my research career for years to come. Dabo has essentially shaped the main theme and the questions that this thesis aims to address. His participation in my journal submissions as a co-author can only make me feel humbled. Concluding, I will never forget how Dabo stood up for me in my time of need. For that, his extreme patience and the opportunities provided to me, I will always be thankful.

I will forever be grateful to Dr. Dimitrios Zafeirakis. Dimitrios is the coordinator of the TILOS Horizon 2020 and a research associate for SEALAB of the University of West Attica. Dimitrios has been a teacher and mentor during my Master of Science in Energy studies, inspiring many of my research interests. It was Dimitrios, that suggested my further academic progress by pursuing a PhD with the Norwich Business School and introduced me to Konstantinos. For that I owe to Dimitrios this entire experience and my life's path. Through Dimitrios' actions and altruistic help, I followed the route that shaped my life for the better.

Special thanks go to Dimitrios Dousios, Robert Jenkins, Sally Piff and Andrea Finegan. They have provided me the opportunity and trust to teach and be actively involved in their modules. They ensured that my experience would be as smooth as possible, throughout my involvement. They expressed, in numerous cases, their sincere interest for my development in the world of academia, as well as cared deeply for my personal well-being. Dear Robert, let's make sure that not all corals will die.

I would like to acknowledge all the kind and sincere support of the NBS administrative staff. Special thanks go to Liane Ward for putting up with all my requests, finding the best appropriate solution to every arising issue. The Norwich Business School would not be the same without you.

I am humbled and grateful to my friends and colleagues Athina Zeriti, Alexis Ioannidis, Zhiteng Feng, Bailuo Lin, Donna Lei and Hai Ahn. They have been present in every good and bad situation that we went through together. They made these years unforgettable and we shaped friendships that will last for a lifetime.

I would like to thank my family; My mother Eleni, my father Konstantinos, my sister Katia for all their support and care.

To my Melanie; mere words for all that you've done cannot cover such a short space. You teach me what devotion, care and love is, every single day of our lives together. To our daughter Eleni Rose; you provided me all the motivation required to pull myself together and focus on completing this thesis. You are, and always will be, our brightest star.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ASEAN	Association of Southeast Asian Nations
BLS	Bureau of Labour Statistics (US)
BP	British Petroleum
BRIC	Brazil Russia India China grouping
C&P	Chemical and Petrochemical
CC	Carbon Content
CDIAC	Carbon Dioxide Information Analysis Center
COP21	The 2015 United Nations Climate Change Conference
EDGAR	Emission Database for Global Atmospheric Research
EIA	Environmental Information Administration
EKC	Environmental Kuznets Curve
EU	European Union
FDI	Foreign Direct Investment
FGP	Flying Geese Pattern
FTA	Free Trade Agreement
GDP	Gross Domestic Product
GHG	Greenhouse Gas
I&S	Iron and Steel
I/O	Input-Output
IDA	Index Decomposition Analysis
IEA	International Energy Agency
INDSTAT2	UNIDO 2015 statistics database edition at the 2-digit level of ISIC revision 3
INDSTAT4	UNIDO 2015 statistics database edition at the 3- and 4-digit level of ISIC revision 3
I-O	Input Output
IPCC	Intergovernmental Panel for Climate Change
IS	Industrial Scale
ISIC	International Standard Industrial Classification
IVA	Industrial Value Added
LMDI	Logarithmic Mean Divisia Index
LPG	Liquid Petroleum Gases
MOSPI	Ministry of Statistics and Programme Implementation (India)
MRIO	Multi-Regional Input Output
N.M.M	Non-metallic Minerals
NCV	Net Calorific Value
NG	Natural Gas
NPE	Number of Persons Employed
NPRD	Non-Pearl River Delta
N-S	Non-Specified
ORNL	Oak Ridge National Laboratory
P. P. P or PP&P	Paper, Pulp & Print
PH	Porter Hypothesis
PHH	Pollution Haven Hypothesis
PHHH	Pollution Halo Hypothesis
PII	Pollution Intensive Industries

PLC	Product Life Cycle
PRD	Pearl River Delta
SDA	Structural Decomposition Analysis
SSA	Shift Share Analysis
T&L	Textile & Leather
TPES	Total Primary Energy Supply
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
UNIDO	United Nations Industrial Development Organization
UNSDD	United Nations Sustainable Development Division
VA	Value Added
W&WP	Wood and Wood Products
YRD	Yangtze River Delta

Nomenclature

CI	Carbon Intensity
CI*eff*	Carbon Intensity Effect
CO_2	Carbon Dioxide
E	Energy expressed in heat
EI	Energy Intensity
EI*eff*	Energy Intensity Effect
Gt	Gigatonne
GW	Gigawatt
GWh	Gigawatt-hour
HHI	Hirschman Herfindahl Index
IS	Industrial Scale
IS*eff*	Industrial Scale effect
J	Joule
Kg	Kilogramme
kt	Kiloton
kW	Kilowatt
kWh	Kilowatt-hour
LP	Labour Productivity
LP*eff*	Labour Productivity effect
PJ	Petajoule
PJ	Petajoule
SWI	Shannon Wiener Index
T	Economic Output
t	Tonne
TJ	Terajoule
TWh	Terawatt-hour
US$	United States Dollar
ΔC	Carbon Change over set period

1. Introduction

1.1 The Industrial Relocation Issue

Industrial relocation is described as the process of manufacturing hubs shift from a region of origin to a new host region (Rathje, 1974) and is deemed as a crucial element for establishing cross-regional economic relations (Wu et al., 2014) through the generated unidirectional cross-regional stream of elements such as capital, technology and labour force (Wu et al., 2014). Industrial relocation essentially enhances economic growth in the origin (Mattila and Strandell, 2006) and host countries (Kwon, 1981) but is associated with risks such as dependency on foreign direct investment (Kim, 2007), environmental degradation (Jänicke et al., 1997) and reduced industrial effectiveness (Pennings and Sleuwaegen, 2000).

The relocation practice of manufacturing firms has been an issue identified by economists since the first half of the 20th century (Hoover, 1937). To understand the implications of industrial relocation, researchers employed concepts that are considered as lacklustre by present standards. The common approach towards examining this theme was mainly constructed around comparative costs methodologies, which subsequently expand for factors accounting market access (Donaldson, 1931) or involve direct data comparison accounting factors including labour costs (Byer, 1937), taxation (Steiner, 1938) and raw materials (Isard, 1948). The limitations of analytical tools used in the era with additional gaps in data reporting and validity, stood as an obstacle for enabling a deeper comprehension and materialisation that would expand the industrial relocation concept towards broader research areas. As a result, the discussion around the industrial relocation concept presented narrow boundaries that were restricted around the economic implications of that shift in manufacturing.

Industrial relocation has enjoyed newfound research interest, reflected on empirical research related to intra-country relocation practices of the private industry in the United States, as obtained from the second world war effort (Turnquist, 1964). Intra-country industrial relocation has been the subject of government incentives, as found in the case of Japan during the decades following the war for balancing intra-country regional production to achieve even economic growth (Okubo and Tomiura, 2012). Following the established research norms, scholars provided parameters to identify additional industrial location drivers, towards models that involve market communication issues (North, 1955), learning curves of labour force (Henderson and Upchurch, 1943), productivity, education, business climate (Blair and Premus, 1987) and other economic externalities (Mueller and Morgan, 1962) as decision factors for selecting attractive manufacturing host locations. What research suggested, regarding market communication, is that the identification of market potential in a specific country set by a firm, would lead towards shifting the production to that country; essentially expanding the argumentation towards the location parameters governing the host country.

Modern research aims in identifying driving factors of industrial relocation that revolves between environmental implications boundaries; as determined by including environmental accounting factors in terms of policy regulation, regional policy discrepancies, social acceptance and governance (Z. Wang et al., 2019). This driver for determining implications has presented an intensified level of research commitment as an increased number of countries point an effort in materialising their stated environmental commitments (INDCs) towards the Paris Agreement (Falkner, 2016). Industrial practices present elevated urgency as high polluting industries have been found having an increased decision capacity of relocations towards, mostly developing (Zheng and Shi, 2017), countries that are classified as "pollution havens", characterised by lax environmental regulations offering reduced mitigation costs. This relocation practice has sparked additional interest with scholars for conducting numerous econometric empirical tests, testing the relationship of FDI and the relocation of carbon emissions, including China (Arce et al., 2016) and ASEAN countries (Baek, 2016). Locating industrial relocation from a scholar's perspective, it is defined as being direct or indirect. Classifying the firms' production transfer practice, the industrial relocation or direct investment between two regions is defined as direct. The indirect industrial relocation between two regions can be described as the result of the growth in consumption or investment of an origin region, results in an increase of the IS in the destination-host region (Yin et al., 2016).

1.2 Theoretical Concepts of Industrial Relocation

Framing the theoretical perspective, scholars have provided individual concepts, aiming towards adopting the drivers output, translating them into objective capacity or broader decision-making models under a macro-analysis prism putting emphasis on the economic factors impact on industrial relocation.

Identifying the problem of analysing the manufacturing location choice patterns and resulting economic implications, Vernon (1966) provided an alternative perspective on the concept of industrial relocation, essentially developing the product life-cycle theory (PLC). The PLC suggests that a product subject to set stages-cycles in its commercial life span. The first stage would have the product manufactured, including raw materials sourcing and labour, in the country of its origin. With the wider adoption of the product on a multinational scale, manufacturing would relocate from the origin country to the new host country of the firm's choice. The target of PLC is to challenge the Heckscher-Ohlin theorem (Heckscher, 1919) and its set expectation of less-developed countries to export products that are characterised by increased labour intensity levels.

Vernon's PLC theory exceeds economic considerations, taking additional factors into account, such as marketing and knowledge access not being freely available to any interested parties seeking to relocate. PLC suggests that industries relocating intra-country to areas of lower development are, at least initially, those with products that require reduced levels of sophistication. The products would have standardised specifications, resulting in being less prone to any implications of remoteness; e.g. textiles, steel, printing. Adjusting the paradigm further in the case of industrial relocation towards developing countries, the theory suggests in addition to the previous, that any advanced means of production should be exportable from the developed to the developing country to close a production output gap. This practice highlights the requirement for external investment to materialise that option, ultimately resulting to products exported from the developing host countries towards the developed countries of origin. This suggestion has presented a new challenge for researchers to confirm, at the time, due to the limited availability of the necessary information that would solidify the statement except for established country-cases of the era such as that of Taiwan.

Vernon in his work, has insightfully pointed towards an existing positive link between foreign direct investment (FDI) in developing economies and manufacturing hubs relocation destinations. Indeed, FDI was confirmed to have a positive relationship, as companies seeking to relocate used FDI flows towards developing countries as a direct result of decreased production cost properties and increased domestic markets capacity (Harrison, 1994). FDI has additionally a positive relationship with industrial output (Shan, 2002) and provides the required capital to overcome the respective domestic capital shortage of host countries (Noorzoy, 1979), or stimulate the domestic investment, complementing the FDI source and paving the way for host-country policies (Tang et al., 2008). FDI has a unidirectional impact on GDP (Hsiao and Hsiao, 2006), while its implications on the economic growth of the recipient country are permanent due to a resulting technological transfer and related spill-over (Huang and Sharif, 2009).

In contrast to the benefits for host country economies, it is pointed out that FDI acts as the necessary means for multinational companies to relocate their most environmental hazardous manufacturing facilities to developing countries (Clapp, 1998); a part of the "pollution haven" concept, even though the generating motive of that practice is disputed among scholars (Javorcik and Wei, 2005). Establishing relocated manufacturing production facilities effectively aids overcoming trade obstacles and future or existing market protectionist schemes, as those are set by existing national policies (Tan, 2002). Large differences in factor costs exercise increased pressure for vertical FDI towards establishing relocated manufacturing facilities in host countries (Kim, 2007) when assessed under preferential trade agreements cases.

Further focusing on theoretical models that examine industrial relocation, enhancing the criteria considered for studying the firms' relocation practices and implications, Akamatsu (1962) initially put forward his analytical model, originally conceived in the 1930s (Kasahara, 2013), described as the "Flying Geese Paradigm" (FGP). Establishing the foundation for his Flying Geese Paradigm, Akamatsu claimed that it is the developmental process of heterogenization; a comparative widened cost divergence trend, and homogenisation; a comparative cost convergence trend impeding trade, between a developed and a developing economy following a flying geese V-pattern. This V-pattern is conceptually formed between a lead economy and the countries that catch up in a hierarchical order of economic progress. Providing further explanatory remarks, Akamatsu effectively used statistical data of numerous commodities to schematically represent FGP patterns that demonstrate the economic development in set historical periods of developing countries. As it preceded PLC as a concept, FGP was subject to further stimulation by Vernon's PLC theory that enabled Japanese theorists to modernise this theoretical concept (Korhonen, 1994).

Akamatsu, shaped his FGP theory by using Japan, the predominant post-war economic development leader of Asia region at the time (Kaldor, 1976), as the lead of the conceptual geese V-pattern. Expanding the concept further, Kojima (2000), clarified the catch-up process of industrialising developing economies of the East Asian region by adopting Akamatsu's FGP, essentially developing three models; agreed specialization, trade oriented FDI and industries diversification/rationalisation, to serve that purpose. Kojima, making a qualitative forecast, argued that multinational manufacturing firms that relocate to less advanced economies of the region, would enable those economies to be linked to their advanced counterparts, resuming the FGP that was stalled due to the Asian financial crisis of 1997 (Deesomsak et al., 2009). Apart from using FDI to stimulate indigenous growth in China and Indonesia as part of FGP, Kojima predicted that further FG development would spread to ASEAN members and India with Japan, but also US and EU acting as the lead geese.

Following, or even preceding Kojima's expansive models, flying geese paradigm has been a research subject by scholars that focus on East Asian countries. Hiley (1999), examined and confirmed that FGP patterns through FDI channels are being evident, leading from an industrial restructuring of Japan to ASEAN countries since the late 1980s, shaping their economies towards industrialization. Dowling & Cheang (2000) and Tung (2003), have disputed the uniformity of validity for the FG model regarding the usage of a specific indicator; the revealed comparative advantage of exports, as offering the opportunity to confirm or refute the FG model when discussing east Asian economies. However, Ginzburg & Simonazzi (2005) disputed those findings and confirmed the FG model as such for the electronics and textiles industries open up FG thinking to an industry-specific context.

The FGP pattern was further researched with China as a case study, validating its FGP patterns, replacing Asian newly industrialised economies (NIEs); Hong Kong, Singapore, South Korea and Taiwan, in final goods production (Ahearne et al., 2008), or intra-country from the coastal regions to the interior (Qu et al., 2013) as observed in the textile and apparel industry (Ruan and Zhang, 2014). China has been subject to debate regarding its place in the FGP V-pattern formation. It is suggested that while presenting the potential to be engaged in cross-country FGP, at a current stage is invested in intra-country relocation of manufacturing activities but presents the potential to increase its rate of FGP towards other countries as wages rise and labour markets become tighter (Xu and Hubbard, 2018). Research finds which developing economies can enter the V-pattern formation as manufacturing destinations. Sub-Saharan countries (Brautigam et al., 2018; Ozawa and Bellak, 2011), India (Haque and Thaku, 2015; Nam et al., 2017) and East Asian developing economies (Anbumozhi and Yao, 2017), though India is still debated about its potential of being a candidate or partly engaged in that FGP formation due to its commodity characteristics that compete with China in the value chain (Balasubramanyam and Wei, 2015).

Industrial relocation has been subject to further assessment in consideration of potential environmental impacts that the firms' practice includes. Industrial relocation incentives can be set by environmental regulations and policies present in the country of origin. These can provide the necessary decision capacity for a shift in production towards a candidate host country. Theorizing on the concept, the Pollution Haven Hypothesis (PHH) is established around the main argument that the pollution intensive manufacturer takes advantage of the liberalisation of trade and investment patterns, effectively materialising a relocation of production activities towards countries that have a lax framework of environmental policies. Scaling up with manufacturers following the PHH, global pollution levels would be expected to increase overall (Gallagher, 2010). Breaking down PHH, it can be based around two similar but distinct core patterns that incentivise the relocation decision. The first pattern is the result of stringent environmental regulations taking place in the origin country if established trade channels between the origin and a host exist. The second pattern reverses that argument and is the result of a significantly different environmental regulation environment existing between the origin and host, assuming trade barriers between them are lowered.

Cole and Elliott (Cole and Elliott, 2005) tried to empirically validate what PHH theory suggests, in regard to the environmental relocation criterion. Studying the outward capital from the US to Mexico and Brazil they suggested that FDI originating from polluting firms will be attracted by countries with high capital endowment and lax environmental regulation. Grether and Melo (2003) studied five pollution intensive industries in 52 countries for the timeline of 1981-1998. They confirmed that lowered trade barriers would drive highly polluting industries to relocate following specific patterns; North to South or developed to developing countries, except for the non-ferrous metals industry.

Testing the pollution haven hypothesis further, Shen et al (2017) analysed the intra-country relocation of industries from Guangdong (China) to other host locations, due to variations in environmental regulation on that provincial basis. They found that hundreds of manufacturers relocated their operations between regions; from Pearl River Delta to Non-Pearl River Delta locations, due to energy conservation and emissions reduction policies, but the introduction of sewage treatment in host locations can potentially prevent the formation of a pollution haven. In a similar context of intra-country movement, Yang et al (Yang et al., 2018) defined common PHH patterns of manufacturers' relocation as new firms are found likely to be driven by high environmental abatement costs.

An alternative, potentially simplified, version of PHH is described as the Environmental Kuznets Curve (EKC). EKC is linked to both PHH; not accounting trade patterns; and the reciprocal to PHH; Pollution Halo, consistent with its U-shape relationship between environmental degradation and environmental improvement. EKC can be described as an inverted U curve of income per capita versus pollution (Grossman and Krueger, 1995). It was first suggested by Simon Kuznets (1963) with the purpose of representing in a cross-axis system, that as the economy grows in a developing nation, the environmental indicator will demonstrate a degradation up to a turning point representing a specific income per capita. As that income becomes reinvested back to environmental protection, as a possible practice, the environmental indicator is restored towards its initial state (Shahbaz et al., 2015).

EKC has been the subject of debate as to its effectiveness in adjusting to modern developing economies. Stern (2004) supports that developing economies are confronting their environmental issues following standards that are present in developed countries; effectively demonstrating a pollution halo practice, in result testing the EKC validity and its limited inclusion of all environmental indicators. Stern's claim was supported by recent research studying an extensive timeline from 1980 to 2010, as the per capita income and per capita CO_2 emissions did not support the EKC model when tested for 26 high-income OECD economies and 52 developing economies (Özokcu and Özdemir, 2017).

Providing further clarification to the Pollution Halo Hypothesis (PHHH) suggested previously, it assumes an established environmental standard that is spread by multinational firms through their FDI engagement practices to the host countries. Through that practice, the cross-country relocation of manufacturing firms provides an extended capacity for the offset of environmental pollution (Cole et al., 2008; Zarsky, 1999). This essential transfer of cleaner technologies and accumulated knowledge to enhance production, is the subject of an extended number of studies in the field. As extended research on PHHH suggests, such a hypothesis is confirmed for the BRIC bloc (Tamazian et al., 2009) and over other models (e.g. EKC) for countries of the belt road initiative (BRI) receiving Chinese outward FDI (Liu and Kim, 2018).

Compatible with the PHHH is the Porter Hypothesis (Porter and Van der Linde, 1995), suggesting that an industrial relocation decision is not directly dependent on the introduction and further stringency of environmental regulations. As such, the relocation argument is being challenged by the Porter Hypothesis claiming that well-thought environmental policies will improve environmental performance indicators or, potentially, stimulate innovation for mitigating the expected environmental impact (Ambec et al., 2013) and eliminate a trigger of the relocation process. Contributing to the Porter Hypothesis (PH) further, a classification of PH suggests three distinguished versions. These include the "narrow" PH; market-based drivers provide the necessary incentives to firms for innovating, the "weak" PH; well-constructed environmental policies drive environmental innovation, and the "strong" PH; efficient environmental policy triggers innovation that is able to offset any added costs for adjustment to those policies, resulting in enhancing the productivity and competitiveness potential of the firm (Jaffe and Palmer, 1997).

Complying with that classification, research finds weak PH favourable in European manufacturing when innovation is expressed as patents (Rubashkina et al., 2015) while Lanoie et al. (2011) find positive weak PH for companies located in 7 OECD countries that include Japan, Germany and the United States. Introducing stringent environmental regulation in China however, was found to reject PH and confirming PHH, with polluting industries seeking relocation when such policies come into effect (Dou and Han, 2019).

1.3 Industrial Relocation Metrics

To determine and evaluate the magnitude of industrial relocation, specific methods have been used by researchers, but no agreement is established for using a unified quantification or measurement standard (Yin et al., 2016). The methods used include the Gini coefficient, the Herfindahl Index, the Location Quotient, the shift-share analysis, and the inter-regional I/O.

The Gini coefficient was established by Corrado Gini (1912) to provide the quantification means for measuring statistical dispersion demonstrating wealth distribution among a nation's residents. A conventional and well established indicator measuring income inequality (Dorfman, 1979; Liu et al., 2019), the Gini coefficient can be decomposed by group, increment, source and incremental source (Chen et al., 2016). It has additionally been used for providing an inequality measurement covering an extended number of inequality indicators such as industrial processes and product quality (Shaban, 2018), CO_2 emissions inequality on an international level (Groot, 2010), education (Ziesemer, 2016) and medical services (Jian et al., 2015) or even disease (Gianino et al., 2018) among the general population or a set study subject sample.

The Gini coefficient measures the average difference in e.g. income between two random subjects contained in a set sample, for example two people who are part of the studied population. As a result, it provides the desired inequality index of the selected sample. The range of the coefficient ranges from 0 to 1, with 0 indicating no inequality in the sample and 1 defined as maximum inequality, for example one subject; a person, of the sample; a country, concentrating all the income. Setting an example related to this research, a value of 1 would indicate a more concentrated industry looking at a sample of PII at a specific geographical location. When the Gini coefficient is used in that manner, it provides the quantification metrics required to locate and extract the forces that drive relocation of industries engaged in PHH practices.

Confirming this capability, Wu et al. (2019) used the Gini coefficient to examine the driving forces of the PIIs distribution in a set location; the Yangtze River Delta (YRD) in China for the timeline of 1999 to 2015. The Gini coefficient application provided the means to measure the agglomeration of PIIs in the region, essentially confirming a rapid expansion of PII industries in the peripheral YRD region, attributed to the PHH practices, allocating this trend towards existing environmental regulations, pointing towards the Porter's Hypothesis for those that remain in the YRD core. In a similar context of using locational Gini coefficient, Ge (2009) examined the FT and FDI link to Chinese industrial agglomeration across a 20 year timeline (1985 to 2005). They concluded that industries that present dependence on FT and FDI tend to operate in regions with easy foreign markets access, while export-oriented and industries operating by FDI funds present greater agglomeration. Shen et al. (2017) used spatial Gini coefficient to analyse the migration and location patterns of PII industries in the Guangdong province from 2000 to 2013, essentially confirming a PHH pattern as present in Guangdong, with hundreds of PII industries relocating from the Pearl River Delta (PRD) to peripheral Non-Pearl River Delta (NPRD).

Okubo and Tomiura (2012, 2010), studied the diversification of the geographical dispersion of Japanese industries by using the Gini coefficient to confirm the appropriate theoretical findings of Baldwin and Okubo (2005). They concluded that low-productivity firms have relocated their operations; diversifying their geographical position intra-country, balancing a regional productivity gap that existed in Japan, as discussed in **Section 1.1**. The Gini coefficient has been the intermediate for determining the presence of an industrial relocation pattern in the Chinese textile and garment industry from 2001 to 2009 (Wu et al., 2013), with the research concluding to highlight an emergent intra-provincial production shift from the developed provinces, towards developing central Chinese regions.

To explore alternate quantification means for measuring industrial relocation intra-country patterns in China, Zhang and Liang (2010) used the Herfindahl index; a metric created and commonly used to measure market concentration, and the Location Quotient, but were unable to distinguish the magnitude of relocation or conclusively determine the origin and host regions per case. The two indices mentioned measure the concentration of industries; and have been the subject of measuring the geographical concentration of PII in the case of China (Zheng and Shi, 2017). For the location quotient index, a value greater than 1, suggests high concentration following a stable trend of a greater value equalling a greater concentration, and can be briefly described as the index resulting from the output value of a specific industry of a selected region versus the national output of that selected industry.

While the location quotient focuses on determining and extracting the change between the industrial structure of a primarily selected region, having the capacity to include additional regions of focus, the Herfindahl index, produces output that has a similar pattern to that of the

Gini coefficient, expressing the change in the output proportion for a selected region (Hu et al., 2019).

Examining further metrics used for evaluating a potential industrial relocation pattern, the Shift Share Analysis (SSA) is a measurement method first adopted by Perloff et al. (1960) in order to comprehend the differentials of regional employment growth rate. Difficulties in its application (Stilwell, 1969) have not been a barrier in its wider adoption by scholars to evaluate or measure the regional (Nijkamp, 1986) or national (Boulhol and Fontagne, 2011) competitiveness. The SSA provides the required capacity to commence its application where the Location Quotient metric is limited. Clarifying this, the latter metric evaluates industrial concentration geographically within a region or a country while the purpose of the shift share analysis is to attribute the growth difference over time, for a selected subject of interest. In this context SSA can attribute the number of jobs created by the regional industrial mix and growth driven by generated competitive advantages of the selected region (Smith, 2003). Recent interest for using SSA as a measurement indicator is demonstrated by Shen et al. (2017), with an analysis of the relocation of wastewater and SO_2 generated by the established regional PII in a set period of time; 2000 to 2013, in the PRD. This study successfully found a shift of SO_2 by-products from specified regions such as Guangzhou, Shenzen and Fonshan towards other intra-country provinces of China with lower environmental policy barriers, providing the essential means to discuss PHH. Approaching relevant research proposals further it was suggested (Keeble, 1980), that SSA provides the capacity to determine industrial relocation by comparing two regions or countries manufacturing industrial scale for a set timeline, essentially determining a differential shift. This application can confirm or reject the existence of industrial relocation patterns within that set geographical location concept.

Defining the concept of industrial relocation, scholars propose a division into two main categories (Li et al., 2018); the narrow and the broad. Identifying the narrow breadth, this refers to either a spatial transfer or industrial facilities expansion. The broader definition refers to a new location selection for industrial production, as a direct result of either the development or decline of the competitive advantage between cross regional industries in a set period of time. Relative to this approach, industrial relocation is additionally defined by researchers as an industrial output changing process; the result of cross-regional change in demand (Yin et al., 2016).

Measuring industrial relocation, the Input-Output (I-O) analysis is an established method for measuring those transfers for either an intra or extra country relocation approach. I-O method is attributed to Wassily Leontief (Leontief, 2008; Leontief et al., 1953) for the measurement of regional implications generated by national forecasts. As the model utilised a general perception of location and space-economy, it would only permit a limited shift of industrial activity between regions or countries, Koopmans (Isard, 1951) with his work shaped the model to include a possible major shift of industrial production. The space factor parameters required by the model have been altered, to allow the inclusion of major variations in the spatial production extent for each of the manufacturers in a geographical production pattern and utilisation of raw materials. Eventually, Leontief (1974), following Isard's work (Isard, 1951) on developing an inter-regional I-O model that enabled regional analyses (Isard, 1951), enhanced the model to incorporate the global economy, essentially developing the I-O multinational model now widely used as Multi-Region Input Output model (MRIO). The general purpose of an I-O model is described as the estimation of the resources required for satisfying demand.

As the I-O can be used for an expanded range of applications, provided that a tracked flow of materials exists, in the following decades it has been the model used to account embodied natural resources (Wright, 1975) and energy (Wright, 1974) as well as providing the necessary quantification means for measuring embodied energy on a national economy level such as China (Chen et al., 2010) or the environmental load through embodied natural resources use in the Asia-Pacific region (Shimoda et al., 2008).

In its present research capacity for determining industrial relocation, I-O is the model that offers a higher degree of detail, accounting the I-O inter-industrial relationship, providing accurate result estimates even at a multi country level. MRIO is used to study the magnitude of industrial production shift of polluting industries between eight Chinese regions (Yin et al., 2016). Its enhanced detail capacity enables the measurement of industrial relocation in applications such as the shift between cities (Li et al., 2018) or energy consumption embodied in the industrial relocation patterns (Zhang et al., 2016).

1.4 Conclusions and Research Aims

This introduction chapter serves for highlighting the industrial relocation issue, not only as a practice, but additionally as a theoretical concept and methodological metrics development. The greater scope of this thesis however is not to perform an application of the concepts and quantification indicators discussed, exploring the capacity and potential of an industrial relocation from the country of origin to host countries. Instead, the research aims at closely examining the implications generated by the industrial relocation practice, through the manufacturing shift at a total and sectoral industrial level. In that context, the economies selected as having a relocation potential are those that retain high levels of growth when compared to global growth of 3.3% (IMF, 2019). Therefore, a shift of production is discussed as an independent event for countries that present a relocation potential; from China towards the East Asian region including India. Across a set examined timeline, the multiple implications of industrial relocation are explored in a synchronous manner. This approach serves the purpose of examining the industrial performance in terms such as economic output, resource input, value, workforce, and environmental implications between selected countries.

Discussing the structure, the present thesis aims to satisfy a set of criteria for exploring the implications of the industrial relocation in a selection of host countries. These are:

- Locate data reporting discrepancies in the largest economy of the region and identify its impact on targets and international comparisons.
- Determine the energy and carbon intensity of the industrial sectors of selected regional high growth rate economies.
- Perform a decomposition of CO_2 emissions change to determine the factors that present the greatest contribution towards generating carbon emissions.
- Examine the energy security of the industrial fuel mix, as a coupling of energy and emissions exists in many developing economies.

Looking into the selection criteria further, India is among the world's top 10 countries for FDI inflows (Kumar, 2018), projected to double its economic size in the next five years to five trillion US$ (Mohan, 2019) providing a strong incentive for examining its industrial relocation implications as additionally suggested by relevant research (Gao, 2018). Indonesia, Thailand and the Philippines have been distinguished as following the flying geese hierarchy (Kenderdine, 2018; Montes and Cruz, 2019), an ASEAN formation now being led by China (Chiu et al., 2019). In the same context, Indonesia, the Philippines, Thailand and India serve as potential pollution havens (Destek and Okumus, 2019; Merican et al., 2007; Murthy and Gambhir, 2018) providing the incentive for pollution intensive industries to shift their production towards them. However, as it is suggested that FDI has a negative relationship with carbon emissions in the ASEAN-5 countries this research adopts a neutral approach and is open to the possibility of a pollution halo (Zhu et al., 2016) by companies that choose to shift their production to other economies of the region. Considering those parameters, it is of elevated importance to dissect the expected impact in a nuanced way not only for the total industrial performance but the individual industrial sectors where the appropriate data are available.

Discussing the thesis chapters in brief, and following the introductory **Chapter 1**, **Chapter 2** demonstrates the methodology applied in each of the explored themes which are highlighted in the bullet points discussed previously. The methodological analysis precedes the research themes with the purpose of keeping a comprehensive flow in later research chapters without raising a barrier in the hypotheses flow. As the following chapters centre around the main theme of industrial relocation, **Chapter 3** explores data carbon accounting discrepancies that are expected to exist, following the work of Guan et al. (2012) by focusing a major economy of the region; India. This approach serves the purpose of locating data reporting accuracy issues as a secondary target. Its primary target is to determine the validity and error margins of accounting methods between international reporting agencies. **Chapter 4** examines and compares the variable energy and carbon intensity levels in a set number of host countries of the East Asian region versus the country of origin. In **Chapter 5** a Logarithmic Mean Divisia Index Decomposition Analysis is performed to attribute the carbon emissions change between different carbon emissions contributing factors. **Chapter 6** discusses the fuel mix concentration by using the Herfindahl-Hirschman Index (HHI) and fuel mix diversity, using the Shannon-Wiener Index (SWI) for every active industrial sector in the countries of choice. Performed as such, HHI and SWI results in highlighting the urgency for the introduction of policies that promote energy security. Concluding, a synopsis of the results is presented in **Chapter 7**, assembling the findings with the addition of proposed future research that is deemed as feasible in a short to mid-term basis, extending further from the findings of this thesis which can serve as the appropriate foundation.

2. Methodology

The present research utilises the IPCC sectoral guidelines for accounting CO_2 emissions (IPCC, 2006) from energy combustion, calculated at the production side. This methodological approach has been the preferred method of accounting, as found in numerous relevant studies (Garg et al., 2017; Guan et al., 2012; Li et al., 2020; Shan et al., 2020, 2016a; Zhou et al., 2018). The IPCC has published three accounting guidelines for CO_2 emissions in mid-term intervals; 1996 and 2006, with the latest in 2019 being an update to the previous. The latest update from IPCC has not been produced in a timely manner to be utilised for the purposes of the present research, but due to its function as a refinement to the 2006 version, it does not alter the accounting process. Therefore, it does not impact the accounting credibility of the results, and it does not produce different output from what is calculated and discussed in the following sections of this thesis.

While several authorities publish carbon dioxide emission datasets, forming a pool of available carbon emission estimates, the raw quantities as reported by the IEA are used for following all the necessary accounting steps, until the carbon emission estimate results are reached. Except for the transparency that the IEA database provides to the interested parties that will approach the present research, it enables the combination of alternate emission factors accounting throughout the steps, where this is the desired outcome, contributing further to the existing international literature. In addition, carbon emission estimates per industrial sector and the subsequent analysis is an under-explored theme for India and developing South-East Asian countries. Global emissions datasets, such as the U.S. Energy Information Administration, Emissions Database for Global Atmospheric Research (EDGAR), Carbon Dioxide Information Analysis Centre (CDIAC), have different accounting scopes and methodologies. They adopt alternate sources of information and as such generate discrepancies by default. However, and most importantly for the purpose of this research, they do not produce a sub-sectoral analysis of the industry's fuel activity levels or CO_2 emissions, for the countries examined (Shan et al., 2020, 2018). As a result, the databases mentioned above are weak in satisfying the detail that this research aims to produce.

The present research considers a matter of elevated importance, to approach CO_2 emissions from an accounting standpoint which sets raw materials as the starting point for producing the output. It follows the sectoral approach as this is set by the IPCC, calculated from the production side. This approach enables the production of novel standalone research which follows the established accounting steps and methodology that utilises concrete foundations; as this is provided by the IPCC guidelines and accepted by the broader scientific community. The chosen database, the International Energy Agency (IEA) satisfies those criteria, by publishing fuel activity and country-specific fuel calorific value data periodically. This data source aligns with the United Nations Industrial Development Organisation (UNIDO), which is the chosen database for extracting economic activity data in the industrial sectors that are to be examined.

Concluding, the level of research is focused on a macroscopic approach that follows a logical top-down order; the total, sectoral and sub-sectoral industrial level. The microscopic approach of examining carbon emissions at the company or manufacturing firm level is avoided. Carbon disclosure in manufacturing firms of developing economies of the region is weak (Luo et al., 2013; Nurdiawansyah et al., 2018), posing a risk to the objectivity of the results and the acquisition of a sample that enables the conduct of comparisons between the industrial sectors of the selected countries.

This research aims to follow all the necessary calculation steps to account the carbon dioxide emitted by the industrial activity of the selected countries. It accounts discrepancies to highlight error margins, existing or potential, following the methodological approach of Guan et al. (2012) and Liu et al. (2015b) with secondary data regarding net calorific values (NCVs) found in **Section 2.1**. It defines the energy and carbon intensity, measuring the impact to the environment and the energy requirements concerning the economic output defining efficiency through a standardised approach as described in **Section 2.2**. It decomposes the carbon emission driving factors of the industry by utilising the Log Mean Divisia Index (LMDI) I method, as this is set by Ang (2015, 2005) and implemented by Lin and Tan (2017) and Boqiang and Liu (2017). Its purpose is to study the direct effect of set factors such as labour productivity and industrial scale have in carbon emissions and determining the existing capacity for automation (**Section 2.3**). From an ontological perspective, a number of methods exist that enable the decomposition of carbon emissions to determine the effect of different factors. These include the Laspeyres index, which was the primary decomposing methodology in the 1980s, equalling its research output with Divisia index during the following decade. Several studies have approached this methodological debate existing in the international literature (Ang et al., 2009; Greening et al., 1997; Pourebadollahan Covich et al., 2016; Wang et al., 2013), but consensus or uniformity in method selection has not been reached. As such, numerous studies do not mention the criteria for which their preferred methodological approach has been selected. The Divisia index is the preferred method of decomposition by the US Department of Energy (Y. Wang et al., 2019). Within the Divisia index methods of decomposition, the Arithmetic Mean Divisa Index (AMDI) is an additional methodological choice. However, a large residual term produced under cross-country decomposition comparison purposes and the inability to produce results when the data set contains zero values generate a strong argument against its usage. The adaptability for decomposing industrial emissions (Liu et al., 2007), strong theoretical foundation, ease of use, result interpretation, simpler formulae when compared to LMDI-II, are reasons for choosing the additive LMDI-I as the preferred decomposition methodology.

Lastly, this chapter (**Section 2.4**) will examine the methodology for determining the concentration or diversity of the industrial fuel mix. The results will present the risk in the security of supply and the capacity for achieving sustainable economic growth as this is closely linked with increased energy consumption in developing economies. The methodological approach utilised by this research has been set by the Hirschman and Herfindahl Index (**HHI**) and the Shannon-Wiener Index (**SWI**). The latter is an established method for evaluating energy supply security, as Stirling (1994) has first introduced. It is an established index metric that expands in a variety of applications such as economics, genetics, ecology (Ralph and Hancock, 2019; Stirling, 1998). HHI, also called the Simpson index, was used to examine the concentration of the fuel mix, acting as an approximate reciprocal to the diversity index. Throughout paradigms located in the international literature for calculating energy supply security, a great debate exists for favouring one index metric over the other (Chalvatzis and Ioannidis, 2017). As such, both the index metrics, HHI and SWI, are to be calculated by the accounting approach utilised by the present research evading an entry to that debate. Arguing towards the benefits of that duplex approach, Cohen et al. (2011) argue that HHI presents the impact provided by the number of options while SWI holds elevated value regarding the contribution of the options present in the fuel mix. Utilising this argument, Chalvatzis and Rubel (2015) have studied the Chinese electricity portfolio historical data by using both SWI and HHI to assess its security of supply.

Observing the application of the chosen methodology across the sections by a more extensive scale perspective, it enables the definition of future pathways for the industries to mitigate the produced carbon footprint and contribute further to the reduction of CO_2. It provides the necessary output for policymakers, complying with the industrial emissions standards that the countries have set in their INDCs to the Paris Agreement. The methodological approach carries novelty, providing a snapshot of industrial performance upon the discussed standards, highlighting areas of improvement.

The factors used between the calculation steps add to an argument of a logical research flow being followed. The accounted output is in cases shared between each chapter as it is a necessary factor used by the methodology and the subsequent analysis. These factors, and how they are shared between chapters, are presented in the following **Table 2**.

Table 2. Common accounted factors between the themes included in the present thesis.

Theme	Factors accounted	Used by a previous chapter
Carbon Emissions Discrepancies	• Heat • CO_2 (India)	
Energy and Carbon Intensity	• Energy Intensity • Carbon Intensity	• Heat • CO_2 (India) for the IEA net scenario
Additive Log Mean Divisia Index (LMDI-I)	• Energy Intensity effect • Carbon Intensity effect • Labour Productivity effect • Industrial Scale effect	• Energy Intensity • Carbon Intensity
Fuel mix concentration and diversity.	• SWI • HHI	Heat

Every methodological approach present in this research, engages an epistemological positivism position. The thesis aims in producing the desired results by extracting the necessary input data and accounting factors, as these are found in established and widely accepted databases of international authorities. It is centred around quantifiable output, and as such, excludes subjective, or prior untested, methodological approaches that would question the credibility of the results. The aim is to provide established methodological steps to verify a reproducible novel output.

2.1 Discrepancies methodology

The calculated carbon dioxide emissions are expressed as the number of physical units of combustible fuel supplied for the production process, multiplied by the respective emission factor (**EF**).

$$Carbon\ dioxide\ emission = Physical\ Quantity\ (kt) * Carbon\ Emission\ Factor \quad (\mathbf{a.1})$$

Focusing on specific sectoral emissions from different fuel types and sectors this has the following form:

$$Carbon\ dioxide\ emission_{ij} = Physical\ Quantity_{i,j} *\ Carbon\ dioxide\ emission\ factor_{i,j} \quad (\mathbf{a.2})$$

Where i, is the fuel type and j is the sector. When assessing the sum of all fuels emissions used in a specific sector then the following equation is valid:

$$Carbon\ dioxide\ emission_j = \sum (Physical\ Unit_i * Carbon\ dioxide\ emission\ factor_i) \quad (\boldsymbol{a.3})$$

To calculate the total emissions from every sector

$$Carbon\ dioxide\ emission_{TOTAL} = \sum (Carbon\ dioxide\ emission_j) \quad (\boldsymbol{a.4})$$

In order to calculate the total emissions of a specific fuel used for every sector, the domestic supply provided by IEA is being used for the provision of the physical quantities. This is the expression of:

$$Domestic\ supply\ of\ energy = Indigenous\ production + imports - Exports \pm Stock\ Change - non\ energy\ use\ of\ fuels \quad (\boldsymbol{a.5})$$

In that context, when assessing the present research, the following order was used in order to extract carbon dioxide (CO_2) emission results for each fuel and sectoral type. It should be noted that where a specified industry sector is selected for the provision of the raw quantities of fuel, this is provided and used "as is" by the selected relevant database; IEA.

$$Heat\ Value_i\ (PJ) = Physical\ Quantity(kt) * \left(Net\ Calorific\ Value\left(\frac{PJ}{Gt}\right)/1000000\right) \quad (\boldsymbol{a.6})$$

The carbon dioxide emissions are extracted by following seven different carbon emission scenarios. These are extracted by the variation of net calorific values (NCVs) and carbon contents (CCs) as described. In a presentation context, NCVs and CCs are extracted by the databases presented in the following **Table 2.1.1**

Table 2.1.1. Different accounting factors for calculating Carbon Dioxide Discrepancies

Physical Quantities	**Net Calorific Value (NCV) per fuel**	**Carbon Content per fuel**
International Energy Agency (IEA)	International Energy Agency (IEA) – **India specific**	IPCC – Low
	IPCC – Low	IPCC – Net
	IPCC – Net	IPCC – High
	IPCC- High	

$$Carbon\ dioxide\ emissions\ (kt) = Heat\ Value\ (PJ) * \left(Carbon\ content\ \left(\frac{kt}{PJ}\right) - Carbon\ Stored\right) * Carbon\ Oxidization\ Rate * \ CtoCO2 \quad (\boldsymbol{a.7})$$

Carbon converted to CO_2 ($CtoCO_2$) always equals to 3.664191 as it is the result of dividing the molecular weight of CO_2 which is 44 to that of carbon which equals to 12. A standard carbon oxidisation rate is used, equal to 0.98. Carbon content minus the carbon stored, is described as the net carbon content.

There is a range of Net Calorific Value (NCV) and Carbon Content (CC) values published for Indian coal (**APPENDIX I**) and those used for the purposes of this research are presented in **Table 2.1.1**. This alteration is the leading cause to estimation uncertainties, which can produce significant emission accounting gaps. Extended accounting factors for emissions uncertainties gap in coal is presented in the following **Table 2.1.2.**

Table 2.1.2. Typical sample of coal NCV values and carbon contents applied for Indian coal by different authorities and actual measurements. Data Source: BP (2015), IEA (2013), IPCC (2006), India Statistics (2015a), Mishra (2009).

Coal Net Calorific Value (kJ/kg)	
India Statistics (Indian Ministry of Statistics and Programme Implementation, 2015a)	19,259
IPCC (IPCC, 2006)	25,000
IEA (International Energy Agency, 2013)	**Coking Coal:** 24,283 **Other Bituminous Coal:** 18,464 **Sub-Bituminous (import):** 18,900
Sample measurements in-situ (Mishra, 2009)	15,056 to 19,690
Carbon Content CC (kg/TJ)	
IPCC (IPCC, 2006)	27.2
BP (British Petroleum, 2015)	25.82

An additional factor, in the Indian energy and emissions, that generates carbon emissions uncertainty is that of physical quantities reporting of energy resources. The EIA reports primary energy data in short tons and require the conversion to metric tons before usage. The heat generated from the consumption of fuels, is frequently expressed as British Thermal Units (BTUs).

To achieve homogeneity and avoid any excessive usage of conversions that would enhance any probability of error, the database selected for the provision of raw quantities is IEA, as previously discussed. The net calorific values (NCVs) used are those of IEA and are specific for India, and the low, mid, upper NCVs as those are reported by the IPCC. The carbon content selected for the purposes of locating the discrepancies is the low, upper and mid that IPCC (2006) is using for its estimations. Therefore, for each total or sectoral discrepancy discussed, the total number of combinations that result from this selected methodology, are seven. This conceptual framework that is followed to achieve the desired results, is graphically presented in **Section 4.2**.

Under those parameters, it is important to highlight the approach adopted from the present research, as it deviates from the approach that IEA uses for accounting carbon dioxide generated by the fuel mix, either on a total or a sectoral basis. This research accounts the carbon dioxide of every fuel activity that is reported either for the total, a sectoral or a sub sectoral basis. The most prolific sources of discrepancies between IEA, IPCC 2006 guidelines and this research for estimating carbon dioxide emissions are attributed to the allocation of carbon stored in the following fuel categories:

- Lubricants (used in two stroke engines)
- Blast Furnace Gas
- By-product gases not used for fuel combustion in the source category of production
- Coals and hydrocarbons injected to blast furnaces
- Cokes used as reductants in inorganic chemical processes.
- Crude oil
- Biofuels (Gas, Liquid and Solid)

The fraction of carbon content stored, in order to calculate the net carbon content, is recommended by IEA in published methodological steps (International Energy Agency, 2012a). Comparing the IEA actual net carbon content with the IPCC carbon emission factors, however, produces different fractions of carbon content than what IEA suggests in the methodology. Therefore, to use the IPCC net carbon content in a justified manner which would be methodologically acceptable, the IEA values are used as the net carbon content, and described as IPCCnet where appropriate, and the high and low IPCC carbon content is adjusted accordingly by following the fraction that produced the net results. This produces the fraction of net carbon, eliminating the need of subtracting the carbon stored from the carbon content, replacing the according part in formula **a.7**. Setting this in a formula:

$$Fraction\ of\ Net\ carbon(per\ fuel) = Net\ Carbon\ Emissions\ Factor\ IEA\left(\frac{kt}{PJ}\right) / Carbon\ emissions\ Factor\ IPCC\ \left(\frac{kt}{PJ}\right)\ (\boldsymbol{a.8})$$

The results that this formula produces on a per fuel basis are included in the following **Table 2.1.3**.

Table 2.1.3. Fraction of Net Carbon Content used for India's total fuel mix.

Fuel	Fraction of Net Carbon	Fuel	Fraction of Net Carbon	Fuel	Fraction of Net Carbon	Fuel	Fraction of Net Carbon
Crude Oil	0.27	**Natural Gas Liquids**	0.34	**Motor Gasoline**	0.27	**Aviation Gasoline**	0.27
Jet Gasoline	0.27	**Jet Kerosene**	0.27	**Other Kerosene**	0.28	**Shale Oil**	0.27
Gas/Diesel Oil	0.27	**Residual Fuel Oil**	0.27	**Liquified Petroleum Gases (LPG)**	0.27	**Ethane**	0.27
Naphtha	0.27	**Bitumen**	0.27	**Lubricants**	0.27	**Petroleum Coke**	0.28
Refinery Feedstocks	0..27	**Refinery Gas**	0.32	**Paraffin Waxes**	0.27	**Other Petroleum Products**	0.27
Anthracite	0.27	**Coking Coal**	0.27	**Other Bituminous Coal**	0.27	**Sub-bituminous Coal**	0.27
Lignite	0.27	**Oil Shale and Tar Sands**	0.19	**Brown Coal Briquettes**	0.21	**Patent Fuel**	0.21
Coke oven Coke	0.28	**Gas Coke**	0.28	**Gas Works Gas**	0.29	**Coke oven Gas**	0.29
Blast Furnace Gas	0.25	**Oxygen Steel Furnace Gas**	0.36	**Natural Gas**	0.27	**Municipal Wastes**	0.33
Industrial Wastes	0.21	**Waste Oils**	0.27	**Peat**	0.28	**Wood/Wood Waste**	0.27
Other Primary Solid Biomass	0.30	**Charcoal**	0.27	**Biogasoline**	0.43	**Biodiesels**	0.28
Other Liquid Biofuels	0.25	**Other Biogas**	0.56	**Municipal Wastes (Biomass)**	0.20	**Coal Tar**	N/A

This fraction of carbon content factor acts as the means of producing the IPCC high and low carbon content factors in kt of carbon to PJ. The complete net carbon content table is located at **APPENDIX I**. As Coal Tar is not combusted, the provision of the fraction of net carbon or carbon content is not applicable, as reflected in the table above. It should be noted that the fuels included in **Table 2.1.3** are not present in India's fuel mix assessed and they are provided for cross-referencing purposes. However, the fuels which present activity, for the purposes of this research, will be analytically approached and examined at the discrepancies' results chapter, following the pattern established in the present methodology.

2.2 Intensity methodology

2.2.1 Data

According to the United Nations Sustainable Development Division (UNSDD), energy intensity is defined as the ratio of energy use to GDP (United Nations Sustainable Development Division, 2005a) and as the final energy consumption divided by the Gross Value Added (GVA) at constant prices (European Environment Agency, 2015). While Eurostat defines the unit of economic output as the GVA, the UNSDD argues that a standardized methodology for calculating energy intensity does not exist (United Nations Sustainable Development Division, 2005b). This claim is evidently supported by the US Office of Energy Efficiency & Renewable Energy, which plainly expresses the energy intensity as energy per unit of output (Department of Energy, n.d.). For the purpose of this research, industrial output is expressed as the total output in current million US dollars. The IEA database is used for extracting energy consumption data per fuel product and industrial flows (International Energy Agency, 2016) and presents a wide range of flows and time series data (International Energy Agency, 2014a). IEA data has been used extensively for research on China (Liu et al., 2015b; Shan et al., 2016b), Indonesia (Alam et al., 2016; Jiang and Guan, 2016), the Philippines and Thailand (Timilsina and Shrestha, 2009). For comparison, regional data provided by Indian authorities (MOSPI) is characterized by limited length of time-series, generic fuel products and inconsistent data provision (Indian Ministry of Statistics and Programme Implementation, 2015b).

Table 2.2.1. Breakdown of products used as input per industrial sector of India, China, Indonesia, the Philippines and Thailand. Data Source: (International Energy Agency, 2014b)

Country	Industrial Sectors	Anthracite	BKB	Biogases	Blast Furnace	Coke oven Coke	Coke oven Gas	Coking Coal	Fuel Oil	Gas Coke	Gas works Gas	Gas/diesel oil	Lignite	LPG	Motor gasoline	Naphtha	Natural Gas	Other Bituminous Coal	Other kerosene	Other Oil	Patent Fuel	Petroleum Coke	Primary Solid Biofuels	Refinery Gas	Sub-bituminous coal
India	Chem.							√	√			√	√	√				√							
	I&S				√	√	√	√	√		√	√	√	√				√							
	Mach.								√			√		√											
	N.M.M.							√	√			√	√					√				√			
	PPP.							√					√					√							
	T&L								√			√	√	√				√							
China	Chem.								√		√	√		√			√	√	√		√			√	
	I&S								√	√		√		√			√	√	√						
	Mach.								√	√		√		√			√	√	√						
	N.M.M.								√	√		√		√			√	√	√						√
	PPP.								√		√			√			√	√	√						√
	T&L								√		√	√		√			√	√	√						
Indon	Chem.								√			√					√	√	√						√
	I&S	√			√	√		√	√			√					√	√							√
	Mach.											√													

	N.M.M.								√			√					√								√
	PPP.																								√
	T&L								√			√													
The Philippines	Chem.								√			√		√					√						
	I&S				√	√						√		√		√			√						
	Mach.								√			√		√					√						
	N.M.M.								√			√		√					√						
	PPP.								√			√							√						
	T&L								√			√		√					√						
Thailand	Chemical								√			√		√	√		√		√						
	I&S				√	√			√			√		√			√		√						
	Machinery								√			√		√	√		√		√						
	N.M.M.								√			√	√	√	√		√	√	√						
	PPP.								√			√	√	√	√		√		√						
	T&L								√			√	√	√			√		√						

Focusing on the breakdown of products and flows found in **Table 2.2.1**, the labels are explained as following according to the IEA standards: "Chemical" refers to the chemical and petrochemical; "I&S" is the iron and steel; "N.M.M." stands for non-metallic minerals; "PPP" as the paper pulp and print; "T&L" as the textile and leather industries; and finally, "N-S" as non-specified. The physical quantities of products (International Energy Agency, 2014c) presented above (**Table 2.2.1**) are being multiplied with their respective NCVs as these are found in IEA datasets (International Energy Agency, 2014a) and organized according to their flows. The formula used is presented below:

$$E_{i,j,k} = Ephy_{i,j,k} * NCV_{i,j,k} \ (\boldsymbol{b.1})$$

This does not apply for gases as these are already converted to heat. Where *E* stands for Energy expressed as Heat in PJ, E_{phy} stands for Energy in physical quantity measured in kilotonnes (kt) and NCV stands for the Net Calorific Value (kj/kg). The indicators stand for i: year; j: product; and k: flow. Where the flow is not specifically described for the NCV, the generic NCV of the industry, according to the IEA data, is used. The heat sum (E) of the products per flow (industrial sector) expressed as E*k* is then calculated. Where *n* stands as the sum of the products (*j*) used for each flow (*k*) as those are specified above (**Table 2.2.1**).

$$Ek = (Ei_{1980}j_1 + Ei_{1981}j_1 + \cdots + Ei_{2011}j_1) + (Ei_{1980}j_2 + Ei_{1981}j_2 + \cdots + Ei_{2011}j_2) + \ (Ei_{1980}j_n + Ei_{1981}j_n + \cdots + Ei_{2011}j_n) \ (\boldsymbol{b.2})$$

Table 2.2.2. Sum of categories for converting UNIDO ISIC rev3.0 industrial output in current million dollars to IEA ISIC rev 4.0 classification. Data Source: (United Nations Industrial Development Organization, 2010)

IEA classification (ISIC Category rev 4.0)	ISIC Category rev 3.0 sums for conversion to rev 4.0
Chemical and Petrochemical	23+24
Iron and Steel	27 (incl. non-ferrous metals)
Machinery	28+29+30
Non-metallic minerals	26
Paper, Pulp and Print	21+22
Textile and Leather	17+18+19

Matching the UNIDO and IEA selected data is not straight-forward as it requires harmonisation of different classifications, which are not established in the literature. However, it is an essential step to perform the calculations described in **Sections 2.2.2 and 2.2.3**; therefore, a proposal is put forward to achieve this conversion (**Table 2.3.2**). For each flow, the respective output in million dollars is being published by the United Nations Industrial Development Organization (UNIDO) (United Nations Industrial Development Organization, 2010). The database used is INDSTAT2 ISIC rev 3.0 as this is provided by UNIDO (United Nations Industrial Development Organization, 2010) and summed up where needed to match the IEA classification (**Table 2.2.2**).

Since the data provided by UNIDO is in current million US$, they must be converted to constant 2005 US$ values to perform a timeline analysis. As a result, the output per year in current million US$ is divided with the index value of the corresponding year with 2005 acting as the base year, as provided by the Bureau of Labour Statistics (BLS) (Bureau of Labor Statistics, 2016). The conversion formula is as following:

$$T_{2005\ constant\ US\$} = \frac{T_{current\ US\$}}{(CPI_{2005\ base\ index}/100)} \quad (\boldsymbol{b.3})$$

2.2.2 Energy Intensity

Applied on an annual time series, the formula produces the industrial output in 2005 constant US$ for 1998-2012. Following the approach for energy intensity being calculated as

Joule/US$, according to international literature (Li and Chen, 2013; Torrie et al., 2016), the following formulas are applied for every flow that sums up the products as already shown.

$$E\ (TJ) = \frac{E\ (PJ)}{1000000}\quad (\boldsymbol{b.4})$$

$$Energy\ Intensity\ = \frac{E_{i,j,k}(TJ)}{constant\ 2005\ million\ US\$}\ (\boldsymbol{b.5})$$

For Thailand and the Philippines, median values have been used in yearly gaps where IEA data is not available to present the energy intensity[1].

2.2.3 Carbon Intensity

Carbon intensity can be expressed as the emissions of CO_2 per total economic output (Department of Energy, n.d.) or CO_2 emissions per total primary energy supply (TPES) according to the IPCC (IPCC, 2007). To calculate CO_2 emissions intensity, the IEA database has been selected as the most appropriate to extract the raw primary energy data of the industrial sectors examined. IEA has a wide variety of flows and respective Net Calorific Values (NCVs) per country, extended time series availability and reporting consistency. The economic total output values have been extracted from UNIDO data and converted to US 2005$ values and ISIC rev.4 to match the reporting methodology of IEA (United Nations Industrial Development Organization, 2010). Physical quantities of fuels are converted to petajoules, and by using the appropriate IPCC net carbon content per fuel (IPCC, 2006), are summed for each industrial sector's total CO_2 emissions. The breakdown of the products and flows has been conducted where each respective activity can be found and follows that presented in **Table 2.2.1**.

The equations followed for extracting CO_2 intensity data are following the pattern of energy intensity as per **(b.1)** and **(b.2)**

$$CO_{2\ (i,j,k)} = Carbon\ content\left(\frac{kt}{PJ}\right) * Carbon\ oxidization\ rate\ * CtoCO_2\ conversion\ (\boldsymbol{b.6})$$

[1] Median values for the extraction of energy intensity results are used for the years 2000, 2002, 2004, 2007, 2011 for the Philippines and 1999, 2001 for Thailand.

The carbon oxidization rates have been accounted as 0.98 for Coal products, 0.99 for Oil products and 0.995 for Natural Gas. The C to CO_2 conversion rate is accounted as the result of the molar mass of carbon dioxide (44) to the atomic mass of carbon (12) resulting to equation **(6)** which accounts the mass of total CO_2 for all fuel products per industrial sector expressed in kt. To calculate the appropriate carbon intensity, equation **(b.7)** is used:

$$Carbon\ Intensity\ (CI) = \frac{CO_{2\,(i,k)}}{E_{(i,k)}}\ (\boldsymbol{b.7})$$

This equation expresses the carbon intensity (CI) for each year and flow, including all products.

2.3 Additive Log Mean Divisia Index (LMDI-I) Methodology

2.3.1 CO_2 Index Decomposition Analysis Rationale

The index decomposition analysis (IDA) using the logarithmic mean divisia index (LMDI-I) approach for analysing CO_2 emissions from energy consumption, is the subject of studies mainly related to China for the total (Wang et al., 2005), the industry level on a generic sum basis of heavy and light industry (Fan, 2010) or specified industrial sectors (Liu et al., 2007). Under that consideration, international literature started to conduct the LMDI-I approach for India in comparison to China (Wang and Li, 2016), as parts of BRICS on a total final energy consumption for CO_2 emissions (Dai et al., 2016), against the energy consumption of developed economies (Lima et al., 2017, 2016) or LMDI decompositions of CO_2 emissions for extended country groups that additionally include S.E. Asian countries like Indonesia and the Philippines (Pani and Mukhopadhyay, 2010).

The present study aims to decompose the industrial CO_2 emissions on a per sector basis. The factors examined are energy intensity, carbon intensity, labour productivity and industrial scale under a historic trend prism. These factors have been selected upon following the paradigm of an originally extended Kaya identity leading to a Logarithmic Mean Divisia Index (LMDI) approach as demonstrated in the international literature (Boqiang and Liu, 2017; Lin and Tan, 2017), minus the effect of energy structure due to limitations discussed in the methodology. These levels and the respective factors are accounted for the total and each respective sector of eleven 3-year periods ranging from 1980 to 2012.

This single-dimensional decomposition analysis; CO_2 by total and specific industrial sectors, is conducted by using a data structure design which dictates that every driver examined is broken down not only a total but also a sectoral basis. Energy and carbon intensity, labour productivity and industrial scale are broken down for each industrial sector. The decomposition steps are described in the methodology sections that follow. In this manner, perfect multilevel decomposition standards of IDA (Ang and Wang, 2015) is satisfied but due to the nature of the study, a multidimensional approach is not feasible; the three countries examined present independent cases. The decomposition results are extracted in the aggregate level (total industry) for each of the three countries and perform the additional steps to extract results for six industrial subcategories. These can consist the aggregate and achieve results that can be considered consistent and meaningful, revealing the factors that drive industrial CO_2 emissions and providing an enhanced level of insight.

The LMDI-I method is following an additive formula approach, using physical units (tonnes of CO_2) to study the change and produce decomposition results, following established methodologies provided by international literature (Ang, 2015, 2005). The Kaya identity can be decomposed in specified variables that affect the industrial CO_2 emissions. These are expressed as following:

$$CO_2eff = \frac{CO_2}{total\ energy\ consumption\ (TOE)}\ X\frac{TOE}{GDP}X\frac{GDP}{Population(POP)}X\ POP\ (\boldsymbol{c.1})$$

The CO_2 side of the equation stands for the total amount of CO_2 emissions to be decomposed. The right hands side of the Kaya identity equation is the result of a series of factors which are to be described and analysed accordingly. The $\frac{CO_2}{TOE}$ stands for the carbon intensity; $\frac{GDP}{TOE}$ stands for energy intensity, or the amount of total economic output per unit of energy, $\frac{GDP}{Population}$ is the GDP per capita and acts as the representation of economic level of development. Finally, POP stands for the population level. Summarising the above, it is evident that carbon intensity, energy intensity, GDP per cap and population act as determinants of CO_2 emissions under the Kaya identity prism.

The characteristics of a country's CO_2 emissions at the industrial level, can be used to alter the Kaya equation accordingly, adjusting the factors where applicable (Boqiang and Liu, 2017; Lin and Tan, 2017). The GDP is being substituted with the total industrial economic output to determine the industrial energy intensity to serve the purpose of this research (Pappas and Chalvatzis, 2016), and the population is substituted with the number of persons employed in the industry following the Lin and Tan (2017) standards. Therefore, the Kaya identity equation is transformed to the LMDI as following.

$$CO_2eff = \frac{CO_2}{EFF} X \frac{EFF}{IVA} X \frac{IVA}{NPE} X\ NPE = CI\ x\ EI\ x\ LP\ x\ IS\ (\boldsymbol{c.2})$$

EFF stands for fossil fuel consumption, **IVA** stands for the industrial value added and **NPE** is the number of the persons employed in the industry. Thus, **CI** is the carbon dioxide emissions caused by each unit of fossil fuel consumption. **EI** stands for energy consumption per unit of industrial total output. **LP** is industrial total output per capita and **IS** equal to NPE, acting as a representative factor to the effect of industrial scale.

$$CI_{eff} = \frac{CO_2(t) - CO_2(0)}{\ln[CO_2(t)/CO_2(0)]} * \ln[CI(t)/CI(0)]\ (\boldsymbol{c.3})$$

$$EI_{eff} = \frac{CO_2(t) - CO_2(0)}{\ln[CO_2(t)/CO_2(0)]} * \ln[EI(t)/EI(0)]\ \ (\boldsymbol{c.4})$$

$$LP_{eff} = \frac{CO_2(t) - CO_2(0)}{\ln[CO_2(t)/CO_2(0)]} * \ln[LP(t)/LP(0)]\ \ (\boldsymbol{c.5})$$

$$IS_{eff} = \frac{CO_2(t) - CO_2(0)}{\ln[CO_2(t)/CO_2(0)]} * \ln[IS(t)/IS(0)]\ (\boldsymbol{c.6})$$

Upon the calculation of carbon intensity effect (**CI_{eff}**), energy intensity effect (**EI_{eff}**), labour productivity effect (**LP_{eff}**) and industrial scale effect (**IS_{eff}**) from year 0 to year t, then the analysis of the contributions of these factors to the change of CO_2 emissions of this period, can be reached and attributed.

Table 2.3.1. LMDI-I factors meaning and abbreviations

Factor	Meaning	Abbreviation
CO_2/EFF	The effect of carbon intensity	CI_{eff}
EFF/TIO	The effect of energy intensity	EI_{eff}
TIO/NPE	The effect of labour productivity	LP_{eff}
NPE	The effect of industrial scale	IS_{eff}

Fossil fuel to total fuel energy consumption effect; the energy structure effect, is excluded from this decomposition, in antithesis with the methodology followed by Lin and Tan (2017). All industrial fuels are classified as fossil fuels, including biofuels as they generate CO_2 and renewable energy has a negligible amount of industrial usage according to the IEA reported consumption figures. The choice to ignore the effect of energy is additionally supported by international literature, that claims that for countries such as India, the structural effect is of less importance compared to others (Voigt et al., 2014).

2.3.2 Energy Emissions Intensity

Following the methods described in the methodology section 3.3.2, energy intensity is used for studying the energy intensity effect through the application of the method LMDI-I. Examining the energy intensity effect towards carbon emissions change for every three-year period, is the aim and final product of applying this exact methodology.

In this context, due to a wide range of flows and data-time availability reported in a consistent manner, the IEA database is used for the reporting of raw materials consumption (International Energy Agency, 2014a). The breakdown, of the products and flows, that is conducted for each respective activity is broken down for three countries; India, Indonesia and The Philippines, matching those found in **Table 2.2.1** with the respective abbreviations described in the relevant section being identical. Extracting energy intensity follows the formulas described in **Section 2.2.2** and the energy intensity effect is calculated according to **formula c.4**.

2.3.3 Carbon Emissions Intensity

The methodology selected for calculating carbon intensity will follow not that of the CO_2 per economic output, but that of CO_2 per total primary supply, or TPES, according to the methodology followed in Section **2.2.3** and **formula b.7**. As a result, in order to calculate CO_2 emissions intensity, IEA is selected as the primary database for extracting the required information. Raw primary data for each fuel that each industrial sector of the selected countries is examined. The variety of flows, data consistency and the provision of NCVs on a per country, per industry and per fuel basis with an annual reporting format is the main factor that leads to be a preferable choice for the purposes of this research.

In the same manner as found previously, calculating carbon intensity requires the provision of the fuels primary data, such as weight, measured in tonnes unless specified otherwise. These are subsequently converted to heat expressed in Joules. The provision of net carbon content per fuel from IPCC 2006 enables the extraction of the total CO_2 emissions per fuel. Summing the CO_2 of each of those fuels consumed to match the fuel mix of each industrial sector provides the total carbon dioxide emissions per annum.

2.3.4 Labour Productivity and Industrial Scale

Labour productivity equals to the economic output per capita; employee, as described in the LMDI-I methodology followed (IVA per NPE). The IVA and NPE per sector is extracted by summing and then dividing between them as appropriate the sums partially present in **APPENDIX II** for the studied timeline following the respective UNIDO reports where the complete primary data are available (United Nations Industrial Development Organization, 2016). Being further explanatory to the industrial scale indicator, NPE equals the number of employees of each specified industry (IS) and is a standalone synonymous figure. It follows the same pattern for extracting results according to the previously described LMDI-I methodology.

The descriptive equations are included and follow the principle below. These are explained further by the conceptual frameworks included in **Chapter 6.2**.

$$Labour\ Productivity\ (LP) = \frac{Industrial\ Value\ Added\ (IVA)}{Number\ of\ Persons\ Employed (NPE)}\ (\boldsymbol{c.7})$$

$$Industrial\ Scale\ (IS) = Number\ of\ Persons\ Employed\ (NPE)\ (\boldsymbol{c.8})$$

2.4 Methodology for estimating the fuel mix concentration and diversity by using the Hirschman-Herfindahl Index (HHI) and the Shannon-Wiener Index (SWI).

The implications to energy security can be measured by resource concentration, alternative described as the concentration of the available fuels used in the energy mix of a chosen activity. While concentration is an established means of measuring energy security (Lefèvre, 2010) and is commonly used by policy makers as an aid to reduce any related risks, it is increasingly giving way as a methodological energy security measurement concept to diversity (Månsson et al., 2014). According to Stirling (1998), identifying diversity in this research case e.g. the industrial fuel mix, can promote growth and innovation or aid in the reduction of any shortages of supply or trade fallouts. A highly diversified fuel mix can enhance the energy security of a system, even against a high usage of imported fuels (Bhattacharyya, 2009), therefore numerous countries have undertaken policy actions to promote energy security (Bazilian and Roques, 2008).

Diversity indices vary in type and application areas and fields. These indices include the Gini for economic statistics, Stirling for energy systems and technology studies and Simpson for biodiversity and ecology indexing among others. For assessing energy systems, the Hirschman-Herfindahl index and Shannon-Wiener index are more commonly used for producing relevant research (Chuang and Ma, 2013) and as such, will be incorporated by the present study for extracting results.

To apply the Hirschman-Herfindahl and Shannon-Wiener indices, the heat from the raw quantities of fuels that present any activity levels, are to be extracted. As a result, the methodological patterns as that found in section 2.1 are followed, but for the broadened country basis that is being examined, per annum. Assessing the **formula d.1, w**here *i*, is the fuel type and j is the sector

$$Physical\ Quantity_{i,j,k}(kt) * \left(Net\ Calorific\,Value\left(\frac{PJ}{Gt}\right)/1000000\right)_{i,j,k} = Heat\ Value_{i,j,k}\ (PJ)\ (\boldsymbol{d.1})$$

The present study is conducted using the total and 10 individual industrial sectors that comprise the former. Calculating the extracted heat for the five countries examined for each selected industrial sector and, subsequently, the total industry on a per country basis, enables the research to determine the concentration (HHI) and diversity (SWI) indices for each selected benchmark of the industrial fuel supply determining factors such as energy balance and supply. The fuel mix balance is to be determined among every fuel that is a part of the used mix as provided by the IEA classification, and not generic fuel categories. As the present research is conducted in a sectoral level of the energy system, it does not examine energy that enters the mix from non-domestic sources. It therefore accounts the indices at the final consumption level only, essentially performing a simplification regarding the domestic production or import, deviating from similar research performed for ASEAN countries (Kanchana and Unesaki, 2014).

The HHI and SWI are extracted based on data acquired for years 1980 to 2012. The primary energy data are extracted from fuel raw consumption quantities converted to heat as per formula **d.1** as these are retrieved from IEA as these are contained in the UK data service and are part of the data extracted and used as described in **sections 2.1**, **2.2** and **2.3** of the present chapter.

2.4.1 Hirschman-Herfindahl Index (HHI)

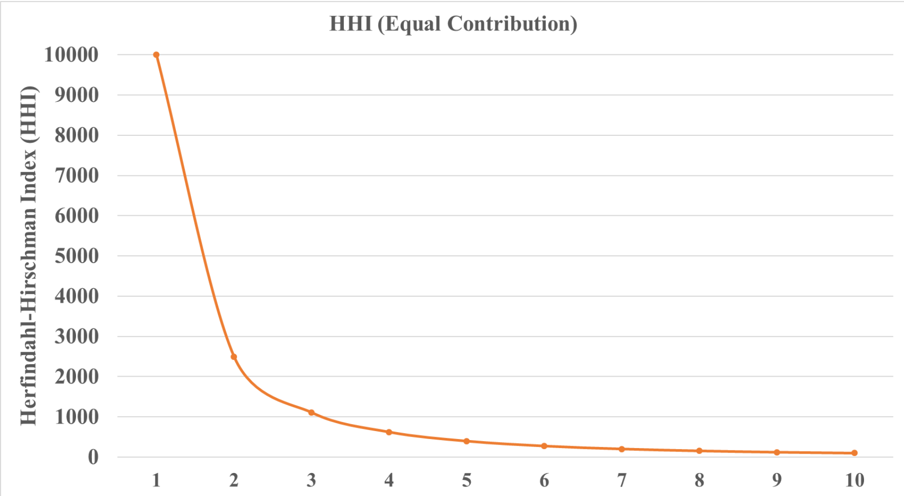


Figure 2.4.1 HHI concentration performance per number of equal weighted fuel options in the energy mix

The Hirschman-Herfindahl index was developed by Hirschman and Herfindahl (Reinert et al., 2016) and is widely used to measure concentration in economics (Hausman et al., 2007), market competition (Hunt et al., 2015) and energy systems (Jun et al., 2009).

$$-\sum_{o=1}^{n} S_o^2 = \boldsymbol{HHI}\ (\boldsymbol{d.2})$$

In equation **d.2** the number of options is expressed as *n* and the proportion of option S_o contains *o* as a percentage expression. To calculate the HHI index, the share squares of each option-fuel used in the energy system; the fuel mix, are summed. To identify this method by using an example, a fuel that is contributing 10% of the total in the fuel mix, the number is squared as if being an integer. Representing equal contribution options in **Figure 2.4.1** it is demonstrated that one option, holding the absolute share in the energy mix; 100% would present an HHI value of 10000. Increasing the options, reaching 10, assuming equal weight at

10% for each in the fuel mix, would present HHI of 100. As more equal weighed options enter the fuel mix, HHI would further be leaning towards zero.

According to FTC directives (Calkins, 2006) an HHI level lower than 1000 presents a market with low concentration while an HHI higher than 1800, showcases a market with high concentration. However, for the purposes of this research, as it will act mainly as a cross-country comparison of the same industrial categories, HHI will be benchmarked at a standalone basis. Concluding, HHI is not able to detect dependencies between fuels (Matsumoto et al., 2012), a case which is not an approach undertaken by the present study, highlighting HHI as an appropriate measurement index and benchmark.

2.4.2 Shannon-Wiener Index

Figure 2.4.2 SWI diversity performance per number of equal weighted fuel options in the energy mix

The Shannon-Wiener index was developed by Shannon (1948) to use entropy for providing a description of uncertainty in information systems. SWI additionally to HHI is a part of the Hill family of indices (Keylock and Lane, 2005), indexing biodiversity (Di Bitetti, 2000; Heip, 1974), ecology (Cook, 1976; Jhingran et al., 1989) and energy diversity (Chalvatzis and Ioannidis, 2016; Skea, 2010).

$$-\sum_{o=1}^{n} S_i * \ln(S_o) = \boldsymbol{SWI\ (d.3)}$$

In equation **d.3** the number of options is expressed as n, the proportional reliance of the selected option is expressed as S_o, and *ln* is the natural logarithm. In SWI, every fuel entering the mix to be used by the industry is accounted as an option. Each of the options accounts as a calculated number percentile. Translating the former to a numeric expression, 0.1 in the SWI index is 10% of the total fuel mix. Demonstrating equal contribution options in **Figure 2.4.2** in case that the energy system is using one option, the SWI equals to zero; the minimum index number. Two options of equal contribution present a diversity index of 0.69 (2dp) and adjusting accordingly as increasing number of options enter the system. As each option accounted stands for a different type of fuel, a case of possible dependencies between options does not exist. Benchmarking SWI, Grubb (2006) followed by Ioannidis (2019) have accounted an output of SWI equal to 1 as a system with a decreased number of fuels in the energy system, showcasing low diversity, while a value of 2 would demonstrate the opposite trend. However, as each case presents different characteristics, the present research will benchmark SWI in comparison to the other countries that are being examined.

3. Emissions Discrepancies

3.1 Introduction

India has experienced a sustained major economic growth during the last decade (IMF, 2018a) that was accompanied by an increase in energy demand (U.S. Energy Information Administration (EIA), 2018). This requirement for achieving sustained economic growth is observed as being a crucial factor, for the majority of the developing nations (Narayan, 2016a). Energy holds a fundamental role in the supply chain of all economic activities (Csereklyei et al., 2016; Hu et al., 2015), underlining the urgency that countries have in securing adequate capacity for production. Secure access to affordable energy resources was prominent in national scale policies and cross-country agreements (Ganguli, 2016), while energy trading supports major global and regional markets (Aalto, 2015; Graaf and Sovacool, 2014).

India's total final energy consumption amounts to approximately 21,417 PJ (International Energy Agency, 2014b), while approximately 300 million people remain without access to grid electricity (Ferris, 2014). The final energy consumption has increased by 186% during 1980-2012, with 61% being the rise in the last 10 years of that period. The industry and power sectors are the largest consumers of primary commercial energy in India (Indian Ministry of Statistics and Programme Implementation, 2015b). India's power sector is predominantly based on indigenous fossil fuels and growing income trends are linked to growing demand for power supply (International Energy Agency, 2015a). India rises in the global metrics as a major GHG emitter, with a share of 6.5% of the total global emissions (Olivier et al., 2015). The country is expected to become, along with China, the biggest energy consumer by 2030 in absolute terms (WEO, 2014).

India's strong coupling of emissions to economic growth, is expected to present increased CO_2 emissions reaching an average 6.3% increase for 2018 (Le Quéré et al., 2018). The country's emissions output highlights an increased probability of surpassing the CO_2 emissions of the EU-28 by 2020 (Dubash et al., 2018), posing a significant potential impact on global climate change mitigation strategies. According to its Intended National Determined Contribution (INDC) to the COP21 Agreement in Paris, India has pledged to increase its coal-based efficiency of 144 aging thermal power generation stations. It will do so by reducing its emissions intensity by 33%-35% up to 2030; and introducing industry initiatives for CO_2

reduction such as the Carbon Disclosure Project of India and the Vehicle Efficiency Programme (UNFCCC, 2015).

India uses coal as a primary energy source for meeting its energy needs (Indian Ministry of Statistics and Programme Implementation, 2015a) and its consumption is bi-directionally linked with economic growth both on short and a long-term outlook (Bhattacharya and Bhattacharya, 2014). The challenge of decoupling emissions to economic activity is unprecedented (MacLachlan, 2016; Pearce, 2016) and it is particularly difficult for the emerging Asian economies, such as that of India which has historically relied on coal for energy supply (Bhattacharya and Bhattacharya, 2014; Fan, 2011; International Energy Agency, 2014b, 2013). Coal offers the highest reserves to production ratio (R/P) among India's fossil fuels, with 94 years (British Petroleum, 2016). Specifically coal-fired power stations represent 61% of the total capacity mix (Central Electricity Authority, 2016), and produce 70% of the total electricity generated in India (Soni et al., 2015). India's domestic supply fuel mix is largely based on coal products (**Figure 3.1**). A variety of coal types and qualities with different carbon content and net calorific values (NCV) are being used for domestic supply as demonstrated in **Figure 3.2**.

This variable mix of coal products is characterised by different carbon content and heat values; therefore, each product has different contribution to the total CO_2 emissions. Nine different coal products are used in this fuel mix category. It includes both indigenously produced and imported coal. The coal product with the highest usage in the fuel mix is other bituminous coal.

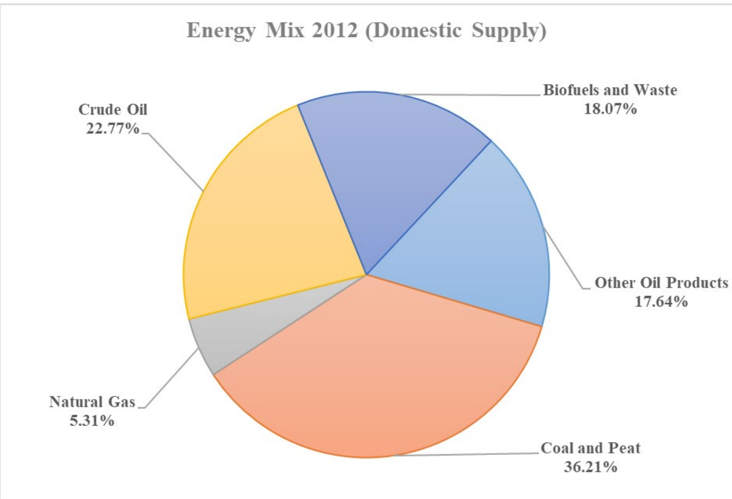


Figure 3.1. India's domestic supply fuel mix in 2012. Data Source: International Energy Agency (2015)

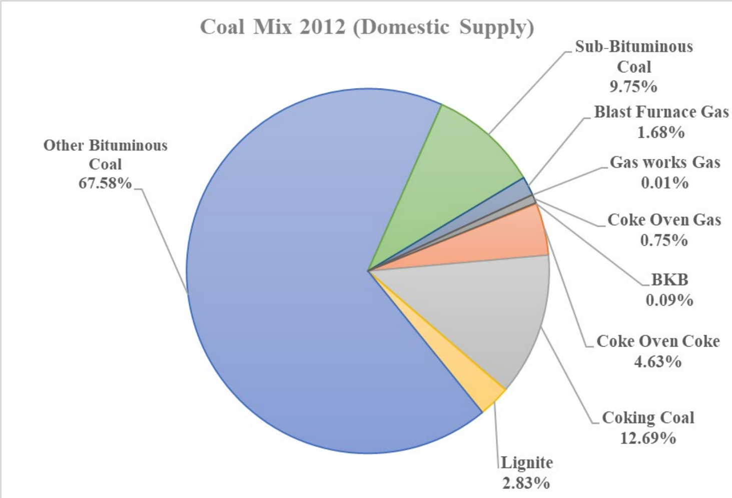


Figure 3.2. India's domestic supply coal mix in 2012. Data Source: International Energy Agency (2015)

3.2 Previous Research and Hypotheses Building

The existing literature on India's CO_2 emissions has mostly been based on estimations rather than actual measurements of the in-situ fuel source characteristics (Azam et al., 2016; Gambhir et al., 2014; Morrow et al., 2014a; Nejat et al., 2015; Saidi and Hammami, 2015; Srinivasan, 2015; Wu et al., 2015). Srinivasan (2015) has examined the relationship of energy consumption, economic growth, and CO_2 in India. The empirical results confirmed the existence of a unidirectional causality running from energy use to CO_2 emissions, and in the short run from CO_2 to economic growth. Similarly, Wu et al. (2015) examined the relationship of parameters such as CO_2 emissions, energy consumption, urban population, and economic growth in the BRIC countries by using World Bank and UN data. Gambhir et al. (2014) used data from the World Development Indicators (WDI) of the World Bank, EIA, BP and IEA to analyse the long-term mitigation options for India to meet a 2ºC reduction commitment, concluding that it could overachieve a 2050 low-carbon target. Morrow et al. (2014) used IPCC data for coal consumption emissions to analyse various energy efficiency measures for India's iron and steel and cement industries. They estimated the savings in electricity, associating them with the respective CO_2 reductions that would occur while Nejat et al. (2015) used IEA data to review the status of CO_2 emissions of the residential sector of ten countries, including India.

International authorities, such as the IEA, do not report on the quantified uncertainty in published emissions data. IEA relies on the Intergovernmental Panel for Climate Change (IPCC) methodologies citing its estimates of uncertainty. The IPCC states that for countries that do not have reliable and consistent energy collection systems, the uncertainty value could reach a ±10% (Marland, 2008). Oak Ridge National Laboratory (ORNL) with its Carbon Dioxide Information Analysis Center (CDIAC) and EDGAR databases, have been found to have a difference of 9.9% or 17.7 Mt of carbon in year 1990.

These differences were assigned to emission factor accounting (Marland et al., 1999) and inconsistencies in national statistics reporting and data collection by the UN and IEA. The sum of the difference between ORNL and EDGAR for the largest 10 emitters was enough to surpass, the remaining 190 countries assessed, presenting the significance of the emissions and energy accounting. The uncertainty in assessing GHG inventories is analysed by various studies (Jonas et al., 2010; Lieberman et al., 2007; Newbold and Daigneault, 2009; Winiwarter and Rypdal, 2001) which conclude in the need for standardisation. This need for international norms to be established, in order for the confidence interval values to be improved and concerns over consumption and income-based approaches of carbon accounting to be overcome, is pointed out even in recent studies (Steininger et al., 2016).

The importance of this issue was recently highlighted with research focusing on revised estimates of Chinese carbon emissions deriving from fossil fuel combustion (Guan et al., 2012; Liu et al., 2015b). The research of Guan et al (2012), compiled Chinese national and provincial carbon inventories, based on two different official energy data sets that were publicly available. The results contradicted the reported figures of the National Bureau of Statistics (NBS), highlighting large discrepancies between reported and estimated data. Extending on the scope leading to those findings, Liu et al (2015b) revised the Chinese energy and clinker (cement) consumption data and calculated the CO_2 emissions through the usage of new and actual measured emission factors of 602 Chinese coal samples from 4,243 coal mines. The authors showed that for 2013, China emitted 14% lower CO_2 from fossil fuel combustion and cement production than those reported by other inventories, extending to a reduced 2.9 Gt of CO_2 when compared to previous estimates for the assessed period of 2000-2013. The same study presented that emission factor variations and different official sources (databases) for the estimation of activity data can lead to deviations in estimated emissions that amount up to 40% in a given year. These reduced national Chinese CO_2 emissions have been reconfirmed to be 12,69% lower, through updated emission factors which have also been extended to a provincial level, in comparison to the IPCC default emission factors being used historically (Shan et al., 2016b). Focusing on studies that have researched emission accounting discrepancies, Greece offers one more example where the statistic authorities were underestimating lignite combustion emissions due to the fact that the actual carbon content of Greek lignite, was lower than what the respective typical values suggested (Kaldellis et al., 2004).

Turning the attention on CO_2 emissions, as these are reported by international bodies and emissions accounting firms, there are evident preliminary findings that point to a reporting pattern revealing significant carbon discrepancies. This usage of estimated CO_2 reporting leads to uncertainty due to generic emission factors, calorific values and carbon content being attributed to the physical quantities of fuels combusted. Moreover, the reported data between different provinces of the same country are posing potential error sources due to variable standards in the data gathering process (Andres et al., 2014; Liu et al., 2015a). Those discrepancies according to the data collection performed, and regarding the case of India, are presented in **Figure 3.3**, then focusing further on those discrepancies and providing a four-year snapshot at **Figure 3.4**, assessing the CO_2 results published by different energy research institutes and agencies.

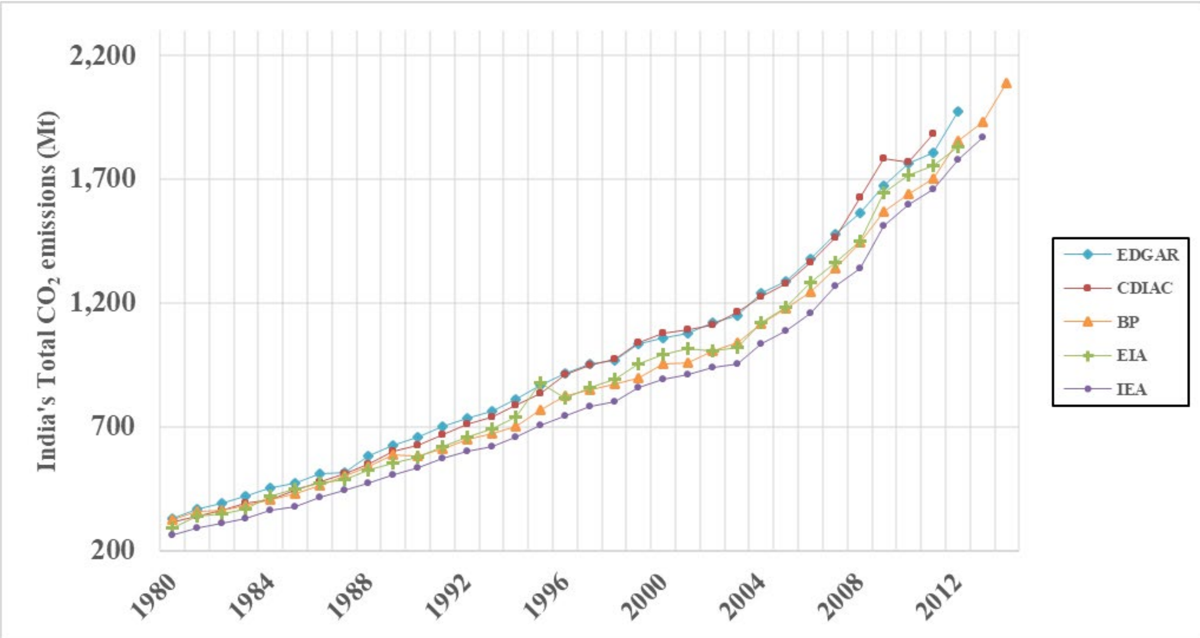


Figure 3.2. India's total CO_2 emissions growth timeline originating from fossil fuels 1980-2014. Data sources: (Carbon Dioxide Information Analysis Centre (CDIAC), 2015), (International Energy Agency, 2015b), Emission Database for Global Atmospheric Research (EDGAR) (European Comission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016)

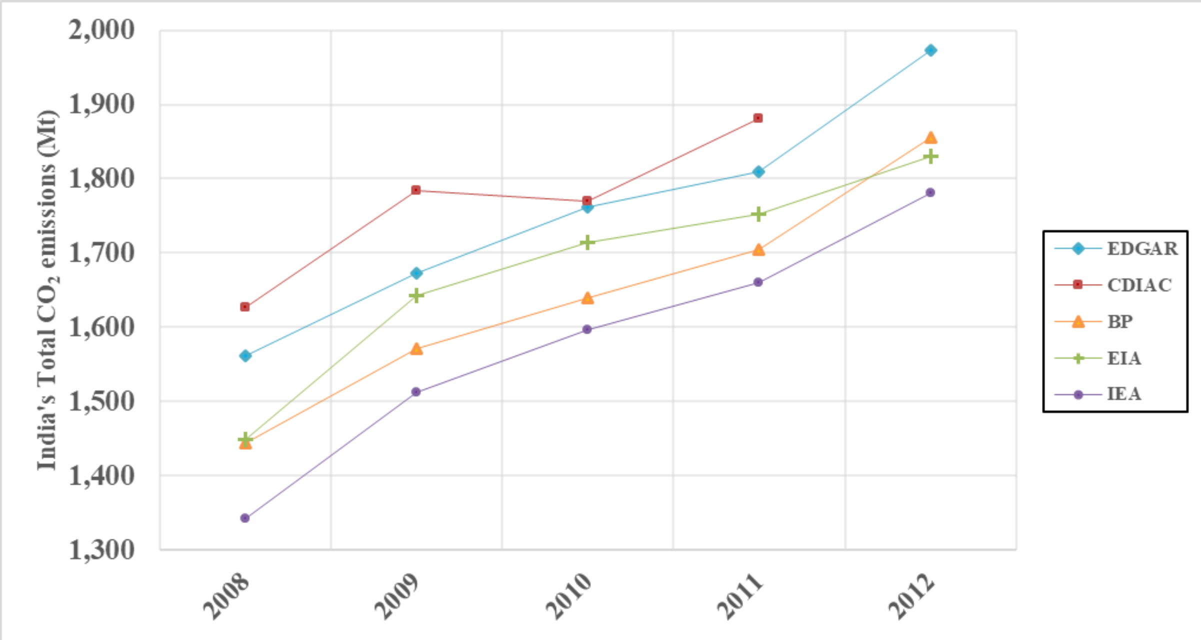


Figure 3.4. India's total CO_2 emissions discrepancies timeline snapshot 2008-2012. Data sources: (Carbon Dioxide Information Analysis Centre (CDIAC), 2015), (International Energy Agency, 2015b), Emission Database for Global Atmospheric Research (EDGAR) (European Comission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016).

The highest CO_2 emissions were estimated by CDIAC with a value of 2,074,345 kt and the lowest by BP with 1,704,145 kt of CO_2 for 2011, a difference of 27.72%. The lowest difference with the CDIAC value can be located at the data published by EDGAR, which amount to 1,809,304 kt of CO_2, a difference of 14,65%. Focusing on the example of accounting physical-raw quantities of specified fuels and following the snapshot example provided in **Figure 3.4**, this research can locate discrepant figures for coal products such as lignite, demonstrated in **Figure 3.5** with its subsequent magnified **Figure 3.6**. By evaluating the findings of those two latter figures, it can be estimated that those discrepancies extend further than different NCV and carbon content factors, traced to the reported raw quantities. However, for the purposes of the present research, the raw quantities will be assumed equal, accounted as discussed in the methodology **Section 2.1**.

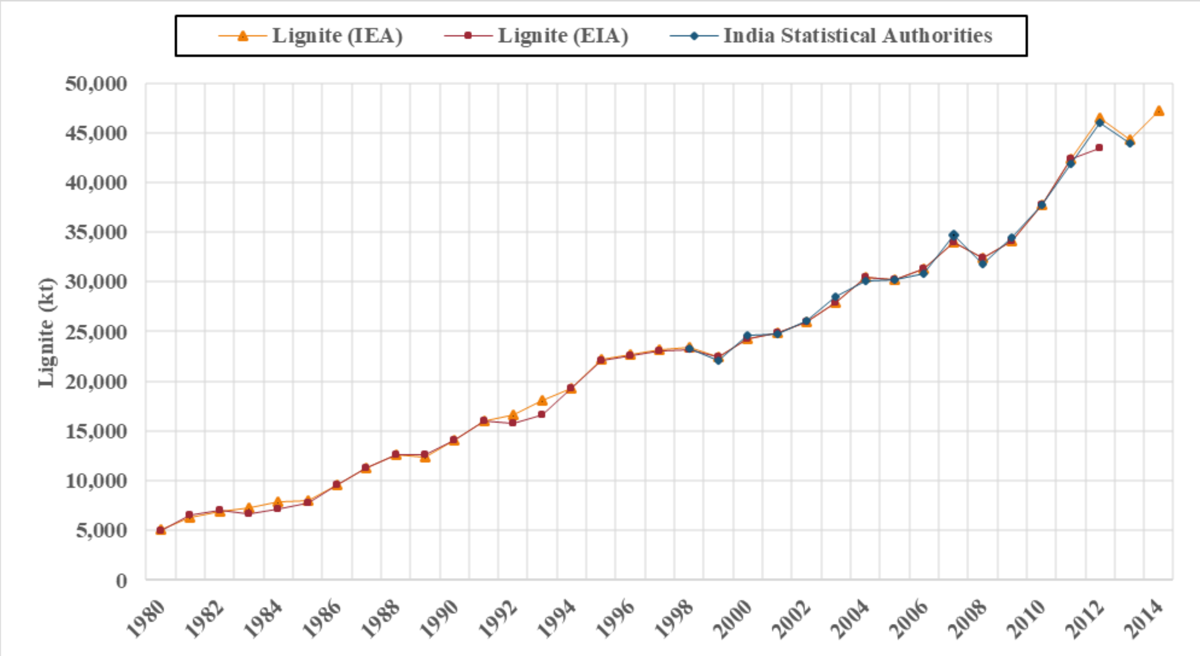


Figure 3.5. Lignite (kt) produced in India during 1980-2014. Data Source: (Indian Ministry of Statistics and Programme Implementation, 2015a; International Energy Agency, 2015c; US Energy Information Administration, 2016)

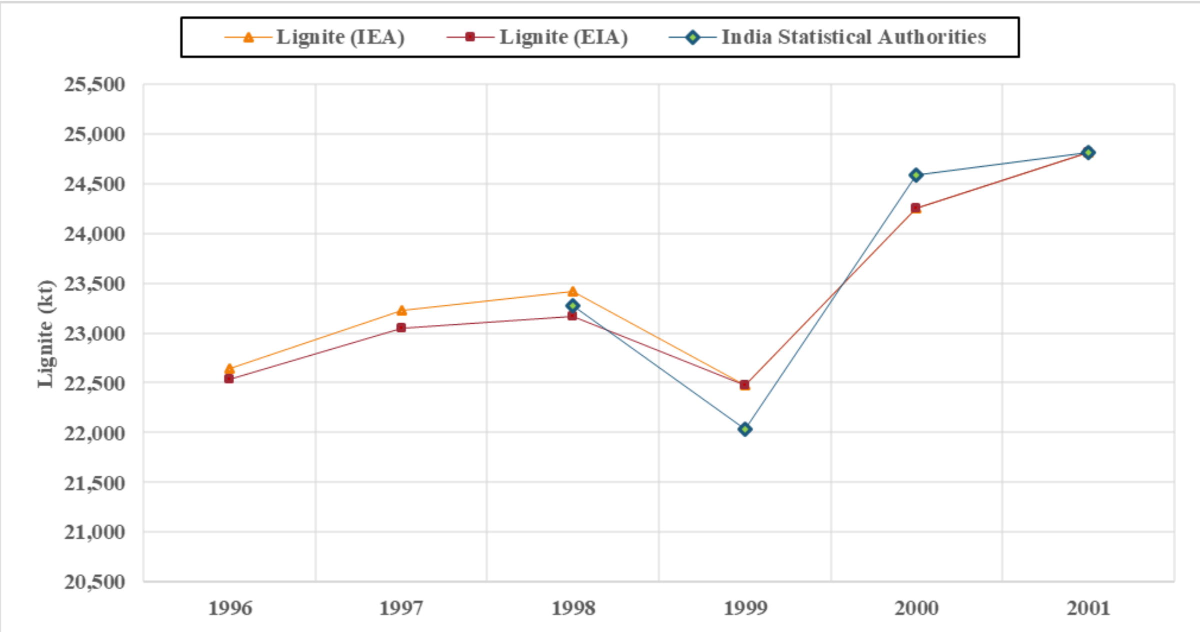


Figure 3.6. Snapshot 1997-2001 of the reported lignite physical quantities (kt) produced in India during 1980-2014. Data Source: (Indian Ministry of Statistics and Programme Implementation, 2015a; International Energy Agency, 2015c; US Energy Information Administration, 2016)

The initial results in the primary data as presented in the figures above, aid this research to assemble and subsequently verify or reject, specific and focused hypotheses. These hypotheses present a high urgency that is specifically important for India due to the country becoming an industrialised economy at an accelerated pace (Yadav and Joseph, 2018).

Therefore, as an essential element of constructing hypotheses this research considers the added uncertainty that is generated, by combining emissions factors of different agencies or organizations, to examine if additional discrepancies are generated. This acts as the basis of the hypotheses formed, therefore:

- There are significant CO_2 discrepancies for the Indian total final energy consumption between published emission inventories data (**H1a**), their combined emission factors as constructed by the present research. (**H1b**), and between them. (**H1c**)
- There are significant CO_2 uncertainties for India's total industry between the discrepancy scenarios that are generated from selected data inventories. (**H2a**)
- There are significant CO_2 uncertainties for specified industrial sectors of India between the discrepancy scenarios that are generated from selected data inventories (**H2b**)

Focusing on specific discrepancies between the studied authorities that provide primary data and factors related to carbon, more hypotheses related to discrepancies do serve the purposes of this study. Constructing these by selecting the values that the IPCC and IEA is using for accounting carbon emissions, this research can be more specific:

- Discrepancy scenarios based on net calorific values and carbon content published by the IPCC, present different CO_2 emission output, when compared to those published by IEA. (**H3**)

The first aspect of the second hypothesis acts as an incentive for arguing towards the last hypothesis (**H4**) that is to be posed by the present research. According to IEA (International Energy Agency, 2012a), the agency uses average net calorific values and average carbon content for its estimations. This fourth hypothesis stands as follows:

- The discrepancy scenarios generated by the IEA and IPCC net calorific values with net carbon content, present convergent CO_2 emission output estimates. (**H4**)

3.3 Conceptual Framework

The schematic process for calculating the Indian emissions discrepancy is based on the methodology, as described in **Section 2.1** of this thesis (**Figure 3.7**).

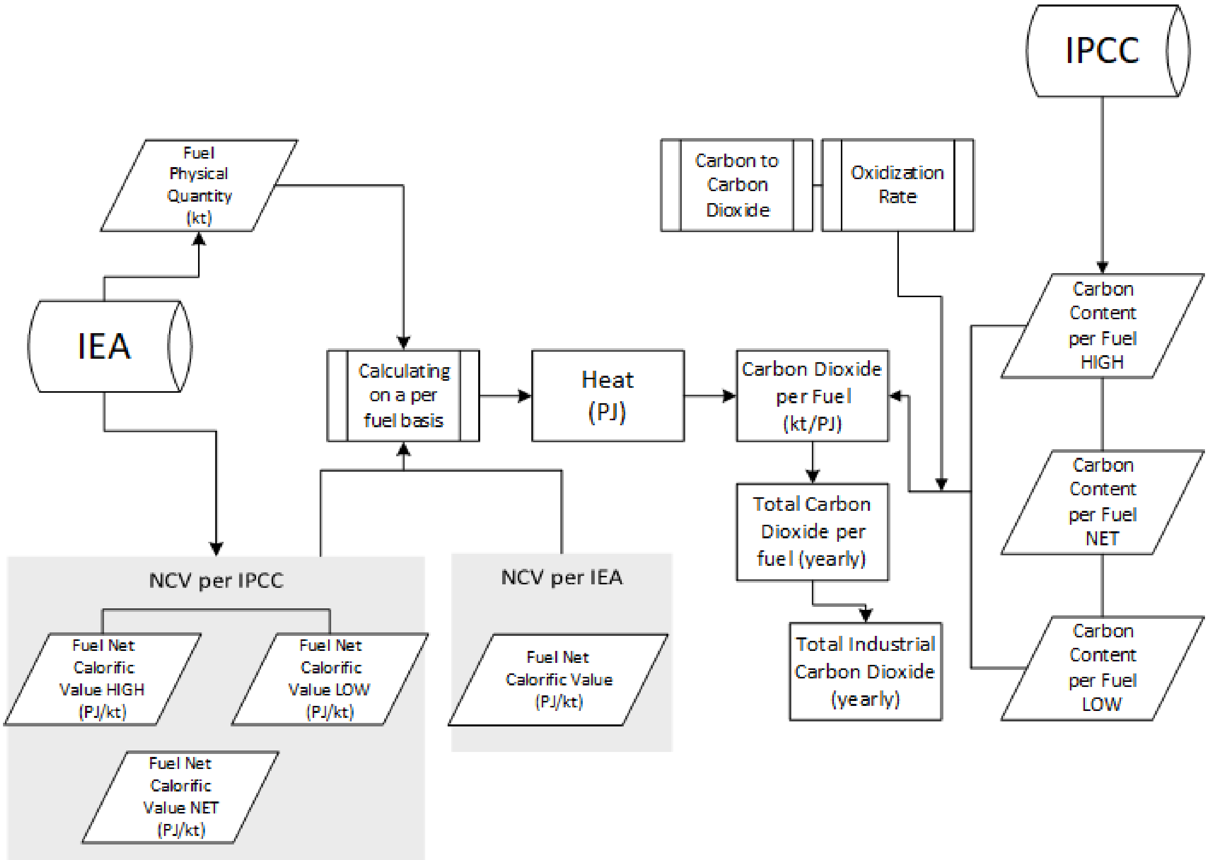


Figure 3.7 Emissions discrepancy calculation process.

The process calculation flow as represented on the above figure, can act as a model of calculating any discrepancies that originate from fuel physical quantities reported in alternative authorities' databases. This research extracts the fuel raw-physical quantities from the International Energy Agency (IEA). Alternative databases include the Indian Statistical Authority, the Environmental Information Administration (EIA) and the annual British Petroleum Statistical Review. The workflow of this research dictates that alternative databases will not be included, and those selected are highlighted in the flowchart of **Figure 3.7**. Alternative databases are mentioned for reference purposes; highlighted and demonstrated in **Figures 3.3-3.6**.

The formulas used to extract results as per the calculation flow process is that used in section 3.1 describing the appropriate methodology. All the steps found in **Figure 3.7** aim to satisfy the criteria needed to perform equations **a.6** and **a.7**, with the different accounted factors described in **Table 2.1.1**. The purpose of selecting the International Energy Agency (IEA) as the database that provides the raw physical quantities, is serving the requirement of homogeneous reported data, that follows a measurement system that essentially communicates with the matching data of IPCC without the need for additional conversions. If such a practice is not applied, a risk for presenting further deviations in discrepancy scenarios becomes evident. Generating discrepancies at that level, would not present any additional research benefit, but only potential sources of increasing error.

3.4 Results

For every section of the results chapter, the CO_2 emissions discrepancies are presented and discussed for six sectors and subsectors. These are; final energy consumption, total industry, iron and steel, chemical and petrochemical and the non-metallic minerals. This is followed by a breakdown of the CO_2 contribution of the fuel mix that presents activity for the sector discussed, under an IEA NCV net and IPCC net carbon content scenario (that will later be discussed as the reference scenario). Finally, except for the total final consumption, a percentage share analysis on a 10-year gap basis is performed, to present the fuel mix change under that timeline selection. The purpose of the discrepancy scenarios is to highlight the added uncertainties generated when published NCVs and CC factors of different agencies; IPCC and IEA, are combined.

3.4.1 Total Final Consumption Discrepancies

The CO_2 emission uncertainties regarding the final consumption of India's total fuels used for every flow activity derive from the sum of energy consumption activity in India. The appropriate calculations for the final consumption of all combustible fuels, or their combustible proportion, have been performed (**Figure 3.8**):

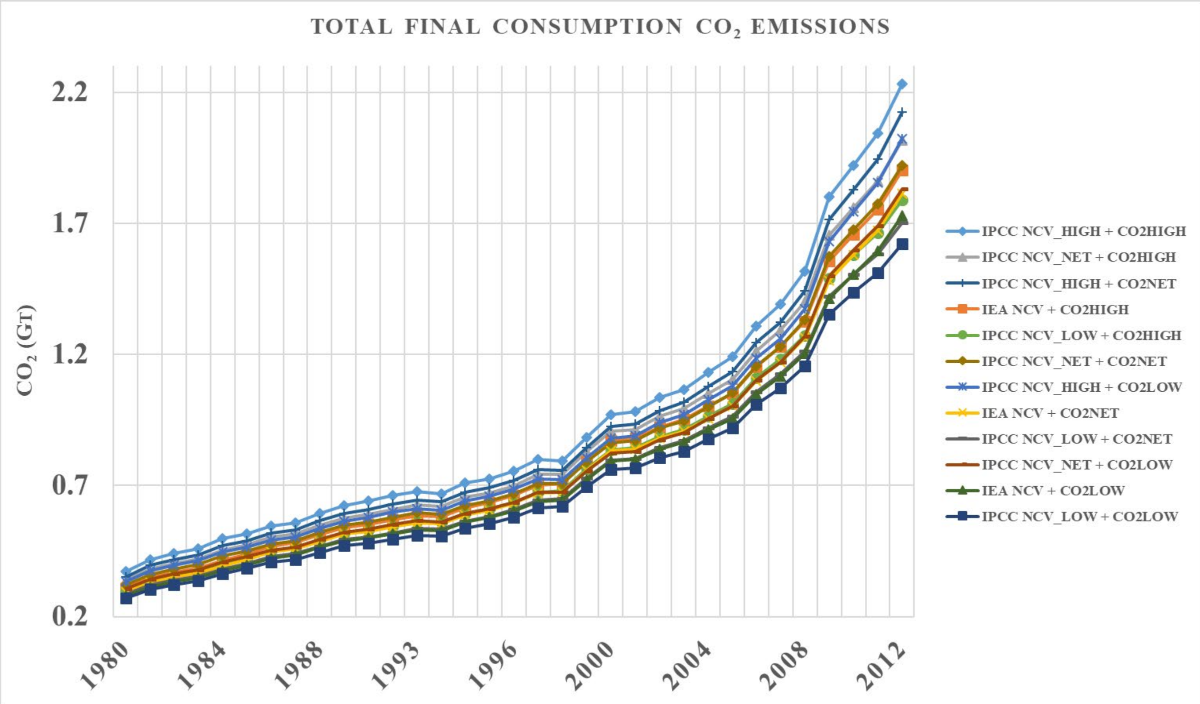


Figure 3.8 Indian CO_2 emissions from final consumption of energy during 1980-2012 under different Indian NCV and carbon content values provided by IEA (standardized NCV) and IPCC on low-net-high scenarios.

Approaching the CO_2 discrepancies for the total final consumption of India, the amount of CO_2 that each scenario generates is distinct. The highest emitting scenario amounts to 2.23 Gt of CO_2, while the net scenarios of IEA and IPCC present an output of 1.81Gt and 1.92Gt of CO_2 respectively, for 2012. The lowest CO_2 emitting scenario is the product of low IPCC NCV and low carbon content, and it amounts approximately at 1.62Gt of CO_2 for the same year. Therefore, the difference of CO_2 output from the final consumption is approximately 518.4% increase from 1980 to 2012. This increase concerns the emissions reference scenario; IEA NCV and net carbon content. This growth in CO_2 presents a peak in percentage terms under the IEA NCV and low carbon content scenario, with approximately 521.7% for the same period. This result deviates from the highest output CO_2 emissions scenario of high NCV and carbon content. The growth percentage under the latter is 501.03% during this examined timeline.

Examining the discrepancies on an annual basis, vertically represented in the graph, the highest difference between scenarios is found in 2012 between high and low NCV and CC scenarios, with a difference of 37.49% or 608Mt of CO_2. This deviates from the average difference between the same scenarios which approximates 32.21% for the entire timeline. The lowest difference between the scenarios exists for year 1999, with a 27.34% but in absolute terms the difference due to the growth of CO_2 emissions reached approximately 189.8Mt of CO_2.

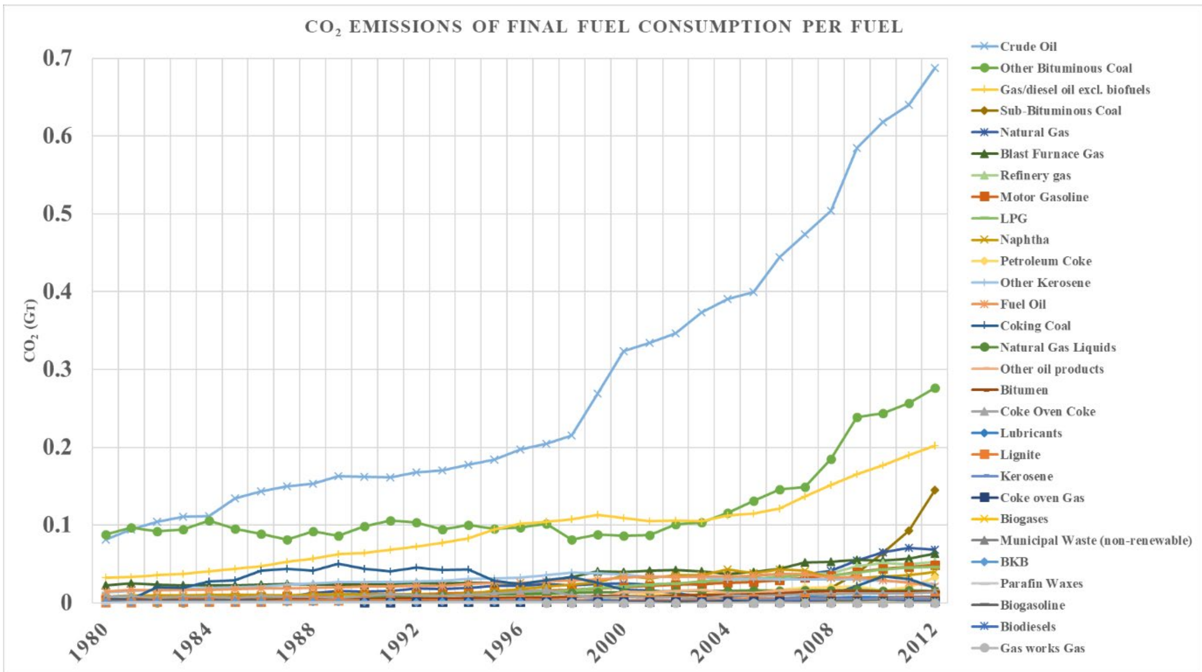


Figure 3.9 Indian CO2 emissions (Gt) from final consumption attributed per fuel during the 1980-2012 specified timeline under an IEA net NCV and IPCC CC net scenario.

The fuels that present the greatest consumption figures presented in the graph above are further analysed in **Figure 3.10** to examine which of those can be designated as the most significant potential contributor in the scenarios that are considered. By following that accounting prism and examining the previous figure a conclusion can be extracted; the fuels with the greatest discrepancies are the coal products. These are the "Other-Bituminous" and "Sub-Bituminous" coals. The first, presents a difference of 84.01% when compared between the lowest and the highest emitting scenario. These low and high emission scenarios are designated as the IEA net calorific value with low carbon content and IPCC high NCV with the IPCC high carbon content respectively. This figure reaches an estimated 204,649kt of CO_2 or 74.09% higher result than the reference scenario which is presented in **Figure 3.9**.

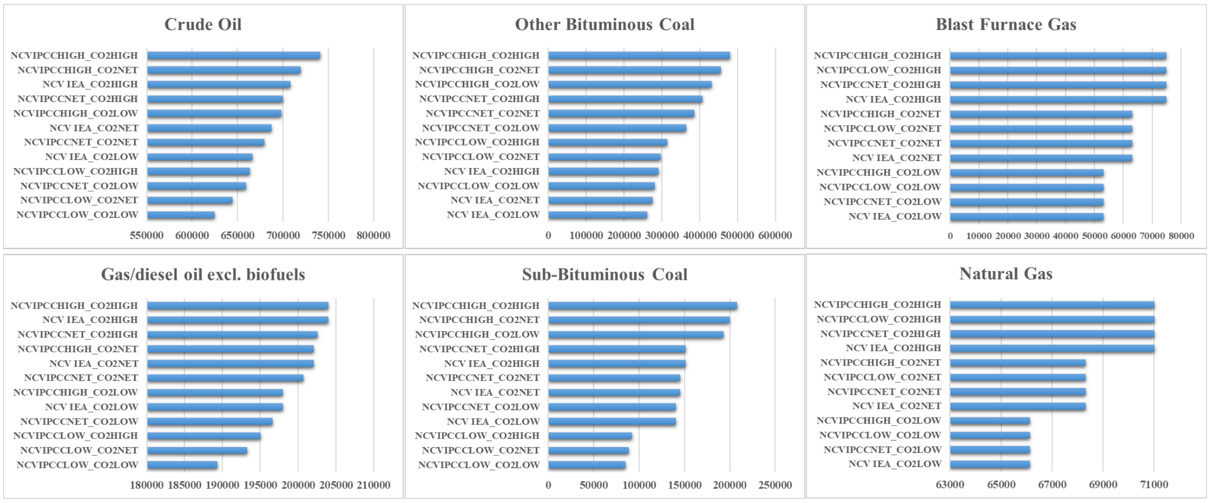


Figure 3.10 CO_2 emissions discrepancies (kt) of final consumption for year 2012 under the various net calorific values and carbon content scenarios.

The established pattern of differed CO_2 output per scenario, is not observed in gas fuels. Natural gas and blast furnace gas present the same CO_2 emission output on an NCV level and differ when the carbon content is changed. This different pattern occurs due to the IPCC and IEA sharing the same NCV values and not altering, under that approach, the fuel heat output on a high, net, and low basis. The output for natural gas per carbon content scenario presents 3.5% rate of change on average while for blast furnace gas, the change is approximately 15%.

Crude oil and gas/diesel oil present CO_2 characteristics similar to the ones of coal products. Nevertheless, the variation between NCV and CC scenarios follows a decreasing output following the highest to the lowest output scenarios. The decrease for crude oil averages at 1.57% following the same directionality of emissions output, while for gas/diesel oil this difference amounts to 0.6% for the same pattern.

However, for the latter fuel discussed, there is an output convergence when assessing the NCV scenarios of IEA and IPCC net. This pattern is also observed in more fuels when those are examined under the same parametric approach. All the fuels that enter the final consumption of India's fuel mix are examined to quantify the repetition of this pattern. This is to confirm that a convergence between IEA and IPCC published NCVs can be confirmed. The fuel quantification and graphical representation is located in **APPENDIX IV**. This leads to 14 out of the 30 fuels showing heat output convergence, either for the IPCC net to IEA NCV parameters, or of every IPCC and IEA NCV parameter. The examined scenarios produce variable output results both in weight and percentage terms between 1980-2012. As observed in **Figures 3.11; 3.18; 3.25; 3.32; 3.39** the different scenarios do not present a stable relative growth pattern between the start and end year of each examined area of focus.

Table 3.11. CO_2 output difference of final energy consumption between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher)

1980 - 2012		
Scenarios (Final Consumption)	Difference (%)	Difference (Mt)
IPCC NCV_LOW + CO2LOW	500.40%	1352.29
IEA NCV + CO2LOW	521.77%	1452.03
IPCC NCV_NET + CO2LOW	499.89%	1525.68
IPCC NCV_LOW + CO2NET	497.34%	1417.35
IEA NCV + CO2NET	518.36%	1520.69
IPCC NCV_HIGH + CO2LOW	505.72%	1688.87
IPCC NCV_NET + CO2NET	496.81%	1599.15
IPCC NCV_LOW + CO2HIGH	495.24%	1487.56
IEA NCV + CO2HIGH	516.05%	1595.08
IPCC NCV_HIGH + CO2NET	502.79%	1770.85
IPCC NCV_NET + CO2HIGH	494.78%	1678.46
IPCC NCV_HIGH + CO2HIGH	501.03%	1859.64

3.4.2 Industrial Discrepancies

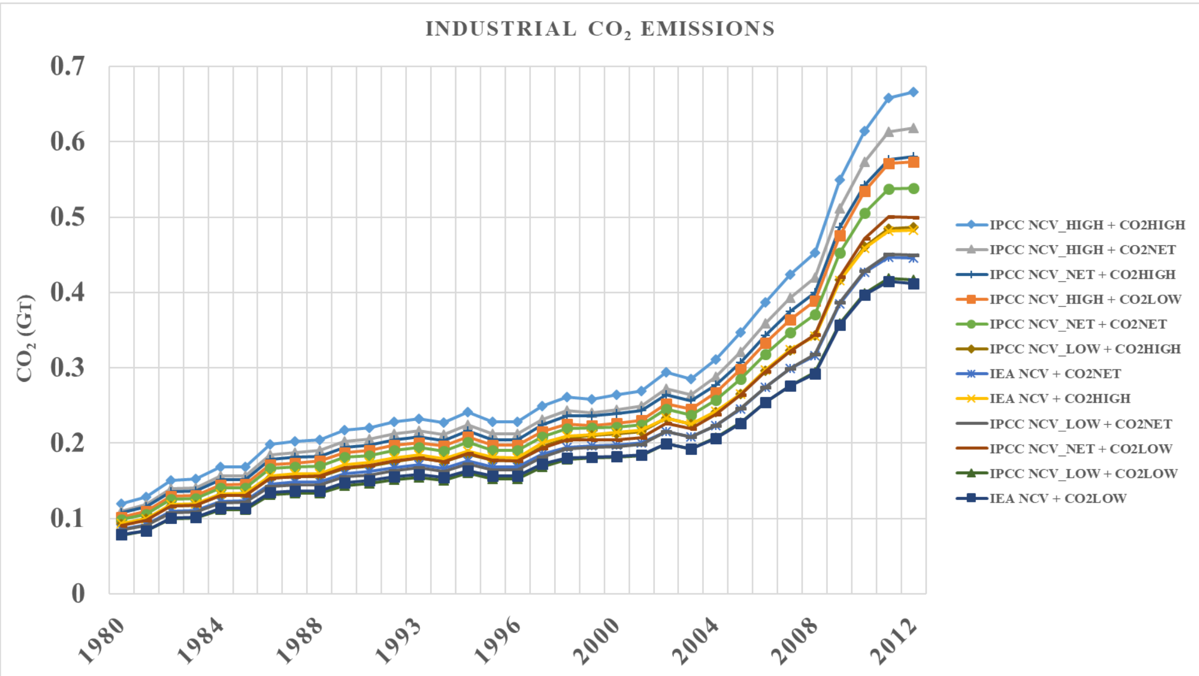


Figure 3.12. Indian total industrial CO_2 emissions during 1980-2012 under different Indian NCV and carbon content values provided by IEA (standardized NCV) and IPCC on low-net-high scenarios.

The total industry of India not only does present an increase of CO_2 emissions over the examined timeline, but also increased CO_2 discrepancies following this annual timeline approach. An increased rate of CO_2 emissions growth is presented from year 2009. Carbon dioxide emissions, across the examined timeline, present an increase that ranges from 33.3Mt of CO_2 for the lowest emitting scenario; IEA NCV and low carbon content, reaching 54.63MtCO_2 for the highest; high NCV and CC. The average difference between the highest and lowest emission scenarios across the timeline is 50.98% or 99.25MtCO_2. The difference in CO_2 emissions output between the net values of IEA and IPCC presents a significant margin, and when quantified, the latter presents a 14.68% or 32.2MtCO_2 higher output values on average. The highest variance of output between those emission scenarios is located at the last year assessed (2012) with a difference that amounts to 59.9%; the minimum is located at 1999, matching that of the total final consumption with approximately 43.4%.

Concluding with the findings' evaluation, the average rise for the 1980-2012 timeline in CO_2 emissions amounts to 418.64MtCO_2 on average. The highest emitting scenario (IPCC NCV high, CC high) presents a rise of 457.5% from the first to the last year examined, or 546.34MtCO_2, while the lowest (IEA NCV, CC high) shows a respective 388.61MtCO_2 or 415.55% increase. However, in absolute numbers of output and weight, the lowest increase is located for the IEA NCV and low carbon content output, with 333.08MtCO_2.

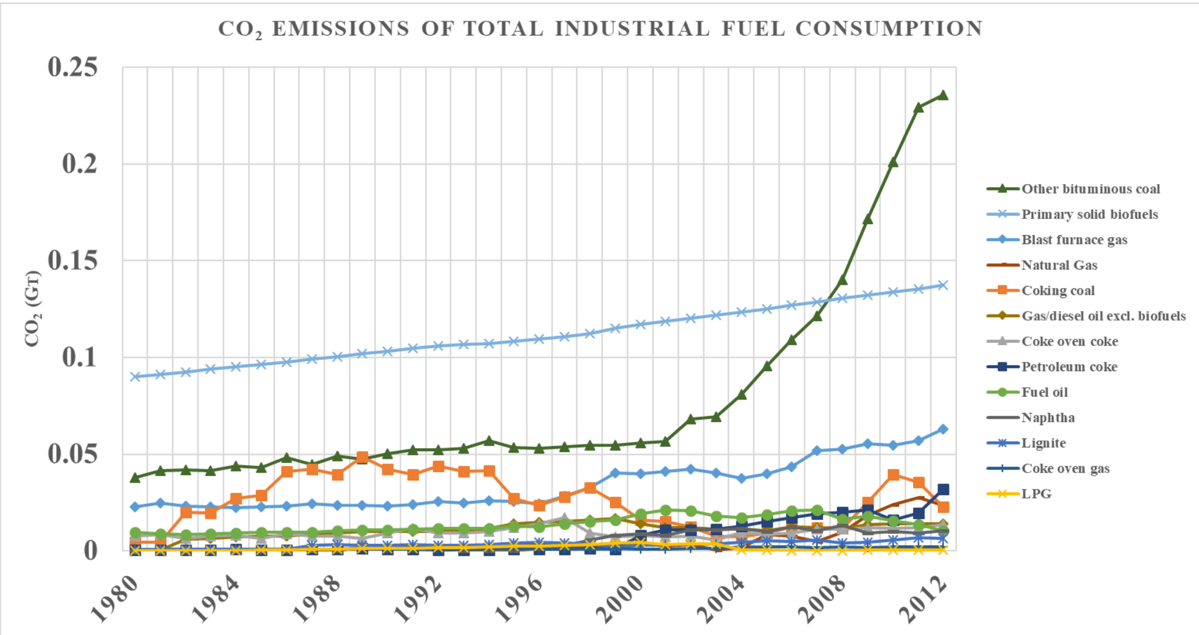
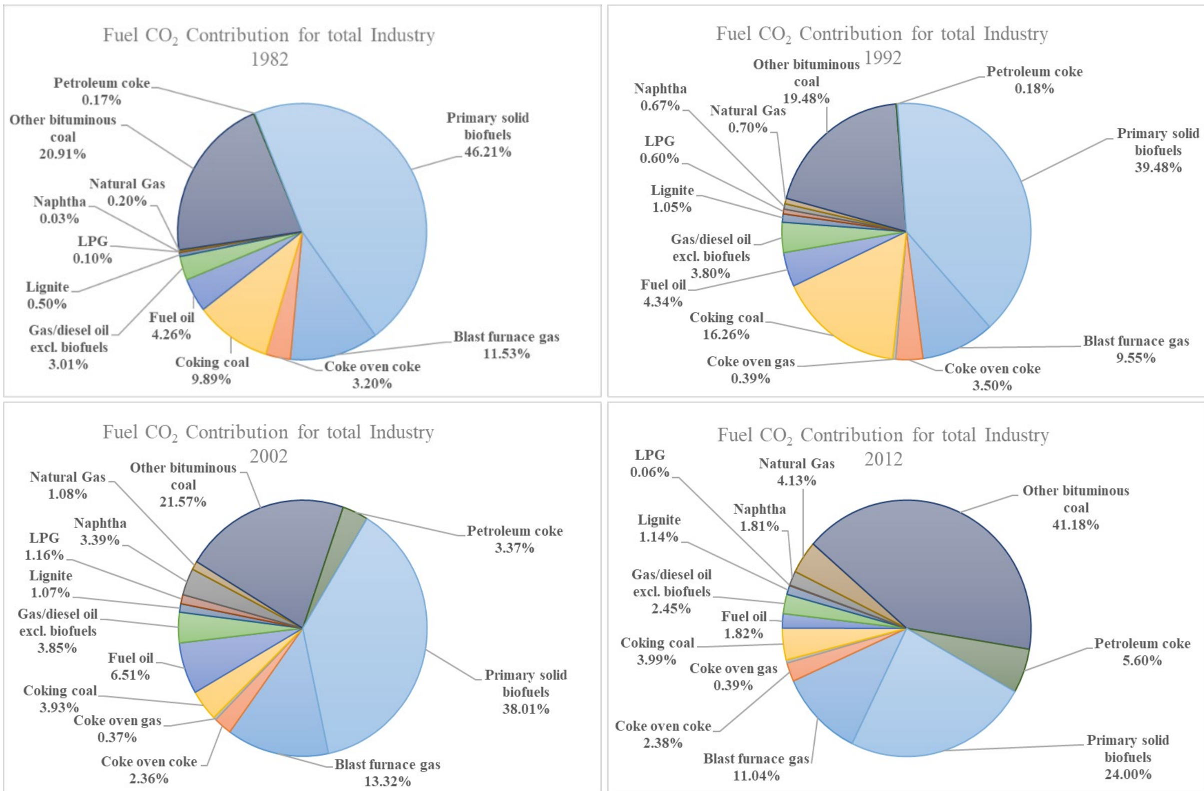


Figure 3.13. Indian total industrial CO_2 emissions (Gt) attributed per fuel during the 1980-2012 specified timeline.

Under the IEA net NCV scenario, the timeline of the fuels that contribute towards the release of CO_2 emissions are assessed in a timeline approach. While primary solid biofuels have been a dominant energy source for the Indian industry, this was rapidly replaced by other bituminous coal in the last decade examined. While this coal product produced 56.68MtCO_2 in 2001, its output has jumped by 20.55% for the next year, and 315.82% when compared to the last year examined, reaching CO_2 emissions output of 235.68MtCO_2. Primary Solid Biofuels still hold a significant role regarding the amount of CO_2 emissions for the last year examined with 137.37MtCO_2, while Blast Furnace Gas follows with an output of 63.17MtCO_2. It should however be highlighted that Primary Solid Biofuels are not considered in the calculations, when approaching the CO_2 emission discrepancy scenarios as those are presented in **Figure 3.12** because IEA does not include the fuel in its methodologies.



Figures 3.14-3.17. Periodic snapshot of Indian CO_2 emissions share attributed to the fuel mix of the total industry.

Examining a probable output convergence between the NCV scenarios of IEA and IPCC net as this was discussed for the final consumption, the 13 fuels that enter the industrial consumption mix are examined. Among those fuels, 7 present heat output convergence between the IPCC net and IEA NCV parameters, or of every IPCC and IEA NCV parameter; NG, blast furnace gas, coke oven coke, coke oven gas, gas/diesel oil, LPG, and primary solid biofuels. As other bituminous coal does not fall into that convergence category, the IPCC net and IEA NCV scenarios differ significantly (**Figure 3.12**).

Analysing the different fuels' contribution towards CO_2 emissions in the total industry (**Figures 3.14-3.17**), in four 10-year gap snapshots covering 1982-2012 there is a rapid increase of other bituminous coal in the fuel mix from 2002 to 2012. While other bituminous coal had a 20% share on average for 1982, 1992 and 2002, this drastically changed to 41.18% in 2012. Other bituminous coal has therefore effectively replaced primary solid biofuels as the main emitter of CO_2 emissions, presenting a reduction in its share amounting to approximately 22% from 1982, placing it as the second most significant contributor of CO_2 in the total industry. Evident is also the increase of natural gas (NG), which triples its contribution towards CO_2 emissions between 2002 to 2012. Due to the lower carbon content of NG, compared to the fuels discussed, that highlights the elevated levels of NG consumption in India's industries.

Table 3.18. CO_2 output difference of the total industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher)

1980 - 2012		
Scenarios (Total Industry)	Difference (%)	Difference (Mt)
IPCC NCV_LOW + CO2LOW	433.76%	338.36
IEA NCV + CO2LOW	424.53%	333.08
IPCC NCV_NET + CO2LOW	448.97%	408.15
IPCC NCV_LOW + CO2NET	428.54%	364.89
IEA NCV + CO2NET	419.84%	359.75
IPCC NCV_HIGH + CO2LOW	464.59%	471.63
IPCC NCV_NET + CO2NET	444.25%	439.21
IPCC NCV_LOW + CO2HIGH	423.68%	393.49
IEA NCV + CO2HIGH	415.55%	388.61
IPCC NCV_HIGH + CO2NET	460.83%	507.61
IPCC NCV_NET + CO2HIGH	439.89%	472.54
IPCC NCV_HIGH + CO2HIGH	457.52%	546.34

3.4.3 Iron and Steel Discrepancies

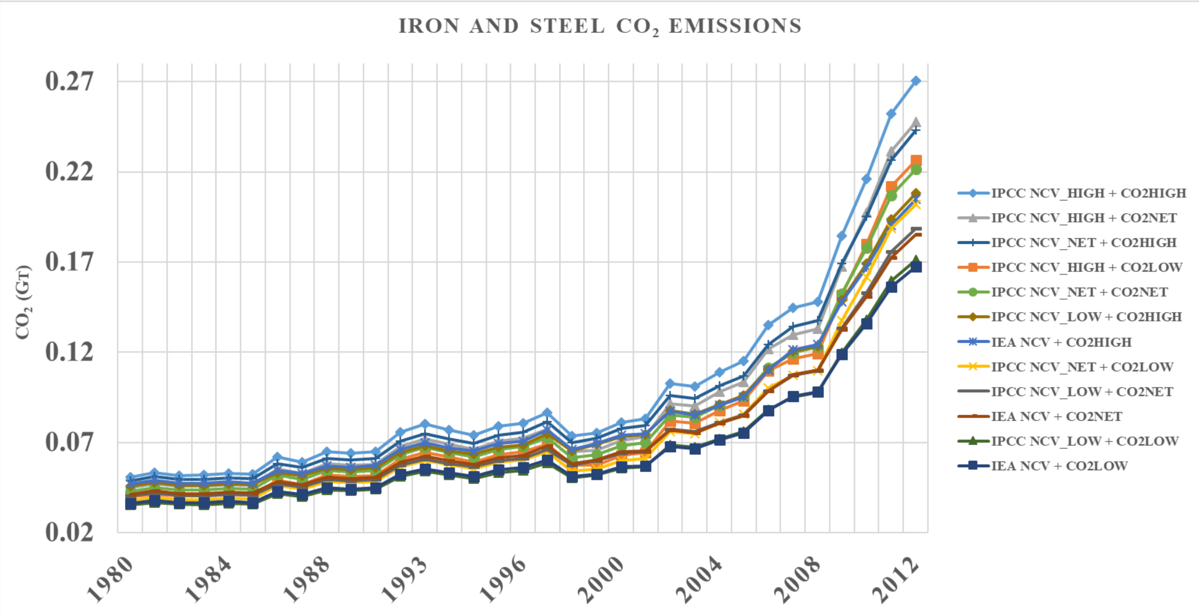


Figure 3.19. Indian Iron and Steel industrial CO_2 emissions during 1980-2012 under different Indian NCV and carbon content values provided by IEA (standardized NCV) and IPCC on low-net-high scenarios.

Examining the iron and steel industry of India, the CO_2 output presents greater discrepancies when measured in weight from 2002 onwards. This output discrepancy is linked to the growth in CO_2 emissions as a result of the industrial growth that this sector presents. The highest emitting scenario, being IPCC NCV high and high CC, produces 270.36MtCO_2 in the final examined year, while the lowest, IEA NCV and low CC is rated at an output of 167.65MtCO_2 for the same year. The reference scenario shows an output of 185.28MtCO_2.

This growth amounts to 347.5% or 143.87MtCO_2 under the IEA net and CC net scenario, on a 1980-2012 basis or 218.5% during the 2000-2012 period. The highest discrepancy between the different NCV and CC scenarios is found to be among the IEA NCV and low CC, with 61.27% for 2011, amounting to a difference of 95.87MtCO_2, while measured in output, the highest difference amounts to 102.7MtCO_2 for 2012. The average difference between the highest and the lowest performing scenario, across the timeline, is rated at 47.17%.

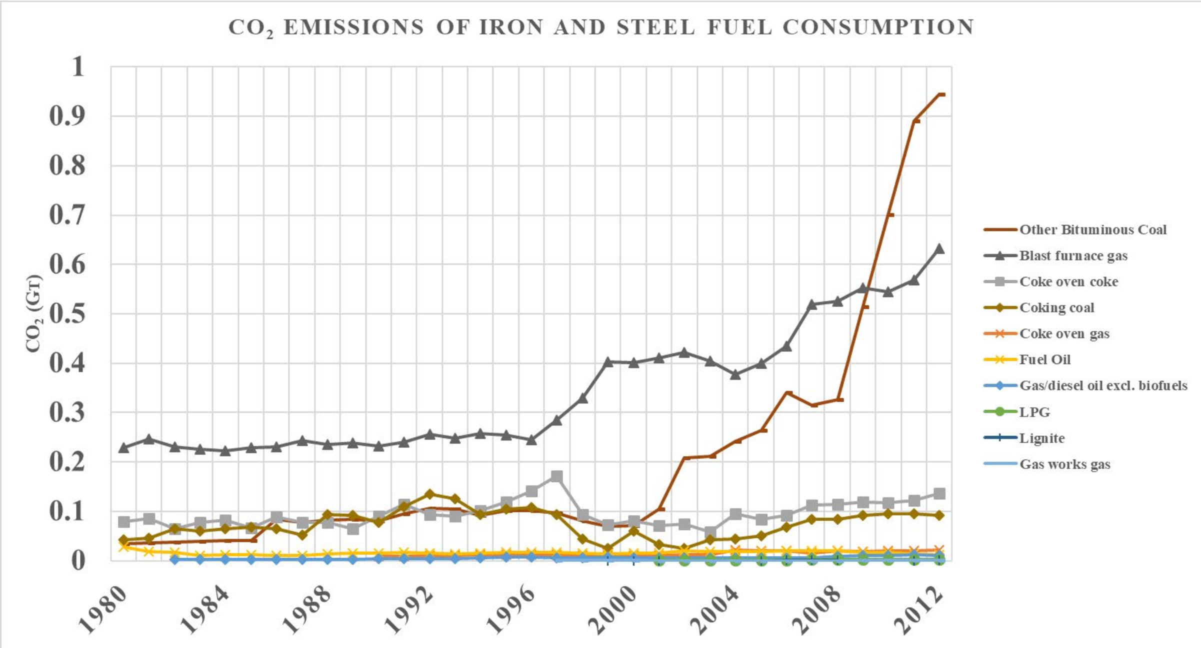
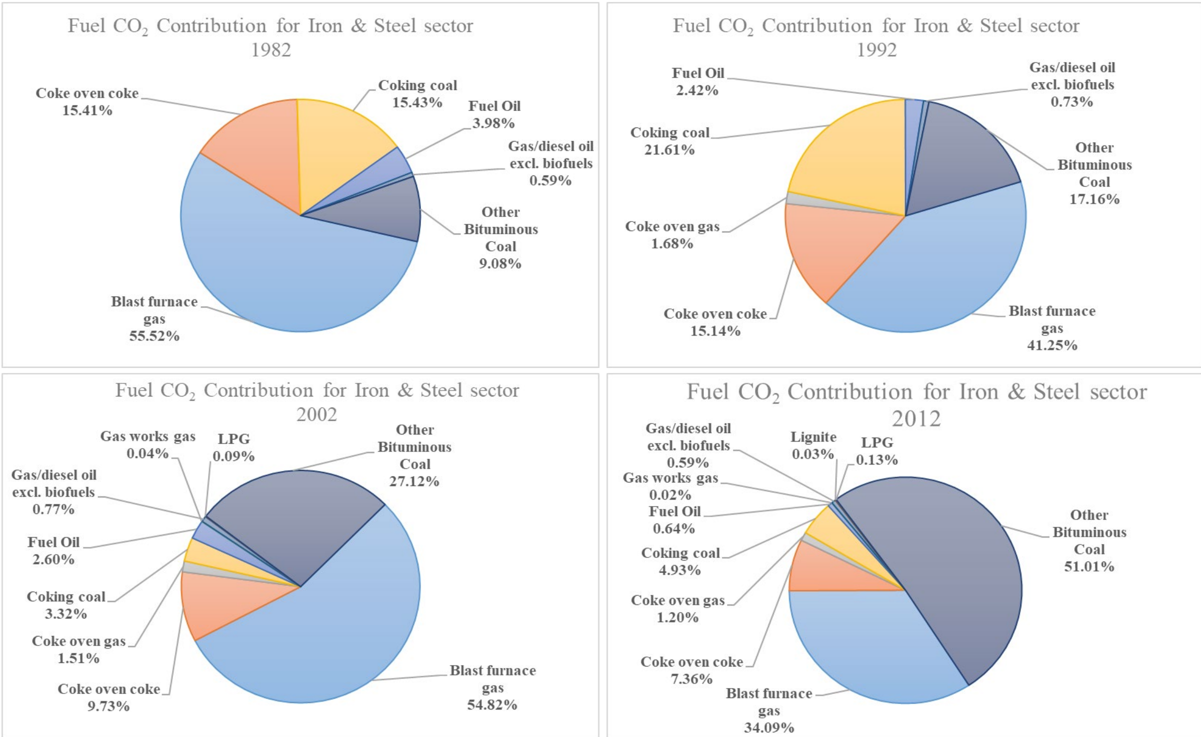


Figure 3.20. Indian Iron and Steel industrial CO_2 emissions (Gt) attributed per fuel during the 1980-2012 specified timeline.

As demonstrated in **Figure 3.20**, the chemical and petrochemical industry is dominated throughout a 30-year period, 1980 to 2010, by blast furnace gas which has also been the highest CO_2 emitter. However, this was replaced by other bituminous coal as the highest emitting fuel from 2010 onwards, as this coal product presented a spike growth of 61.86MtCO_2 or 189.52% for the period of 2008-2012, reaching an output of 93.5MtCO_2 for the latest year. Blast furnace gas is the second emitter following at 63.17MtCO_2 of output for 2012.

Approaching the probability of an output convergence when examining the NCV scenarios of IEA and IPCC net, 9 fuels enter the fuel mix and subsequently present carbon emissions activity. Examining those, 5 present convergence in their NCV between the IPCC net and IEA NCV values or under the scenarios additionally mentioned in the previous sectors discussed; blast furnace gas, coke oven coke, coke oven gas, gas/diesel oil and liquid petroleum gases (LPG). Bituminous coal and coking coal are not included into this convergence category, the IPCC net and IEA NCV CO_2 emissions scenarios differ by 8.92%, as those are presented in **Figure 3.19**.



Figures 3.21-3.24. Periodic snapshot of Indian CO_2 emissions share attributed to the fuel mix of the Iron & Steel sector.

Performing a decade periodic snapshot approach of the fuel mix in the Iron and Steel industrial sector, we can observe the growth of using other bituminous coal as a main fuel source. That growth subsequently contributes to the observed growth (**Figures 3.21-3.24**) in CO_2 emissions from 1982 to 2012. Blast furnace gas was effectively replaced as the main CO_2 emitter, dropping from 55.52% to 34.09% in the latter period examined. A similar drop is valid for coke oven coke, 15.41% to 7.36%, and coking coal with a 3-fold drop from 15.43% to 4.93% respectively for the duration of the periods assessed. As other bituminous coal has a lower carbon content than blast furnace gas, its emissions contribution in the mix, 51.01%, displays its major share in the fuel mix as it did for the total industry of the country. The contribution of other bituminous coal in CO_2 emissions presents an approximate 2-fold CO_2 increase at 23.89% accounted between 2002 to 2012. The contribution of other bituminous coal amounts at 51.01% of the I&S total CO_2 output.

Table 3.25. CO_2 output difference of the I&S industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher)

1980 - 2012		
Scenarios (I&S)	Difference (%)	Difference (Mt)
IPCC NCV_LOW + CO2LOW	382.73%	135.62
IEA NCV + CO2LOW	360.91%	131.28
IPCC NCV_NET + CO2LOW	432.84%	164.14
IPCC NCV_LOW + CO2NET	367.72%	148.40
IEA NCV + CO2NET	347.50%	143.87
IPCC NCV_HIGH + CO2LOW	469.54%	186.68
IPCC NCV_NET + CO2NET	414.87%	178.60
IPCC NCV_LOW + CO2HIGH	353.94%	162.41
IEA NCV + CO2HIGH	335.22%	157.69
IPCC NCV_HIGH + CO2NET	449.61%	202.46
IPCC NCV_NET + CO2HIGH	398.27%	194.28
IPCC NCV_HIGH + CO2HIGH	431.13%	219.46

3.4.4 Chemical and Petrochemical Discrepancies

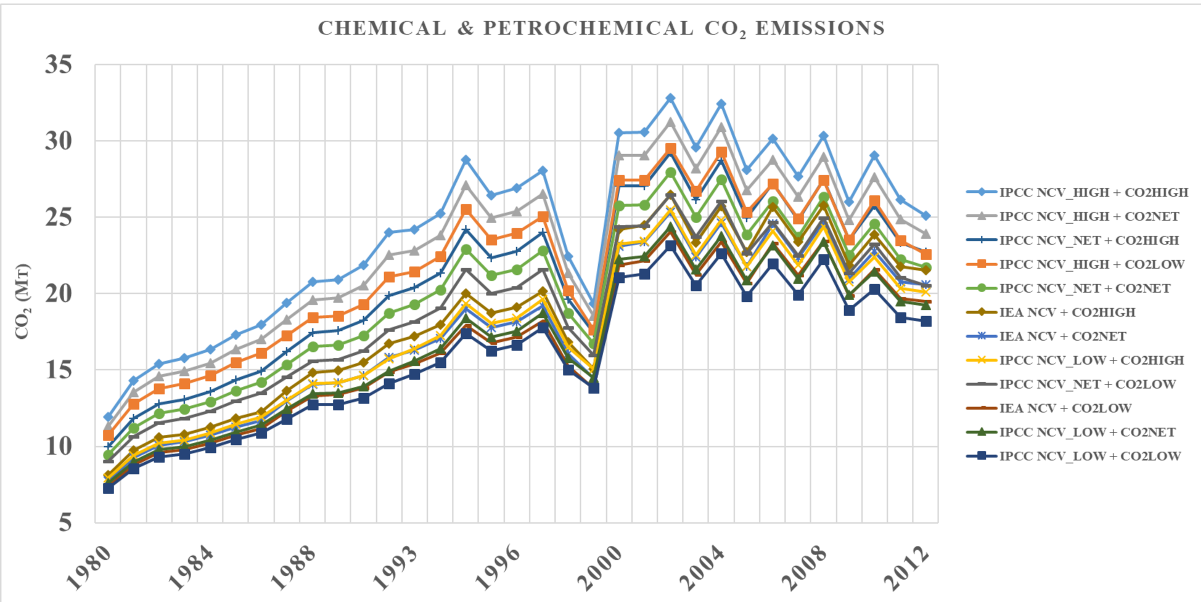


Figure 3.26. Indian Chemical & Petrochemical industrial CO_2 emissions during 1980-2012 under different Indian NCV and carbon content values provided by IEA (standardized NCV) and IPCC on low-net-high scenarios.

The chemical and petrochemical industry in India presents mixed results since it does not follow an established pattern of rising CO_2 emissions over time, as observed in other industrial sectors. While the respective CO_2 emissions have increased for the reference scenario by 12.84MtCO_2 or 165.6% during 1980-2012, they present an overall decrease from 2002-2012 that amounts to 18.8% or 477.4ktCO_2. Additionally, in 1998-999 a steep decrease in CO_2 emissions is observed when compared to the previous year, amounting to 24.7% or 4738ktCO_2 before rebounding during the following year.

The peak of CO_2 emissions is in 2002 presenting an output of 25.37MtCO_2 under the reference scenario. For 2002, the difference between the highest and lowest CO_2 output scenarios as presented in **Figure 3.26** amounts to 9.66MtCO_2 having a difference of 41.67%. The average difference between the highest and the lowest CO_2 output scenarios is 54.03% or 8178ktCO_2. The average CO_2 emissions gap between the two scenarios (IEA as reference and IPCC) is approximately 15% for 1980-2012 or 2.395MtCO_2.

The highest CO_2 emissions increase between the scenarios examined for 1980-2012, concerns the reference scenario, while the lowest regards the IPCC high NCV and high carbon content (CC). This last scenario examined, presents a growth of 110% or 13.14MtCO_2.

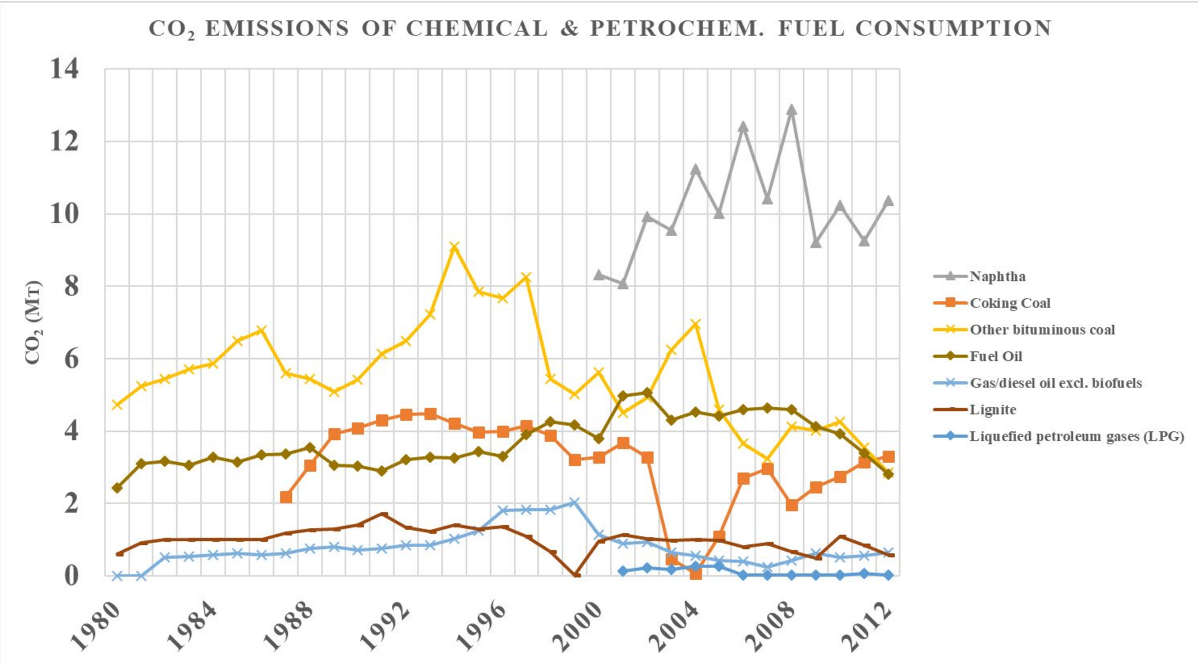


Figure 3.27. Indian Chemical & Petrochemical industrial CO_2 emissions (Gt) attributed per fuel during the 1980-2012 specified timeline.

Examining the fuels that contribute towards CO_2 emissions in the chemical and petrochemical industry, it can be observed that other bituminous coal is the most significant contributor between 1980-1999. Naphtha has entered the fuel mix as the leading contributor of CO_2 emissions from its year of introduction; 2000, with 8313 ktCO_2 surpassing other bituminous coal by 2685 ktCO_2. It has remained a significant emissions contributor until the last year examined with 10,374 ktCO_2 emitted. The chemical and petrochemical fuel mix comprises of seven fuels. Two of those fuels present the convergence characteristics between their IPCC and IEA NCV net as similarly observed in the previous sections; Gas/diesel oil and liquid petroleum gases (LPG). Coking coal has presented CO_2 emissions increase from 2009 to 2012, proving it the second largest contributor for the last year examined, surpassing other bituminous coal and fuel oil in the relevant spectrum. The contribution of LPG and lignite is deemed insignificant, with 606 ktCO_2 for 2012.

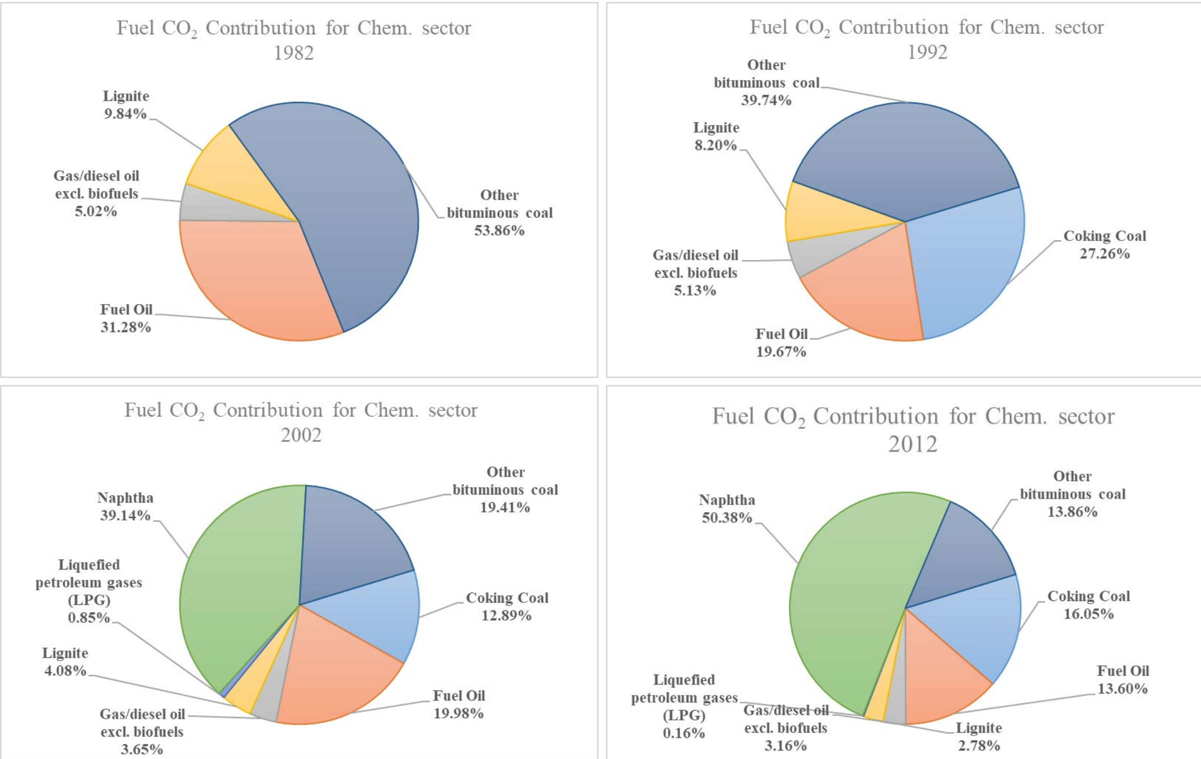


Figure 3.28-3.31. Periodic snapshot of Indian CO_2 emissions share attributed to the fuel mix of the Chemicals & Petrochemicals sector.

Approaching the CO_2 contribution of energy sources shares for the chemical and petrochemical fuel mix, a reverse picture is observed, when compared to the total or the specific industries examined previously (**Figures 3.14-3.17, 3.21-3.24**). The CO_2 that is emitted as a result of the usage of other bituminous coal presents a dramatic decline of approximately 40% from 1982 to 2012 (**Figures 3.28-3.31**). As it becomes evident, the introduction of Naphtha as an energy source in the industry, has contributed to that change. Naphtha contributed 39.14% and 50.38% in 2002 and 2012 in total sectoral emissions respectively, and while it was not present in the snapshot emissions mix of 1992 since its introduction it has become the leading fuel contributor to CO_2 emissions. In that respect, fuel oil has seen a declining share over the studied period, from being the second largest contributor of CO_2 emissions with a 31.28% to 13.6% in 2012.

Table 3.32. CO_2 output difference of the C&P industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher)

1980 - 2012		
Scenarios (C&P)	Difference (%)	Difference (Mt)
IPCC NCV_LOW + CO2LOW	151.75%	10.99
IEA NCV + CO2LOW	163.98%	12.10
IPCC NCV_NET + CO2LOW	128.19%	11.54
IPCC NCV_LOW + CO2NET	153.43%	11.66
IEA NCV + CO2NET	165.61%	12.84
IPCC NCV_HIGH + CO2LOW	110.76%	11.87
IPCC NCV_NET + CO2NET	129.25%	12.25
IPCC NCV_LOW + CO2HIGH	152.89%	12.16
IEA NCV + CO2HIGH	164.68%	13.40
IPCC NCV_HIGH + CO2NET	111.37%	12.60
IPCC NCV_NET + CO2HIGH	128.21%	12.78
IPCC NCV_HIGH + CO2HIGH	109.97%	13.14

3.4.5 Non-metallic Minerals Discrepancies

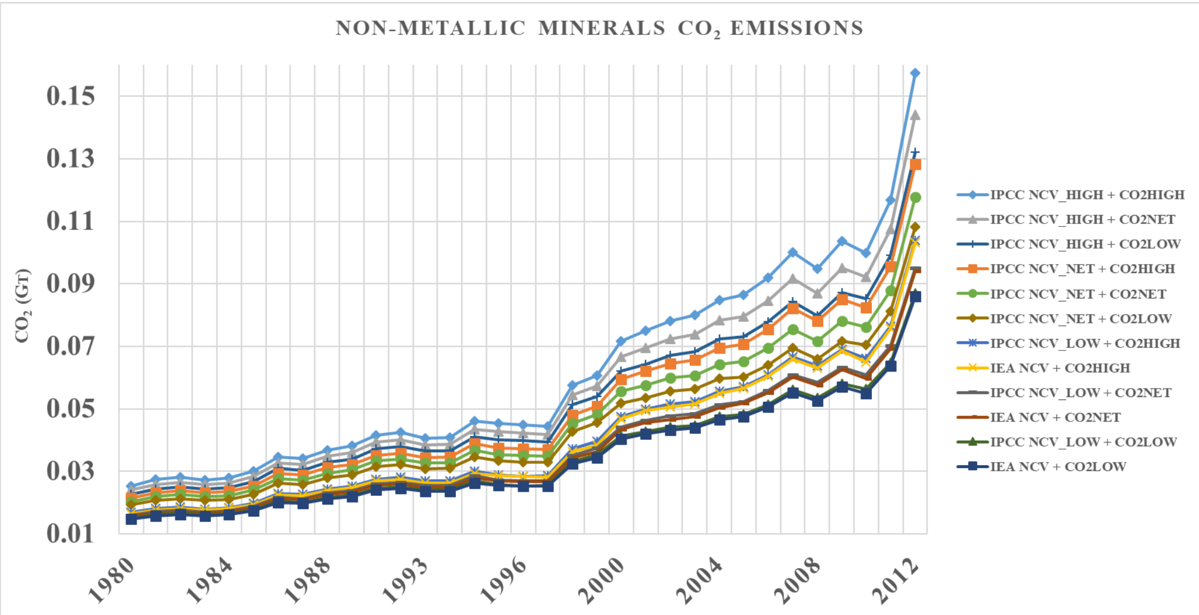


Figure 3.33. Indian Non-Metallic Minerals industrial CO_2 emissions during 1980-2012 under different Indian NCV and carbon content values provided by IEA (standardized NCV) and IPCC on low-net-high scenarios.

The non-metallic minerals industry in India presents a rapid CO_2 emissions growth under all emissions scenarios examined. Approaching the reference scenario, the CO_2 growth for the 1980-2012 timeline is 499.5% or 78.4MtCO_2. Under the same scenario, the CO_2 output is 103.316MtCO_2, showcasing the humongous growth that the sector has experienced, with the subsequent impact in CO_2 emissions.

Regarding discrepancies, the average difference between scenarios is rated at 76.83%, with the highest difference being approximately 83.34% or 71.58MtCO_2 for year 2012 between the highest and lowest CO_2 output scenarios; IEA NCV with low CC and IPCC high NCV and high carbon content. For every scenario assessed, the highest growth is presented for the latter scenario discussed (IEA NCV, CC high) and amounts to 523.86% or 86.76MtCO_2, with the lowest rated at 460.86% or 88.96MtCO_2. In output terms, the highest growth is presented for the IPCC high NCV and carbon content, with 132.11MtCO_2 increase, while the lowest is for IEA NCV and low CC with 71.05MtCO_2 increase of CO_2 output.

The non-metallic minerals sector has experienced a growth of 6.1% per year on average, with the industry however increasing its rate of growth from 1999 onwards with 8.04%. During the last two years examined, 2011 and 2012, this rate of annual growth amounted to 16.14% and 35.63%. Comparing the net scenarios (IEA and IPCC) there is a great lack of convergence that is quantified at 29.2% or 10.37 MtCO_2 on average.

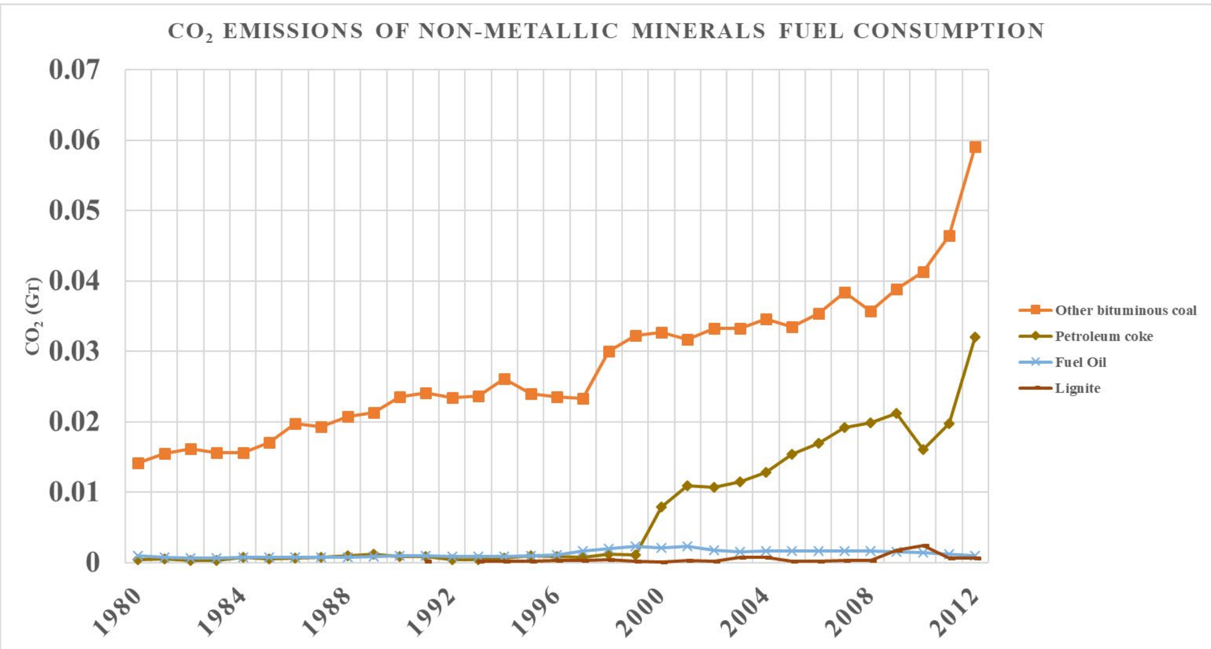
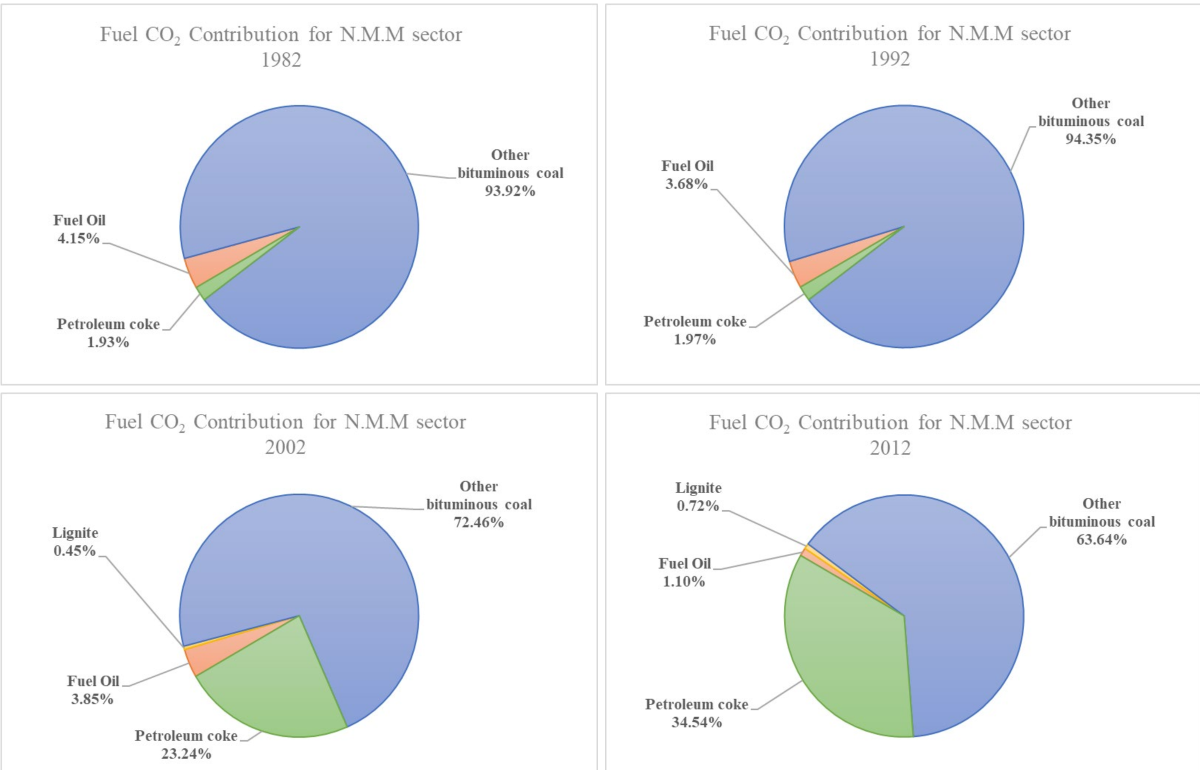


Figure 3.34. Indian Non-Metallic Minerals industrial CO_2 emissions (Gt) attributed per fuel during the 1980-2012 specified timeline.

Following the designated timeline, it is evident that Other Bituminous Coal is a dominant fuel for the non-metallic minerals industry energy mix. This coal product is the fuel with the highest CO_2 emissions when compared to the rest that present activity within the industry. It produced a total of 59.1MtCO_2 in 2012, the year that presents the highest emissions output in total for the industry. The CO_2 emissions of other bituminous coal have been dominant until the introduction of petroleum coke which entered the fuel mix in larger quantities in 2000. petroleum coke presents increased CO_2 contribution when examined under a total timeline perspective that amounts to an approximate 293.3% increase between 1999-2012. In the final year examined, it has an output of 32.07MtCO_2 (**Figure 3.34**). Fuel oil and lignite show a negligible contribution in CO_2 emissions due to their limited input as an energy resource in the non-metallic minerals industry. This is evident in **Figures 3.35-3.38** that are following.



Figures 3.35-3.38. Periodic snapshot of Indian CO_2 emissions share attributed to the fuel mix of the Non-Metallic Minerals sector.

Approaching the emissions mix that originate from the fuels used in the non-metallic minerals industry, the CO_2 emissions mainly originate from coal products, specifically other bituminous coal, throughout the snapshots that are examined. Its share, however, has declined during the 1982 to 2012 timeline, from a 93.92% to 63.64%. The introduction and continuous share growth of the petroleum coke is the main reason for that emissions share change, from 1.93% to 34.54% for the same period. Fuel oil and lignite present a small share when compared to the other fuels, at a combined total of approximately 4.15% to 1.82% from the first snapshot to the last. Lignite has not recorded any activity during the first two snapshots. The industry, as also presented in **Figure 3.34**, has not been satisfying its energy requirements by using a diverse fuel mix.

The findings confirm **hypothesis 2a** and **2b** that is posed in **section 2** of the present research chapter. Discrepancies in the industry and every industrial sector, are evident across the timeline range of 1980 to 2012, applying to all the seven scenarios that are generated and examined. No convergence is evident, and in contrast, variable rates of divergence exist.

Table 3.39. CO_2 output difference of the C&P industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher)

1980 - 2012		
Scenarios (N.M.M.)	Difference (%)	Difference (Mt)
IPCC NCV_LOW + CO2LOW	473.96%	71.85
IEA NCV + CO2LOW	478.84%	71.05
IPCC NCV_NET + CO2LOW	460.86%	88.96
IPCC NCV_LOW + CO2NET	492.56%	78.97
IEA NCV + CO2NET	499.46%	78.40
IPCC NCV_HIGH + CO2LOW	481.93%	109.43
IPCC NCV_NET + CO2NET	477.07%	97.39
IPCC NCV_LOW + CO2HIGH	514.47%	87.00
IEA NCV + CO2HIGH	523.86%	86.76
IPCC NCV_HIGH + CO2NET	499.75%	120.07
IPCC NCV_NET + CO2HIGH	496.31%	106.88
IPCC NCV_HIGH + CO2HIGH	521.02%	132.11

3.5 Discussion of the Results and Further Analysis.

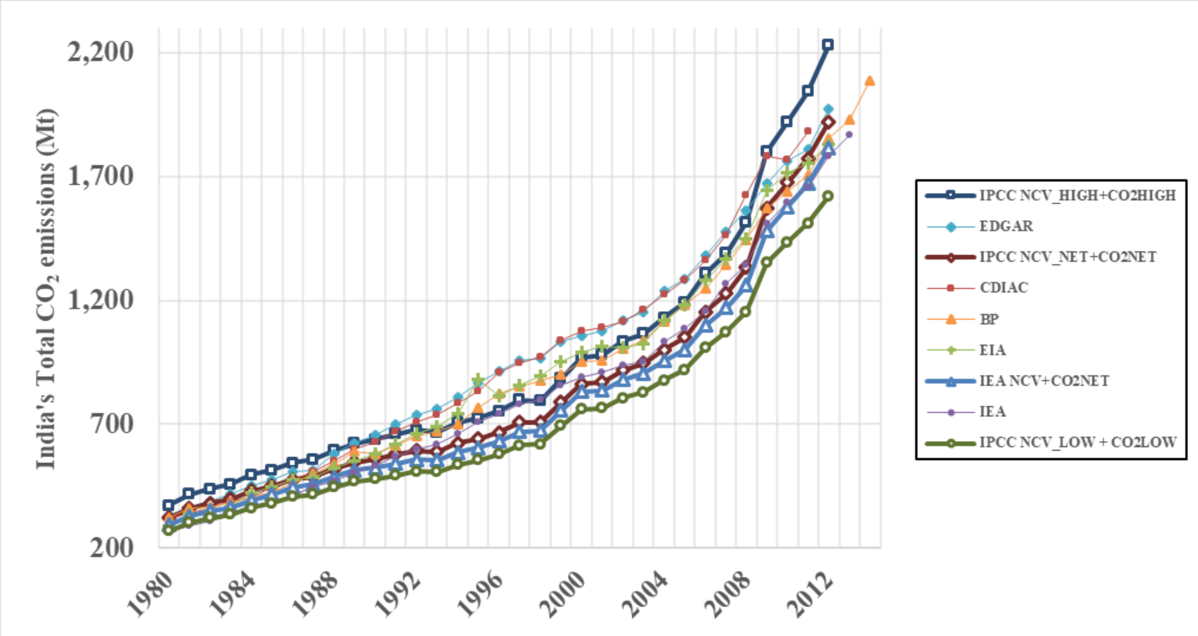


Figure 3.40 India's total CO_2 emissions growth timeline from Final Consumption during 1980-2014 in comparison with selected emission discrepancy scenarios. Data sources: (Carbon Dioxide Information Analysis Centre (CDIAC), 2015), (International Energy Agency, 2015b), Emission Database for Global Atmospheric Research (EDGAR) (European Comission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016).

This research is pointing towards a broader understanding of the factors that contribute towards emissions discrepancies. Examining the official data published by the authorities responsible for reporting emissions, shows a consensus regarding the CO_2 output growth for the total final energy consumption in India, over time. The focus of this work, however, is that attention is needed in the accounting factors, as the presented discrepancies of section 3, is the result of different sets of accounting factors. Combining or sharing different sets of accounting factors expand those uncertainties further, underlining the urgency required for addressing emissions uncertainties.

Examining the CO_2 emissions timeline (**Figure 3.3; 3.40**) for India, summing the output published by the respective organizations and authorities, significant discrepancies in the estimated figures are evident. This research confirms those uncertainties and examines them in that timeline basis. They present different CO_2 emissions output, as demonstrated individually in the figures mentioned above and extend in a specified range (**Figure 3.41**). However, it becomes clear that the discrepancy in output, measured in weight of CO_2, presents variable rates from the minimum to the maximum for each year.

Constructing a chart to examine the discrepancy rate over time (**Figure 3.42)** highlights the argument. By examining the minimum versus the maximum reported rate, it can be concluded that the discrepancy between BP, IEA, EIA, EDGAR and CDIAC is high, in absolute terms peaking in 2008 with 284.74MtCO_2 or 21.22%. The rate of discrepancy between the authorities, at peak, is found in year 1982 and has reached a 26.75% difference from the minimum (IEA) to the maximum (EDGAR), which is measured at approximately 82.8MtCO_2. This gap in reported CO_2 output presents a downward trend over time from 25.43% in 1980, to 10.84% in 2012; the last year examined. A reverse spike rate, found in 1987, is the result of EDGAR producing a lower growth rate in CO_2 emissions than normal, compared to those of IEA. Historically, EDGAR is producing the highest emissions output, while IEA the lowest (**Figure 3.40**).

The emissions discrepancies exist, as a result of either inconsistent emission factors or fuel consumption activity levels used in the accounted inventories (Zhao et al., 2011). Authorities such as IEA, BP and MOSPI make the activity levels available to the public but with contrasting results as a first source of error as this research demonstrates in **Figures 3.5-3.6**. The available activity levels (British Petroleum, 2016; Central Statistics Office, 2016; International Energy Agency, 2014b) or emission factors (Gómez et al., 2006; International Energy Agency, 2012a) that are disclosed deviate in their estimations, generating further uncertainties that contribute to the problem.

The discrepancy rate between official CO_2 output estimations of India's final energy consumption (**Figure 3.42**) is measured at approximately 21.1% on average for the examined timeline, which can confirm the first part of the first hypothesis (**1a**) to be tested; found in **Section 3.2**. Extending this conclusion, even at the lowest discrepancy rate, as this was discussed previously, the difference in output is measured at 192.95MtCO_2.

Examining the scenarios generated by this present research for final energy consumption, discrepancies are evident across the timeline. While the results have been extensively discussed for the seven scenarios generated (**Figure 3.8**), for comparing the variable rates of 1980-2012, the IPCC lowest and highest scenarios have been selected. To construct **Figure 3.43** a similar pattern as that found in **Figure 4.42** is followed. Discrepancies between those selected high-low scenarios is conclusive, as expected, generating higher rates when compared to official data. The CO_2 output in weight (**Figure 3.40**) presents discrepancies between those scenarios of 608.28MtCO_2 at max, found in 2012, also generating the highest rate of discrepancy at 37.49%. On average, the discrepancy rate across the timeline is 32.22% approximately;

translating to an average 226.98MtCO_2 difference in weight, with the lowest rate located in 1999 with a discrepancy rate of 27.34%.

The calculated results, as presented in **Figure 3.8; 3.40; 3.43**, can be conclusive towards confirming **hypothesis 1b**, as the discrepancies, either on a weighted or rate basis, between the generated scenarios is high across the timeline.

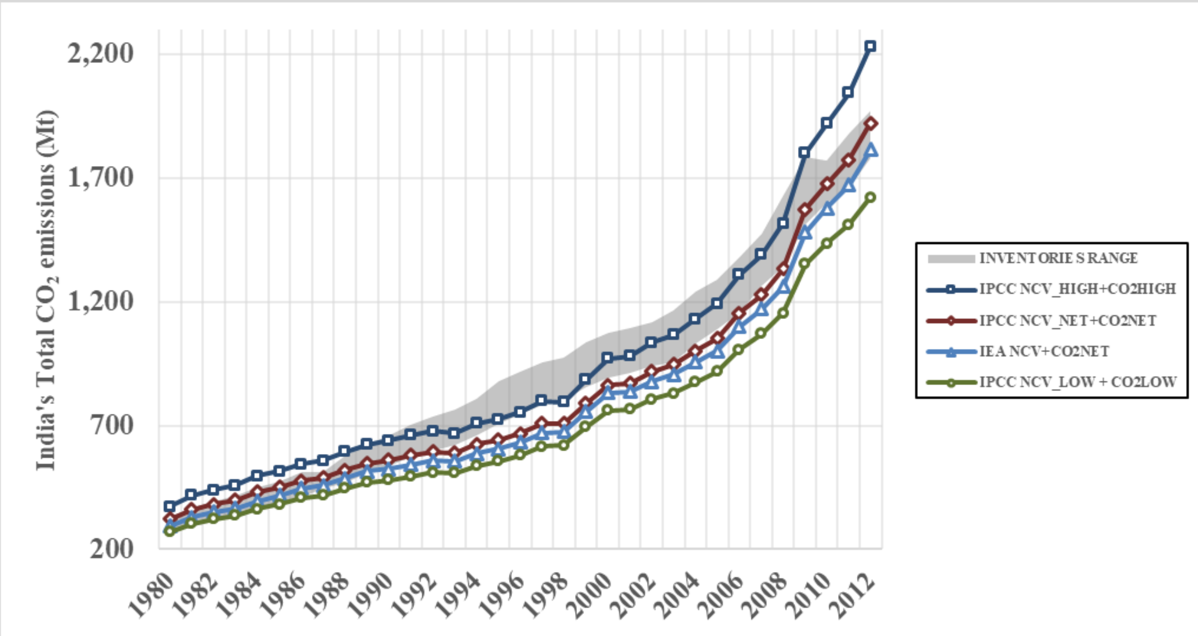


Figure 3.41 Range of India's total CO_2 emissions growth timeline, highlighted in grey, from Final Consumption during 1980-2012 in comparison with selected emission discrepancy scenarios. Data sources: (Carbon Dioxide Information Analysis Centre (CDIAC), 2015), (International Energy Agency, 2015b), Emission Database for Global Atmospheric Research (EDGAR) (European Comission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016).

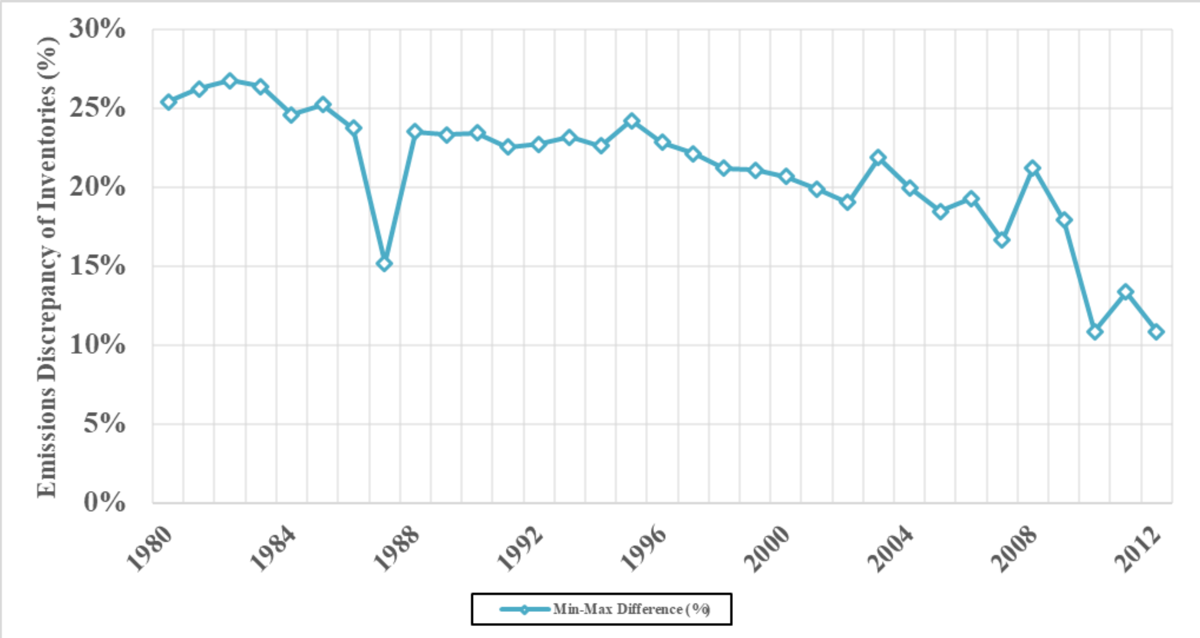


Figure 3.42 Discrepancy between minimum and maximum output of official published CO_2 emissions produced from Indian final total consumption of energy. Data sources: (Carbon Dioxide Information Analysis Centre (CDIAC), 2015), (International Energy Agency, 2015b), Emission Database for Global Atmospheric Research (EDGAR) (European Comission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016).

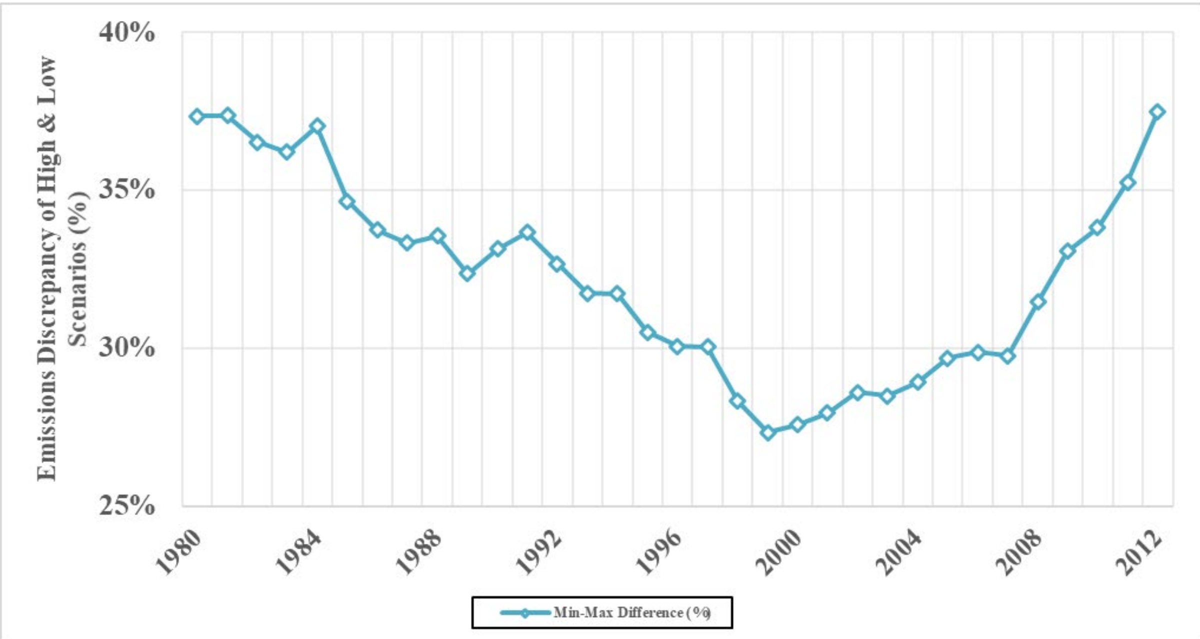


Figure 3.43 Discrepancy between selected high-low CO_2 emissions scenarios (IPCC NCV CC High – NCV CC Low) for Indian final total consumption of energy. Data sources: (Carbon Dioxide Information Analysis Centre (CDIAC), 2015), (International Energy Agency, 2015b), Emission Database for Global Atmospheric Research (EDGAR) (European Comission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016).

Forming a comparison between the official published data of various authorities and the seven different scenarios generated by the present research, the analysis is further conducted considering similar research regarding CO_2 uncertainty levels performed in the literature (Guan et al., 2012; Liu et al., 2015b), to examine the calculated discrepancies between them. To reach conclusions that will highlight the results that are associated with **hypothesis 1c**, those calculated CO_2 output scenarios are weighed as average, deviating from what is displayed in **Figure 3.41**.

The following **Figure 3.44** compares the official databases output, of **Figure 3.3** and the assembled output scenarios of the research as demonstrated in **Figure 3.8**. The different scenario results are extracted as two separate averages. The first average regarding the official published data and the second regarding the seven output scenarios as described in the methodological chapter and presented in the results of **section 3** of this chapter. These extracted averages, highlight a relative convergence in terms of weight ($MtCO_2$), deviating from the comparison of output scenarios approached individually in **hypothesis 1b**. The average research scenario presents lower CO_2 output for an extended timeframe (**Figure 3.44**) compared to the official averages. However, for the last two years examined (2011-12), this trend is reversed, with 6.14$MtCO_2$ to 50.05$MtCO_2$ higher output respectively.

Comparing in share terms (%) (**Figure 3.45**), the results highlight the relationship between the scenarios CO_2 average output from the different datasets. The scenario average, has a maximum 9.97% higher output, produced in 1981. At its lowest output, the production of CO_2 is lower by 20.34% compared to the official data averages. It is important to notice, that for the last three years examined; 2010-2012 convergence exists, with a difference of 0.32% lower than the official data. Concluding with the findings, the total timeline of 1980-2012 shows a lower average CO_2 output measured at 7.49% to exist when compared to the official data. Extending this discrepancy further in weight terms, it is concluded that for the total period of 1980-2012, the produced CO_2 is 2199.38$MtCO_2$ less than what the official estimations suggest, highlighting the severity of the generated uncertainty. As a result, **hypothesis 1c** can be confirmed.

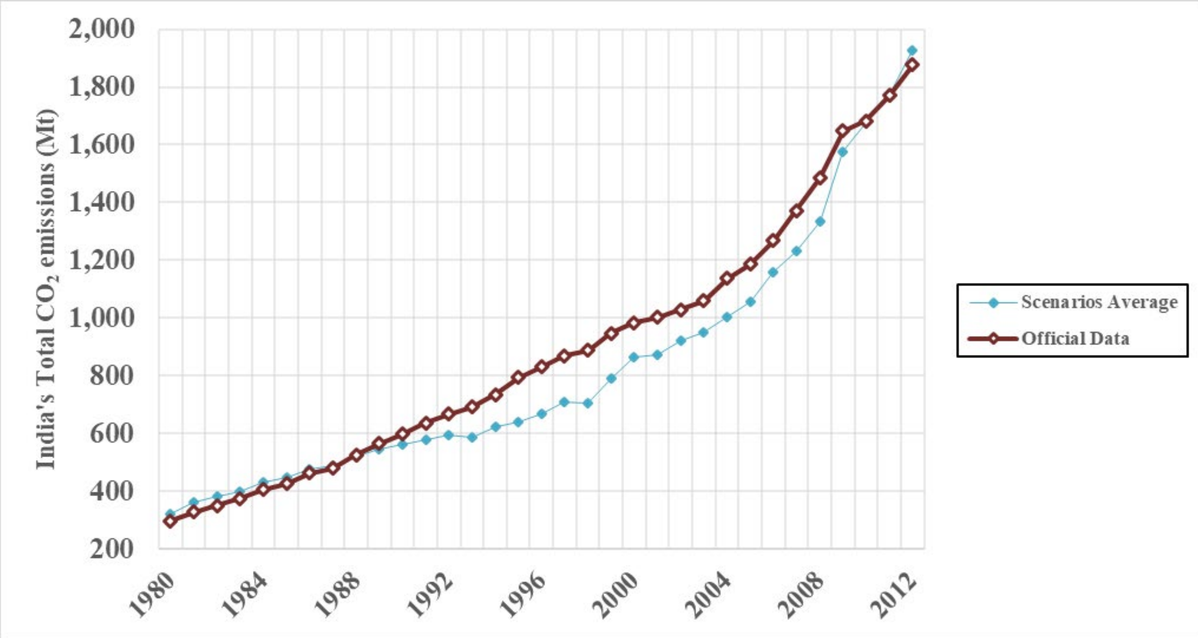


Figure 3.44 Comparison of official and research scenario averages for India's total CO_2 emissions growth timeline from energy final consumption during 1980-2012. Data sources: (Carbon Dioxide Information Analysis Centre (CDIAC), 2015), (International Energy Agency, 2015b), Emission Database for Global Atmospheric Research (EDGAR) (European Comission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016).

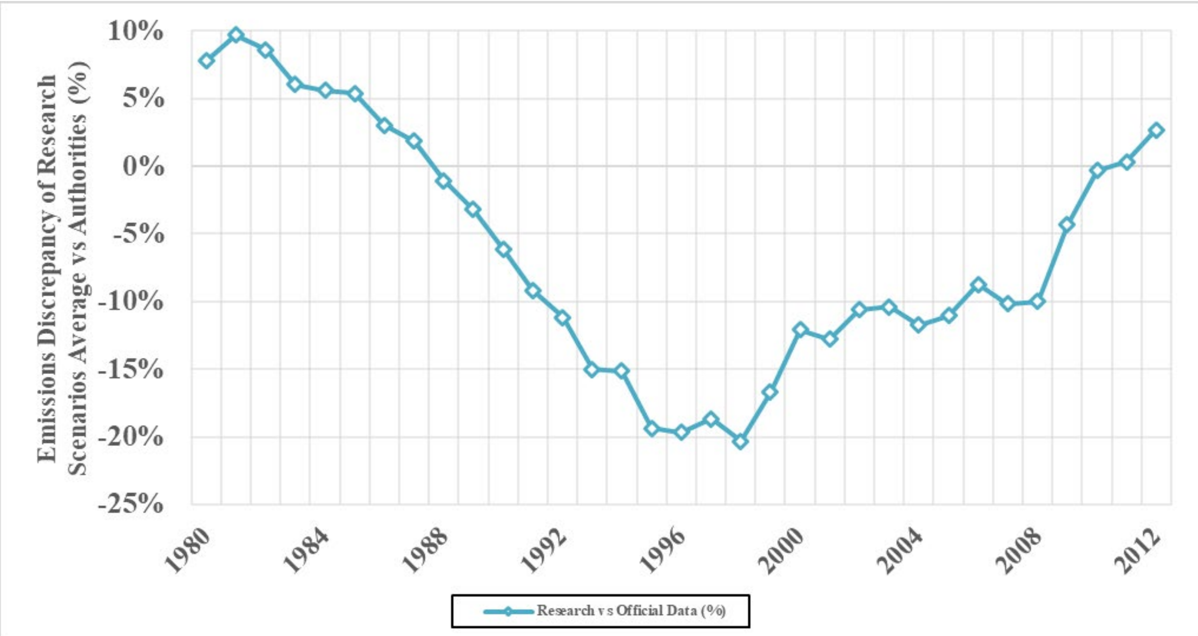


Figure 3.45 Discrepancy for the average of the emission scenarios generated form this research and bodies publishing CO_2 emissions for India's final total consumption of energy. Data sources: (Carbon Dioxide Information Analysis Centre (CDIAC), 2015), (International Energy Agency, 2015b), Emission Database for Global Atmospheric Research (EDGAR) (European Comission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016).

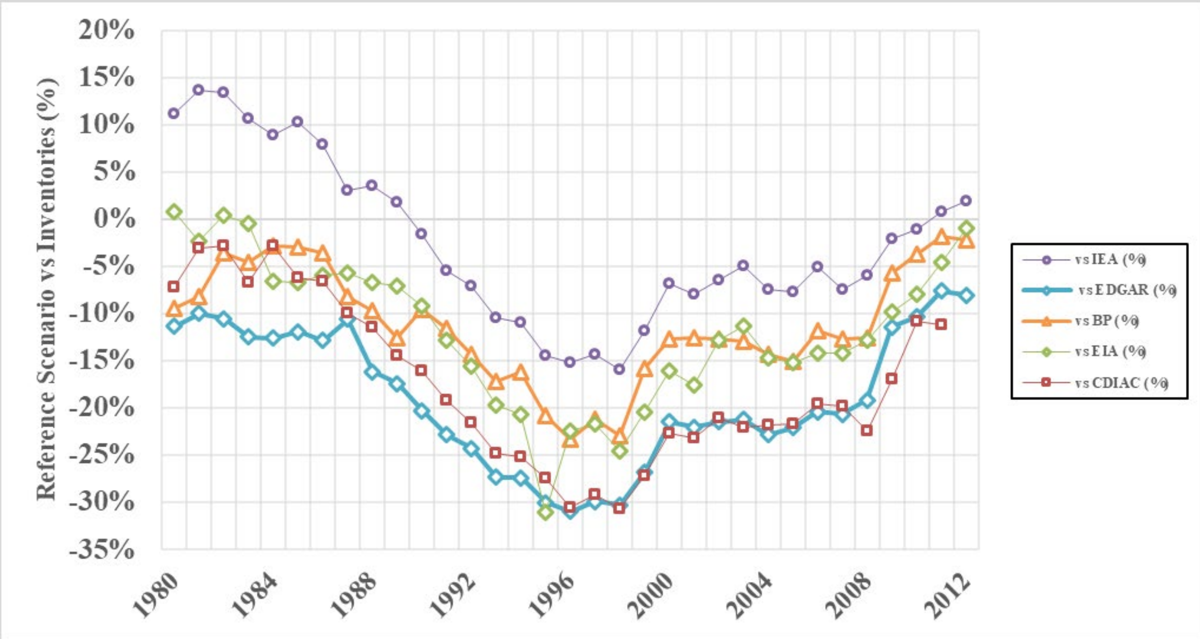


Figure 3.46 Reference Scenario (NCV IEA and CC NET) versus the Emission inventories of EDGAR, BP, EIA, CDIAC following a rate of discrepancies (%) on a timeline basis. Data sources: (Carbon Dioxide Information Analysis Centre (CDIAC), 2015), (International Energy Agency, 2015b), Emission Database for Global Atmospheric Research (EDGAR) (European Comission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016).

The output discrepancies of CO_2 from final energy consumption that are observed between the reference scenario and the authorities and organizations, are presented in **Figure 3.46**. Comparing the reference scenario in a wholistic timeline approach, IEA presents a figure that exceeds the former by 2.54% on average, established as the official database estimate that has the highest convergence rate. That rate acts as confirmatory to the methodologies used by this research to assemble the reference scenario; the NCV originates from IEA databases. It can therefore be considered, that the average discrepancy figure falls within an error margin.

However, the discrepancies of the reference scenario versus the IEA results vary greatly throughout the timeline, with a 13.6% highest output in 1981 and lowest by 15.94% in 1998. This can be attributed to a deviated carbon content used by the methodology, that of IPCC, and adjusted to IEA following **Table 2.1.3**. The average discrepancies of BP and EIA are convergent, producing 11.21% and 11.85% higher CO_2 output, with the same finding applying to CDIAC and EDGAR with 18.94% and 17.4% higher output following the same terms. In sum, the reference scenario is producing a lower CO_2 output by 12.39%, when compared to the average of the official data using the same calculation with **Figure 3.44**. It shows convergence to the IEA scenario but is rejected for the rest of the examined databases results.

Conducting a similar calculation approach between the official output and the IPCC net scenario (**Figure 3.47**), a limited convergence is demonstrated in relation to the scenario acting as reference. This generated discrepancy has a 3.71% higher output, and a lower for BP, EIA, CDIAC and EDGAR with 5.57%, 6.22%, 12.08% and 13.78% respectively. The average discrepancy between the previous and the IPCC net scenario averages at a 6.79% lower CO_2 output. Concluding regarding this deviating rate, it is apparent that the reference scenario and the IPCC net present divergent rates, accounted in **Figure 3.48**. This divergence is rated at 5.62% on average, with a minimum of 3.87%, found in year 1992 and a maximum of 7.11% found in year 1984.

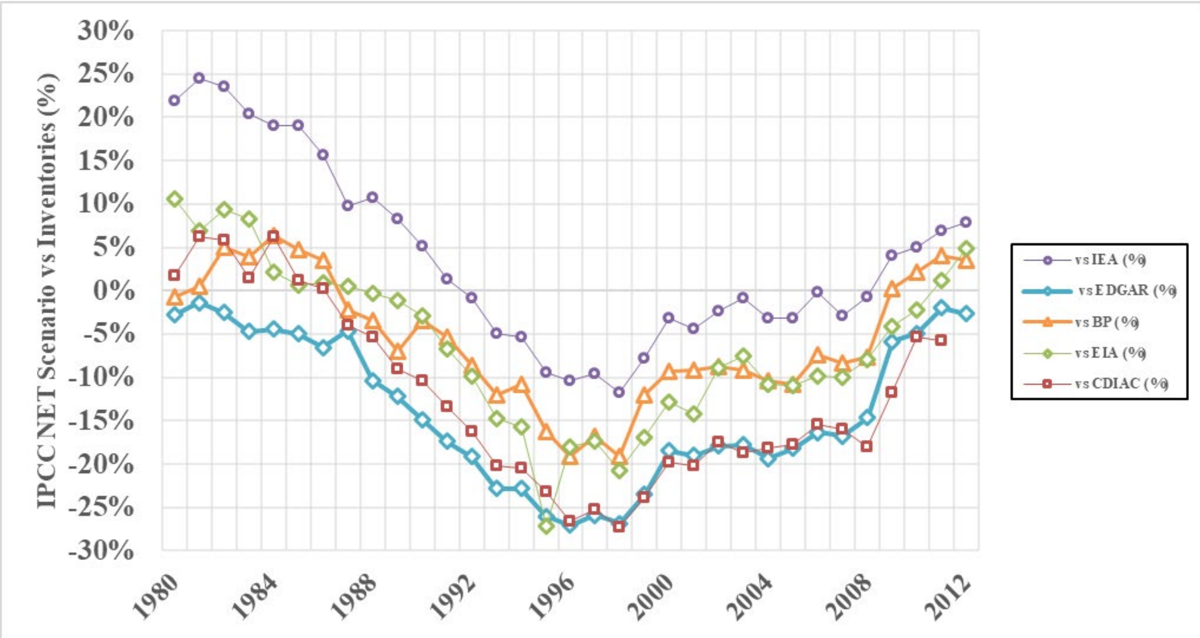


Figure 3.47 IPCC NET NCV and net carbon content scenario versus the Emission inventories of EDGAR, BP, EIA, CDIAC following a rate of discrepancies (%) on a timeline basis. Data sources: (Carbon Dioxide Information Analysis Centre (CDIAC), 2015), (International Energy Agency, 2015b), Emission Database for Global Atmospheric Research (EDGAR) (European Comission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016).

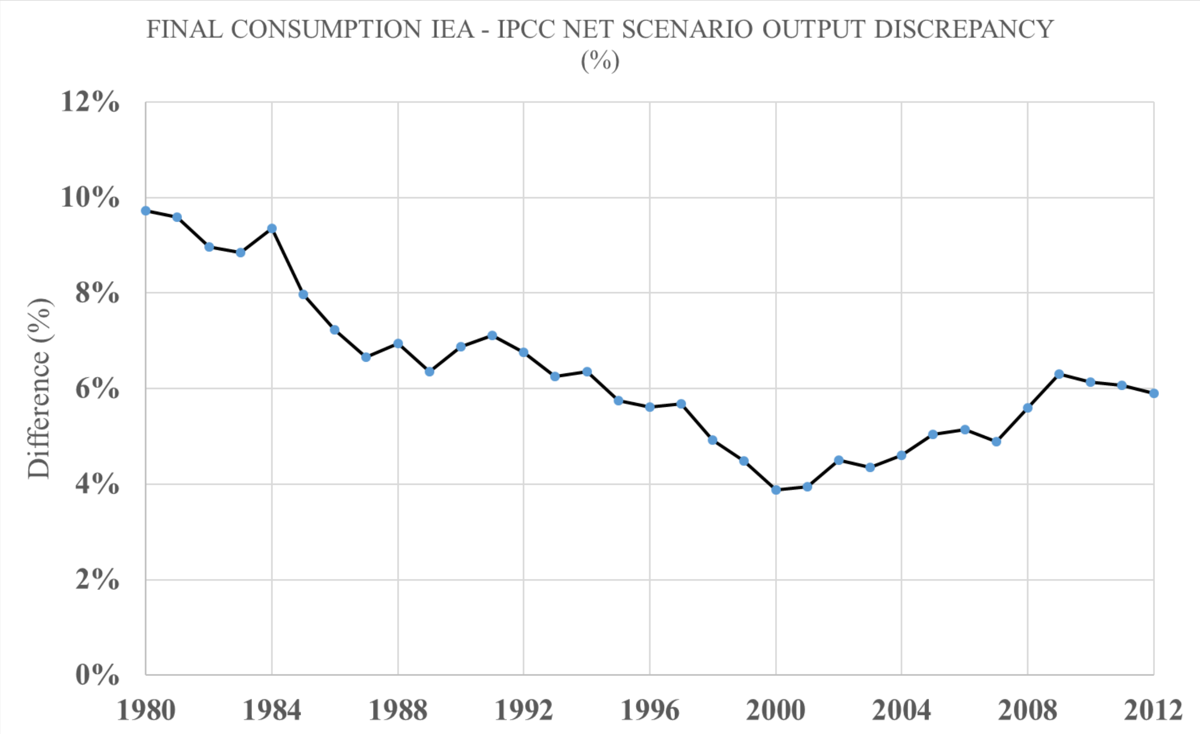


Figure 3.48 Difference (%) of net IPCC and IEA carbon dioxide emissions discrepancy scenarios output of the total final consumption.

Extending the reference and IPCC net scenarios relationship for the total industry and the three industrial sectors included in this chapter, observed discrepancies point towards a divergence between them (**Figures 3.49-3.52**). The total industry (**Figure 3.49**) presents divergency rates that extend from 11.83% in 2000 or a difference of 23MtCO_2 to 20.8% and 92.64MtCO_2, observed in 2012. The average discrepancy rate for the timeline has reached a rate of 14.69%.

The Iron & Steel industry presents a lower rate of divergence between the two scenarios. It averages at 8.9% for the assessed timeline, with 1981 presenting a relative convergence at 3.97%. This convergence is the result of an energy mix comprised by the limited amount of four fuels. The rapid rise of other bituminous coal and blast furnace gases in the past decade (**Figure 3.20**), increases the rate of discrepancy to 19.63% in 2012. This variance of output is the result of different NCV and CC estimates by IPCC and IEA, for bituminous coal and blast furnace gas, highlighting a higher rate of convergence for those parameters.

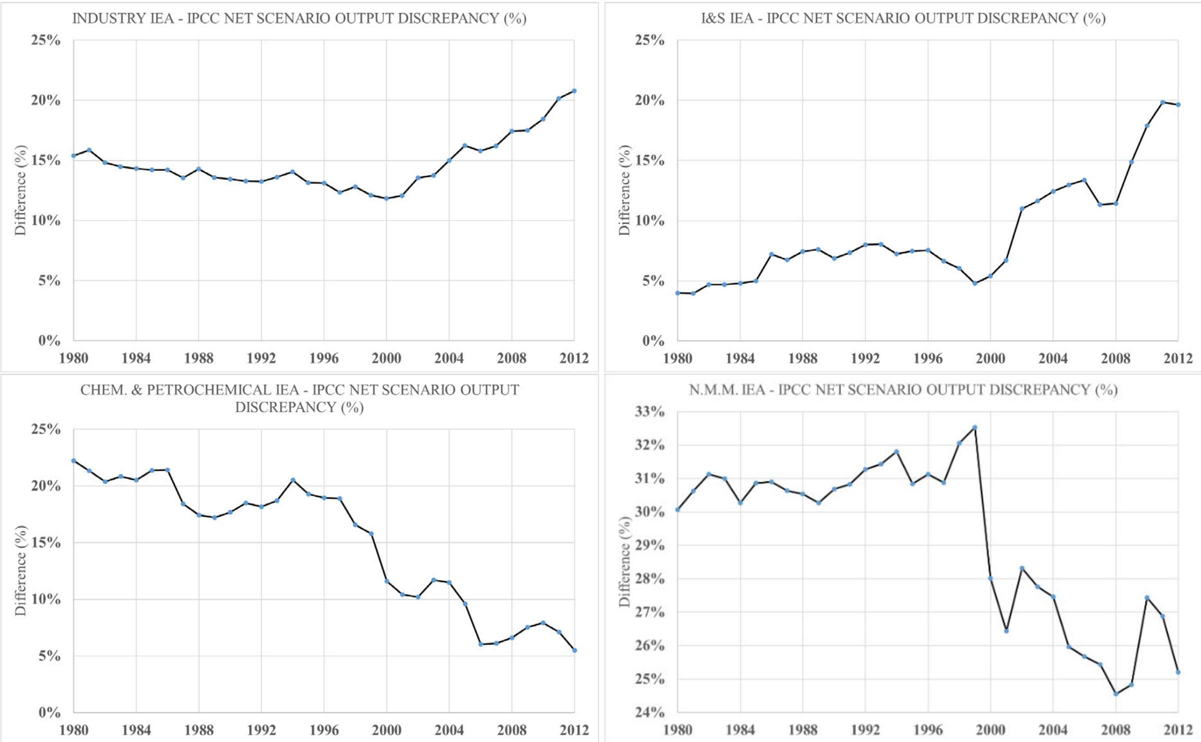


Figure 3.49-3.52 Difference (%) of net IPCC and IEA carbon dioxide emissions discrepancy scenarios output of the total industry, iron and steel (I&S), chemical & petrochemical and non-metallic minerals industrial sectors.

Discussing the chemical and petrochemical sector under the same light, a reverse trend is forming. Other bituminous coal was phased gradually out after reaching its peak in 1994. As observed in **Figure 3.51**, this also is a year with high divergence between scenarios; 20.52%. The divergence between the reference and IPCC scenarios averages at 15.03%, with the lowest figure presented in 2012; 5.51% or 113.42MtCO_2. The divergence rate is decreasing in a stable rate, pointing towards convergence. However, this has not been achieved at the latest year. A similar case is observed regarding the non-metallic minerals industry (**Figure 3.52**). Compared to the total industry and the other examined sectors, the non-metallic-minerals industry has produced the highest divergence rates between the reference and the IPCC net scenario. The average discrepancy is approximately 29.2% throughout the timeline. It has peaked in 1993 with 32.53% or 11MtCO_2 for the IPCC net scenario, while the lowest is observed in 2008 with 24.55% or 14.13MtCO_2. The increasing convergence rate is the result of other bituminous coal reducing its share while petroleum coke is entering the fuel mix at an increasing rate (**Figures 3.34-3.38**).

3.6 Conclusions

The Paris Agreement (COP21) has kept India on track regarding further application of programmes such as its Integrated Energy Policy (IEP) plan for mitigating GHG emissions (Government Of India, 2010; UNFCCC, 2015) or the introduction of increasing energy efficiency (NMEEE). Despite India's plans, it becomes evident through the research findings, that high uncertainty levels exist for concluding towards an accurate level of India's CO_2 emissions. These discrepancies, between authorities or the research scenarios generated by the combination of accounting factors that the authorities use, can produce dramatic changes in output, putting either the country's COP21 targets at risk, or at ease.

Locating and accounting emissions discrepancies in India's final energy consumption, total industry and specific industrial sectors, offers an enhanced perspective regarding CO_2 emissions uncertainties. These uncertainties are extracted not only from the published results of respective authorities, but are broken down to their accounting factors, demonstrating additional uncertainty result "trees" when combined. Various output rates and attributed shares are then produced per every sector examined providing responses to the initial hypotheses that have been posed in this chapter, as following:

H1a: A significant discrepancy rate, between the authorities and organizations that publish India's CO_2 emissions output from final energy consumption, exists across the examined timeline range; therefore, confirming this hypothesis (**Figures 3.40-3.42**).

H1b: Significant discrepancies, between the CO_2 emissions from final energy consumption scenarios generated from the combination of different emission factors exist across the examined timeline range; therefore, confirming this hypothesis (**Figures 3.8; 3.40-3.41; 3.43; 3.48**).

H1c: Significant discrepancies, between selected Indian final consumption CO_2 emissions scenarios generated from this research, and scenarios accounted by authorities and organizations, exist across the examined timeline range; therefore, confirming this hypothesis (**Figures 3.40-3.41; 3.46-3.47**).

H2a: Significant discrepancies for India's total industry between the CO_2 emissions scenarios generated by this research exist; therefore, confirming this hypothesis (**Figure 3.12**).

H2b: Significant discrepancies, for each of the examined industrial sectors of India between CO_2 emissions scenarios generated by this research, exist; therefore, confirming this hypothesis (**Figures 3.19; 3.26; 3.33**).

H3: Discrepancy scenarios based on NCVs and CCs published by the IPCC, do present divergent CO_2 emission figures when compared to those published by IEA; therefore, confirming this hypothesis (**Figures 3.8; 3.10; 3.12; 3.17; 3.26; 3.33; 3.40; 3.41; 3.49-3.52**).

H4: The discrepancy scenarios generated by IEA and IPCC NCVs with net CC, does not present convergent CO_2 emission result estimates for every total and/or sector examined; therefore, rejecting this hypothesis (**Figures 3.48-3.52**).

Limitations of this research include the usage of secondary data to feed the model input, as variations between reported levels of activity and emission factors exist. The limited access to region-specific fuel emission factors is prohibiting accurate estimations that would produce what would generate a more precise reference scenario. However, this emphasises the enhanced potential for future research. Acquisition of specific carbon content factors for India's main fuel category, other bituminous coal, could enhance the accounting model value and solidify the existing CO_2 uncertainty argument.

Establishing a connection between CO_2 emission mitigation pathways and considering the pressure that uncertainties pose for keeping national INDCs for Paris Agreement under a feasible perspective, benchmarking the levels of activity against CO_2 emissions becomes a necessity. Establishing an energy and carbon intensity benchmark model, shifting the focus to India's economic locomotive and regional developing economies with high levels of growth, industry (Ivanic and Martin, 2018; MOSPI, 2019; Suryahadi et al., 2009), acts as the means to examine the production growth potential against satisfying the environmental targets that have been set in governmental policy.

4. Energy and carbon intensity: The challenge of a cross-country industrial shift from China to India and SE Asia

4.1 Introduction

While China has been firmly established as the main locomotive of the global economy, it is also identified as a global industrial production hub. However, the economic performance of the country shows evidence of slowing down with its economic growth rate being in decline, from 6.7% to 6.2% between 2016 and 2018 (IMF, 2017). In a similar economic trend, Indonesia, the Philippines and Thailand are experiencing a 5.1%, 6.7% and 3.2% growth rate respectively for 2017 (IMF, 2017, 2016a, 2016b; IMF Communications Department, 2016a). India's GDP growth stood at 6.7% in 2017 and is expected to accelerate to 7.4% and 7.8% in 2018 and 2019 respectively (IMF, 2018b, 2016c).

Overseas firms focus on India, among others, for establishing their production lines, with India surpassing China for greenfield FDI by $6.4 billion in 2015 (Fingar, 2016; Iyengar, 2015) aided by initiatives such as the "Make in India" programme aimed in attracting foreign investors. In contrast to the anaemic growth of crisis hit countries in the EU (Chalvatzis and Ioannidis, 2016) and other regions, SE Asia provides promising industrial hub destinations. Apart from India (Donaldson, 2016), Thailand, the Philippines and Indonesia are discussed as potential destinations by industries wanting to relocate from China (Chu, 2013; de Vera, 2014). In that context and in comparison to China, India, Indonesia, the Philippines and Thailand present young demographic characteristics which enhance their potential as destinations for manufacturers (HKTDC Research, 2013a; Yang, 2016). However, they also present different energy and emission inventories (Kanchana and Unesaki, 2014). From a manufacturer's point of view, industrial relocation from China to SE Asian countries can be preferable for a range of factors such as ageing population and the respective increased social security costs (Chomik and Piggott, 2013), increased labour and production costs (Zhai et al., 2016), higher environmental regulation standards (Zheng and Shi, 2017), higher land value and less attractive tax policies (Chang et al., 2013; Policy Department Economic and Scientific Policy, 2006a).

Cross-country shift of industrial output presents different scales of production challenges that generate further impacts. The increase in production costs can be the result of increased energy input, defined by energy intensity; the ratio of energy consumption per economic output (Fan et al., 2016). With the Chinese emissions taking the lead globally from 2005 onwards (Xu et al., 2017), carbon emissions are mainly driven by economic growth and energy consumption. Indeed, focusing on the case of China, India, Indonesia, the Philippines and Thailand, economic growth is strongly linked to increased energy consumption (Narayan, 2016b). Empirical evidence shows that a unidirectional causality exists, running from economic growth to energy consumption (Chiou-Wei et al., 2008). This causality has also been found to be valid in the case of the Philippines and Thailand, from gross fixed capital formation to energy consumption (Azam et al., 2015).

Industrial production in the countries studied follows a growing trajectory with India's output rising by 60% from 2000 to 2012 (OECD, 2017). Improving energy and carbon intensity acts as a basic element of sustainable development for mitigating the pressure posed by increased energy demand and environmental policies against climate change. Energy intensity improvements aid industrial sector competitiveness due to decreased energy costs and exposure to energy price volatility. On an economy-wide scale, effects on trade-balance can be observed not only in imported energy resources but on energy resources which are produced domestically. This is due to increased energy resources being available for export, with the potential of achieving high prices in international markets (Eichhammer and Walz, 2011).

India's energy intensity of various industrial sectors; including cement, iron & steel, paper pulp & print, has been evaluated for the period of 1973-1994 (Sanstad et al., 2006) using a "base-year" methodology. Voigt et al. (2014) used the World Input Output Database (WIOD) to analyse energy intensity trends of 40 major economies, including China, India and Indonesia for 1995-2007. They attributed China's energy intensity reduction to efficiency improvements. India was classified as the only country of the sample that initially presented high energy intensity and slow energy intensity reduction. This study highlighted a shift of the global economy gross output from countries with low energy intensity; e.g. US, Japan, to countries with higher energy intensity such as China and to India in a lesser extent during that timeframe. Sadorsky (2013) used a compiled model of heterogeneous panel regression techniques to measure the effect of industrialization and urbanization on energy intensity in developing countries such as China, India, the Philippines, Thailand and Indonesia and concluded that policies aimed at speeding up industrialization will increase energy intensity, only to be countered by income growth offsetting the impact of the former.

Energy intensity measures energy consumption per economic output and the examined countries have progressed differently in developing the examined industrial sectors (Forin et al., 2017). This should lead to use of different technologies, with different attributes in relation to energy consumption to produce the specific industrial goods (Tan and Lin, 2018). Therefore, constructing a first hypothesis:

- When a specific industrial sector is being examined, countries will have different energy intensity per economic output (**H1**).

Energy intensity relies largely on the technologies used and gradually cross-country knowledge transfer progresses by either governmental schemes or multinationals active in several countries (Duan et al., 2018). As a result, a second hypothesis states that:

- Different countries' energy intensity for the same industrial sectors will converge over time (**H2**).

When estimating carbon intensity, the specific fuel mix of every industrial sector is important as every fuel has significantly different emission factors (Gómez et al., 2006). This impact is different when carbon intensity is estimated per energy used and per economic output (Grubb et al., 2004a, 2004b). From those parameters, a third hypothesis is formed, stating:

- Different countries will present significantly different carbon intensity patterns, even for the same industry, when carbon intensity is estimated as a function of energy used and economic output (**H3**).

Moreover, while technological convergence can be expected, fuel mix convergence might be significantly more difficult to achieve as countries prioritise their indigenous fuel reserves. Therefore, the final hypothesis is formed, which is that:

- Different countries' carbon intensity per energy used will not converge in a short time (**H4**).

The IEA has directly linked lower energy intensity to emission reduction; in extension to carbon intensity, and increased energy security (Chalvatzis and Ioannidis, 2017; International Energy Agency, 2012b). However, countries differ from one another in energy and carbon intensity levels, presenting research interest for evaluating their performance, enabling further appraisal of their potential for intensity levels reduction. Calculating sectoral energy and carbon intensity is a first necessary step in locating the country needs not only for technological progress but also output structure, technical efficiency, capital and labour energy ratio as these factors act as energy intensity drivers (Wang, 2013). The relocation's impact on industrial CO_2 emissions is complex to estimate and depends on the specific country shifts, their relative energy intensity and their relative emissions intensity.

While the extent and trajectory of industrial relocation between the aforementioned countries is an issue for debate in the literature (De Felice et al., 2015; Pappas and Chalvatzis, 2016), in this manuscript, the energy and emissions intensity of China, India and selected SE Asian countries is compared, to better understand the required energy for producing the same industrial output and the CO_2 impacts of a potential industrial relocation. A range of industrial sectors are investigated, in order to capture the intricacies in the examined countries. Therefore, this work provides a methodological contribution in reconciling energy, emissions, and financial output datasets from the IEA and UNIDO (see methodological details in Chapter 3). Furthermore, this research improves the understanding of the impact that potential relocations of industries have in terms of emissions, and more significantly identifies which industrial sectors might be best and worst placed to accommodate relocation activities in the short-term future. Therefore, the existing research is being advanced; by clarifying the methods and providing the results for country and industrial sector specific hierarchies in energy and carbon intensity.

4.2 Conceptual Framework

The schematic process for calculating energy intensity is presented in **Figure 4.1**.

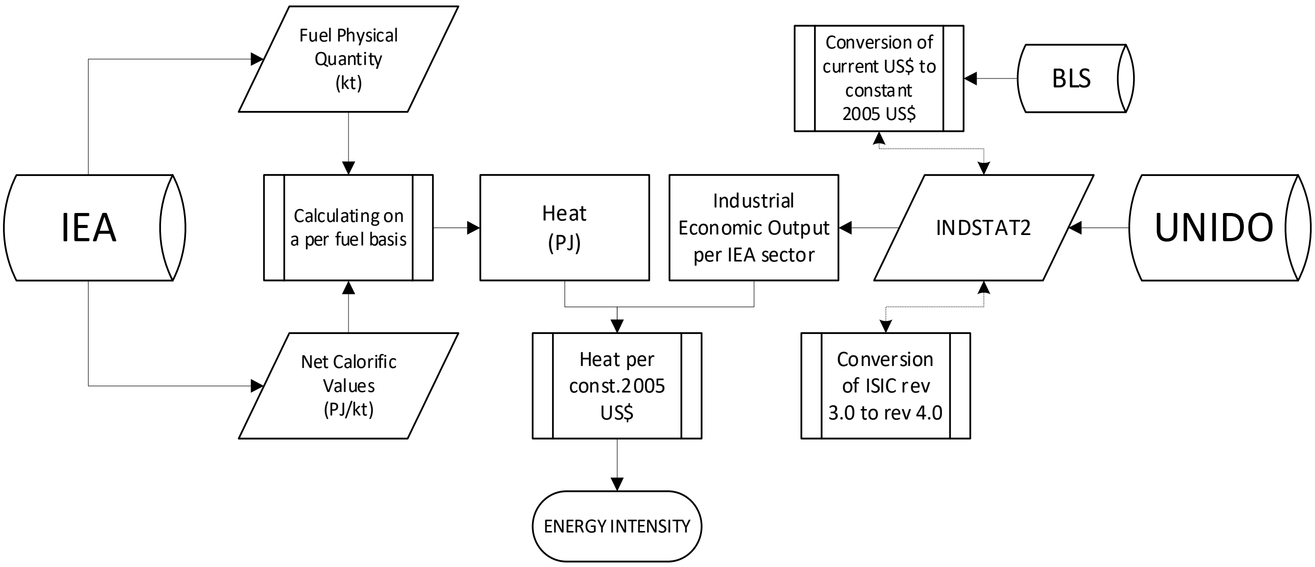


Figure 4.1 Energy intensity calculation process.

The schematic process for calculating carbon intensity per total primary energy supply (TPES) and per economic output are presented in the following **Figures 4.2 and 4.3**.

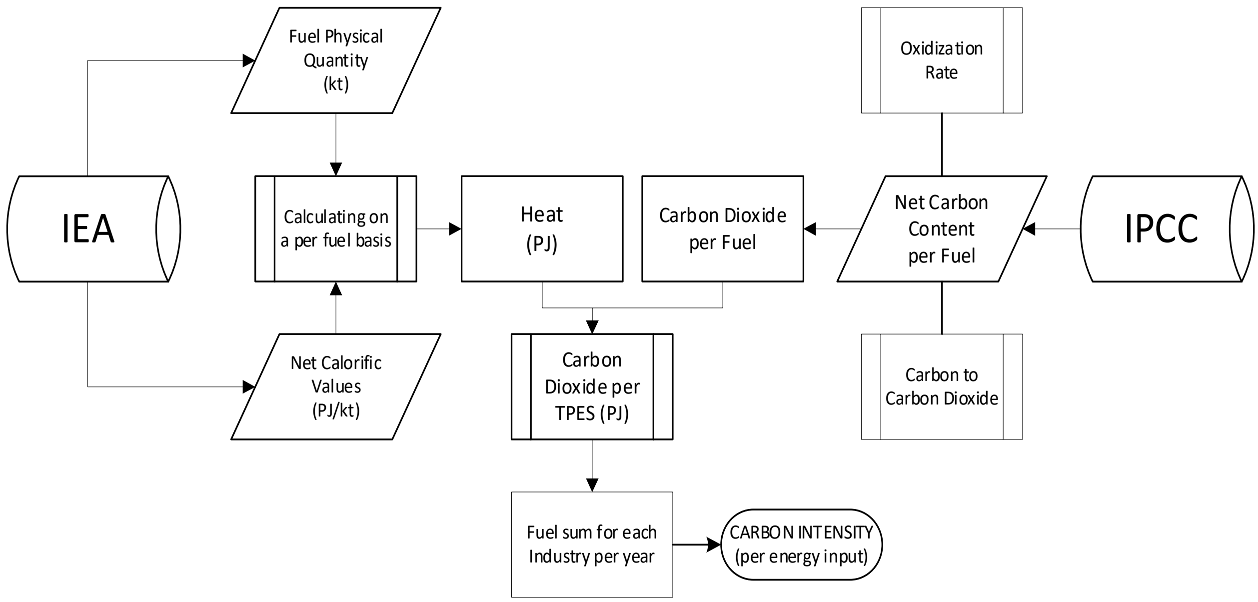


Figure 4.2. Carbon intensity per TPES calculation process.

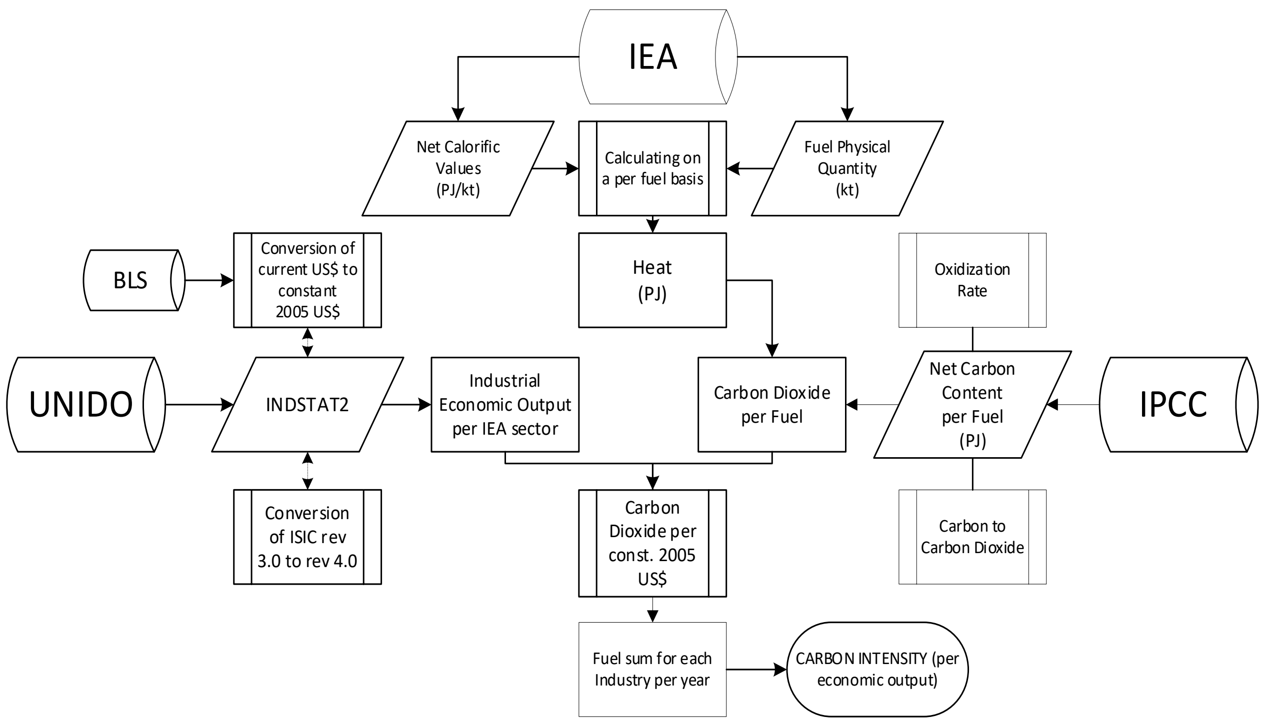


Figure 4.3. Carbon intensity per economic output calculation process.

4.3 Results

4.3.1 Energy Intensity

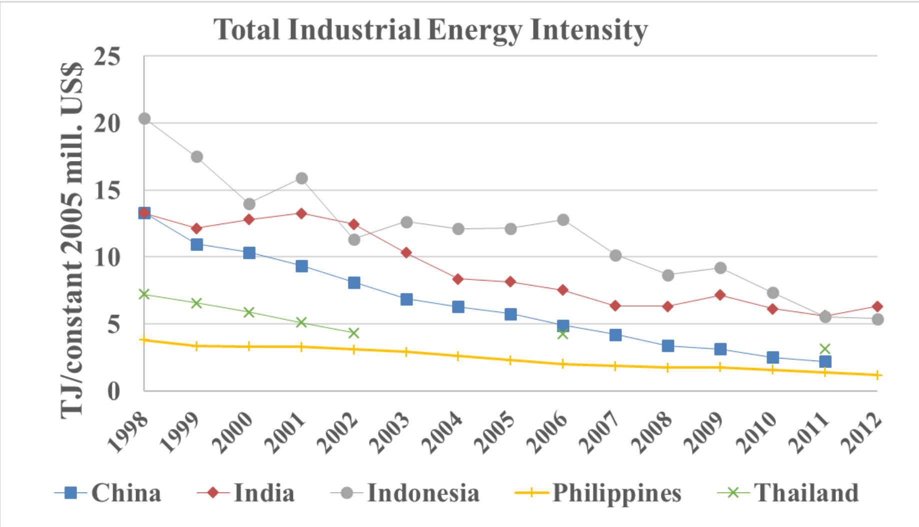


Figure 4.4. Total industrial energy intensity timeline of China, India, Indonesia, Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015c; United Nations Industrial Development Organization, 2016)

Determining and evaluating the energy intensity trends of India, comparing them with other major developing economies, is setting the benchmark of past and existing energy-to-GDP intensity. The overall industrial energy intensity in India is more than double that of China (**Figure 4.4**). Specifically, the energy intensity of India has shown a progressively continuous decline except for 2009 and 2012. This declining trend is similar to the one observed in China, which from 1999 onwards has been decreasing. In absolute terms, however, China needs approximately half the energy India needs to produce the same economic output. Despite the different levels of energy intensity in absolute terms between the countries assessed, it can be observed that they all present a decreasing trend which leads to a convergence with the way the industrial sectors of 19 OECD countries reduced their energy intensity during the 1990s (Mulder, 2015). This has led to a convergence of the countries that have been lagging in relevant terms.

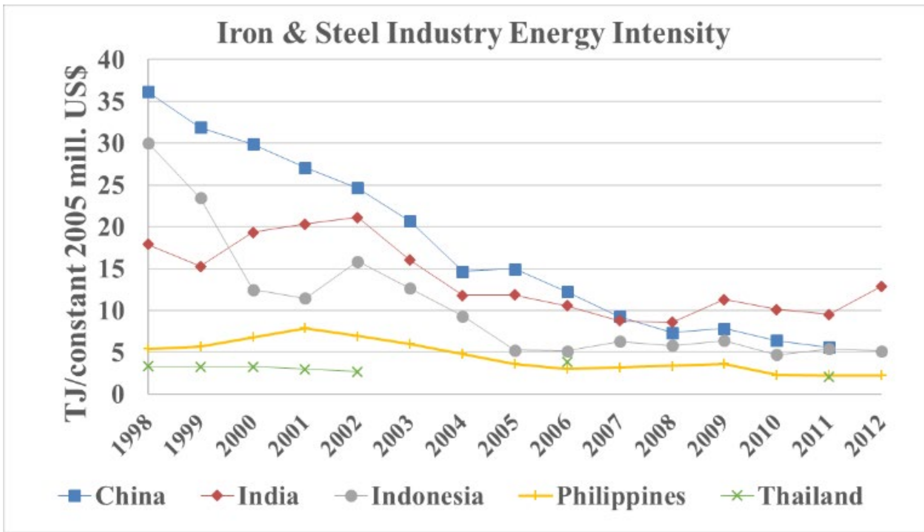


Figure 4.5. Iron & Steel industrial energy intensity timeline of China, India, Indonesia, Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015c; United Nations Industrial Development Organization, 2016)

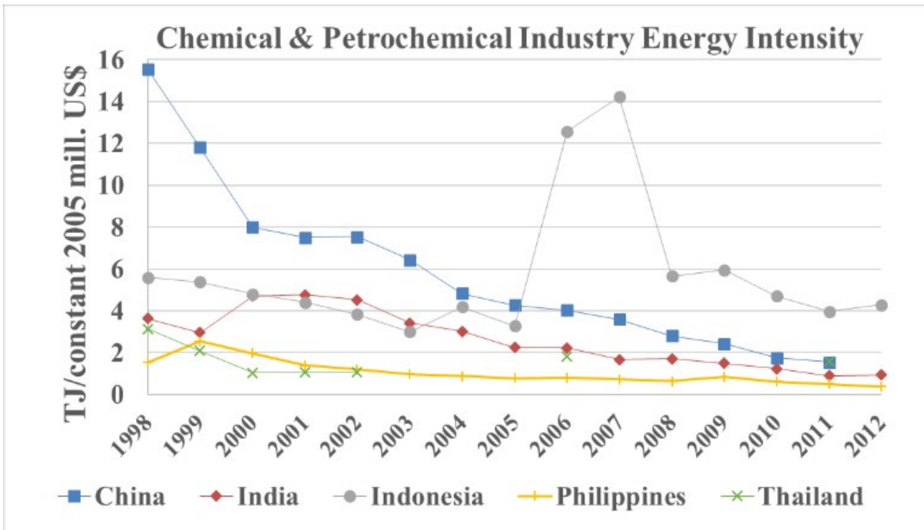


Figure 4.6. Chemical and Petrochemical industrial energy intensity timeline of China, India, Indonesia, Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015c; United Nations Industrial Development Organization, 2016)

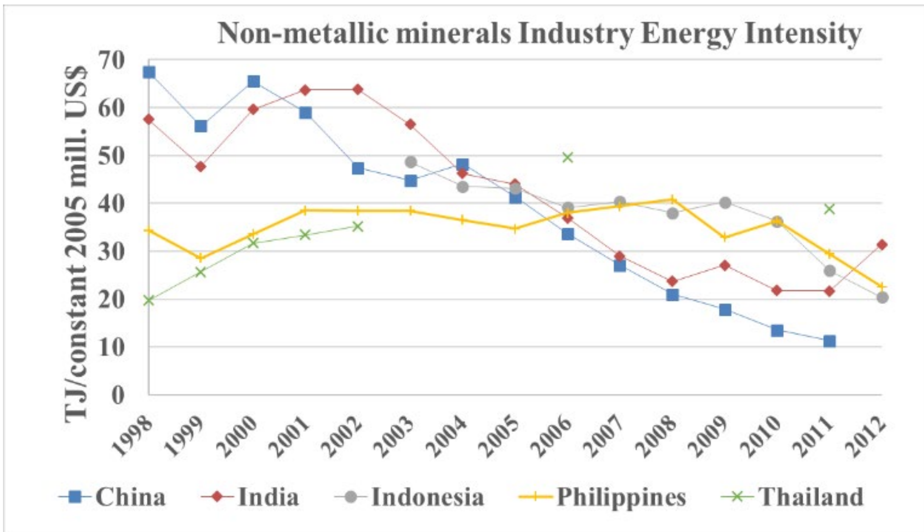


Figure 4.7. Non-metallic minerals industrial energy intensity timeline of China, India, Indonesia, Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015c; United Nations Industrial Development Organization, 2016)

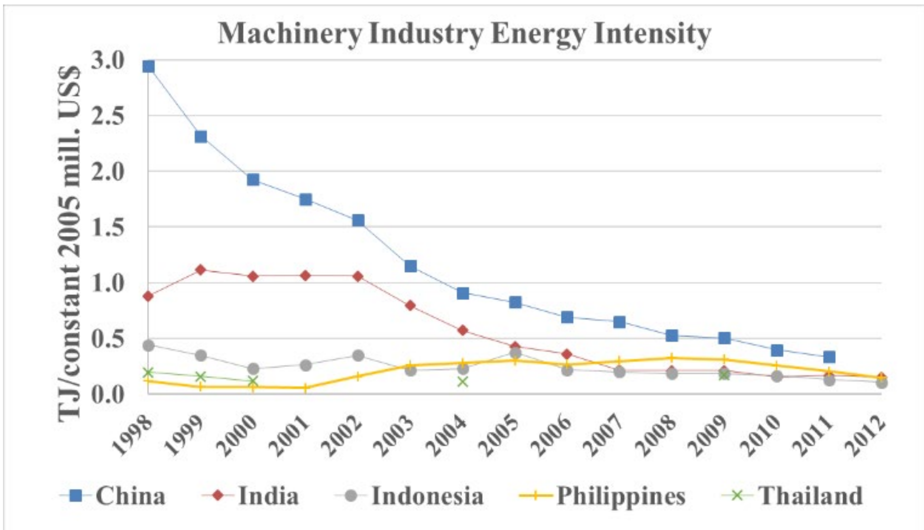


Figure 4.8. Machinery industrial energy intensity timeline of China, India, Indonesia, Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015c; United Nations Industrial Development Organization, 2016)

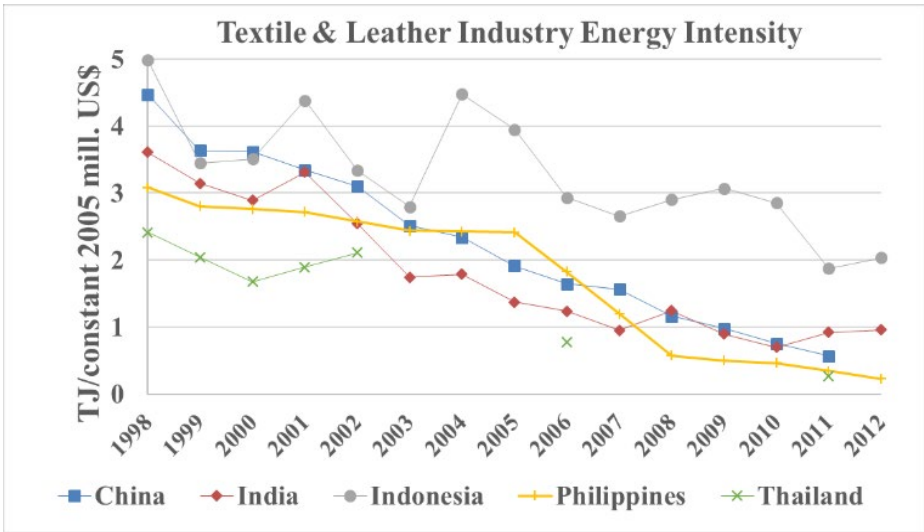


Figure 4.9. Textile & Leather industrial energy intensity timeline of China, India, Indonesia, Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015c; United Nations Industrial Development Organization, 2016)

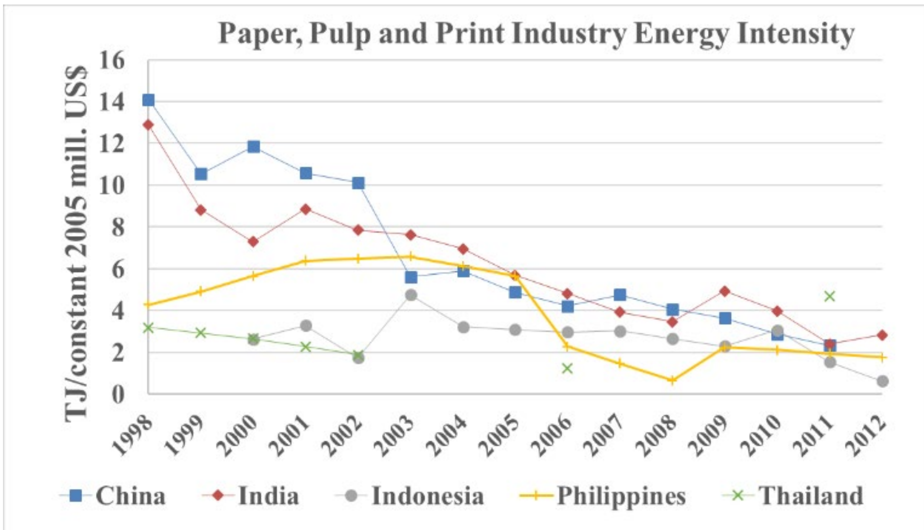


Figure 4.10. Paper, Pulp and Print industrial energy intensity timeline of China, India, Indonesia, Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015c; United Nations Industrial Development Organization, 2016)

However, not all industrial sectors are equal in terms of energy use and economic output and they present significant differences throughout the examined countries (**Figures 4.5 to 4.10**). Focusing on Indonesia, the Philippines and Thailand, a two-fold increase in energy intensity is found in the non-metallic minerals industry when compared to China. Indonesia has higher energy intensity in the chemical and petrochemical as well as the textile and leather industrial sectors comparing to the rest. Thailand has higher energy intensity in the paper, pulp and print industry.

Thailand, the Philippines and Indonesia hold an advantage over India when compared to China for the iron and steel industry, while for the chemical and petrochemical industry, India presents lower energy intensity levels than China. Only Indonesia shows significantly higher energy intensity than the rest of the countries by a three-fold figure at least for the most recent period. Further examination of the cement industry performance (non-metallic minerals), presents all the countries having higher energy intensity levels, when compared to China, by at least a two-fold margin; Thailand reaches a four-fold higher energy intensity, surpassing all other countries. In the machinery industrial sector though the figures present a reverse order. However, the energy intensity differences among the studied countries do not differ significantly and the energy requirements per economic output are low. Paper pulp and print industrial energy intensity shows that Thailand and India are more energy intense than China, while the Philippines and Indonesia present lower respective values. Textile and leather present a large margin between Indonesia and all the other countries including China by two-fold.

4.3.2 Carbon Intensity

Emissions intensity for total industry is presented in relation to economic output and consumed energy (**Figure 4.11**). India's emissions intensity per economic output is approximately 3 times higher than that of China and the Philippines, and almost 2 times higher when compared to Indonesia and the Philippines. China, Indonesia and India present a declining trend with China experiencing the steepest and most continuous decline.

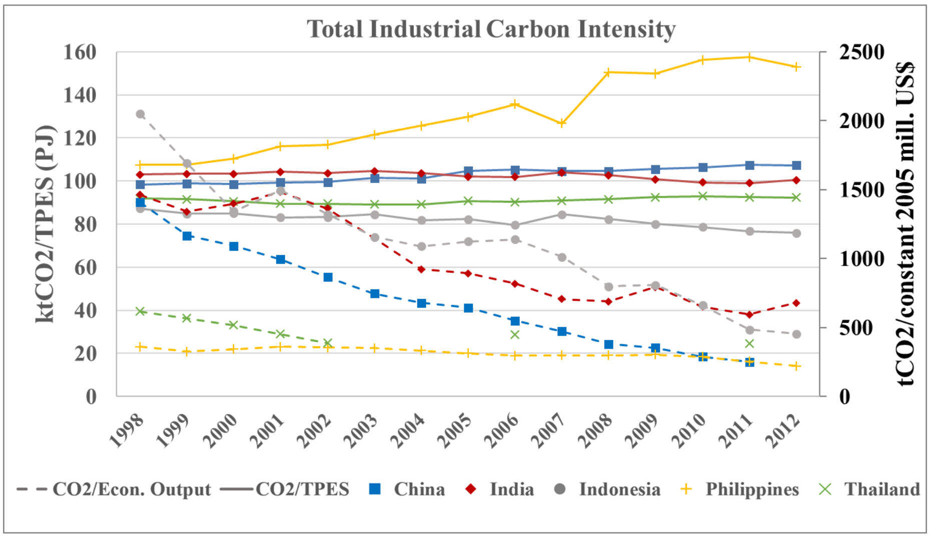


Figure 4.11. Total industrial emissions intensity CO_2/million US$ 2005 and $ktCO_2$/PJ timeline of China, India, Indonesia, the Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015d; IPCC, 2006; United Nations Industrial Development Organization, 2016)

However, when comparing the emissions intensity per consumed energy, the trends appear to be stable for all countries but the Philippines. China and India produce approximately 30% higher CO_2 emissions per energy input than that of Indonesia. Under that prism, the Philippines shows a vast divergence, with 60% higher emission intensity than India and approximately 55% higher than China.

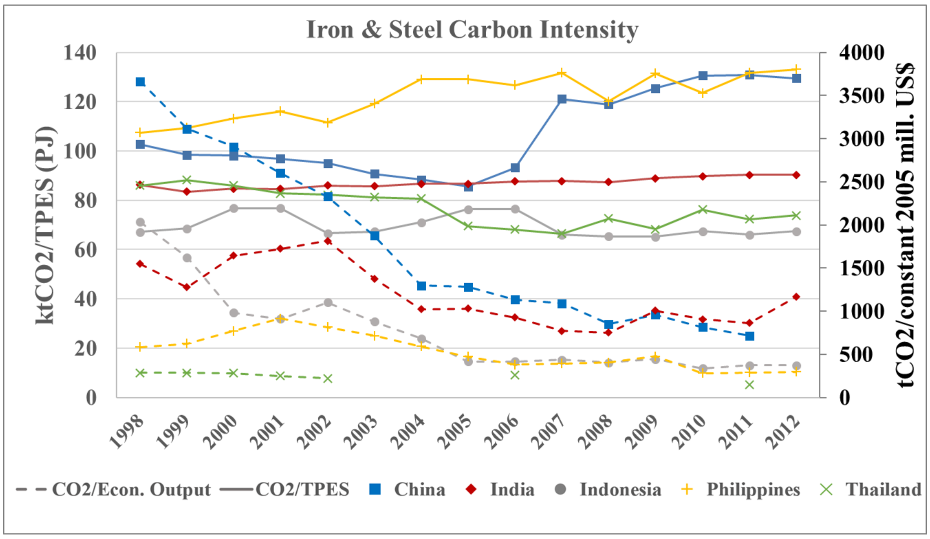


Figure 4.12. Iron & Steel emissions intensity CO_2/million US$ 2005 and $ktCO_2$/PJ timeline of China, India, Indonesia, the Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015d; IPCC, 2006; United Nations Industrial Development Organization, 2016)

While there is a wider electrification trend with innovative technologies in industry (Zafirakis et al., 2014) and transport (Hofmann et al., 2016) it is necessary to look in more detail at the decomposed sectoral analysis. China's iron and steel (**Figure 4.12**) emissions intensity per economic output follows a steep decline between 1998 and 2004 and then continues on the same trend at a slower pace. India surpasses China in 2011 and stands at almost 3 times higher intensity than Indonesia and the Philippines. China and the Philippines present the highest emissions intensity per energy input, at approximately double the level of the other countries.

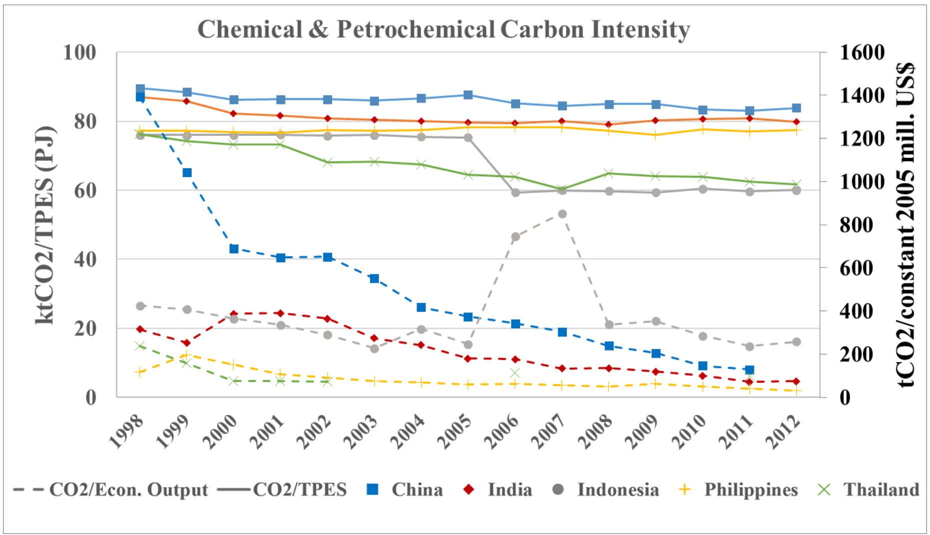


Figure 4.13. Chemical & Petrochemical emissions intensity tCO_2/million US$ 2005 and $ktCO_2$/PJ timeline of China, India, Indonesia, the Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015d; IPCC, 2006; United Nations Industrial Development Organization, 2016)

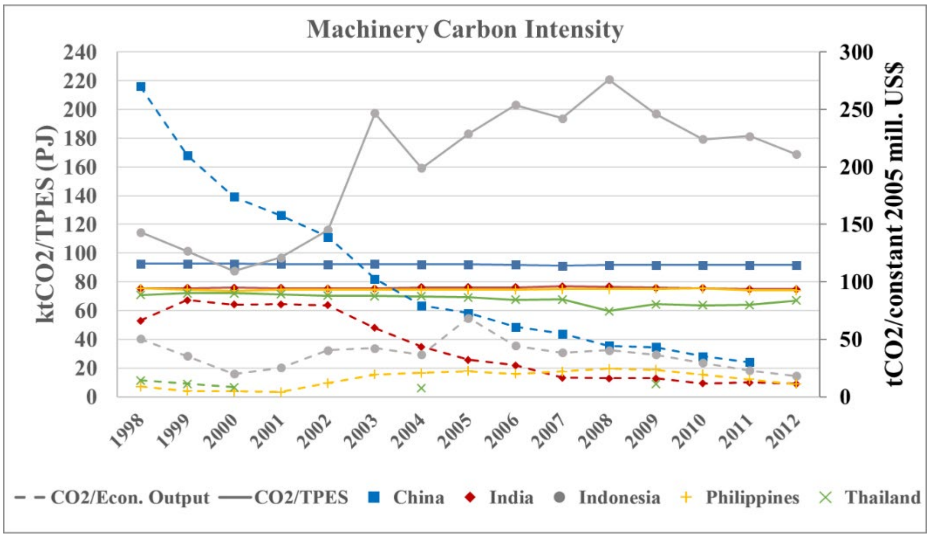


Figure 4.14. Machinery emissions intensity tCO_2/million US$ 2005 and $ktCO_2$/PJ timeline of China, India, Indonesia, the Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015d; IPCC, 2006; United Nations Industrial Development Organization, 2016)

The emissions intensity in the chemical and petrochemical industry (**Figure 4.13**) shows Indonesia having the highest emissions intensity per economic output among the rest of the countries, surpassing China and India by two-fold and three-fold respectively. However, China, India and the Philippines have the highest emissions intensity per energy input with Indonesia and Thailand having an approximately 35% lower intensity.

Similarly, the trend of Chinese emissions intensity per economic output for the machinery industry (**Figure 4.14**) presents a continuous declining trend at an approximate stable rate that ranges from 1998 to 2011. However, China is the most emission intense country per economic output, averaging a 30% higher rate than India for 2008-2011. The rest of the examined countries present a high convergence since 2007. All countries apart from Indonesia present negligible changes in their emissions intensity per energy input. Indonesia presents 50-60% higher emissions intensity than China. Focusing on non-metallic minerals industry (**Figure 4.15**) when examined on an economic output basis, the most intense countries are Thailand and the Philippines. Those countries have a significantly higher intensity than China by almost four and two-fold respectively. India has the highest emissions intensity per energy unit, but its difference to China is narrow averaging at 13%.

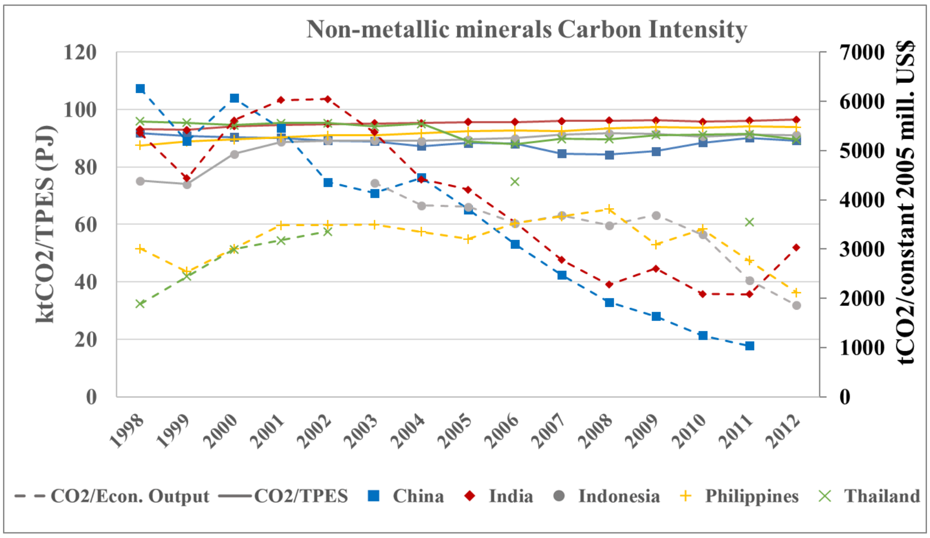


Figure 4.15. Non-metallic minerals emissions intensity tCO_2/million US$ 2005 and $ktCO_2$/PJ timeline of China, India, Indonesia, the Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015d; IPCC, 2006; United Nations Industrial Development Organization, 2016)

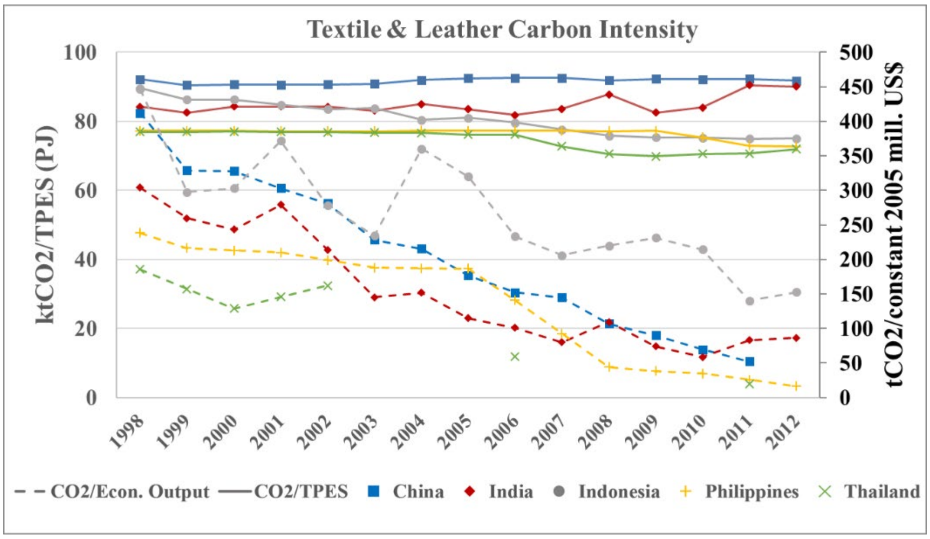


Figure 4.16. Textile & Leather emissions intensity tCO_2/million US$ 2005 and $ktCO_2$/PJ timeline of China, India, Indonesia, the Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015d; IPCC, 2006; United Nations Industrial Development Organization, 2016)

In textile and leather industries, Indonesia has the highest emissions intensity per economic output (**Figure 4.16**), approximately 55% higher than India, three-fold higher than China and six-fold higher than the Philippines. China and India have the highest emissions intensity.

Carbon dioxide per economic output in the paper, pulp and print industrial sector (**Figure 4.17**) presents mixed emission intensity between the examined countries throughout 1998-2012. Nevertheless, China's intensity per economic output has been in continuous decline and was surpassed by India in 2009. India retains the highest intensity, almost three-fold higher than Indonesia.

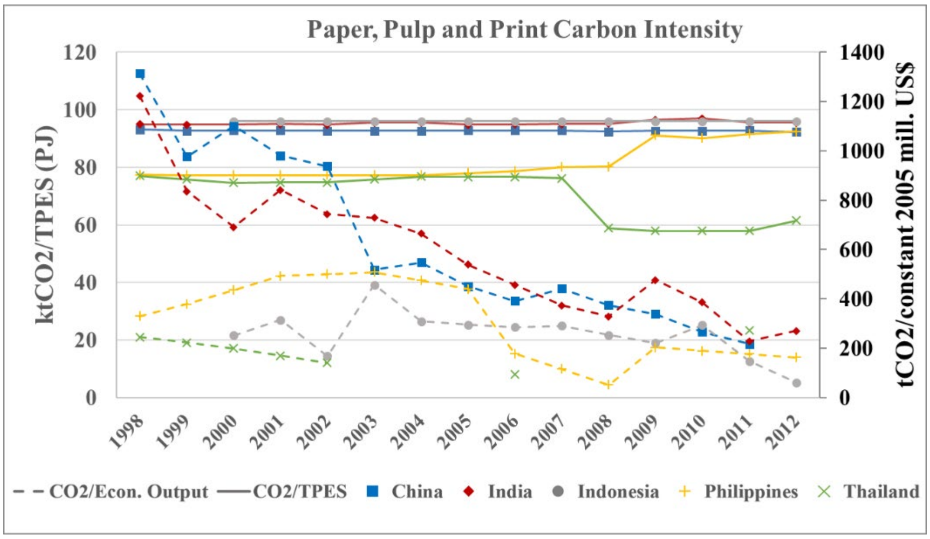


Figure 4.17. Paper, pulp and print emissions intensity tCO_2/million US$ 2005 and $ktCO_2$/PJ timeline of China, India, Indonesia, the Philippines and Thailand 1998-2012. Data Source: (International Energy Agency, 2015d; IPCC, 2006; United Nations Industrial Development Organization, 2016)

4.4 Discussion of the Results

4.4.1 Energy intensity results

Understanding the interplay of the key variables and the emerging patterns is a key focus of this research. It is found that gradual energy intensity reduction is commonplace among all industries and countries. Besides this observation, specific industries do not present universal energy intensity reduction patterns, which appear to be country specific.

The largest consumers of primary commercial energy in India are the power and industry sectors (Indian Ministry of Statistics and Programme Implementation, 2015b). As any coal-based power sector that of India is responsible for the emission of air pollution and greenhouse gases (Kaldellis et al., 2004). However, amongst the most energy consuming industrial sectors in the country are aluminium and cement (non-metallic minerals), and the leading industry in energy consumption is iron and steel.

India's energy intensity per economic output is significantly higher than that of China which presents the urgency for innovation that will lower energy costs and maximize profit margins. This comes in light of the fact that the industrial capacity of India is expected to continue its growth aided by programmes such as the "Make in India". The share of added value that originates from the industrial sector is expected to climb at 25% of India's total GDP by 2030 (PwC, 2014) from approximately 8% in 2013 according to the World Bank WDI. Competitive advantages such as a large working-age population that reaches 70% of the total (Chomik and Piggott, 2013), low labour costs and social expenditure (Grinin et al., 2014) while maintaining a significant innovation potential (Cooper, 2009; Thornton, 2013) incentivise manufacturers to turn their production focus from China to India. This case presents similarities with a transition to Indonesia, which presents a faster improvement rate in the recent years. This implies that a transition of industrial activity from China to India will result in excessive energy use and potential emissions growth.

While looking at the disaggregation of specific industrial sectors, emissions control is important predominantly within the industrial and energy sectors as improvements in other sectors, such as transport, mainly concern electrification which can be entirely ineffective without decarbonization (Hofmann et al., 2016).

Evidently, the non-metallic minerals sector in India, Indonesia, the Philippines and Thailand presents a significantly higher energy intensity than in China. Also, India presents higher energy intensity than China in the iron and steel industrial sector. The share of these two industrial sectors in total energy use, reaching more than 45%, makes them a pressing priority as a potential transition from China to India would result in significant emissions growth.

Subsequently, energy intensity reduction can be achieved with improving and modernising the technologies used in production processes. Energy intensity improvement of the paper, pulp and print industry is feasible through making the kraft process used in paper mills more efficient. That is achieved by utilizing cogeneration; making the paper mills net exporters of electricity and heat (Jönsson and Algehed, 2010). Improvement on energy intensity can also be achieved through the introduction of fuels that can be used in higher efficiency combustion cycles; bark and bunker oil have combustion energy efficiency reaching 67% and 80% respectively (Musa et al., 2009). Iron and steel industries follow a common path of using ore and coke in blast furnaces for producing pig iron, then processed in basic oxygen furnaces (BOF) or the least efficient open-hearth furnaces (OHF). Smelt and direct reduction (DR) are more advanced processes of iron production, with the electric arc furnace (EAF) mostly using scrap to produce steel. Options of improving energy intensity in the industry have different time frame availabilities, such as pulverized coal and plastic waste injection in the short term and hydrogen flash melting in the medium term (Bassi et al., 2009). Technological innovation can provide solutions to improving energy efficiency directly but must be supported by bold policies in the same direction (Murphy, 2014; Zafirakis et al., 2014).

4.4.2 Carbon intensity results

Carbon intensity per economic output presents similar patterns to those of energy intensity precisely because of their common denominator in monetary units. The gradual reduction observed does not depend on industry. It is also found that carbon intensity per energy output does not present any distinct pattern regardless of industry or country.

The continuous steep decline in China's carbon intensity per economic output (Section 5.3.2) is a result of central organization and robust policies applied in the country (Chalvatzis, 2009; Chalvatzis and Rubel, 2015). Discussing carbon intensity per energy input, the divergence that the Philippines show has its origins in the increasingly coal reliant fuel mix between 1994-2014 which resulted in an eight-fold increase in CO_2 emissions originating from its coal fuel mix and the use of blast furnace gas fuel; a source with high energy intensity value (IEA, 2016).

The Indian iron and steel industry is accounted as the third largest iron and steel industry in the world, surpassing that of the Unites States in total crude steel production in 2015 by 10,181 metric tons (WSA, 2016). Focusing on processing technologies being used in the Indian iron and steel sector, the domestic availability of coal combined with its lower price when compared to natural gas, leads to the usage of coal-based direct reduced iron feedstocks (DRI) supplying blast furnace – basic oxygen furnaces (BOF) and electric arc furnaces (EAF) (Morrow et al., 2014a). Classifying the carbon dioxide emissions of metallurgical processes used in India, EAF on steel scrap which follows an increasing trend in capacity, has the lowest carbon footprint due to not requiring coal and coke as reducing agents (Kuramochi, 2016). Blast furnace BOF and EAF DRI have an intermediate position (Lisienko et al., 2016), providing an explanation to India's average CO_2/PJ performance (Figure 5.14). The production of iron and steel based on BF and BF BOF technologies is evident in China and the Philippines. This route of production has differences both in carbon and energy intensity when compared to EAF. Blast furnace BOF requires 0.5 tonnes of coal equivalent (tce) per tonne compared to 0.3tce/t of EAF (Wen et al., 2014) and emits 2.1tCO_2/t compared to 0.6tCO_2/t respectively (Yellishetty et al., 2011). China has been unable to increase its EAF production short-term due to imposed scrap price limits (Wübbeke and Heroth, 2014) but the scrap supply share is expected to increase sharply in the next years (Wang et al., 2014).

Examining the carbon dioxide per energy required, the lower carbon intensity of Indonesia and Thailand in the Chemical and Petrochemical industry is attributed to the countries use of natural gas for covering their energy requirements. The machinery industry of Indonesia presents a previously discussed high carbon intensive mix, when compared to China. This is the result of the country's reliance on gas/diesel fuel, when compared to a more diverse Chinese fuel mix.

Diversity in the industrial fuel mix is not widespread throughout all Chinese industrial activities. The non-metallic minerals industrial sector demonstrates a high reliance on bituminous coal, similarly to the reliance of the same sector in India. India and China, the largest cement producers in the world, make use of rotary dry kilns (Morrow et al., 2014b) which can be improved by adopting a range of technological interventions for cement production (Ray, 2011). These include blended cement with additives that lower the clinker content and kiln shell heat loss reduction, presenting the highest improvement amongst other optimisation processes (Morrow et al., 2014b). Moreover, a reduction of clinker content in cement is achievable through granulated blast furnace slags (GFBS), a common practice in Europe which is feasible in developing countries (CSI/ECRA, 2009). The discussed increase in efficiency can also be extended for the case of other countries such as Thailand, a country that makes exclusive use of dry kiln processes (Hasanbeigi et al., 2010).

Excessive use of specific types of coal such as lignite and other bituminous fuels, classify China and India as the countries with the highest carbon intensity (CO_2/PJ) level in the textile and leather industries. Their reliance on satisfying production requirements with coal products, results in significant carbon intensity divergence from Indonesia, the Philippines and Thailand.

It should be noted that the converging Chinese, Indian and Indonesian carbon intensity per energy input of the paper, pulp and print industry implies a technological and fuel mix convergence. Future production process technologies that can lower carbon intensity in that sector, involve a more efficient drying technology in medium term or black liquor gasification to be introduced in the long term (Bassi et al., 2009).

4.5 Conclusions

Studying the potential relocation of industrial activities from China to India and SE Asian countries under an emissions intensity prism will alter the energy use and emissions output depending on the industrial sector in focus. In response to the initial hypotheses included in this chapter, it is found that:

H1: Even when focusing on the individual industrial sectors, the examined countries present significantly different energy intensity for every one of the examined years; therefore, confirming this hypothesis (**Figures 4.4-4.10**).

H2: Despite substantial energy intensity differences even in the latest examined year, for all industrial sectors it is found that energy intensity converges significantly over time; therefore, confirming this hypothesis (**Figures 4.4-4.10**).

H3: As expected, because of their estimation parameter differences carbon intensity per economic output and carbon intensity per energy used present different patterns over time; therefore, confirming this hypothesis (**Figures 4.11-4.17**).

H4: While carbon intensity per economic output converges over time for all industrial sectors, it is found that carbon intensity per energy used does not present converging results for any of the examined industries; therefore, confirming this hypothesis (**Figures 4.11-4.17**).

China demonstrates a stable trend of reducing emissions intensity per economic output, despite an overall growth in living standards and non-industry consumer consumption, due to factors such as increased energy efficiency (Pothitou et al., 2017, 2016). However, its high emission intensity per energy input in many of the industrial sectors is a determinant of technological structure being orientated towards high energy consumption (Yuan and Cheng, 2011). However, assuming equal demand for economic output, industrial relocation from China to India, Indonesia, the Philippines and Thailand could increase total regional emissions significantly. This presents a challenge, especially in light of the regional INDC commitments toward the Paris Agreement [82]. The industrial sectors for iron and steel, chemical and petrochemical, non-metallic minerals, paper pulp and print and textile and leather present lower emissions intensity per economic output in China than in India and SE Asian countries.

Expanding this research to an energy per economic output basis consideration with the disaggregated energy intensity of the industrial sectors in China, India, Indonesia, the

Philippines and Thailand further conclusions can be extracted. This research concludes that although generally India's industrial energy intensity is double that of China, it is the iron and steel and the non-metallic mineral sectors, that are responsible for that difference. Looking at Indonesia, the Philippines and Thailand, the non-metallic minerals industry presents at least twice higher energy intensity than China. Indonesia has higher energy intensity in the chemical and petrochemical as well as the textile and leather industry. Thailand has higher energy intensity in the paper pulp and print industry while in iron and steel and textile and leather industries, the Philippines present lower energy intensity. It is essential that emissions control is being looked at predominantly within the industrial and energy sectors to facilitate the scope of sustainability in industrial parks which can act even in isolation of the country-wide systems (Spyropoulos et al., 2005; Zafirakis and Chalvatzis, 2014). With energy intensity being an indicator linked to greenhouse gas emissions and air pollution indicators (International Atomic Energy Agency, 2005), actions taken would be expected to have a direct effect on both carbon and emissions intensities.

Regional policies might be best suited to maintain an optimal balance between economic and industrial development and a stronger driver for technological innovation and knowledge transfer (Kaldellis and Chalvatzis, 2005). Regional markets with innovative technologies have the capacity to facilitate progress while not compromising emission control commitments (Zafirakis et al., 2015). With focus on the policy implications of this work on the Paris Agreement (United Nations, 2015) and the respective INDC planning for the examined countries the results highlight that industrial relocation could signal differentiated levels of industrial competitiveness and affect the industries by national environmental agendas and future relevant policies (National Development and Reform Commission of China, 2015; Office of Natural Resources and Environmental Policy, 2015; Republic of Indonesia, 2015; Republic of the Philippines, 2015; UNFCCC, 2015; United Nations, 2015). As the energy and carbon intensity per economic output depend extensively on a country's economic structure and its technological and technical capabilities, governments should prioritise private-public investment partnerships to facilitate industrial technological leaps. Technological advancement will lay the ground for deeper structural industrial changes and enable countries to escape fuel-mix lock-ins on incumbent industries.

Testing the hypotheses has led towards constructing and presenting an energy and carbon intensity trend timeline overview for the selected countries. A detailed study is being performed for the energy and carbon intensity trends, in both an aggregated and disaggregated sectoral industrial basis, providing a comparison between the specified industry sectors per country.

Quantitative limitations of this research include a limited availability of primary data; cross-referencing raw primary fuel in each coal product and net calorific value data in detail for extended timelines is available in a very limited range of databases. In a wider context, carbon dioxide emissions due to industrial cross-country shift, energy and carbon intensity indicators are not the exclusive drivers responsible for mitigating carbon dioxide emissions.

Furthermore, the exploration of the potential learning curves for industrial improvements in emissions intensity across different industrial sectors is suggested as well as and the role of factors such as indigenous fuel availability, industrial economies of scale and commitment to emissions reduction. Finally, extended research should additionally focus on the role of industrial electrification and subsequently the electrification options and decisions (Malekpoor et al., 2017) that are required to control and impact on energy and carbon emissions intensity.

This may further spring interest in the innovation interplay between utilities and energy users (Rutter et al., 2017). A concrete case of CO_2 emissions determinants should additionally to the prior; energy and carbon intensity, take into account indicators such as the labour productivity, industrial scale and energy structure effect in the industry concluding in their proportional significance.

This methodological approach is conducted in the following chapter, for all the countries discussed minus Thailand due to its limitation in available data, limiting the safe extraction of conclusions and China. The purpose for conducting this approach is to enable the present research to allocate the significance that these specific determinants hold towards their effect in production of industrial carbon emissions. By determining the parametric effect in carbon emissions change per allocated time periods, extracting conclusions towards specific factorial improvement is feasible.

This methodological approach is classified as additive logarithmic mean divisia index decomposition approach which determines and quantifies the effect that the aforementioned drivers have in industrial CO_2 emissions.

5. Decomposing the Total and Sectoral Industrial CO_2 Emissions through the application of Additive Log Mean Divisia Index Analysis.

5.1 Introduction

Cost-sensitive foreign companies seek to relocate their manufacturing hubs to India and SE Asian countries due to younger demographic characteristics (HKTDC Research, 2013b; Yang, 2016), lower social security, labour and production costs, lower land value and reduced taxation (Chang et al., 2013; Chomik and Piggott, 2015, 2013; Policy Department Economic and Scientific Policy, 2006b). While India remains interested in attracting companies willing to relocate (Ozawa, 2015), Indonesia and the Philippines are also discussed as candidate industrial destinations by Chinese and other industries considering their relocation options (Chu, 2013; de Vera, 2014).

The countries discussed, present a strong economic outlook. They are either undergoing a phase of strong industrialization (**Figure 5.1**) or present increased productivity for their existing industrial capacity (**Figure 5.2**). Among major global economies, India presents the highest GDP growth rate, at 6.7% rate for 2017 expected to reach 7.4% and 7.8% for 2018 and 2019 respectively (IMF, 2018b, 2016c). Indonesia and the Philippines, expect their relevant growth rates to reach 5.1% and 6.7% respectively during 2017 (IMF, 2016b; IMF Communications Department, 2016b).

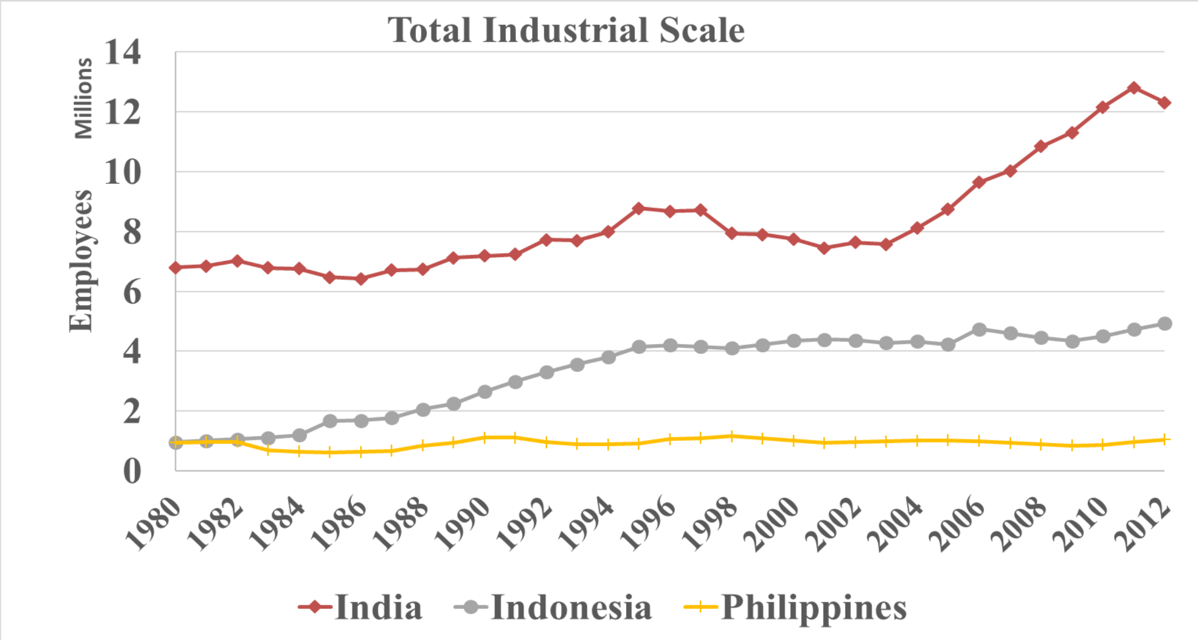


Figure 5.1. Total industrial scale (employment) of India, Indonesia and the Philippines 1980-2012 (United Nations Industrial Development Organization, 2016).

Energy intensive industries present higher energy requirements. Coal is the main industrial fuel for India, and alongside oil products and a significant contributor for the Philippines and Indonesia (International Energy Agency, 2014c). A potential cross-country industrial shift can lead to altered emission levels as a result of regulatory differences (Zheng and Shi, 2017) and different emission characteristics (Kanchana and Unesaki, 2014). Additionally, it may require a varying energy input for producing the same economic output. (Pappas et al., 2018, 2017).

The emission coefficients of the coal and oil products used in a fuel mix, are higher when compared to those of other fossil fuels (IPCC, 2006). As a result, the existing fuel mix presents a scenario of an industrial growth not being able to follow the intended national determined contributions (INDCs) for reducing CO_2 emissions, as submitted by those countries to the 2015 Paris Agreement (Republic of Indonesia, 2015; Republic of the Philippines, 2015; UNFCCC, 2015; United Nations, 2015).

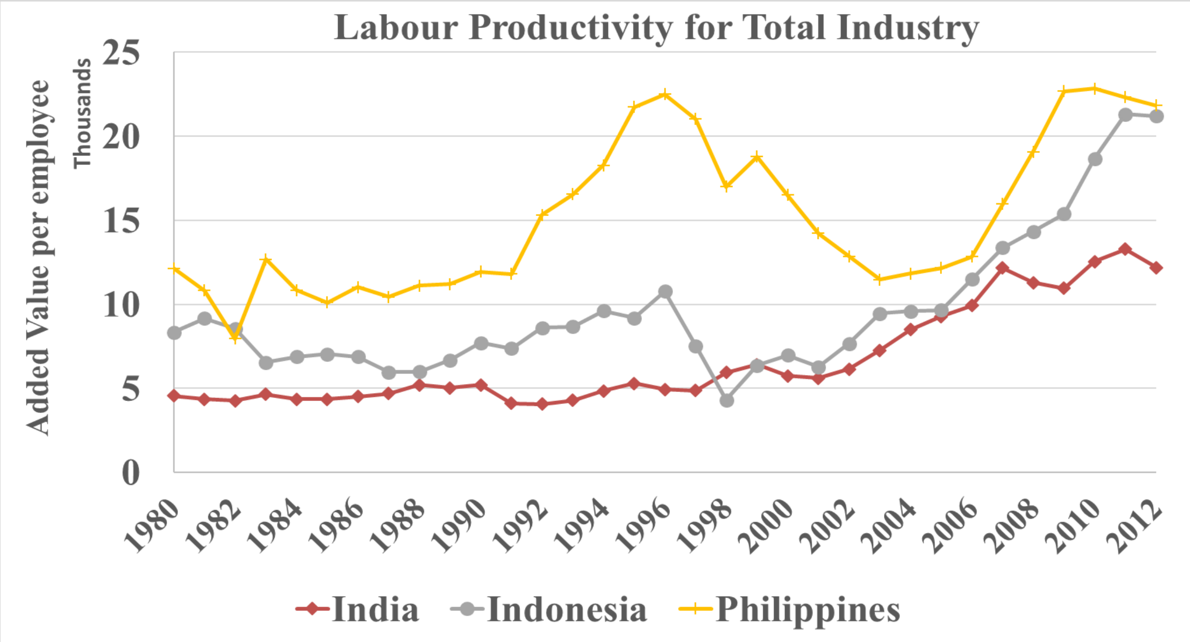


Figure 5.2. Total industrial labour productivity of India, Indonesia and the Philippines 1980-2012 (thousand const. 2005 US$ per employee).

With industrial sectors growing in scale and produced value improvements in labour productivity (**Figure 5.2**) or energy provision changes could absorb partly or in total, the respective emissions growth. However, such interventions are considered impossible in a short-term basis resulting in higher CO_2 emissions. Determining the relationship between CO_2 emissions, industrial scale and economic output, which is the aim of this chapter, can direct the focus towards the specific requirement for innovation in manufacturing processes. The capacity increase of energy-intensive industrial sectors equals to increased environmental pollution (Intergovernmental Panel on Climate Change, 2014). Policies incentivizing the utilization of technological innovation in heavy industries act as catalysts to the reduction of CO_2 emissions by reducing high energy demand and replacing inefficient industrial processes (Brown et al., 2012).

Therefore, identifying the importance of specific factors in driving CO_2 emissions is material to understanding any industrial sector's workings. Combining that information across industrial sectors in different countries is critical in estimating the impacts of relocation and prioritising emission control actions. The contribution that factors of different dimensions present towards the change of CO_2 emissions, This work is feasible by the Index Decomposition Analysis (IDA), a widely used and adaptable (Ang, 2004; Ang et al., 2015b) analytical tool that can study past developments in the form of aggregate changes. Among different methodologies of performing IDA, the Logarithmic Mean Divisia Index (LMDI) presents the advantages of aggregation consistency and breakdown definition as discussed in the methodology (see **Section 2.3**).

The purpose of this study is to define the allocation of the effect that each of the major attributing factors have on the level of CO_2 emissions of the industrial sectors discussed. To achieve that, an index decomposition analysis of CO_2 emissions using the Log Mean Divisia Index method (LMDI-I) is performed, on each one of the countries: India, Indonesia and the Philippines. The additive LMDI-I is performed for the total industry and six main industrial sub-sectors located in each country. The selected sub-sectors are Iron and Steel, Chemical and Petrochemical, Non-metallic Minerals, Machinery, Textiles and Leather and the Paper Pulp and Print sector per the IEA classification, due to involving energy-intensive processes for production (Bataille et al., 2018; Meng et al., 2018) as well as satisfactory data consistency to perform a complete decomposition.

In summary, as industrialization is leading an impressive economic growth observed in the three studied countries, it is important to determine the implications in terms of challenges that each one is facing, considering a historical outlook, to determine the potential for further improvement. It is therefore concluded that the following hypotheses to be confirmed for each of the industrial sectors examined:

- The four decomposition factors will differently influence each country's industry induced CO_2 change. (**H1**)
- CO_2 emissions change has a positive relationship with industrial automation. (**H2**)
- CO_2 emissions change has a negative relationship with energy efficiency (**H3**)

The selection of IDA and its subsequent LMDI-I method has the purpose of analysing how energy intensity, carbon intensity, labour productivity and industrial scale drove CO_2 emissions in India, Indonesia and the Philippines. Subsequently, the specific supporting agendas on innovation and sustainable change are discussed in the light of the results. The index decomposition analysis presents the drivers that have had significant effect on CO_2 emissions on the sectoral level of each country's industry, either in isolated intervals or in a constant or periodic repetition basis. As a relationship between environmental degradation, energy consumption and economic growth is confirmed to be running in an extended timeline for India, Thailand (Aye and Edoja, 2017; Jamel and Abdelkader, 2016; Sadorsky, 2013) or temporarily in the case of the Philippines (Lean and Smyth, 2010) it is important to decompose the potential for improvement in this methodological setting. The results provide the required capacity of facilitating growth without compromising emission targets and control (Zafirakis et al., 2015) capturing the CO_2 emission factors that require improvement, in order to achieve sustainable manufacturing operations (Duflou et al., 2012). Advanced technological means of production, facilitate an export-oriented approach and increase competitiveness for manufacturing firms; a target that the countries in the present research aspire to achieve (Singla et al., 2018).

5.2 Conceptual Framework

The schematic process for performing the additive index decomposition analysis as this is described in methodology **Section 2.4** is presented in the following **Figure 5.3**. The conceptual framework schematic for LMDI-I, does not include the energy and carbon intensity calculation method and conceptual process as this is already described in **Section 4.2**.

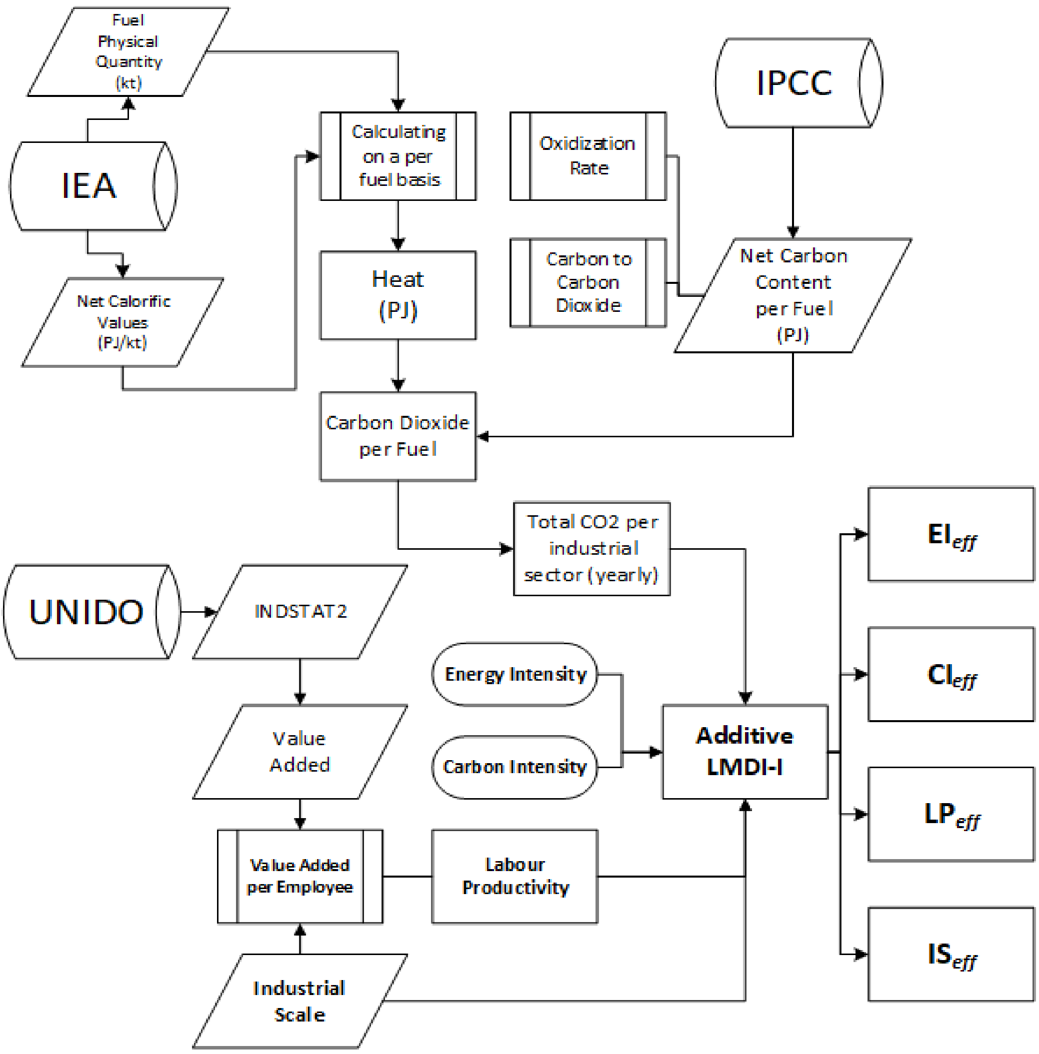
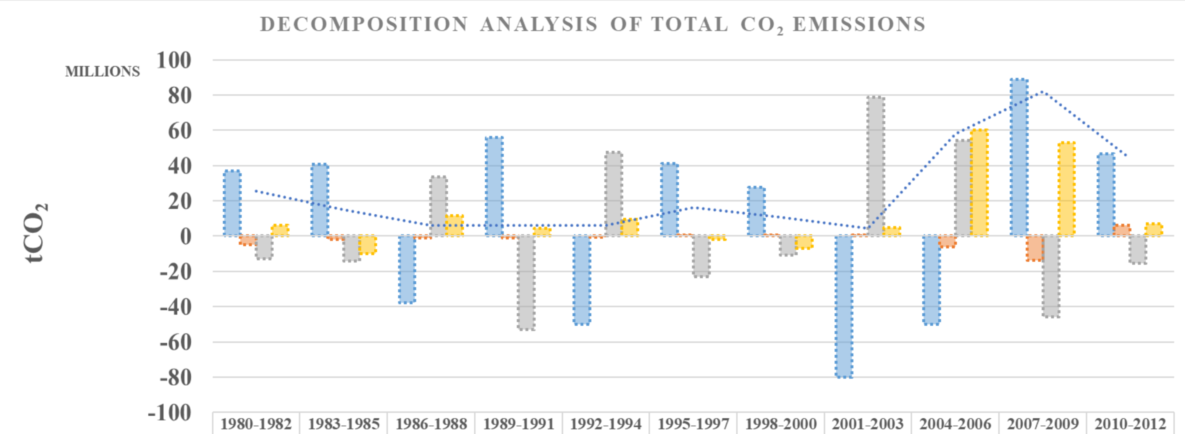


Figure 5.3. Index decomposition analysis process followed per country and industrial sector.

5.3 Results

5.3.1 Total Industry

The total industry is accounted by IEA and UNIDO and is synthesized by every industrial sector that presents energy consumption and economic activity. The decomposition analysis of CO_2 emissions is performed for the three countries both for total industry and for six industrial sectors in the following sections of this chapter.

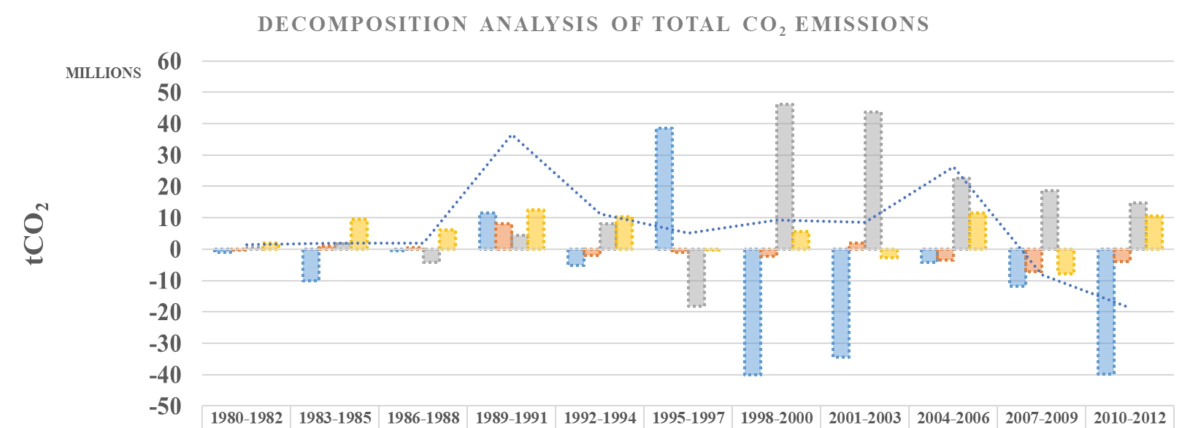


	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	36799569.7	40711401.0	-37872808.	56007065.9	-50132304.	41051102.3	27718376.7	-80037433.	-50061290.	88909280.8	46543731.7
ΔC_CI	-4827859.7	-2002105.1	-1134143.8	-1188726.3	-693438.2	273812.5	626022.6	659395.2	-6152031.3	-13667870.	6019498.4
ΔC_LP	-12715969.	-14075221.	33779816.3	-53007246.	47476253.4	-23177604.	-10597977.	78930186.3	54251550.8	-45926913.	-15233726.
ΔC_IS	6099671.7	-9819516.3	11513849.1	4414292.8	9383123.7	-1883988.4	-6983381.2	4706534.2	60069492.1	53020202.0	6774562.1
ΔC	25355412.7	14814557.7	6286713.3	6225385.5	6033634.4	16263321.9	10763040.7	4258682.6	58107720.7	82334698.7	44104065.8

Figure 5.4. India total industrial CO_2 emissions decomposition analysis.

Indian CO_2 emissions change (**Figure 5.4**) presents a stable increasing trend for each of the time periods that are being examined, even though with variable rates of change. The largest increase is located during the 2007-2009 period, where it sums up to an amount of 82.33 million tonnes of CO_2 higher than the previous time interval figures extracted. The performed additive LMDI-I attributes this figure to two factors; an increased energy intensity (EI) and industrial scale (IS) contribution towards a positive carbon emissions change. India's industry has higher energy intensity level of, from 31.65 TJ per million 2005 US$ in 2007 to 38.72 TJ per million 2005 US$ in 2009. However, when approaching earlier time periods (2001-2003, 2004-2006) energy intensity (EI) is found to contribute significantly in reducing CO_2 emissions change, amounting at 80.09 $MtCO_2$ and 50.06 $MtCO_2$ respectively towards that decreasing effect. Industrial scale expansion is found to have a significant effect on CO_2 emissions, either negative or positive. As the industrial scale effect on the change of CO_2 is deemed to be significant, as an indicator it presents impressive growth. During two intervals, 2004-2006 and

2007-2009, it shows the scale of the country's commitment in being converted to an industrial production hub, where it is found to present an increase from 8.11 to 9.63 million and from 10.03 million to 11.31 million employees respectively.

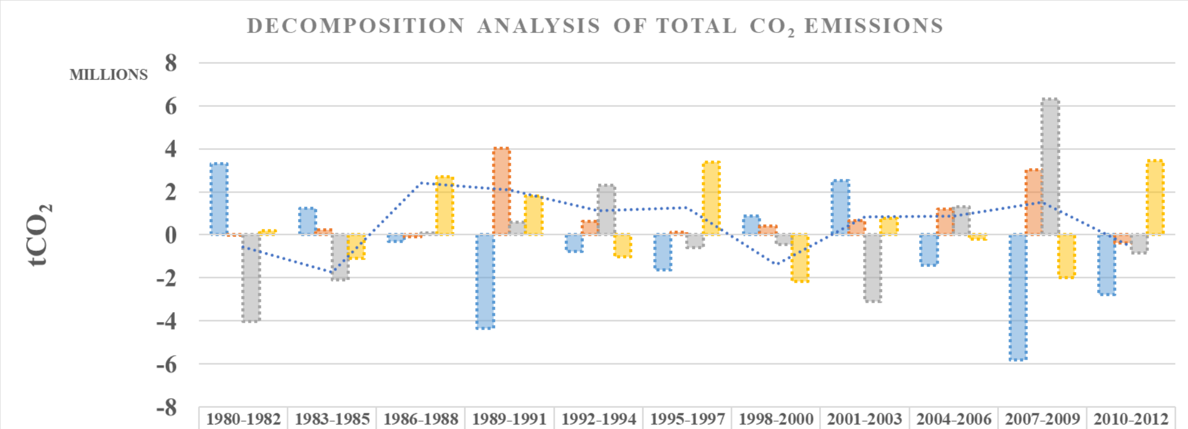


	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	-981249.1	-10023403.	-489790.8	11587413.9	-5135638.7	38561103.3	-40025227.	-34354661.	-4317797.5	-11744553.	-39874192.
ΔC_CI	-155463.2	874714.1	512230.5	8065458.1	-2049782.0	-1044065.0	-2351224.8	1941666.1	-3383107.8	-7167808.5	-3925409.4
ΔC_LP	576100.3	1684711.5	-4131187.5	4401118.4	8009645.0	-18152926.	46104714.2	43741484.1	22636089.5	18736081.1	14693674.7
ΔC_IS	1986290.3	9506228.5	5999233.8	12599300.2	10395821.4	-117193.1	5540199.1	-2762561.8	11426239.3	-7842868.4	10521256.6
ΔC	1425678.3	2042250.8	1890486.0	36653290.7	11220045.7	5039122.5	9268460.8	8565927.3	26361423.5	-8019148.9	-18584670.

Figure 5.5. Indonesia total industrial CO_2 emissions decomposition analysis.

For Indonesia (**Figure 5.5**), focusing on the period of 1998-2000 onwards, it is observed that the labour productivity (LP) effect is consistently the most influential factor in CO_2 emissions change. The country's CO_2 emissions present a continuous increase, with two positive spikes observed, during time intervals of 1989-1991 and 2004-2006. During the former of the periods mentioned, all drivers have been found to contribute positively to a ΔC increase. The second spike in emissions growth, observed during the 2004-2006 interval, shows that the industrial scale (IS) effect is a significant contributor, only second to that of LP, with the other drivers contributing negatively. From 2007 onwards, the change of CO_2 emissions (ΔC) is negative, attributed mainly to a large decrease of energy intensity (EI), because of increased efficiency driving decreased CO_2 level rate of change. The Indonesian total industrial EI was halved, from 26.32 TJ per million 2005 US$ in 2007, to 13.45 TJ per million 2005 US$ in 2012. Further studying the drivers' effect on the total industrial CO_2 emissions, it is also feasible to locate the industrial scale (IS) effect as a dominant reason regarding the increase in CO_2 emissions, excluding only three of the time periods examined (1995-1997, 2001-2003, 2007-2009). Carbon intensity (CI) does not present a clear trend effect in how it drives CO_2 emissions change. The CI effect is found to contribute towards a reduction in CO_2 emissions during seven intervals (1980-1982; 1992-1994; 1995-1997; 1998-2000; 2004-2006; 2007-

2009; 2010-2012) however, presenting an overall decreased significance effect when compared to the other three factors (EI, LP, IS).

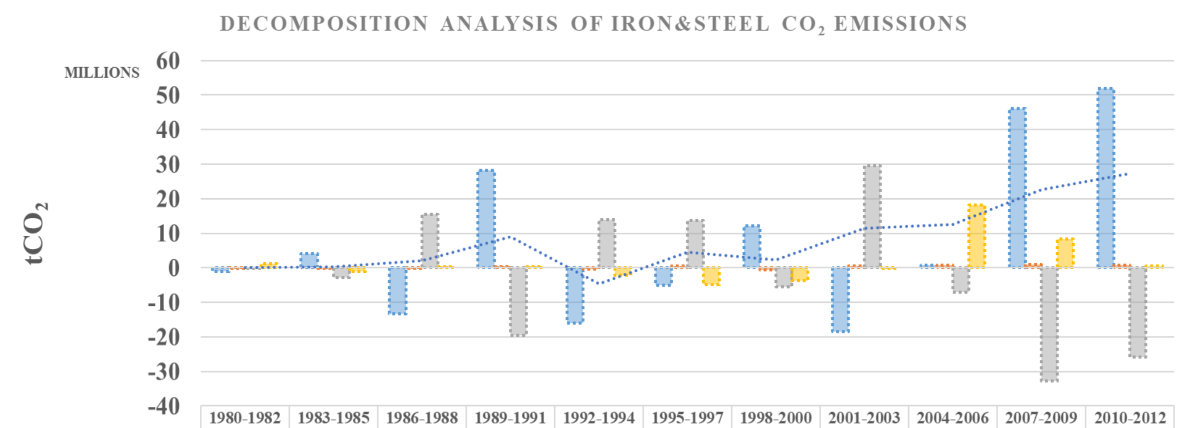


	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	3290375.4	1230687.2	-303076.0	-4333586.7	-777493.6	-1632213.8	863453.4	2526972.0	-1410955.7	-5794183.1	-2760657.8
ΔC_CI	-1510.1	213979.6	-83988.7	4008744.5	621517.3	120717.3	416665.4	656396.7	1205577.7	3001313.3	-380636.6
ΔC_LP	-4036467.3	-2094339.0	75596.7	587911.3	2305017.7	-591764.7	-463746.7	-3103471.0	1301577.1	6306698.4	-849100.3
ΔC_IS	198142.2	-1098570.5	2713565.1	1813006.7	-1015963.2	3379839.3	-2179659.3	776122.5	-214451.4	-1992768.9	3450482.3
ΔC	-549459.8	-1748242.7	2402097.1	2076075.8	1133078.2	1276578.1	-1363287.2	856020.2	881747.7	1521059.7	-539912.4

Figure 5.6. The Philippines total industrial CO_2 emissions decomposition analysis.

Focusing on the total data provided by the Philippines industry, (**Figure 5.6**) the change of CO_2 emissions has mainly demonstrated a positive rate of change, except for four three-year periods (1980-1982; 1983-1985; 1998-2000; 2010-2012) out of the eleven examined. The LP effect acts as the main contributor towards that increase during the 2007-2009 period. Labour productivity (LP) has indeed increased from 15,961 to 22,676 const. 2005 US$ per employee. The effect of carbon intensity (CI) is a significant contributor towards a positive rate of change of CO_2 emissions, especially in the periods 1989-1991 and 2007-2009. Examining the factors contributing to a CO_2 emissions change reduction, the effect of energy intensity (EI) is significant and acts as the main factor for carbon emissions change in 2007-2009 and 2010-2012, where it contributes towards a 5.79 and 2.76 $MtCO_2$ decrease respectively. The industrial scale (IS) has an unstable effect on ΔC throughout the studied time. However, in the most recent time interval studied (2010-2012), its effect is the main contributor towards a CO_2 emissions change increase.

5.3.2 Iron and Steel Industry

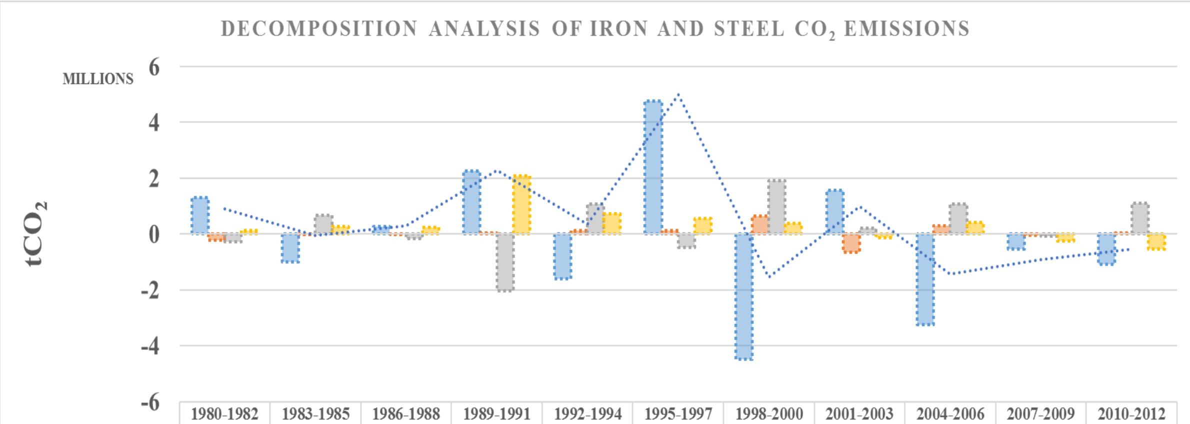


	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	-978646.3	4155156.4	-13232970.	28112570.3	-16006642.	-4975877.2	12124470.1	-18492363.	665488.2	46038110.8	51911256.1
ΔC_CI	-4295.2	-241143.4	-194091.4	70559.5	-390425.5	541450.3	-652092.9	611657.3	743665.0	995807.6	798959.6
ΔC_LP	-173521.1	-2740661.3	15427886.7	-19602201.	13815269.4	13662182.7	-5611853.2	29496881.9	-6970682.1	-32750214.	-25940230.
ΔC_IS	1168168.4	-982303.8	168179.2	352556.8	-2067121.4	-4767443.7	-3640274.8	-213822.5	18154217.1	8405815.5	612855.0
ΔC	11705.8	191048.0	2169004.0	8933485.0	-4648920.5	4460312.1	2220249.1	11402353.6	12592688.3	22689519.7	27382840.8

Figure 5.7. India CO_2 emissions decomposition analysis of Iron & Steel industrial sector.

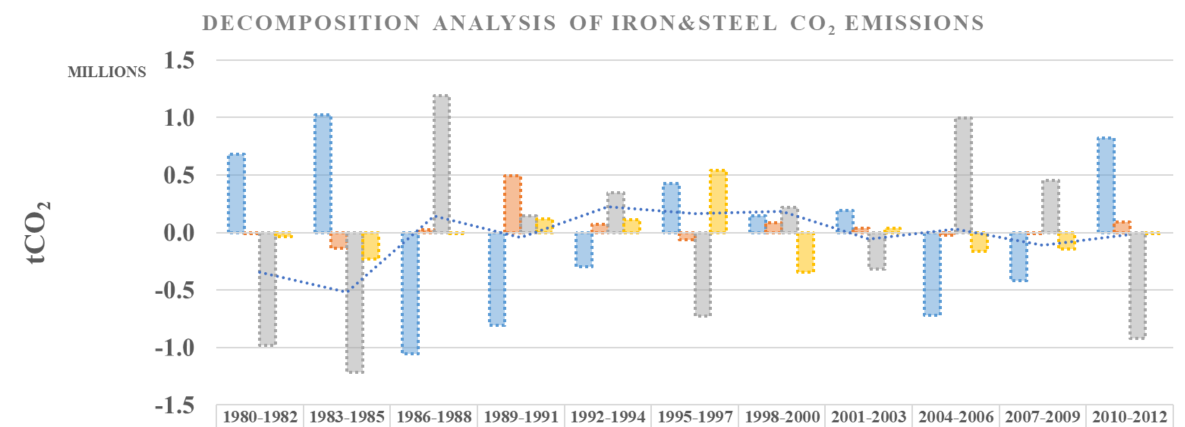
Following up to the analysis of the drivers for India and its iron and steel industrial sector, the most significant factors of CO_2 emissions change throughout the assessed timeline are energy intensity (EI) and labour productivity (LP). While the change in CO_2 emissions (ΔC) has been positive throughout the timeline with one exception (1992-1994), the specific effect of the examined factors is unstable; with LP and EI having a reciprocal effect in driving CO_2 emissions change from 1983 onwards. Energy intensity (EI) presents its most significant effect regarding the overall increase of CO_2 emissions change for 2007-2009 and 2010-2012. Labour productivity (LP) is underlined as the most important driving factor towards a decrease of CO_2 emissions regarding the exact time periods mentioned for EI. The change of carbon emissions attributed to LP can be linked to a significant reduction of the value produced per worker, from 28,138.05 to 19,064.85 const. 2005 US$ during 2007-2009. This trend is additionally observed when approaching the time interval of 2010-2012 which follows a similar pattern. If the effect of LP was not significant, a 2-fold increase in CO_2 emissions would be possible in comparison to that interval calculated output. This link between CO_2 emissions change and driver contribution is also present when approaching energy intensity (EI) and industrial scale (IS). In the latter, increased automation, requiring fewer employees, would contribute to an increase in CO_2. This conclusion originates from a carbon intensive energy mix for the industrial sector. India's iron and steel industry uses a fuel mix of blast furnace gas, coke oven coke and other bituminous coal to satisfy the industry requirements in energy (**Table 2.3.1**). A further extraction of results by using the additive LMDI-I method (**Figure 5.7**), presents the country's iron and steel sector carbon intensity as having a minimal impact on CO_2 emissions throughout the examined timeline, and as a result it presents reduced significance rate.

Figure 5.8. Indonesian CO_2 emissions decomposition analysis of Iron & Steel industrial sector.



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	1304667.4	-993458.1	261250.7	2244158.3	-1592185.8	4749274.2	-4491245.9	1567849.3	-3237047.8	-530211.2	-1076931.5
ΔC_CI	-233855.1	-12206.6	-21283.7	5539.5	135567.8	129535.6	646039.2	-652083.8	309903.4	-51009.8	965.9
ΔC_LP	-290094.3	680224.2	-165168.6	-2041127.9	1061142.9	-467110.1	1899556.5	198927.2	1083070.4	-79403.5	1095001.4
ΔC_IS	119688.5	266498.8	227901.8	2070623.5	740976.3	568310.8	391636.1	-133559.2	414093.7	-255931.4	-542974.9
ΔC	900406.5	-58941.7	302700.2	2279193.4	345501.2	4980010.5	-1554014.1	981133.6	-1429980.3	-916556.0	-523939.0

Approaching the Indonesian iron and steel analysis, the results demonstrate that a change in CO_2 emissions have not been producing a positive rate of change but instead a declining pattern is evident from 2004-2006 onwards. The main contributor to this decrease in CO_2 emissions was energy intensity (EI), as observed in many of the examined time periods (1998-2000; 2004-2006; 2007-2009; 2010-2012) (**Figure 5.8**). The labour productivity (LP) effect presents moderate significance, as a CO_2 increase driving factor. Upon examining time intervals prior to 2004-2006 though, this trend is reversed. Energy intensity (EI) is the main contributor to positive CO_2 emissions change in 1989-1991 and 1995-1997 with the latter showing a contribution of 4.75 $MtCO_2$ of the total increase of 4.98 $MtCO_2$. Approaching the effect that the other examined factors have on CO_2 emissions, industrial scale (IS) had a significant and positive effect, except for time intervals 2001-2003; 2007-2009; 2010-2012 while CI has a mostly insignificant yet unstable effect on CO_2 emissions.

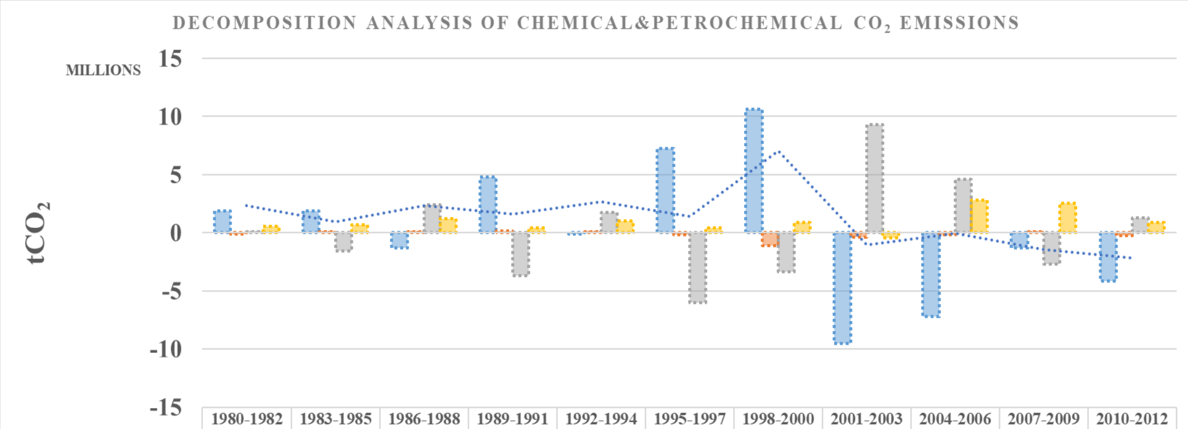


	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	683495.9	1019436.9	-1054388.8	-806840.3	-298200.4	422684.3	145820.4	190689.1	-723306.0	-416433.1	819209.0
ΔC_CI	-12540.1	-137893.4	23207.7	493952.3	69087.8	-63858.8	81443.0	35975.4	-26626.0	-1861.2	89678.5
ΔC_LP	-980078.8	-1212999.5	1190239.5	146783.1	342389.4	-729367.3	220117.4	-316846.6	994342.2	452336.6	-921635.1
ΔC_IS	-34799.9	-232616.3	-11272.3	120214.7	110392.8	536752.4	-344541.3	34939.5	-160949.0	-142342.6	-2435.6
ΔC	-343923.0	-516509.4	142551.2	-45890.1	223669.6	166210.6	184776.1	-55242.6	32028.6	-110484.1	-15183.3

Figure 5.9. The Philippines CO_2 emissions decomposition analysis of Iron & Steel industrial sector.

Concluding with the analysis of the Philippines iron and steel sector, it does not reveal any definite trends. The CO_2 emissions change (ΔC) have been declining in various time periods; 1980-1982; 1983-1985; 1989-1991; 2001-2003; 2007-2009; 2010-2012. Energy intensity (EI) and labour productivity (LP) have a destabilising effect throughout these periods. In each of the periods examined, EI and LP have an opposing effect on the CO_2 emissions change, with the exception of the 1998-2000 interval, where EI and LP both drive a carbon emissions increase. Examining peak contributions, LP increases ΔC over 1.19 $MtCO_2$ in 1986-1988 and it has driven emissions reduction of 1.21 $MtCO_2$ in 1983-1985. The increase of emitted CO_2 observed on the 1986-1988 interval, is reflected on an enormous 3-year increase of LP output from 10,019.8 to 31,973.47 constant 2005 US$. A similar decrease of produced CO_2 observed in the 1983-1985 interval reflects an LP decrease from 37,965.3 to 18,990.21 const.2005 US$, demonstrating a strong directional interconnection that exists between CO_2 and LP*eff*. Industrial scale (IS) effect has an insignificant effect when compared to the other three factors, except for 1995-1997 and 1998-2000 where it contributes positively and negatively to CO_2 emissions change respectively. Carbon intensity (CI) follows an unstable and insignificant pattern in several of the time intervals, except for that of 1989-1991 where it was a leading contributing factor towards CO_2 increasing change rate (**Figure 5.9**).

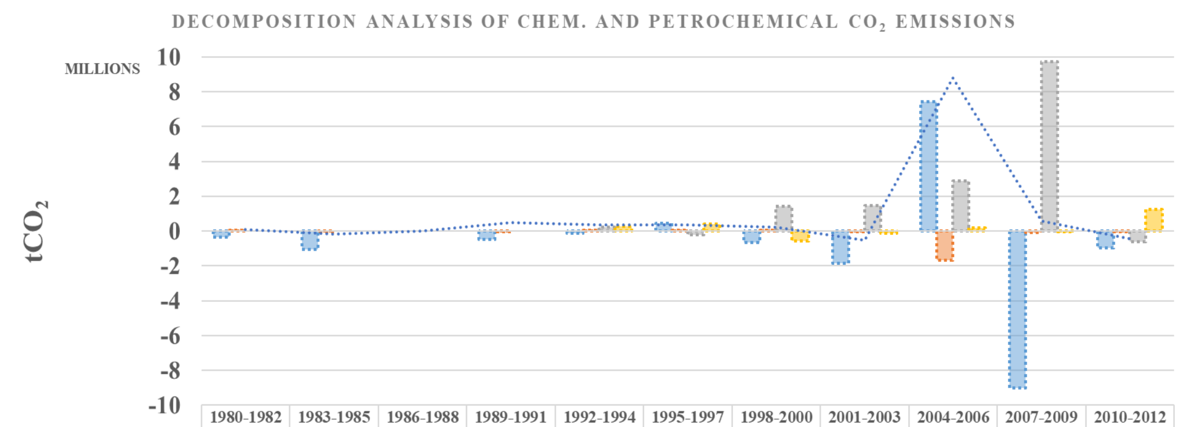
5.3.3 Chemical and Petrochemical Industry



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	1846764.5	1846736.7	-1275987.4	4808747.6	-147468.8	7260621.8	10653503.5	-9525768.3	-7219631.2	-1297390.9	-4161702.1
ΔC_CI	-104463.2	24849.4	73920.6	152129.3	75940.6	-177975.1	-1108352.5	-349119.6	-178974.0	57888.3	-217693.1
ΔC_LP	57205.0	-1571313.3	2385505.3	-3728739.6	1749926.8	-6030846.2	-3343075.4	9283982.0	4569173.8	-2723046.6	1284132.7
ΔC_IS	543882.9	666152.2	1178457.8	397017.3	1005462.5	381554.1	849405.3	-423161.4	2769150.2	2540120.3	891350.2
ΔC	2343389.3	966425.0	2361896.3	1629154.5	2683861.0	1433354.7	7051480.9	-1014067.3	-60281.2	-1422429.0	-2203912.3

Figure 5.10. India CO_2 emissions decomposition analysis of Chemical & Petrochemical industrial sector.

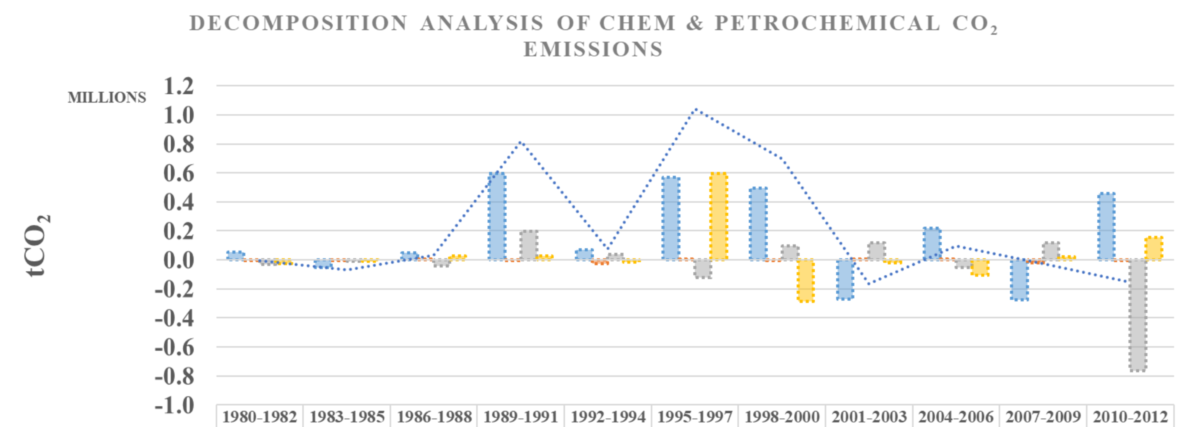
Switching to India's chemical and petrochemical industrial sector, it is observed that energy intensity (EI) and labour productivity (LP) have a significant impact on carbon emissions. Their contribution does not form a trend of CO_2 emissions change (ΔC) but has a variable effect, positive or negative. Confirming that, during 1995-1997 and 1998-2000, energy intensity (EI) is a main contributor increasing CO_2 emissions. In the subsequent 2001-2003 and 2004-2006 periods, EI is the main factor in reducing carbon emissions while in the same time intervals LP presents a countering contribution in emissions change to that of EI (**Figure 5.10**). Industrial scale (IS) effect is contributing positively to CO_2 emissions change, however with that not following the same pattern during the time interval of 2001-2003. During the latter interval, IS presents a decrease from 826,078 to 810,954 workers employed in the industry. Carbon intensity (CI) does not contribute significantly relative to the other factors, with the effect mostly being unstable throughout the examined timeline.



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	-345337.7	-1073066.4	0.0	-497215.4	-126166.9	432771.7	-663261.9	-1856842.9	7449259.3	-9008134.5	-975721.1
ΔC_CI	5125.9	-33220.0	0.0	-6704.9	5435.9	6253.8	748.2	-4911.3	-1676913.9	-104384.7	-62071.0
ΔC_LP	0.0	0.0	0.0	0.0	213833.4	-200433.6	1438042.0	1457675.8	2854120.3	9734941.3	-634891.9
ΔC_IS	0.0	0.0	0.0	0.0	267762.9	385917.1	-552478.6	-121430.6	184241.4	-47971.7	1243772.5
ΔC	101459.0	-189688.0	0.0	474864.4	360865.3	355719.3	223049.7	-525508.9	8810707.1	574450.4	-428911.6

Figure 5.11. Indonesia CO_2 emissions decomposition analysis of Chemical & Petrochemical industrial sector.

The Indonesian chemical and petrochemical industrial sector present inconsistent results for an extended timeline range. This is mainly attributed to the country not producing employee data to be included in the UNIDO database between 1980 and 1990. This practice, results in restraining the index decomposition analysis for the factors of labour productivity (LP) and industrial scale (IS) during this timeframe. From 1990 onwards, it is found that the rate of carbon emissions change presents an increase, albeit low when compared to other industrial sectors. This trend changes when approaching 2004-2006, with ΔC presenting a spike in positive increase, that is being attributed mainly to the effect of energy intensity and labour productivity, countered only by carbon intensity which contributes negatively to ΔC (**Figure 5.11**). The effect that labour productivity (LP) has on carbon emissions, is significantly positive during 2007-2009. This effect, however, is largely countered by the energy intensity effect, with a 9.08 $MtCO_2$ decrease, which is not adequate to drive a total negative carbon emissions rate of change, as LP is positively contributing 9.73 $MtCO_2$.

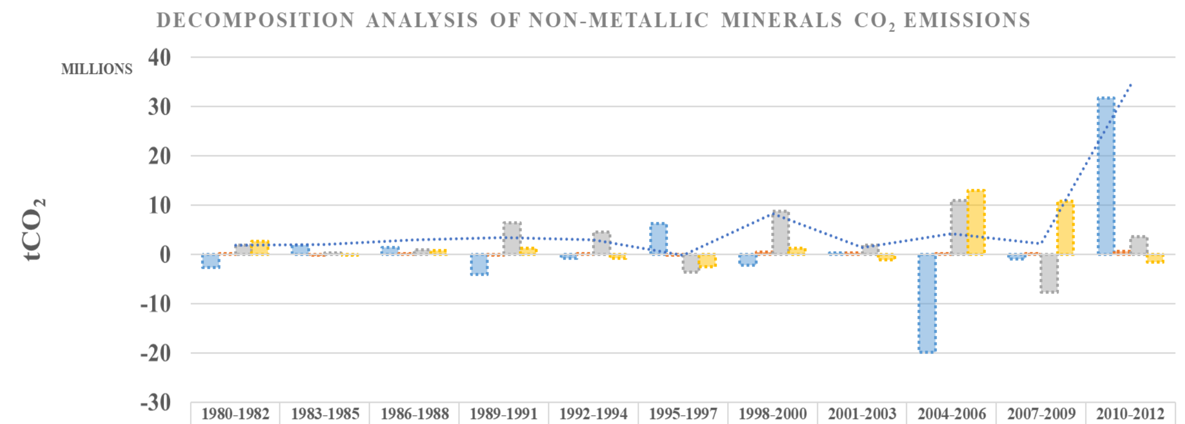


	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	51476.2	-50745.4	50275.1	595641.0	72125.7	566704.6	492473.0	-271432.1	220382.8	-275792.6	458841.2
ΔC_CI	-188.4	-351.1	77.7	-1076.1	-24606.4	3348.8	-5465.6	5340.7	6192.2	-18699.5	-1689.9
ΔC_LP	-31272.9	-8225.1	-40189.2	196914.4	39771.1	-123341.3	94198.9	120010.6	-51654.3	116815.9	-764085.4
ΔC_IS	-26440.3	-7341.1	24693.7	28492.5	-13447.6	594806.0	-283978.7	-19623.4	-107754.0	23357.8	153323.3
ΔC	-6425.4	-66662.7	34857.3	819971.7	73842.8	1041518.1	695358.0	-165704.2	96927.2	-26627.5	-153610.9

Figure 5.12. The Philippines CO_2 emissions decomposition analysis of Chemical & Petrochemical industrial sector.

The Philippines results demonstrate variable characteristics regarding CO_2 emissions change (ΔC) compared to that of the other countries. Energy intensity is contributing towards an increase in carbon emissions during 1989-1991; 1992-1994; 1995-1997; 1998-2000; 2004-2006 and 2010-2012. The EI effect is the most significant when compared to other factors in carbon emissions increase. Specifically, energy intensity contributes to an increase of CO_2 emissions between 1980 and 2012, from 0.9774 to 3.5388 TJ/million US$. The EI effect is only surpassed by that of industrial scale (IS) during 1995-1997. The primary data for IS state that the number of employees increased from 47,300 to 59,800 demonstrating a rapid three-year expansion of the industry. Labour productivity during 2010-2012 contributes in reaching a negative ΔC, countering the positive contribution of both EI and IS. Carbon intensity (CI) presents a minimal and unstable effect in carbon emissions change (**Figure 5.12**), an established trend observed in the three countries assessed.

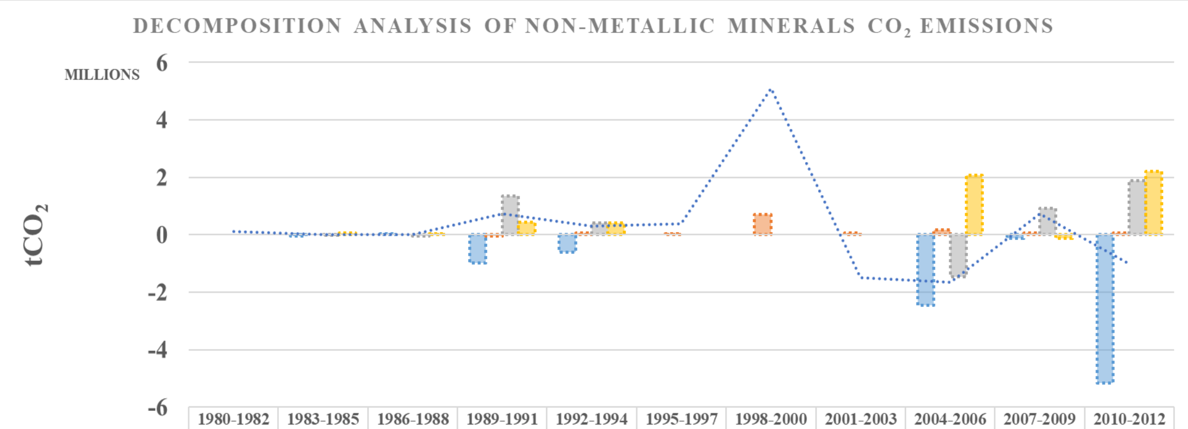
5.3.4 Non-metallic minerals Industry



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	-2623491.6	1763071.5	1341935.7	-4066805.4	-751678.1	6190194.0	-2184653.0	323593.5	-19869964.6	-929543.3	31735528.4
ΔC_CI	17100.5	-31703.5	5980.3	-29491.1	34372.3	-180182.4	499296.4	289522.8	195993.3	132951.7	594016.3
ΔC_LP	1760340.0	217736.4	856969.0	6319483.4	4455593.5	-3689867.1	8696311.6	1895087.1	10978578.1	-7745495.0	3614616.3
ΔC_IS	2615407.6	-12052.5	677614.7	1205115.8	-770806.8	-2561063.0	1263571.1	-1198652.7	12866809.0	10704873.6	-1561353.6
ΔC	1769356.4	1937051.9	2882499.7	3428302.7	2967480.9	-240918.5	8274526.0	1309550.8	4171415.8	2162786.9	34382807.3

Figure 5.13. India CO_2 emissions decomposition analysis of non-metallic minerals (cement) industrial sector.

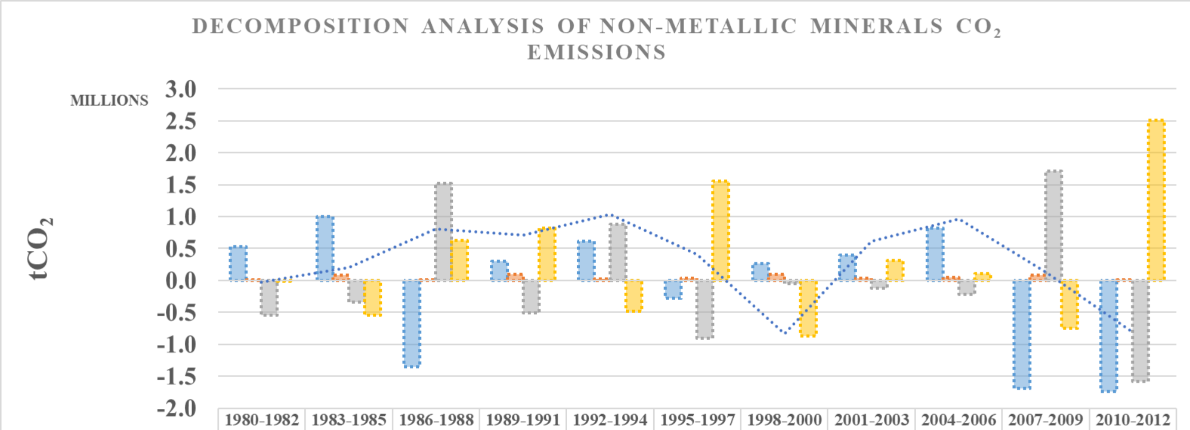
The CO_2 change of India's non-metallic mineral industry is characterized by a low to moderate increasing trend throughout the entire timeline, minus the period 1995-1997 where the negative change observed is marginal. However, during 2010-2012, this change presents a growth spike, mainly attributed to a rise in the effect of energy intensity (EI). During that latter interval, energy intensity has increased rapidly from 75.09 to 114.21 TJ per million const. 2005 US$ presenting a reverse trend from that of 2004-2006, in which a carbon emissions change decrease is evident, from 157.54 to 108.96 TJ per million constant 2005 US$. Labour productivity (LP) is also found to contribute positively in emissions increase (ΔC) throughout the timeline, except during 1995-1997 and 2007-2009. Industrial scale (IS) is a significant contributor in emissions change, either positive or negative in a non-stable trend, during 1998-2000, 2004-2006 and 2007-2009 (**Figure 5.13**).



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	0.0	-38885.4	29961.6	-972319.0	-608622.3	0.0	0.0	0.0	-2445693.9	-128791.3	-5164370.8
ΔC_CI	0.0	0.0	0.0	-49462.2	71178.0	42399.5	717616.2	71801.3	176277.1	73190.9	74648.8
ΔC_LP	0.0	-7017.0	-54060.5	1338405.0	416067.7	0.0	0.0	0.0	-1466571.9	911217.3	1882985.8
ΔC_IS	0.0	52129.5	21686.7	427591.7	420034.2	0.0	0.0	0.0	2073293.9	-116993.1	2207741.8
ΔC	108160.8	6227.1	-2412.3	744215.5	298657.6	386037.1	5092511.7	-1491308.9	-1662694.7	738623.8	-998994.3

Figure 5.14. Indonesia CO_2 emissions decomposition analysis of Non-metallic Minerals (cement) industrial sector.

Indonesia is presenting data gaps in energy intensity and number of employees for 1980-1982; 1995-1997; 1998-2000; 2001-2003. Carbon intensity and energy intensity is has also inconsistently reported for a range of time intervals (**Figure 5.14**). Those data reporting errors limit the extraction of results which lead to safe conclusions about the entirety of the examined timeline. The CO_2 emitted per energy consumption produces the exact same result of carbon intensity during 1981-1988, showing either a remarkable consistency or a reporting error, subject to further research and clarification. Therefore, the performed LMDI-I index decomposition analysis for those years can be classified as either limited or requiring caution, not only regarding the factors missing, but also those that have a complete dataset. In that context, the spike in CO_2 emissions change, observed in 1998-2000 can only be partially accredited to the effect of carbon intensity (CI). Contrasting the previous inconsistent picture, a provision of credible and complete data from 2004 onwards exists, estimating a negative carbon emission change during 2004-2006. This is attributed to the effect of energy intensity (EI) and labour productivity (LP), while industrial scale (IS) acts as a contributor towards an increase. Energy intensity (EI) also contributes to an emission decrease in 2010-2012. Its effect is a negative change of over 5.16 $MtCO_2$, in contrast to LP and IS with a 1.88 and 2.21 $MtCO_2$ increase respectively.

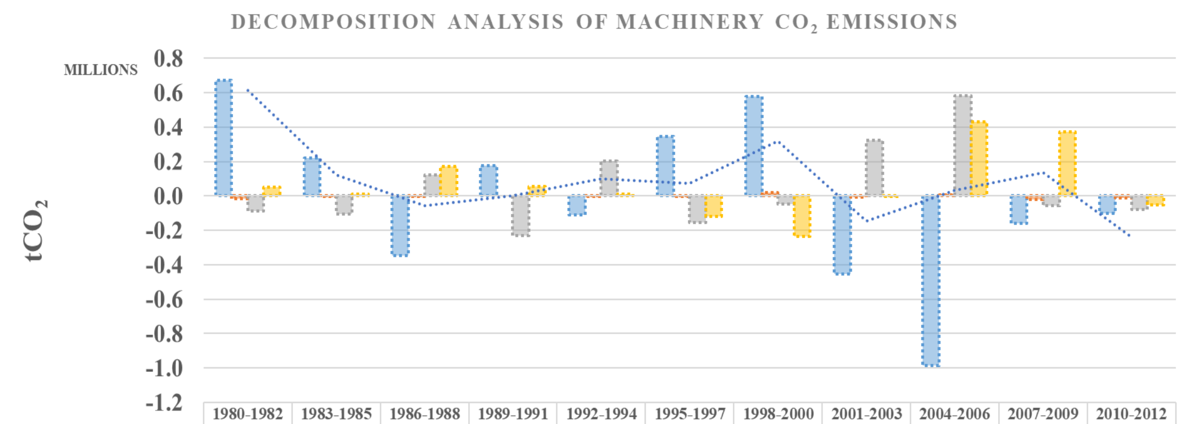


	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	528545.8	1003412.2	-1350108.3	300665.7	615700.2	-277310.3	268105.6	397743.9	817488.7	-1696083.2	-1743235.2
ΔC_CI	8669.4	87517.8	13267.8	97848.6	22800.1	36070.5	93740.1	31628.9	47611.3	87420.0	10283.7
ΔC_LP	-548792.9	-337445.0	1515032.0	-512884.9	881079.9	-902022.0	-50275.0	-128526.4	-215322.3	1708926.5	-1586898.1
ΔC_IS	-14888.1	-550391.9	622989.1	823767.5	-486348.5	1553878.7	-870650.4	309377.9	111605.4	-750748.0	2503140.5
ΔC	-26465.8	203093.0	801180.6	709397.0	1033231.7	410616.9	-840854.2	610224.3	961893.6	135851.3	-816709.1

Figure 5.15. The Philippines CO_2 emissions decomposition analysis of Non-metallic Minerals (cement) industrial sector.

The Philippines do not present the same data gap characteristics as those of Indonesia. Therefore, the data provided enable a detailed examination of the effect of those factors on CO_2 emission changes. While EI, LP and IS present an unstable trend in their effect, they are significant in their contribution towards CO_2 emissions change. Highlighting carbon dioxide emissions change in the most recent period studied (**Figure 5.15**) the Philippines experience a significant negative growth in CO_2 emissions change during 2010-2012 attributed mainly to EI and LP effect. Their contribution in decreasing CO_2 by 1.74 and 1.59 $MtCO_2$ respectively. However, this is countered by a 2.5 $MtCO_2$ increase by industrial scale (IS), which results in a total decline of 0.82 $MtCO_2$. Carbon intensity (CI) effect is minimal, a pattern which is observed throughout the timeline. Carbon intensity is contributing consistently towards increasing emissions of the non-metallic minerals industry for each of the time intervals examined.

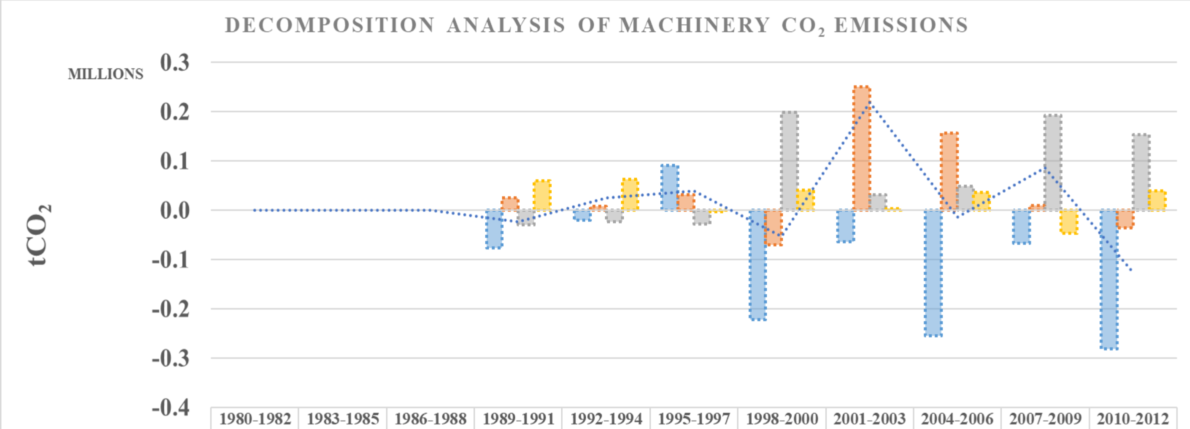
5.3.5 Machinery Industry



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	670226.3	220728.3	-347958.8	175654.3	-108865.2	346698.0	579739.7	-455507.2	-983958.1	-161583.0	-101581.6
ΔC_CI	-18106.3	-4005.8	-2590.0	0.0	-2061.7	-2933.5	17121.8	-7462.6	1380.9	-22051.7	-10149.2
ΔC_LP	-90000.9	-104336.5	122320.3	-228806.4	202194.7	-153228.0	-47278.4	322797.0	583879.6	-56550.3	-78791.1
ΔC_IS	52284.3	10549.8	169911.4	53152.0	8442.8	-118623.4	-233205.6	-3656.1	430955.8	374316.5	-50063.2
ΔC	614403.4	122935.7	-58317.1	0.0	99710.5	71913.2	316377.5	-143829.0	32258.2	134131.5	-240585.2

Figure 5.16. India CO_2 emissions decomposition analysis of Machinery industrial sector.

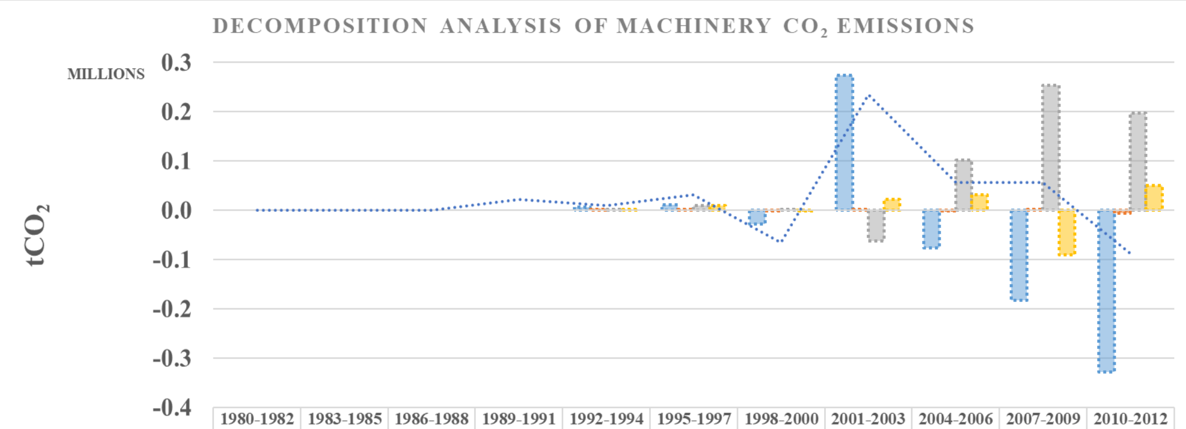
Performing an index decomposition analysis on the machinery sector of India, energy intensity (EI) is a major contributor, with a positive or negative effect towards the change of CO_2 emissions, for each of the time intervals assessed. EI counteracts the effect of labour productivity (LP) demonstrates. Examining closely the 2004-2006 interval, the EI contribution for reducing CO_2 emissions is 0.98 $MtCO_2$ while labour productivity (LP) and industrial scale (IS) contribute positively at a rate of 0.58 and 0.43 $MtCO_2$ respectively. However, energy intensity has not consistently contributed towards a decrease of CO_2 emissions change. Specifically, EI has an increasing effect on CO_2 emissions for the intervals of 1980-1982; 1983-1985; 1989-1991; 1995-1997; 1998-2000. Carbon intensity confirms a commonly observed pattern in the industry basis, as holding an unstable and insignificant effect in driving emissions. Concluding the study of machinery industry, it is notable that during 2010-2012, all factors contributed to a reduction of CO_2 emissions change (**Figure 5.16**).



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	0.0	0.0	0.0	-77600.9	-20100.6	90304.4	-222679.9	-65075.1	-254925.0	-67682.4	-281314.8
ΔC_CI	0.0	0.0	0.0	24781.7	7347.2	30417.9	-70900.2	249194.9	156454.8	9619.1	-35893.2
ΔC_LP	0.0	0.0	0.0	-29226.9	-23838.2	-27857.8	199100.8	31465.9	48494.5	191738.8	152386.1
ΔC_IS	0.0	0.0	0.0	58791.7	62040.0	-2582.9	40966.5	3165.9	35493.8	-47896.8	38437.0
ΔC	0.0	0.0	0.0	-23254.4	25448.4	38388.2	-53512.7	218751.6	-14481.9	85778.7	-126384.8

Figure 5.17. Indonesia CO_2 emissions decomposition analysis of Machinery industrial sector.

Indonesia does not present any industrial activity in the machinery sector from 1980 to 1988. From 1989-1991 onwards, the effect that the four examined factors have in carbon emissions change is moderate in scale until 1995-1997. During the following intervals, energy intensity (EI) the decreases carbon emissions. This effect is peaking in 2010-2012 with a contribution of 0.28 $MtCO_2$, and carbon intensity (CI) effect follows as secondary. Contrasting to that, CI is observed to drive the increase of CO_2 emissions change during 2001-2003 and 2004-2006. An increase from 96,931 tCO_2/PJ in 2001 to 203,326 tCO_2/PJ demonstrates an established relationship regarding this effect. Labour productivity (LP) leads as a main driver increasing CO_2, found to be peaking in 1998-2000 and constantly contributing to an increase during 2001-2003, 2004-2006, 2007-2009 and 2010-2012.

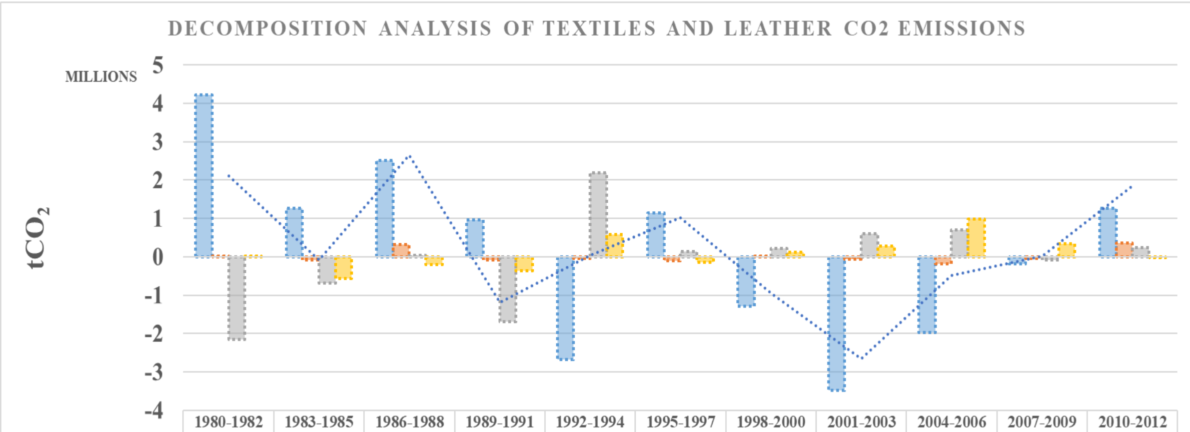


	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	0.0	0.0	0.0	0.0	5450.5	11540.6	-27618.9	273793.7	-77143.0	-183631.0	-328234.9
ΔC_CI	0.0	0.0	0.0	0.0	129.9	912.5	-1397.1	441.7	-311.2	983.5	-6547.0
ΔC_LP	0.0	0.0	0.0	0.0	2308.0	9721.4	1918.9	-61986.5	101818.3	253402.5	196706.6
ΔC_IS	0.0	0.0	0.0	0.0	1524.5	9799.5	-490.0	22538.1	31358.7	-89989.8	50175.5
ΔC	0.0	0.0	0.0	21644.8	9413.0	31974.1	-66341.1	234787.0	56074.0	56914.9	-87899.8

Figure 5.18. The Philippines CO_2 emissions decomposition analysis of Machinery industrial sector.

The industrial activity in the machinery sector of the Philippines is following the general pattern as this seen in Indonesia, with the exception that it does not pick up until 1990. Therefore, the period 1989-1991 cannot be examined, with the index decomposition analysis being performed from 1992-1994 onwards. The contribution of the factors is minimal and unstable in CO_2 emissions change until 2001-2003, where a significant increase is evident (**Figure 5.18**) mainly due to the contribution of energy intensity (EI), with 0.273 $MtCO_2$. However, this is reversed on the periods that follow, with its contribution in reduction peaking in 2010-2013, driving a total reduction result of CO_2 emissions change (ΔC) of 0.088 $MtCO_2$. Labour productivity is the main factor driving an increase of CO_2 emissions during 2004-2006, 2007-2009 and 2010-2012.

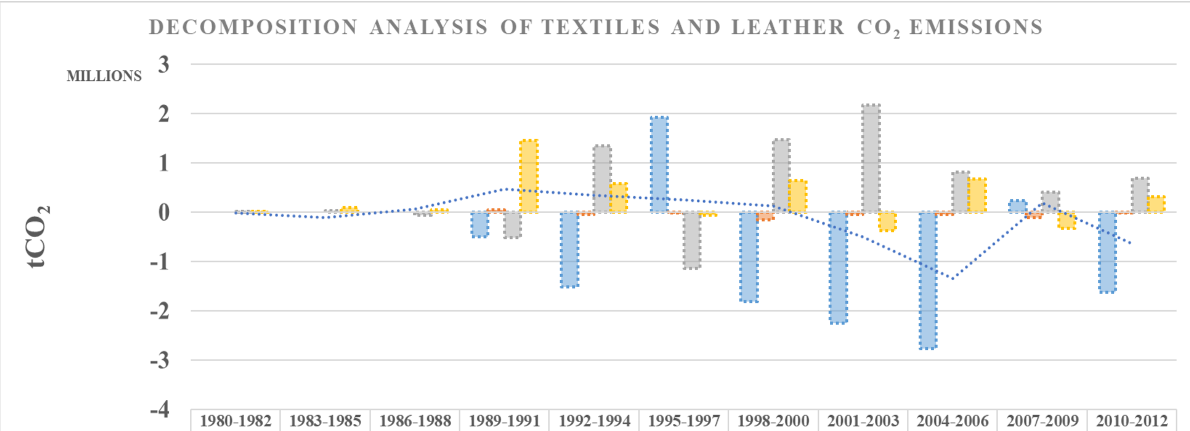
5.3.6 Textiles & Leather Industry



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	4226260.5	1254409.4	2505629.4	951391.1	-2684708.9	1134255.0	-1281755.1	-3477551.7	-1984114.8	-177342.8	1256899.4
ΔC_CI	15323.4	-74982.5	309875.4	-78506.2	-49741.5	-99897.9	5622.1	-73738.9	-180682.6	-51651.3	351302.9
ΔC_LP	-2148803.0	-689703.0	27456.5	-1699978.6	2195556.4	134625.5	210882.9	603279.6	697331.3	-77113.1	242924.2
ΔC_IS	23222.9	-570564.9	-198989.2	-361674.1	583448.2	-150342.7	106949.3	283941.1	987222.6	327500.9	-2772.0
ΔC	2116003.8	-80840.9	2643972.1	-1188767.8	44554.2	1018639.9	-958300.8	-2664069.9	-480243.5	21393.7	1848354.5

Figure 5.19. India CO_2 emissions decomposition analysis of Textiles & Leather industrial sector.

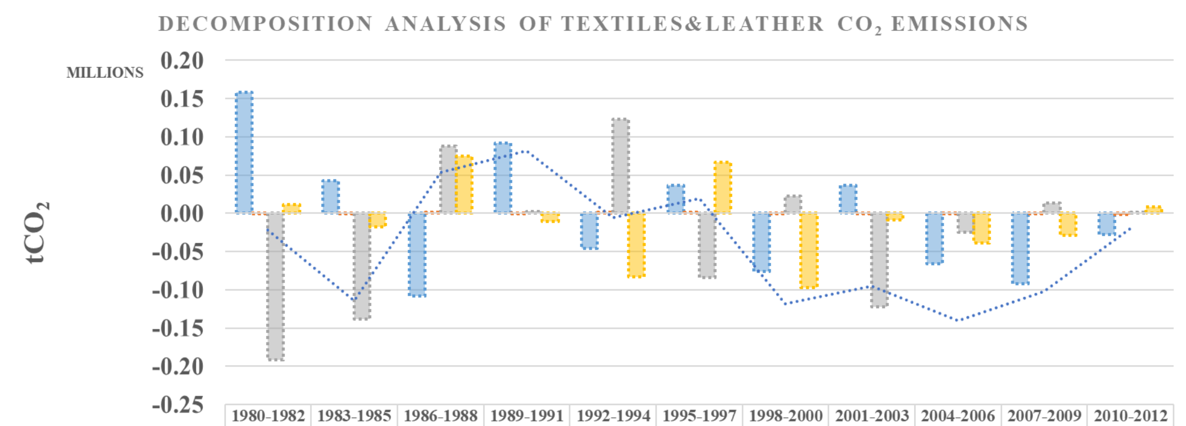
Decomposing each factor in the Indian textiles and leather industrial sector, it is observed that energy intensity (EI) is significant in driving the change of CO_2 emissions. EI contributes towards increasing CO_2 emissions during 1980-1982; 1983-1985; 1986-1988; 1989-1991; 1995-1997; and 2010-2012. The EI effect is major towards any change in carbon emissions, negative or positive, for every time interval with the exceptions of 1989-1991 and 2007-2009 (**Figure 5.19**). Carbon emissions peak increase happens during 1986-1988, with added 2.64 $MtCO_2$ and peak decrease in 2001-2003, with 2.66 $MtCO_2$. Labour productivity (LP) and carbon intensity (CI) contribute to carbon emissions change following an unstable pattern with the latter (CI) deemed insignificant in all time intervals except for 2010-2012 where it was 0.35 $MtCO_2$ of increase, second after EI.



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	0.0	0.0	0.0	-506206.5	-1517217.3	1919550.0	-1821520.9	-2251631.6	-2772553.4	234473.8	-1624766.8
ΔC_CI	0.0	0.0	0.0	37036.7	-47823.6	-10687.2	-159475.3	-46972.2	-50258.7	-117962.7	-12674.7
ΔC_LP	14732.8	32977.9	-71824.5	-517134.4	1334227.8	-1141057.6	1468228.2	2166546.8	813714.8	403322.8	690625.3
ΔC_IS	9340.3	84804.5	47572.3	1447526.0	577432.4	-73274.2	633502.4	-374884.2	662109.8	-334379.0	303304.6
ΔC	-22263.8	-114370.9	54004.9	461221.7	346619.3	246045.9	120734.3	-506941.2	-1346987.6	185454.8	-643511.6

Figure 5.20. Indonesia CO_2 emissions decomposition analysis of Textile & Leather industrial sector.

As observed in the data used from the International Energy Agency, the Indonesian textiles and leather industry does not present any energy consumption activity due to the lack of reported data. During the same period UNIDO does report employees and added economic value which is how calculating LP and IS, is achieved. However, a decomposition is incomplete for reaching critical conclusions regarding the attribution of the factors' effect, during 1980-1988, as EI_{eff} and CI_{eff} are missing. The effect of energy intensity is a major contributor in driving CO_2 emissions change from 1992 onwards (**Figure 5.20**). EI has significant impact in decreasing CO_2 emissions during 1992-1994; 1998-2000; 2001-2003; and 2004-2006. During 2004-2006 EI has contributed to a reduction of CO_2 emissions by 2.77 $MtCO_2$ leading to a total decrease (ΔC) of 1.35 $MtCO_2$. Labour productivity contributes to an increase in CO_2 emissions during most of the examined intervals with its peak effect observed in 2001-2003 where it reaches 2.16 $MtCO_2$.

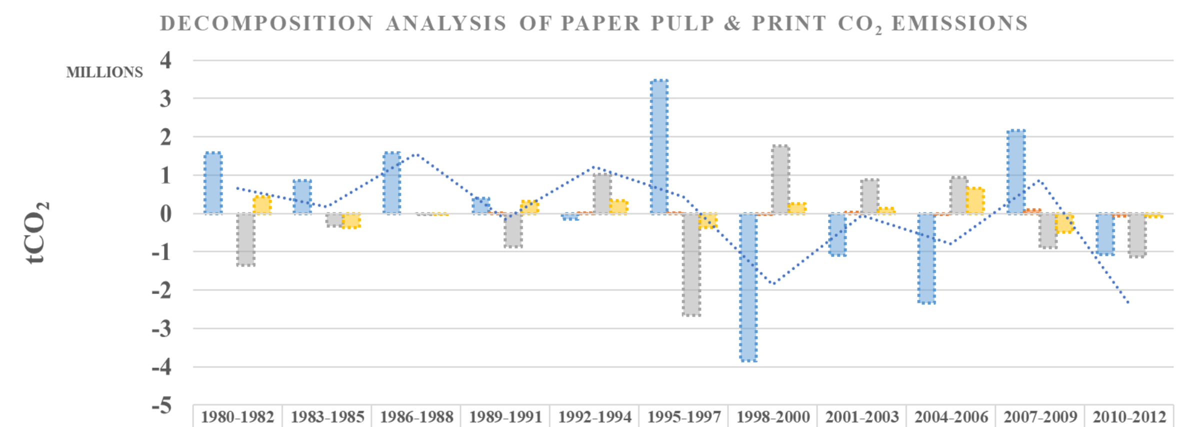


	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	158004.9	42091.8	-108075.0	91396.5	-46292.1	36496.4	-76222.0	36158.4	-66011.9	-92450.1	-27323.1
ΔC_CI	-92.4	-265.1	120.5	-336.2	399.4	464.8	-723.3	-153.0	-115.2	-67.6	-1579.4
ΔC_LP	-192045.9	-138494.4	87514.3	2116.2	123029.1	-84109.5	22407.4	-122512.8	-24643.9	13162.0	614.2
ΔC_IS	11869.7	-17703.2	74445.1	-10972.7	-83304.4	66355.6	-96723.5	-8844.6	-39000.2	-28864.3	8801.3
ΔC	-22263.8	-114370.9	54004.9	82203.8	-6168.1	19207.4	-117955.2	-95352.0	-139943.9	-101713.1	-19487.0

Figure 5.21. The Philippines CO_2 emissions decomposition analysis of Textile & Leather industrial sector.

Focusing on the carbon emissions change in the Philippines regarding the textiles and leather industrial sector, it is observed that three factors have significant effect. These are energy intensity, labour productivity and industrial scale, with carbon intensity having only a minor contribution. Labour productivity is a critical contributor to mitigating a steep increase in carbon emissions, countering the effect of energy intensity in 1980-1982 and driving carbon emissions decrease during the next period (1983-1985). However, the trend observed previously is reversed during 1986-1988 with LP and IS driving carbon emissions increase, the highest observed for the total sample of the periods assessed. The CO_2 emissions change is negative from 1998 onwards, with a peak during 2004-2006. During that period all factors drive a change decrease which is approximately 140kt CO_2. However, the LP_{eff} contributed towards an increase in emissions in 2007-2009 and added an IS_{eff} increase in 2010-2012 (Figure 5.21) with energy and carbon intensity acting as reciprocal.

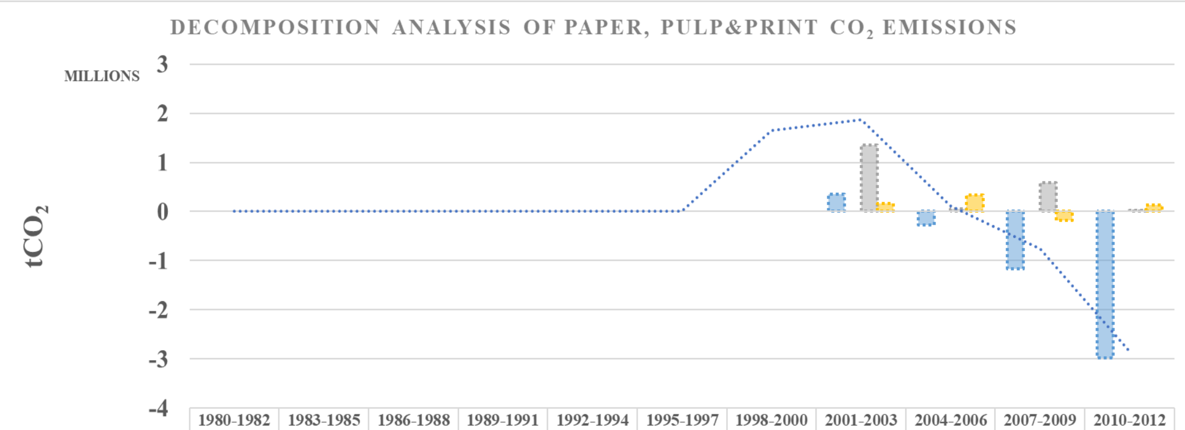
5.3.7 Paper Pulp & Print industrial sector



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	1573698.6	857835.4	1584016.3	391899.8	-139360.0	3476479.9	-3856668.1	-1097757.7	-2349460.8	2168690.0	-1072800.3
ΔC_CI	0.0	0.0	0.0	13621.3	12259.6	5823.5	-12009.1	30317.0	-33989.2	83037.2	-78063.5
ΔC_LP	-1356640.7	-327695.4	-5924.8	-882355.1	1020093.6	-2663858.1	1759592.7	881148.9	936714.7	-887176.0	-1126098.6
ΔC_IS	443117.7	-365096.2	-12187.8	322276.8	324874.5	-375432.8	252361.6	135353.3	659533.6	-483603.2	-82983.5
ΔC	660175.6	165043.9	1565903.7	-154557.2	1217867.6	443012.5	-1856722.9	-50938.5	-787201.7	880948.0	-2359945.9

Figure 5.22. India CO_2 emissions decomposition analysis of Paper Pulp & Print industrial sector.

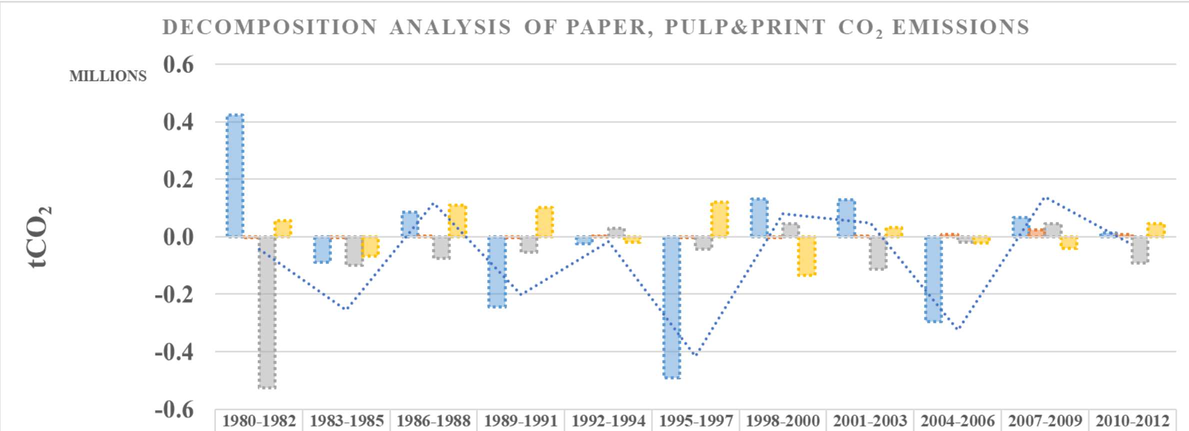
Energy intensity (EI) and labour productivity (LP) were found to be the main contributors to CO_2 emissions in India's paper, pulp and print industry. EI has historically been the most significant factor both in increasing (1995-1997) and decreasing (1998-2000) carbon emissions. Industrial scale (IS) contribution is moderate and carbon intensity (CI) has a negligible impact. However, all drivers have contributed towards negative CO_2 emissions change in 2010-2012, amounting to a decrease of 2.36 $MtCO_2$ (**Figure 5.22**).



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	0.0	0.0	0.0	0.0	0.0	0.0	0.0	349044.5	-274349.7	-1163678.6	-2977448.9
ΔC_CI	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
ΔC_LP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1352397.4	60428.7	590813.1	4652.9
ΔC_IS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	160522.2	330161.6	-179528.7	136523.8
ΔC	0.0	0.0	0.0	0.0	0.0	0.0	1650617.5	1861964.1	116240.7	-752394.1	-2836272.3

Figure 5.23. Indonesia CO_2 emissions decomposition analysis of Paper Pulp & Print industrial sector.

The Indonesian primary data is inconsistently reported, not allowing a complete index decomposition analysis. The international energy agency (IEA) does not provide reports regarding energy consumption activity during 1980-2000; thus, there are no estimations for energy intensity, carbon intensity and CO_2 emissions results data, despite UNIDO presenting the respective number of persons employed. Additionally, the division of CO_2 to energy (PJ) from the year 2000 onwards produces the same result (96ktCO_2/PJ) leading the decomposition analysis returning null contribution for CI towards carbon emissions (**Figure 5.23**). From 2004-2006 onwards, energy intensity is the main contributor to the decrease in carbon emissions, following a rapid decrease in the next intervals. Energy intensity's role peaks during 2010-2012 with 2.98 MtCO_2 contribution in reducing CO_2 emissions. The effect of labour productivity presents a stable trend towards increasing carbon emissions, while the effect of IS does not present a stable pattern.



	1980-1982	1983-1985	1986-1988	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012
ΔC_EI	423856.6	-88025.6	84229.0	-245035.5	-23737.8	-491882.3	130087.2	129167.1	-296164.9	65909.5	13291.8
ΔC_CI	-95.2	-357.7	162.8	-615.2	541.7	-334.4	-175.6	56.0	7137.1	24628.5	6719.3
ΔC_LP	-524803.2	-98427.0	-76930.6	-54713.1	28195.7	-43558.2	45272.7	-113721.8	-18227.6	46332.4	-91506.9
ΔC_IS	56514.2	-67504.5	110154.6	99989.6	-20645.1	119123.7	-135068.0	32206.8	-21981.2	-39829.2	45001.3
ΔC	-44527.6	-254314.8	117615.8	-200374.3	-15645.4	-416651.2	79298.3	47708.2	-324299.8	139042.2	-26494.5

Figure 5.24. The Philippines CO_2 emissions decomposition analysis of Paper Pulp & Print industrial sector.

Decomposing the factors' effect for the Philippines it is found that all but carbon intensity has a significant role in driving CO_2 emissions change. Labour productivity in 1980-1982 has caused a reduction of 0.52MtCO_2, while energy intensity caused an increase in the same period of 0.045 MtCO_2. A reduction of CO_2 due to energy intensity is observed in several intervals (1983-1985; 1989-1991; 1992-1994; 1995-1997; 2004-2006) with 1995-1997 presenting the largest reduction at 0.49 MtCO_2. Overall, most of the examined intervals show decreasing CO_2 emissions and 2007-2009 shows the highest increase at 0.013 MtCO_2 (**Figure 5.24**).

5.4 Discussion

5.4.1 Total and Sectoral Industry Decomposition Analysis of India

Performing the additive LMDI-I of the total industry of India, shows that energy intensity plays the most dominant role in driving the change (ΔC) of carbon emissions for each time interval. Additionally, the effect of labour productivity is significant throughout the timeline, through positive or negative contributions in driving ΔC. Industrial scale is of equal significance, from 2004 onwards only to be surpassed by the energy intensity effect during the latest interval. Energy intensity is the main contributor to carbon emissions change in the total industry of India, with an average share of 51.7% throughout the examined period. It dwarves carbon intensity (3.2%) and industrial scale (13%) and surpasses labour productivity which holds a 32.1% share (**Figure 5.26**). While energy intensity has a major impact as measured by average contribution, the cumulative carbon emissions change attributed to industrial scale is 43.1% (**Figure 5.25**). Contrasting the rest, carbon intensity contributes to negative ΔC, approximating 2MtCO_2 on average between time intervals. The average carbon emissions change amounts to an increase of 24.96MtCO_2 while the cumulative ΔC of 1980-2012 approximates 274.55MtCO_2 (**Figure 5.27**).

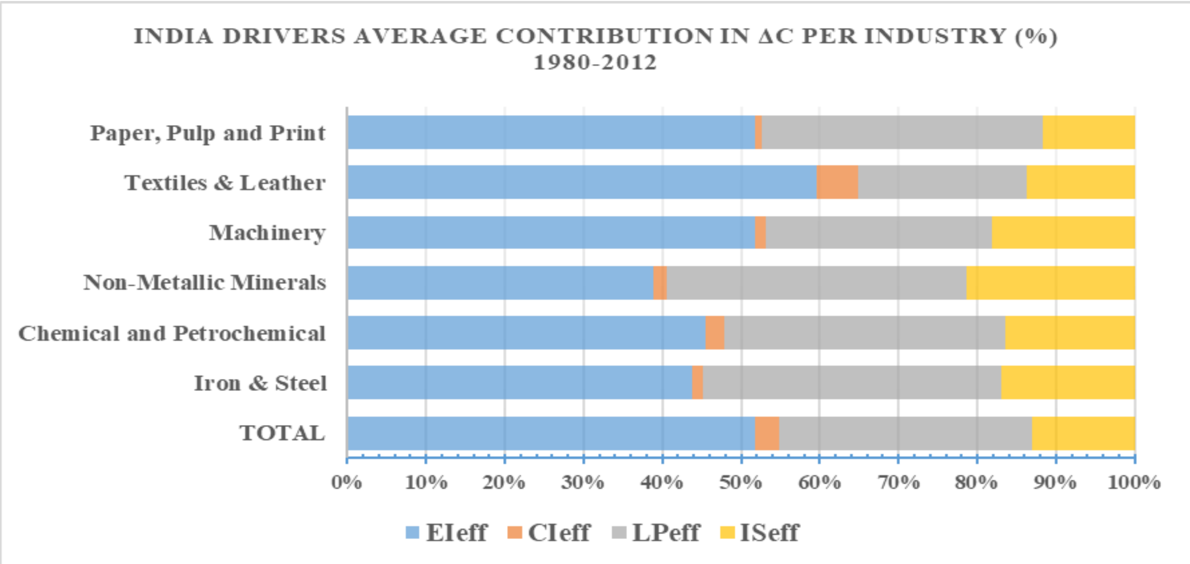


Figure 5.25. India average CO_2 contribution of drivers per industry (%) for the 1980-2012 timeline.

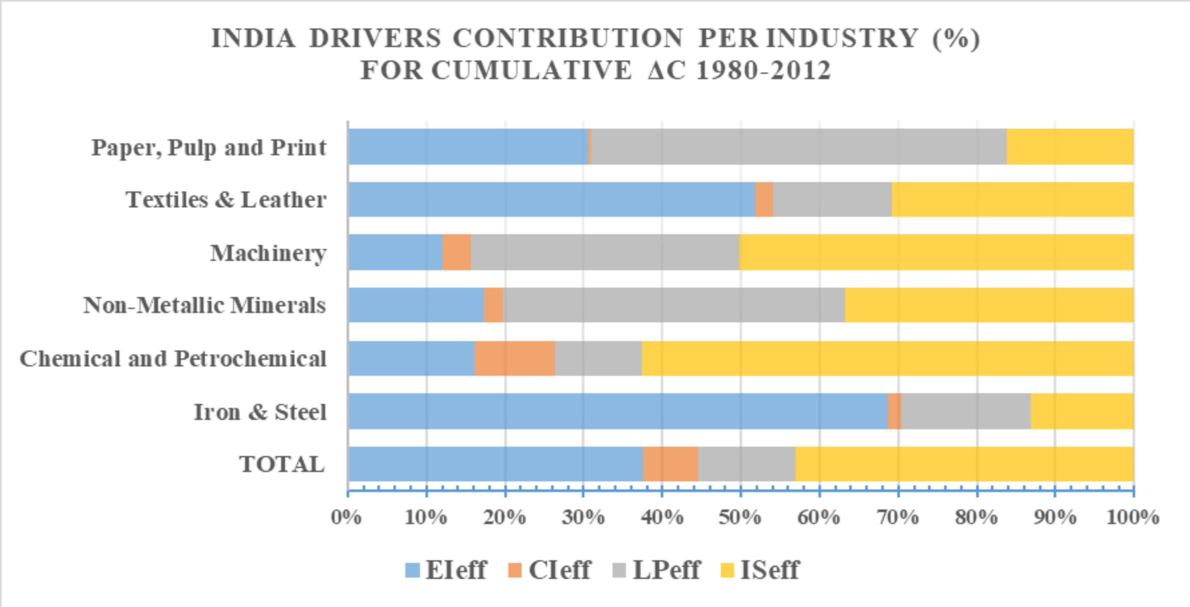


Figure 5.26. India CO_2 contribution of drivers per industry (%) as for the cumulative ΔC for the 1980-2012 timeline

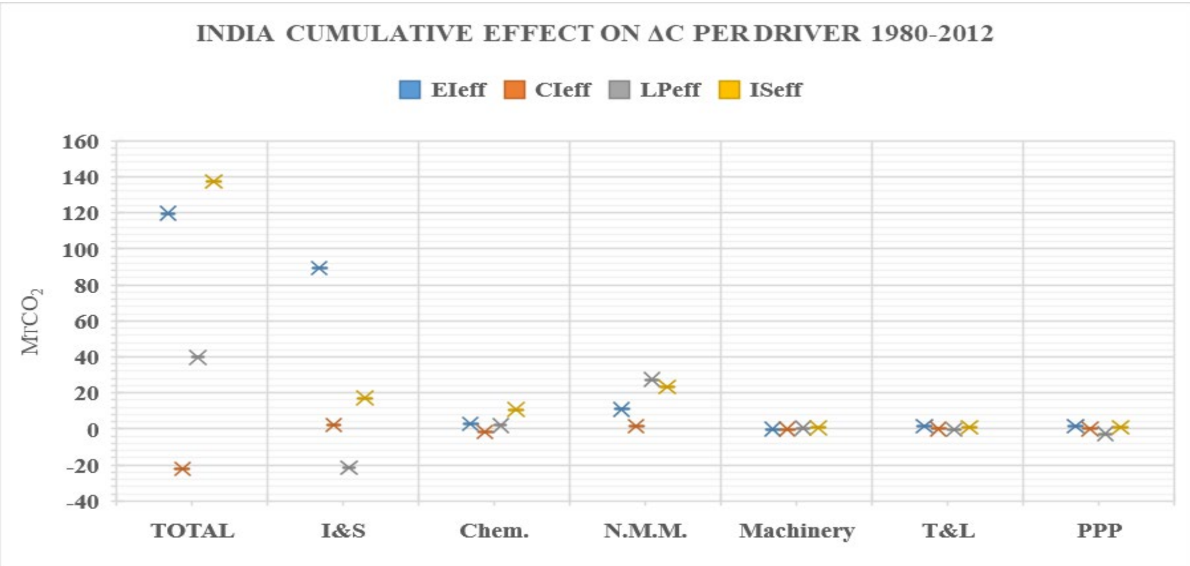


Figure 5.27. India cumulative effect of drivers on ΔC per industrial sector ($MtCO_2$) for the 1980-2012 timeline.

In the iron and steel industry, energy intensity is driving an increase in carbon emissions during 2007-2012, with labour productivity countering that carbon emissions increase. However, this contribution in emissions change is following a reverse trend during 2001-2003. It is observed that 2004-2006 industrial scale contributes positively in ΔC increase. Energy intensity (43.7%) and labour productivity (37.9%) are the main contributors in carbon emissions change, while industrial scale and carbon intensity have a lower impact at 16.9% and 1.5% respectively (**Figure 5.26**). Three out of the four drivers present a ΔC increase in cumulative terms, EI_{eff}, CI_{eff}, IS_{eff} with positive contributions of 89.32$MtCO_2$, 2.28$MtCO_2$ and 17.19$MtCO_2$ respectively for 1980-2012 (**Figure 5.27**). However, LP_{eff} results in a cumulative decrease in emissions change for the same period, approximately at 21.39MtCO_2 or 1.94MtCO_2 per time interval on average. India, not being an ANNEX I country did not have any Kyoto Protocol obligations for reducing its carbon emissions. This included its industry and subsequently its iron and steel industry (Mathiesen and Mœstad, 2004). However, beyond Kyoto India voluntarily pledged to reduce the I&S emissions intensity per GDP unit according to the Copenhagen agreement which is not legally binding (International Institute for Sustainable Development, 2009). While India claims that its industry emission intensity (by GDP) was reduced by 12% between 2005 and 2010 (UNFCCC, 2015), the country's total industrial steel output leads to a significant increase in CO_2 emissions under every forecasted scenario (Pal et al., 2016). The latter is confirmed by the industrial decomposition performed in this chapter (see indicatively **Figure 5.7**.

In the chemical and petrochemical industrial sector, international literature demonstrates by a qualitative approach that the sector can benefit from set environmental benchmarking practices such energy efficiency improvement (Singh et al., 2016). Applying a quantitative index decomposition approach, it is found that energy intensity is a contributor to ΔC at a 45.6% average rate (**Figure 5.25**). Energy intensity is the main contributor to ΔC increase during every interval included in 1995 to 2000. This reverses to negative, from 2001 to 2012, matching the reported improvement in energy efficiency that the Indian government has claimed achieving from 2007 onwards. Industrial scale and labour productivity are positive contributors during the 2007-2009 and 2010-2012 intervals (**Figure 5.10**), with ΔC decreasing during each of those periods. Industrial scale has a major share in contributing to cumulative carbon emissions, with 62.5% (**Figure 5.26**) while on average that contribution holds reduced significance, at a rate of 16.4%.

The non-metallic minerals sector of India is classified as the second largest in the world with 6% of the global cement output (Garg et al., 2017). Approximately 97% of the produced cement comes from major cement producers (Department of Industrial Policy and Promotion, 2011). the non-metallic minerals sectoral ΔC is marginally increasing throughout the assessed time periods. However, this margin has two exceptions. The first is a positive spike in 1998-2000 of 8.27 MtCO_2 which is attributed to labour productivity. The second is a 31.74MtCO_2 ΔC positive spike explained as an unprecedented positive contribution in carbon emissions caused by energy intensity. Labour productivity holds a share of 38% on ΔC average contribution reaching a 43,4% on cumulative, while EI accounts for 38.9% but with a limited cumulative share of 17.3% (**Figure 5.25; 5.26**). Energy intensity is generally found as countering the effects of positive industrial scale and labour productivity during 2004-2006, therefore keeping the rate of carbon emissions change to marginally increasing levels. Energy consumption in India's cement industry is a major indicator when approaching methods for sustainable manufacturing performance increase and subsequently achieving a reduction of raw materials consumption and emission levels (Singh et al., 2018). The Indian cement industry holds large potential for energy efficiency improvement (Morrow et al., 2014b). The non-metallic minerals sector has not made full use of energy efficiency options leading to carbon emissions increase during 2010-2012 (**Figure 5.13**).

Focusing on the machinery industrial sector, ΔC presents mixed levels of output, expanded to all drivers (**Figure 5.27**). Energy intensity is a major contributor, driving ΔC to negative levels during two time intervals, 2001-2003 and 2004-2006 with 57.7% and 49.2% rate respectively. However, during the last period, industrial scale and labour productivity counter EI performance; both being positive contributors. Industrial scale is a permanent positive contributor while the rest are found to drive negative carbon emissions contribution during 2007-2009. Sectoral decomposition during 2010-2012 shows all drivers having a negative contribution. Industrial scale is the leading factor in cumulative ΔC at 50.2%, with 0.69MtCO_2, while EI has contributed 12% (0.17MtCO_2), followed by labour productivity with a cumulative contribution rate of 34.1%, increasing CO_2 by 0.47MtCO_2 (**Figures 5.26, 5.27**).

In textiles and leather industrial sector of India, the energy intensity and industrial scale drive carbon emissions increase throughout the timeline with an average rate of 59.7% and 13.8% (**Figure 5.25**). Industrial scale in 2010-2012 contributes towards a decrease of 2772 tCO_2, not following the previous established trend. Paper pulp and print sector presents a mixed ΔC throughout the timeline. However, its cumulative rate of carbon emissions change in 1980-2012 shows a decrease of 0.28MtCO_2 (**Figure 5.27**). All factors contribute to negative ΔC in 2010-2012 with the effect of EI and LP leading, while their rates reach 45.5% and 47.72% respectively.

5.4.2 Total and Sectoral Industry Decomposition Analysis of Indonesia

Examining the additive index decomposition analysis of the total industrial activity of Indonesia, it is concluded that all four drivers have positively contributed towards carbon emissions increase during the interval of 1989-1991. Labour productivity is the driver which presents the highest contribution towards emissions change from 1998-2012. Energy intensity effect on carbon emissions is a significant contributor, almost equal to labour productivity, with

33.9% and 32.1% respectively (**Figure 5.28**). However, energy intensity contributes greatly towards a reduction of carbon emissions by 8.8MtCO_2 on average between intervals, reaching a total contribution in reduction of 96.8MtCO_2 throughout the timeline (**Figure 5.30**). Energy efficiency in the country requires further improvement through the introduction of more advanced technological means of production (Sasana and Aminata, 2019).

Industrial scale has a significant effect to carbon emissions (26.8%) while the effect of carbon intensity is limited at 7.2% reaching an average reduction of 8.68MtCO_2 throughout the timeline (**Figures 5.28; 5.30**). However, looking at cumulative contributions, the effect of labour productivity is the highest at 45.9% (**Figure 5.29**) presenting a cumulative effect in the 1980-2012 timeline increasing emissions by 138.30MtCO_2 (**Figure 5.30**).

As 96% of the energy used in Indonesia is classified as potentially harmful to the environment (Mujiyanto and Tiess, 2013), the application of automation for improving labour productivity would directly result in emissions increase. Emissions change shows an average increase of 6.90MtCO_2 per examined period, presenting a cumulative increase during 1980-2012 that amounts to 75.86MtCO_2.

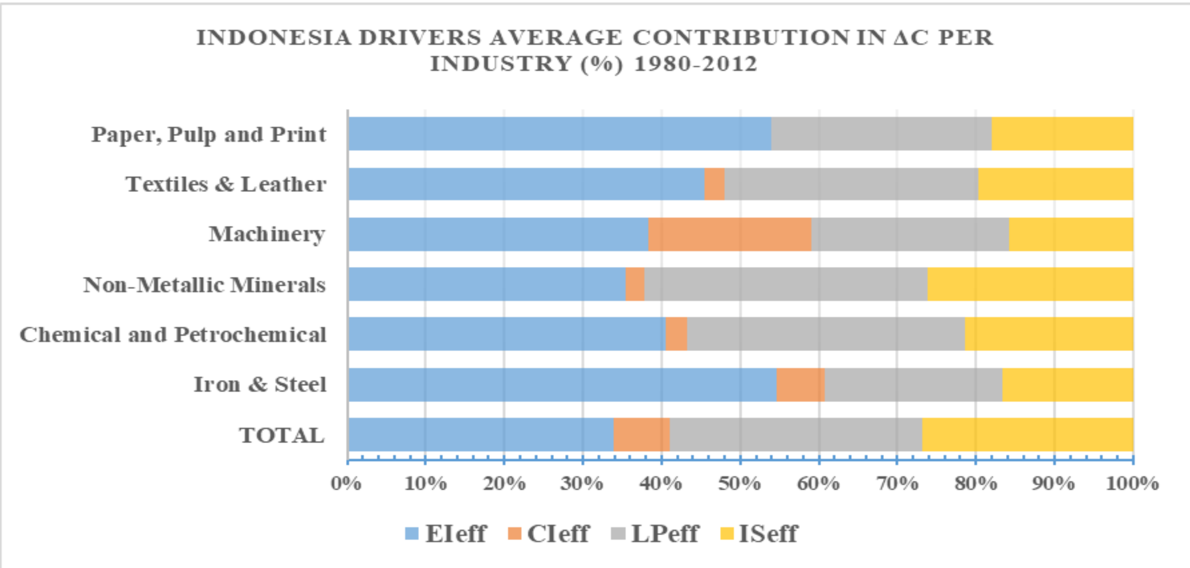


Figure 5.28. Indonesia average CO_2 contribution of drivers per industry (%) for the 1980-2012 timeline

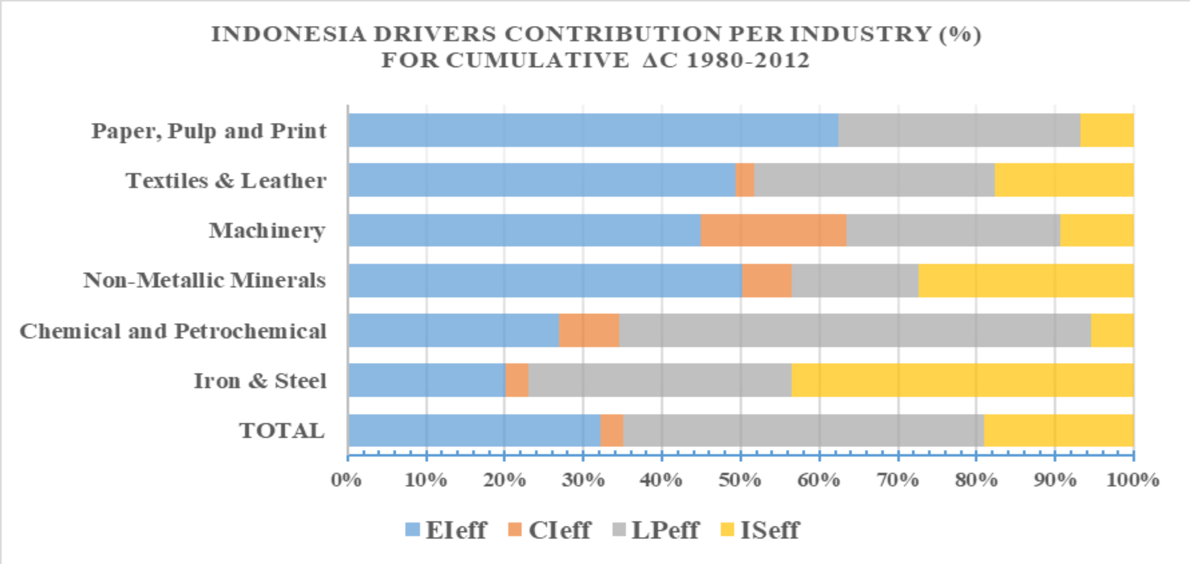


Figure 5.29. Indonesia CO_2 contribution of drivers per industry (%) for the cumulative ΔC of the 1980-2012 timeline.

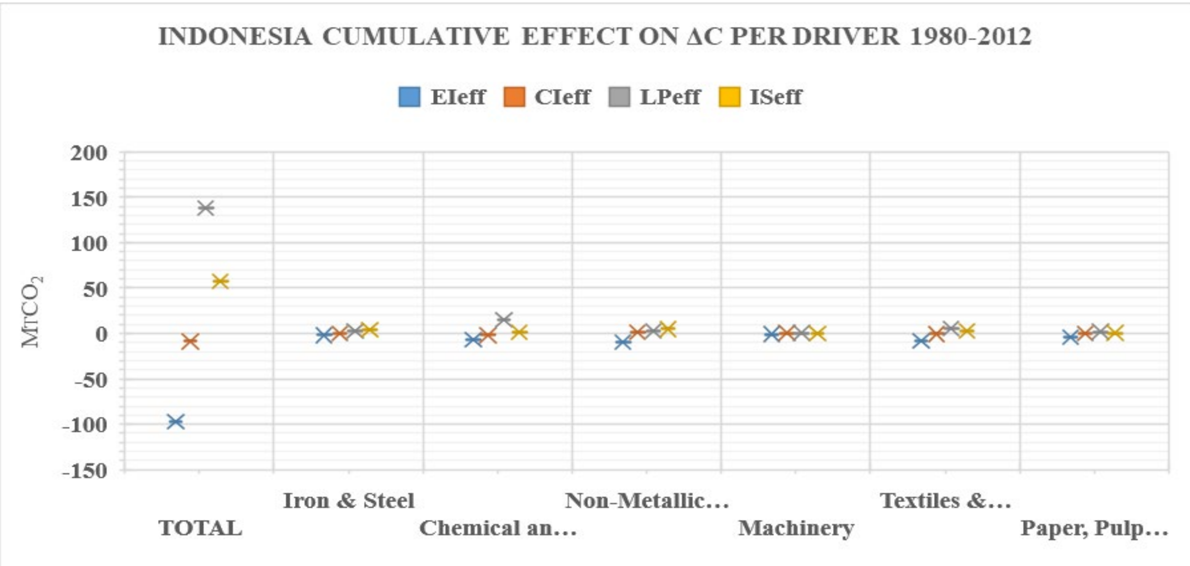


Figure 5.30. Indonesia cumulative effect of drivers on ΔC per industrial sector ($MtCO_2$) for the 1980-2012 timeline.

Focusing on sectoral index decomposition and more specifically in the iron and steel industry, energy intensity drives a ΔC increase spike during 1995-1997, with 4.75$MtCO_2$ while 1998-2000 onwards this spike is reversed by 4.49$MtCO_2$, driving a reduction in carbon emissions of 1.55$MtCO_2$, with an exception located at the 2001-2003 period (1.94$MtCO_2$). The effect of EI is also evident in its average contribution rate to ΔC, amounting at 54.6% (**Figure 5.28**). Labour productivity presents a positive ΔC contribution performance trend from 1998 onwards averaging at cumulative contribution rate of 33.5% and 2.97$MtCO_2$ respectively

(**Figures 5.29; 5.30**). However, industrial scale has the highest rate towards emissions increase at 43.5% with 3.86MtCO_2 (**Figures 5.29; 5.30**).

The Indonesian chemical and petrochemical industrial sector presents a spike in ΔC, in 2004-2006 (8.8MtCO_2), attributed to energy intensity (61.2%) and labour productivity (23.5%). This carbon emissions change is rebalanced in 2007-2009 with energy intensity having a negative (9MtCO_2) contribution and labour productivity acting as a reciprocal with a 9.73MtCO_2 increase. The effect of labour productivity is the main contributor to cumulative carbon emissions, adding 14.86 MtCO_2, with 60% attributed as per cumulative and 35.4% in average terms (**Figures 5.29; 5.30**).

Approaching the 2004-2006 interval of the Indonesian non-metallic minerals industry, a ΔC decrease is attributed to energy intensity and labour productivity, a factor trend not regularly observed towards carbon emissions change. Carbon emissions decrease during 2010-2012, mainly attributed to energy intensity Overall, carbon emissions change during 1980-2012 shows a cumulative increase of 3.22MtCO_2, mainly attributed to energy intensity and industrial scale, at 50.1% and 27.3% respectively (**Figure 5.29; 5.30**). EI presents a cumulative reduction of 9.33MtCO_2 while IS increases ΔC by 5.08MtCO_2. Inconsistencies between ΔC and the results (**Figure 5.14)** are attributed to the lack of data in all drivers during periods 1980-1982 and the intervals between 1995-2003.

The Indonesian machinery industrial sector ΔC presents an increase in the examined timeline by carbon intensity (0.15MtCO_2) and labour productivity (0.54MtCO_2), while energy intensity is a negative contributor in emissions with approximately 0.9MtCO_2 (**Figure 5.30**). Carbon intensity and energy intensity reverse the observed trend of increasing emissions during the last period of 2010-2012, with the highest decrease in observable ΔC of the timeline; with EI having a contribution of 30%. The effect of energy intensity in average is the most significant at 38.4%, followed by labour productivity (**Figure 5.28**). The same significance order is found in the cumulative carbon emissions with 44.9% and 27.1% respectively (**Figure 5.29**).

The textile and leather industry carbon emissions show an average rate of change that approximates a neutral effect (-0.11MtCO_2). However, the cumulative change in emissions during the timeline approaches 1.22MtCO_2, mainly attributed to the 2010-2012 interval. During that period, energy intensity is responsible for 61.1% driving emissions negative by 8.34MtCO_2. Typically, ΔC shows energy intensity as the most important contributor in driving down total carbon emissions from 1998 onwards, averaging at 45.5% (**Figure 5.28**) while labour productivity (32.3%) and industrial scale (19.7%) show a reciprocal contribution on ΔC, except for the 2007-2009 interval where all driving factors have a negative effect on CO_2 emissions change, except for labour productivity (LP).

Paper pulp and print industries present a limited availability of data as these have been discussed in **Chapter 2**. However, energy intensity drives carbon emissions change, especially during 2010-2012 with an unprecedent 95.5% contribution in emissions change, a result that can largely be attributed to lacklustre data. The trend of carbon emissions change is downward, while the cumulative emissions remain positive at 0.04MtCO_2.

5.4.3 Total and Sectoral Industry Decomposition Analysis of the Philippines

The Philippines is part of the ASEAN countries that present a steady increase in carbon emissions, a trend explained by its accelerated economic development and use of fossil fuels (Lean and Smyth, 2010). An important aspect to notice is that carbon intensity is a significant contributor towards that increase, a trend rarely observed in the decomposition of the other countries examined in this chapter. In the 2007-2009 interval, a usual shaped trend is observed, with the contribution of energy intensity countered by that of labour productivity. Industrial scale is the sole positive contributor increasing ΔC during 2010-2012. Carbon emissions are mainly driven by the effects of industrial scale (30.8%), energy intensity (29.8%), labour productivity (27.4%) and carbon intensity (12%) (**Figure 5.32**). Carbon emissions increase is approximately at 0.54MtCO_2 between time intervals, while the cumulative ΔC is 5.95MtCO_2 during the timeline. Energy intensity and labour productivity drive emissions negatively throughout 1980-2012 by 9.1MtCO_2 and 5.62MtCO_2 respectively (**Figure 5.33**).

Focusing in specific sectors which comprise the total industry, iron and steel shows an overall marginal rate of change in carbon emissions throughout the examined timeline where the cumulative ΔC is -0.38MtCO_2 (**Figure 5.33**). Drivers of increased significance in the sector from 2004 onwards in average contribution terms, are energy intensity (37.5%) and labour productivity (43.5%) which show competing trends. However, all drivers but carbon intensity act towards decreasing CO_2 emissions, with labour productivity having the highest contribution at 54% with 0.81MtCO_2 (**Figure 5.32; 5.33**).

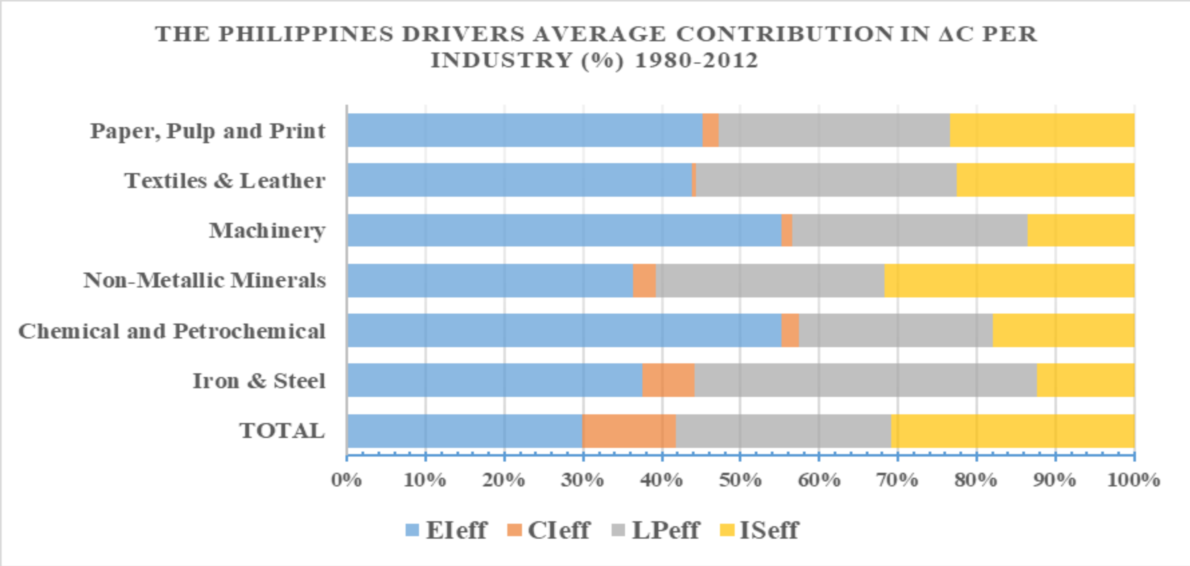


Figure 5.31. The Philippines average CO_2 contribution of drivers per industry (%) for the 1980-2012 timeline.

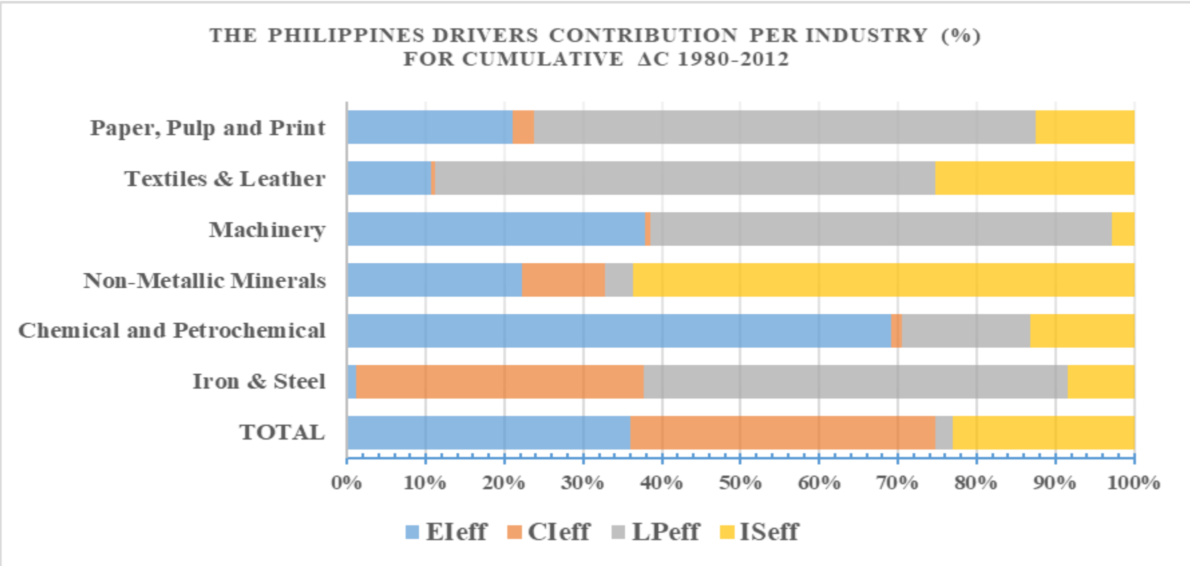


Figure 5.32. The Philippines CO_2 contribution of drivers per industry (%) as for the cumulative ΔC for the 1980-2012 timeline.

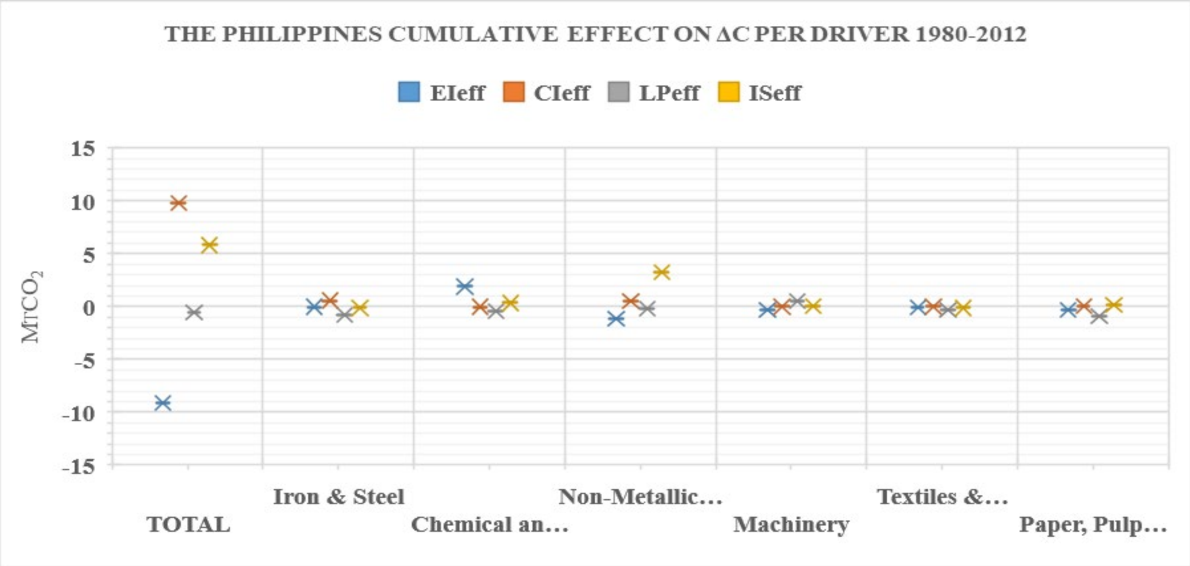


Figure 5.33. The Philippines cumulative effect of drivers on ΔC per industrial sector ($MtCO_2$) for the 1980-2012 timeline

The chemical and petrochemical industry shows positive ΔC spikes, observed during 1989-1991 (0.82$MtCO_2$), 1995-1997 (1.04$MtCO_2$) and 1998-2000 (0.69$MtCO_2$). Energy intensity is the main contributor to that increase driving carbon emissions with a cumulative contribution at 69.1% (**Figure 5.32**). EI is followed by industrial scale during 1995-1997 with 43.51%. Labour productivity lowers carbon emissions during 2010-2012 having a cumulative contribution ratio of 55.45%.

The non-metallic minerals sector presents an extensive timeline of rising carbon emissions between 1980 and 1997. Industrial scale is the main positive contributor in 1995-1997 with 1.55 $MtCO_2$ and 56.11% share but it acts as a main negative contributor in 1998-2000 with 0.87$MtCO_2$ at 67.87%. The same trend is observed for labour productivity in 2007-2009 (1.7$MtCO_2$) and 2010-2012 (-1.59$MtCO_2$). The 2007-2009 of ΔC increase is countered by energy intensity; its effect decreasing carbon emissions by 1.70$MtCO_2$. Additionally, industrial scale shows an unprecedented contribution driving positive ΔC in 2010-2012 with 2.5$MtCO_2$. Overall, carbon emissions change in cumulative terms shows an increase of 3.18$MtCO_2$ with industrial scale having a share of 63.7% in cumulative emissions (**Figure 5.32**).

In the machinery sector, the Philippines data is lacklustre. Energy intensity and labour productivity have competing impact during the last time interval of 2010-2012. Specifically, the effect of energy intensity is negative 0.33$MtCO_2$. Whereas energy intensity has the largest share on average contribution, it is surpassed by labour productivity in cumulative terms at 58.6% (**Figure 5.31; 5.33**).

Examining the textiles and leather industry, the negative rate of carbon emissions change from 1998 onwards is attributed to all drivers. Total cumulative carbon emissions decreased by 0.46MtCO_2 (**Figure 5.33**). LP and IS have contributed positively but at a low level for the last two time intervals. Looking at the cumulative effect of all drivers, this is found to be negative, with labour productivity having the highest share at 63.7% (**Figure 5.32**). For average rate of contribution between drivers, energy intensity is the most significant with 43.7% (**Figure 5.33**).

For the paper, pulp and print industry, ΔC follows a mixed but cumulatively decreasing trend, at approximately 0.90MtCO_2. The most influential driver is energy intensity at 45.2% on average. (**Figure 5.31**) On a cumulative contribution rate, labour productivity is the main driver with 63.7% (**Figure 5.32**), especially pronounced in its input for driving emissions towards a decrease during 1995-1997 and 2004-2006.

5.5 Results - Conclusions

Decomposing CO_2 emissions produced from the industrial activities of the total industry and the six specific sectors of India, Indonesia and the Philippines, under the additive logarithmic mean divisia index, presents the different effect that the studied factors have on each industrial sector in focus. Responding to the initial hypotheses stated in **Section 5.1**, it is found that:

H1: Focusing on the total or each of the individual industrial sectors, the CO_2 emissions change is affected differently by the four decomposition factors, for each of the time intervals examined and for the entirety of the timeline. Therefore, this hypothesis is confirmed. (**Figures 5.25-5.32**)

H2: Introducing industrial automation, is an indicator of raising labour productivity. Decomposed carbon emissions, present labour productivity as a direct contributor to carbon emissions change for every industrial sector of each of the counties assessed. As a result, a positive relationship exists, and the hypothesis is confirmed (**Figures 5.3-5.32**).

H3: Energy efficiency is the reciprocal of energy intensity. Decomposition results show that energy intensity is a main driver of carbon emissions change for the three countries for the total and each of the six industrial sectors examined. Therefore, a positive relationship exists, and the hypothesis cannot be confirmed (**Figures 5.25-5.32**).

This study decomposes the CO_2 emissions of the total and six industry sectors of India, Indonesia and the Philippines for the 1980-2012 timeline in eleven symmetric three-year periods. Following the additive Logarithmic Mean Divisia Index (LMDI-I) method to achieve perfect decomposition (Ang and Wang, 2015), four drivers are compiled and then modelled to decompose the change in CO_2 emissions (ΔC) in an independent country-by-country case approach. Energy intensity, carbon intensity, labour productivity and industrial scale have their change rate measured in tonnes of CO_2 contribution determined in the given time frame. The analysis of the factors driving industrial emissions in each country, describes their contribution, for the duration of the studied timeline of 1980 to 2012 both in an average and a cumulative basis.

India presents an accelerated growth of CO_2 emissions during the complete timeline. It is argued that the average contribution of energy intensity in India's industrial activities is the most significant. While energy intensity remains a significant factor regarding its positive contribution towards total cumulative CO_2 emissions for the iron & steel, non-metallic minerals and textile & leather industries, the empirical results show that labour productivity and industrial scale also drive the growth of CO_2 emissions.

A reduction of the massive industrial scale of India (United Nations Industrial Development Organization, 2016) would contribute towards a decline in total industrial carbon emissions. However, this decline can be countered by innovative measures improving labour productivity, such as automation. This result would occur due to higher energy usage leading an increase in carbon emissions when achieving the same production output (Gazheli et al., 2016). Certain forecast scenarios present the country to hold a potential of mitigating industrial CO_2 emissions by a range of 12-26% by 2050, when compared to 2005 levels (Wang and Chen, 2019). India's iron and steel energy intensity contribution, points towards an urgency in innovating in its production processes, increasing energy efficiency (Kuramochi, 2016; Moya, 2017), further enhancing progress and control of its carbon footprint. Improving the ratio of energy consumption to economic output is achievable by implementing more efficient processes and less carbon-intensive procedures (Murphy, 2014). This improvement has additionally been claimed as feasible by introducing alternative solutions such as big data analytics in its manufacturing hubs (Dubey et al., 2016).

Following the established pattern observed in India, the average contribution of energy intensity in Indonesia is of equally high significance. However, the results show that for the total industry, energy intensity drives cumulative emissions to a negative trend, countering the effect of labour productivity and industrial scale. Carbon intensity of the Indonesian industry presents negative contribution towards CO_2 emissions. As a result, there is increased headroom for switching manual labour to automated processes. That potential industrial scale reduction, can result in increased labour productivity enhancing the opportunities for leapfrogging by promoting technological innovation for industrial production (Hung et al., 2014). As the energy and carbon intensity of the industry present a negative contribution to CO_2, increased capacity for a greater reduction of industrial CO_2 emissions through automation is feasible. Increased CO_2 emissions are of particular concern for Indonesia, as its CO_2 growth shows a historic positive link to GDP, energy consumption and financial capital (Jafari et al., 2012). Indonesia is a G20 member and is expected to be the 4th largest economy in the world by 2050 (PWC, 2017) but its current level of economic activity is not yet expected to contribute significantly to global CO_2 emissions (Sasana and Aminata, 2019). However, allocating the significance that the decomposed factors hold is important, since there is very little company level information available, with only 10% of the listed companies reporting on their emissions (Faisal et al., 2018).

For the Philippines it is concluded that carbon intensity is the most significant cumulative contributor for the total industrial activities of the country. Switching to less carbon intense (per total primary energy supply) production means for the industrial sector presents a desired potential for reducing carbon emissions, a valid observation for the iron and steel industrial sub sector. Increasing labour productivity by introducing automated means of production, requiring increased energy input would result in emissions growth due to the high levels of carbon intensity of the fuel mix. However, there is capacity for increasing LP, for the sectors of machinery, textiles and leather, paper pulp and print. A reduction of industrial scale would benefit policy makers in shaping emission standard targets, especially in the light of the Paris Agreement INDCs of the country (Republic of the Philippines, 2015; United Nations, 2015). Energy intensity contributes to CO_2 increases in the chemical and petrochemical sector, showing the country lagging in energy efficient production means for generating economic output.

Future research on this topic should perform a spatial decomposition analysis based on the findings of this chapter, using a methodological approach as discussed by Ang et al. (2015b) including an increased number of countries of the ASEAN group. This approach can include either an index or an additive performance comparison examining the drivers' relative contributions in CO_2 emissions change.

Examining the capacity that India and the SE Asian countries have for altering industrial CO_2 emissions requires a disaggregation of the active fuel mix throughout the studied timeline. Understanding fuel mix diversity and concentration offers the insight required for highlighting the capacity for sustainable production and economic growth while complying with environmental targets.

6. Industrial Fuel Mix Concentration & Diversity

6.1 Introduction

Countries of the SE Asia region have been experiencing high levels of economic growth for the past decade (International Monetary Fund, 2019). That economic development has consistently been coupled with higher energy demand (Azam et al., 2015) and is expected to be strengthened further in the mid-term future (Silberglitt and Kimmel, 2015). India and China present a strong bi-directional causality between coal consumption and economic growth (Bildirici and Bakirtas, 2014) while Thailand, Indonesia and the Philippines are also confirmed to have their growth linked to energy demand (Apergis and Tang, 2013). The energy requirements of those countries, present an increase of approximately 60% over a 15 year period starting at 2003 to 2017 (IEA, 2017a).

The level of economic growth that the selected five countries experience, highlights an urgency for solidifying access to a diverse set of energy resources. This is achievable through the deployment of resource seeking investment such as in the case of China (Alon et al., 2014; Zweig and Jianhai, 2005) , or investment in domestic resources to satisfy the intra-country energy requirements (K Lahiri-Dutt, 2016), more common in the case of India. Consequently, energy security is becoming an increasingly challenging issue, acting as the means for achieving sustainable economic growth (Kumar, 2016), which as a direct result, can limit economic vulnerability (Sovacool and Mukherjee, 2011). China, India and SE Asian countries examined in this study (Indonesia, the Philippines and Thailand), establish economic growth expectations on manufacturing output; a sector with high energy requirement levels (ESMAP, 2011; Pappas et al., 2018; Tian et al., 2017). Their coupling of economic growth and energy demand essentially projects an urgency for using a diverse set of energy resources to sustain further development. Achieving fuel mix diversity, is pointing towards an uninterrupted and efficient energy supply for sustaining that projected economic growth.

Examining the level of economic growth of these economies over the years, China and India are under the spotlight due to the size of their economies in a global scale, but all of the countries examined in this chapter present high growth rates that exceed those observed in developed economies (OECD Development Centre, 2015). As this is reflected in the national GDPs (**Figure 6.1**), China is leading with an average rate of 11.36% during 1980-2014, surpassed by India from 2016 onwards. Thailand presents an average growth of 7.9% with

Indonesia at 7.87%, India at 7.44% and the Philippines at 6.6%. When that economic output is adjusted as GDP per capita China had the lowest output at $282 in 1982 advancing to $6329 for 2012 (**Figures 6.2-6.5**) leading between the selected countries group. India, while having the highest annual GDP growth in the end of the examined period produces the lowest GDP per capita rate (**Figure 6.5**) at $1482 in current prices (2012), however, surpassing the GDP per capita poverty line (World Bank, 2016). The share that total investment holds as part of the GDP acts as a key element for the per capita economic growth (Blomstrom et al., 2006). This share is deemed as significant for all the examined countries (**Figures 6.11-6.15**). China holds an investment contribution that accounts at 20% at the lower end between annual periods when discussing the last decade examined, ranging up to approximately 45% in the latest year examined in that approach; 2016. Starting in 2015 and up to mid-2016, the Chinese GDP growth experienced an extended slowdown (Riley and Yan, 2015), due to the Chinese stock market exchange crisis (Duggan, 2015). The Shanghai Composite Index has eventually lost half of its value in a year. Subsequent spill-over effects were realised for all the neighbouring or major economies of that region (Denyer, 2015) and the countries examined in this chapter (**Figure 6.1**).

The high level of investment that the assessed countries have, as contribution to their GDP, is greatly reflected on the total industrial economic output growth during 1980-2012. China presents an unparalleled 58-fold increase with Indonesia following at a 21-fold, while Thailand and India increased their manufacturing output value by approximately 12-fold and the Philippines by 5-fold (**Figures 6.6-6.9**). Comparing the total industrial output as an index metric with 2010 acting as a base year (**Figure 6.10**), it becomes evident that all countries present an output increase, both in relation to the preceding years, or, take steps in retaining that industrial output; for the case of Thailand. This approach brings in light the importance that the industrial sector holds for the five countries examined. It underlines an existing significance for measuring its historic actions towards establishing a sustainable energy supply.

As the SE Asian economies have been growing by an annual average of 5.8% during 1990-2010 and expect a further increase in growth by 6.4% on average between 2011 to 2030 (ADBI, 2014) it is important to examine their energy diversity level between different indices, as those have been established in the international literature, with the purpose of determining capacities, highlighting any specific requirements set for improvement in the examined sectors.

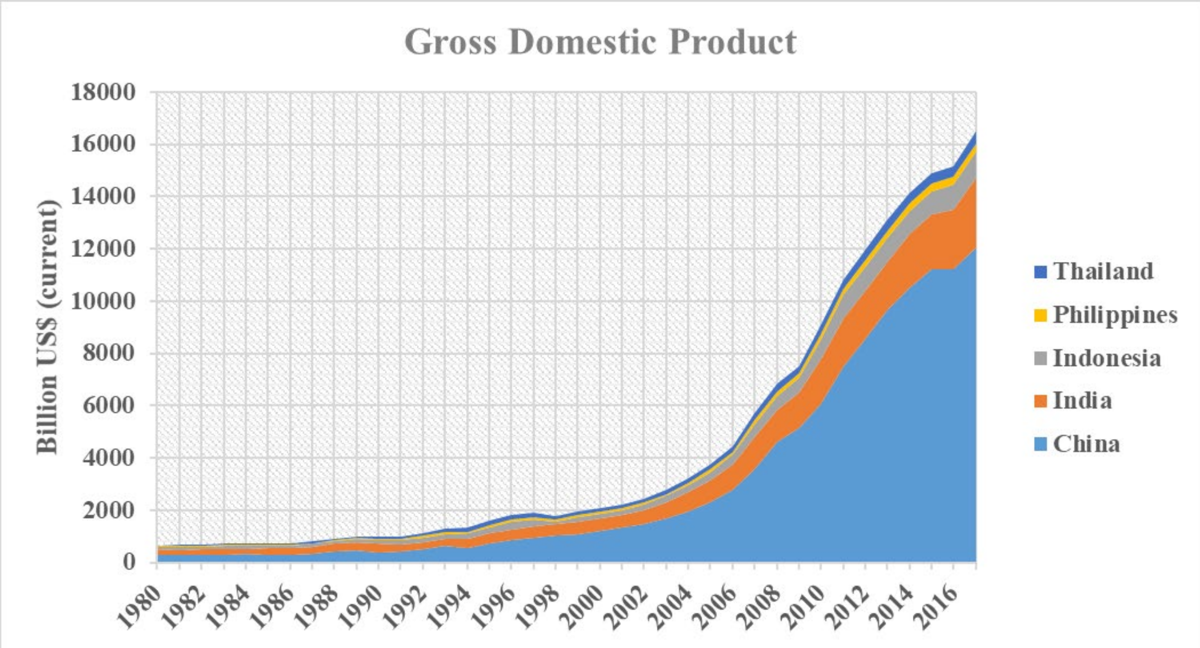


Figure 6.1 GDP and GDP comparison between China, India, Indonesia, the Philippines and Thailand for 1980-2017. Source: (International Monetary Fund, 2019)

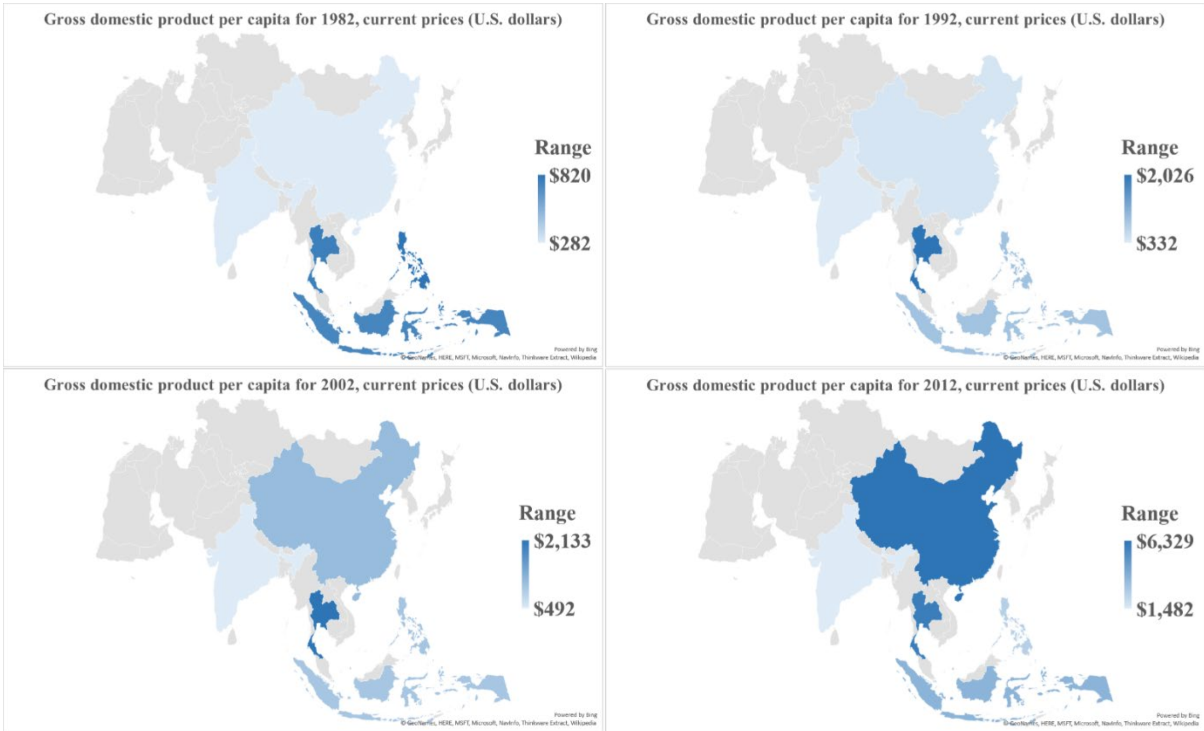


Figure 6.2-6.5 GDP per capita map comparison of India, China, Indonesia, The Philippines and Thailand per ten-year periods covering 1982-2012. Source: (International Monetary Fund, 2019)

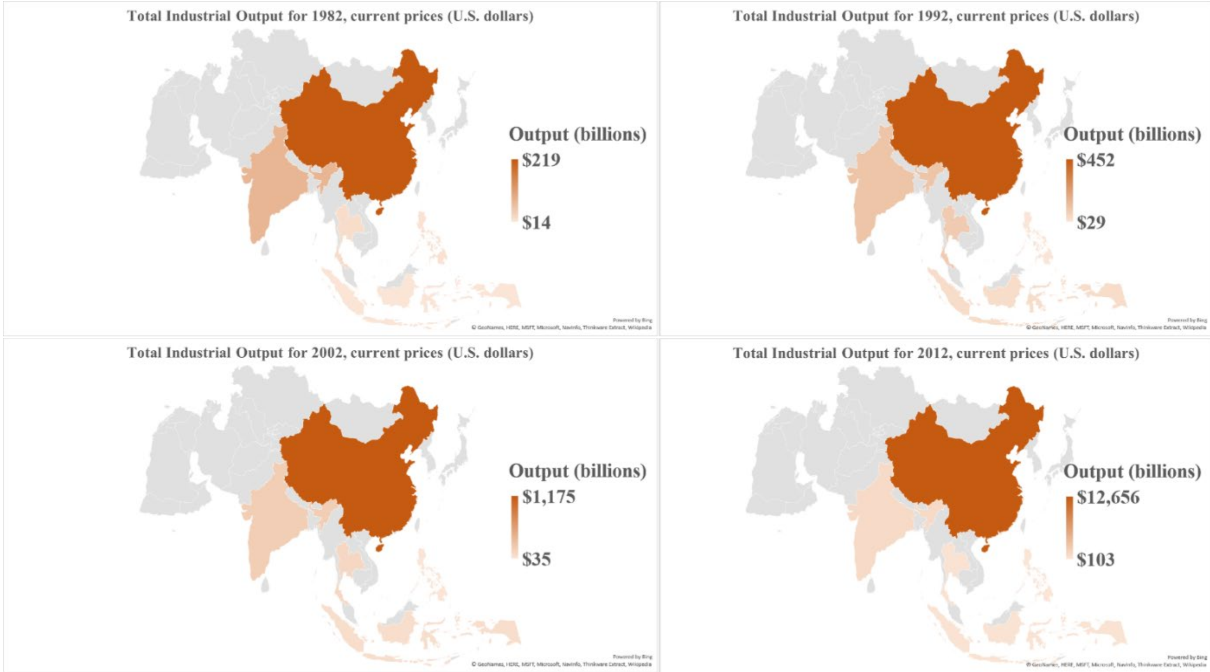


Figure 6.6-6.9 Industrial output in billion US$ (current prices) comparison of India, China, Indonesia, The Philippines and Thailand per ten-year periods covering 1982-2012. Source: (UNIDO, 2016)

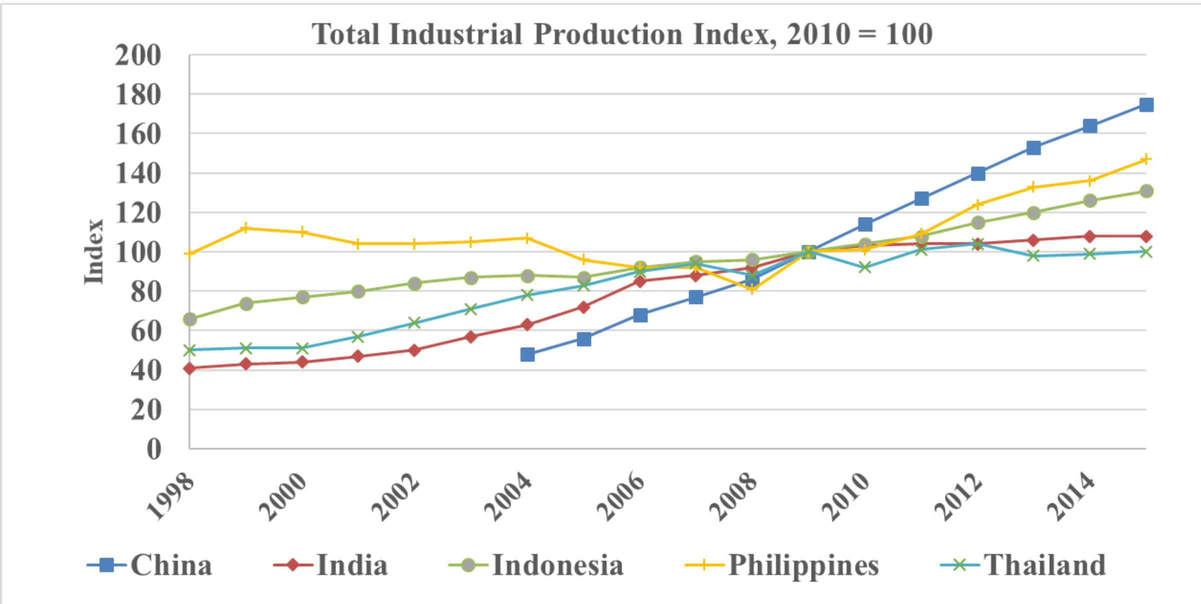


Figure 6.10 Total Industrial output index comparison of India, China, Indonesia, The Philippines and Thailand 1998-2015.

Figure 6.11-6.15 GDP and investment share of GDP for China, India, Indonesia, The Philippines and Thailand, 1980-2017. Source: (International Monetary Fund, 2019)

6.2 Research Background – Building Hypotheses

Focusing on previous research on energy security in a Asian regional context, Hippel et al (2011) defined a relationship between energy security and sustainability for NE Asia, providing a broader conceptual definition that covers data requirements that include sectoral fuel supply as a metric prerequisite. Sovacool (2013) used IEA and EIA examined twenty indicators that relate to economic, political, social and environmental parameters, for determining the energy security of eighteen Asian countries on a total consumption level, from 1990 to 2010. Among the countries studied in this chapter, Indonesia, China and the Philippines presented marginal improvement, while India and Thailand presented marginal decrease. Martchamadol and Kumar (2012) have used IEA data for calculating SWI (Shannon-Wiener Index – see details in Chapter 2 Methodology). Accounting the fuel mix diversity between coal, oil, NG, hydro, nuclear and renewable energy, among other assessment indicators, they determined the energy security trends for Thailand between 1986-2009 by published results, performing an additional forecast up to 2030. Tongsopit et al. (2016) analysed energy availability to determine the energy security of countries that belong in the ASEAN group while Yao and Chang (2014) performed similar research in regard to China and Narula et al. (2017) used the same quantification metrics for India.

In a similar assessment approach, the international literature has examined India (Garg et al., 2017; Gunatilake et al., 2014; Sharma, 2007), China (Wu, 2014; Xia et al., 2011), Indonesia (Kumar, 2016; Resosudarmo et al., 2012), the Philippines (Brahim, 2014) and Thailand (Selvakkumaran and Limmeechokchai, 2013) to determine energy security in regard to energy availability and the use of fossil fuels, by integrating numerous indicators. However, a detailed focus on industry as an aggregate or sectoral level using fuel diversity and concentration metrics, presents an identified gap in the literature (Kanchana and Unesaki, 2014) that this research aims to cover.

According to Ang et al. (2015a) energy security can be determined through the exploration of energy availability, as a major identified theme. While a commonly accepted definition for energy security as a concept does not exist (Checchi et al., 2009; Chester, 2010, 2009; Löschel et al., 2010), it is a main benchmark for evaluating energy policies (Chalvatzis and Ioannidis, 2017). Assessing the diversification of energy supply sources is identified as an energy security measurement indicator by major studies (Gadonneix et al., 2013; The World Economic Forum, 2015). Balancing the energy supply by using an increased number of fuel sources available for consumption, also referred in the present study as options, does offer further enhancement to energy mix diversity.

Focusing further on scope and providing an aligned approach of this research towards the existing international literature, Dorian et al. (2006), clarified the concept of energy security as the provision of reliable energy supply to support industrial and economic activity; a dimension which is central to energy security (UNDP, 2011). The aim of this chapter is to evaluate energy security of the total (aggregate) and individual industrial sectors of the five countries examined, by determining the number and balance of options used by the industry; identifying concentration (HHI) and diversity (SWI). This practice falls in line with the guidelines set by Grubb et al (2006) and Sovacool (2011). Grubb et al proposed the HHI for examining the shares of fuel in total primary energy supply as an assessment index for determining energy security, while Sovacool has examined the case of diversification of energy suppliers acting specifically as a metric of Asian energy security. Regarding the choice of data interpretation through the parallel use of HHI and SWI, Chalvatzis and Rubel (2015) claim that this practice supports the discount of diversity uncertainties with the separate index results present consistency through their opposite nature (**Figures 2.4.1-2.4.2**).

The fuel mix used in the industries of India, China, Indonesia, Thailand and the Philippines will be analysed for the period of 1980 to 2012, by using appropriate methodological approach as described in **Section 2.4**. As previously mentioned, it will be measured against HHI and SWI indices, confirming or rejecting the research hypotheses that are described below:

- Concentration (**H1a**) and diversity (**H1b**) indices in the total and specific industrial sectors of India have improved over the years 1980 to 2012 for all fuel options and those that exceed a contribution of 5% in the fuel mix (**H1c**).
- Concentration (**H2a**) and diversity (**H2b**) indices in the total and specific industrial sectors of China have improved over the years 1980 to 2012 for all fuel options and those that exceed a contribution of 5% in the fuel mix (**H2c**).
- Concentration (**H3a**) and diversity (**H3b**) indices in the total and specific industrial sectors of Indonesia have improved over the years 1980 to 2012 for all fuel options and those that exceed a contribution of 5% in the fuel mix (H3c).
- Concentration (**H4a**) and diversity (**H4b**) indices in the total and specific industrial sectors of the Philippines have improved over the years 1980 to 2012 for all fuel options and those that exceed a contribution of 5% in the fuel mix (**H4c**).
- Concentration (**H5a**) and diversity (**H5b**) indices in the total and specific industrial sectors of Thailand have improved over the years 1980 to 2012 for all fuel options and those that exceed a contribution of 5% in the fuel mix (**H5c**).

For the purpose of this research, a detailed study is performed to reach conclusions regarding each industrial sector. However, each of the hypotheses described, H1 to H5, will be confirmed in the event of all results from each industrial sector concur; improvement of HHI or SWI between 1980 and 2012.

6.3 Conceptual Framework

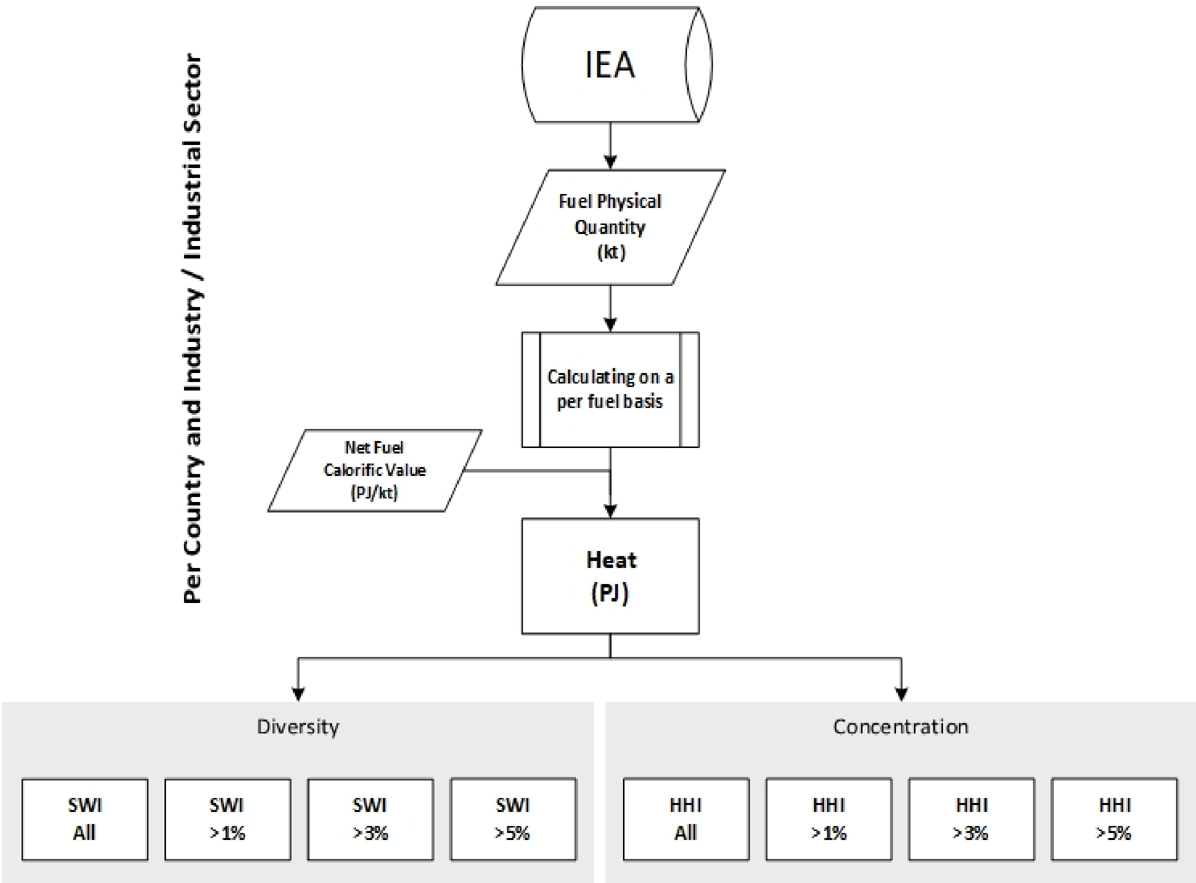


Figure 6.16. Concentration (HHI) and Diversity (SWI) calculation process for the selected country examined.

The methodology as discussed in **section 2.4** follows the conceptual framework as this is expressed in **Figure 6.16** above. Each fuel is converted to heat; expressed in petajoules, prior to its evaluation of share (%) in the fuel mix. This conceptual framework follows the calculation concept for the total industry and the ten selected industrial sectors of each examined country. The research results are presented in the following **section 6.4**. The total industry acts as the aggregate of the industrial sectors, considering the IEA database as a complete demonstrator of industrial activity. The activity levels are extracted from the IEA published results regarding final fuel consumption and match the activity levels of energy domestic supply, as presented in **formula a.5** of the methodology followed in **section 2.1**. HHI and SWI present sensitivity to the number of energy supply options used in the fuel mix. An expanded number of options with small contribution can present a disproportionate diversity or concentration improvement, distorting the results. To mitigate a distorted image of the fuel mix diversity and concentration, figures are plotted for HHI and SWI with options that contribute more than 1%, 3% and 5%

following the methodological pattern found in the relevant literature (Chalvatzis and Ioannidis, 2017), highlighting the issue where this exists. The respective figures are extracted, following the final step found in the conceptual framework.

6.4 Results

Approaching the results four figures will be produced for each of the concentration (HHI) and diversity (SWI) indices of the fuel mix. The figures include findings for India, China, Indonesia, Thailand and the Philippines, pointing out any limitations in available data, a phenomenon common for SE Asian countries (Sharifuddin, 2014). In categories that India does not produce results, the results are included in the non-specified industries category, due to the established primary data reporting approach to IEA. Each of the four figures of HHI and SWI is plotted against the contribution of the fuels used in the energy mix; the options. Those are all options, options that exceed 1%, 3% and 5% as a contribution heat share of the total. The options of >1% and >3% are presented in order to provide further clarification to the reader, further distinguishing the contribution of energy sources in the national energy mix. For that reason, those two options will only be discussed briefly, and will not be included in the results discussion, as further detail would inhibit the extracted results with unnecessary noise.

The industrial sectors examined follow the classification set by IEA and apart from the total, are the following: Iron & Steel; Chemical & Petrochemical; Non-Metallic Minerals; Machinery; Food & Tobacco; Wood & Wood products; Paper Pulp & Print; Textile & Leather; Mining; and Non-specified industries. The concentration and diversity results are estimated as a timeline, starting from the year 1980 up to 2012. A reciprocal performance is empirically expected between HHI and SWI.

6.3.1 Total Industry

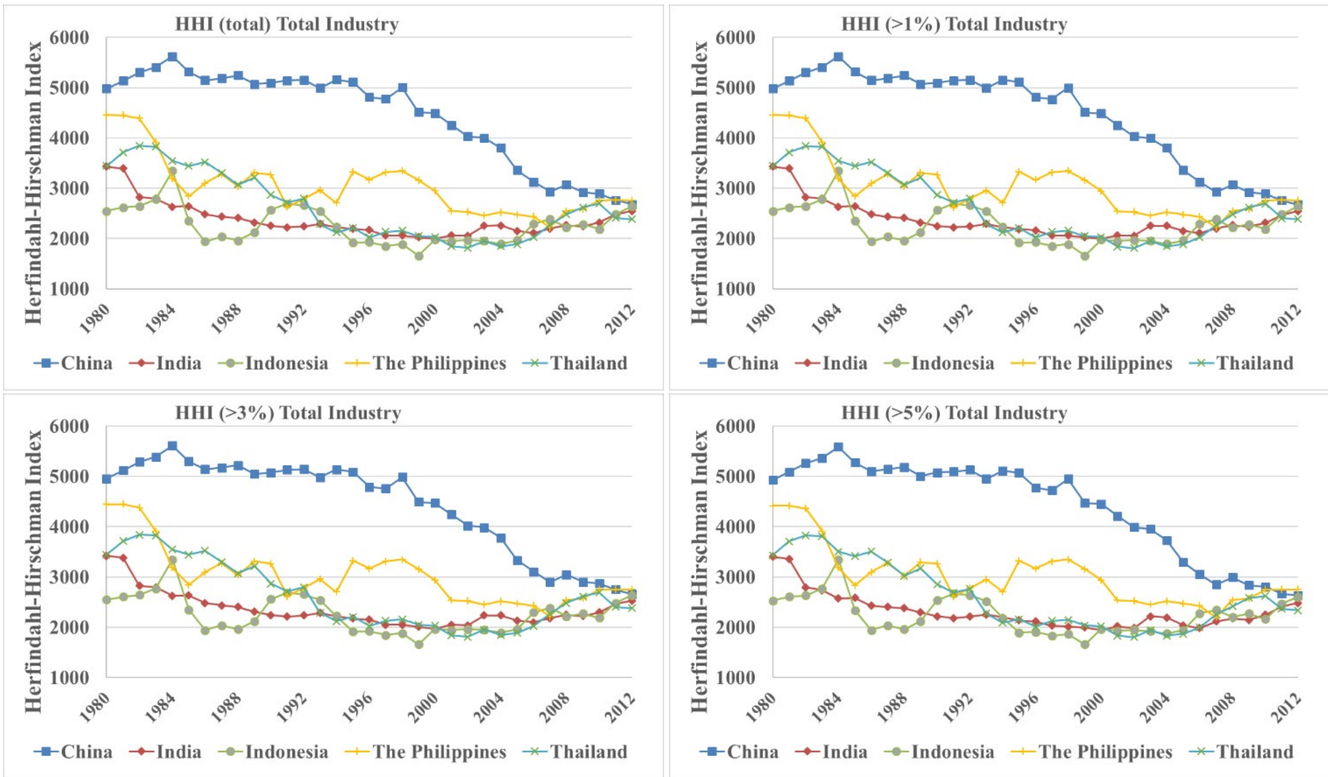


Figure 6.17-6.20 Total industry fuel mix concentration measured with HHI for the 1980-2012 timeline

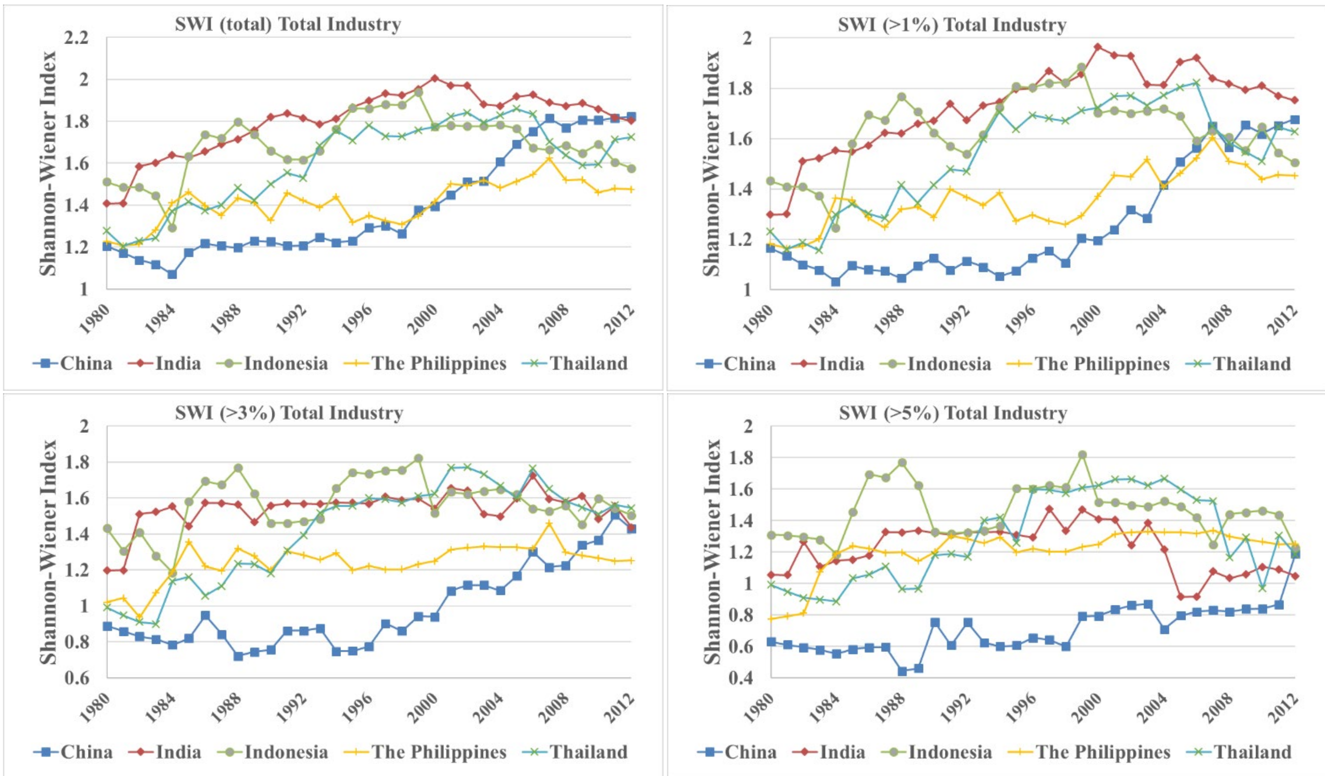


Figure 6.21-6.24 Total industry fuel mix diversity measured with SWI for the 1980-2012 timeline

Evaluating HHI for the total industry (**Figure 6.17-6.20**) it is evident that India presents the lowest concentration on average when all options are accounted for (**HHI=2365**). Its improvement over the 1980-2012 timeline accounts to 25.62% for all accounted options, but that improvement does present a reversed concentration trend during 2000-2012 with an 27.77% concentration. India presents a declining concentration (HHI) when the additional options scenarios are examined. China, the economy with the largest GDP growth and industrial output over the same period (**Figure 6.1-6.15**) vastly reduced its fuel mix concentration over 2000 to 2012 by 46.21%. This figure is improved to 46.55% when the options are limited to those contributing more than 5%, highlighting the consumption from its respective fuel mix of 4 options (>5%) is weighted towards a more equal share in the fuel mix. Examining the concentration trend in all options scenario, the country showcases huge leaps in lowering its fuel mix concentration (Ouyang and Lin, 2015), introducing 7 additional options in the fuel mix, two of them at a share higher than 5%. Indonesia presents an HHI increase of 3.67% between 1980 and 2012, but its HHI has increased from 2000 up to the final year at a rate of 33.52%. This increase is attributed to the aggressive introduction of natural gas in the fuel mix. However, Indonesia has a lower concentration level (**HHI=2642**) than China (**HHI=2677**) and the Philippines (**HHI=2760**) for 2012. Thailand has the lowest concentration of the examined countries with a decrease of 30.74% that expands to 31.88% when fuels that contribute more than 5% of the total are considered.

Measuring diversity using SWI (**Figure 6.21-6.24**), China produces mixed results. The country uses a diverse fuel mix from 2005 onwards with the highest diversity found in the final year, when all options are included. This output is gradually reversed when options with small contribution are eliminated. China in the >5% scenario has a non-diverse fuel mix for the duration of the timeline; it is the worst performing country across the range but 2012, due to a higher consumption of natural gas and other oil products that surpass the selected methodological threshold. Chinese industries use a sum of 10 options to satisfy their energy supply requirements; 5 of those exceed 5% of the total at the final year, rising from 3 options previously used. Similar is the case with India; the country presents an increased mix of primary energy supply options, with a high improvement of 28.03% in total, but at the >5% scenario this trend does not exist. The country is the worst performer at the final year and does not show any significant diversity change over time when only highly contributing options are considered. It is measured at 0.63% for the timeline sum, highlighting the ratio of underdeveloped or secondary options and its heavy reliance on other bituminous coal for satisfying its energy requirements; measured at 43.73%, highlights the result significance. India has not introduced additional fuel options that exceed 5% when looking specifically at the start and end years, 1980 to 2012, as it has only replaced fuel options for using others. Blast furnace gas in exchange to natural gas and petroleum products, replacing fuel oil.

Thailand presents a diversity increase of 34.96% for all options, 55.79% for those that exceed <3% but limited to 19.6% for those exceeding 5%. The country presents decreasing diversity, pronounced at the 2000-2012 period for options that exceed 5% due to limiting the contribution of fuel oil and gas/diesel oil in the industrial fuel mix. The Philippines present a reversed trend. Diversity has improved by 20.19% for all options and 61.65% for >5% options. There is an increased and approximately equal contribution between primary solid biofuels and coal, at 33.85% and 36.03% respectively, and oil products. Indonesia presents a growing diversity trend for all options (4.21%) for the total examined period. However, this trend is reversed for <5% options with as a diversity decrease by 6.24% accelerated at 19.10% rate for 2000-2012.

6.3.2 Iron & Steel Industry

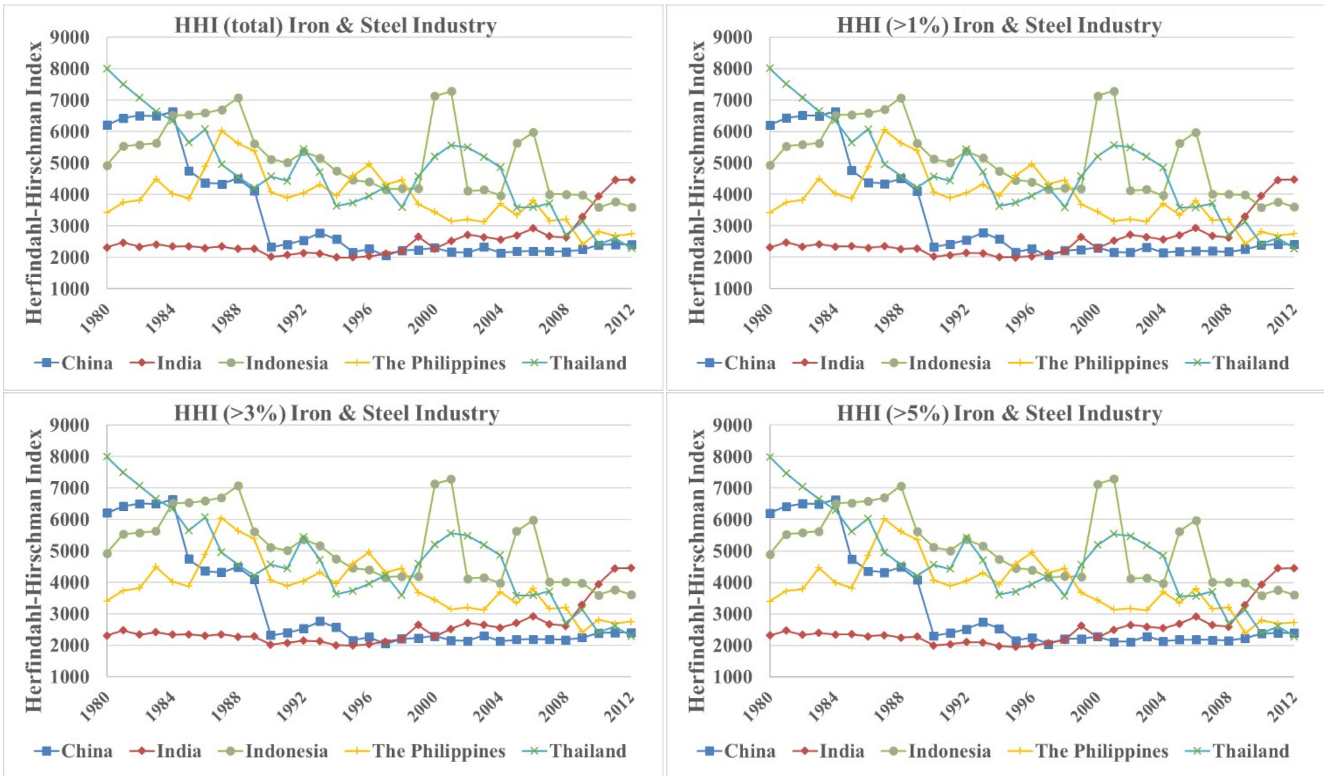


Figure 6.25-6.28 Iron and Steel industrial fuel mix concentration measured with HHI for the 1980-2012 timeline

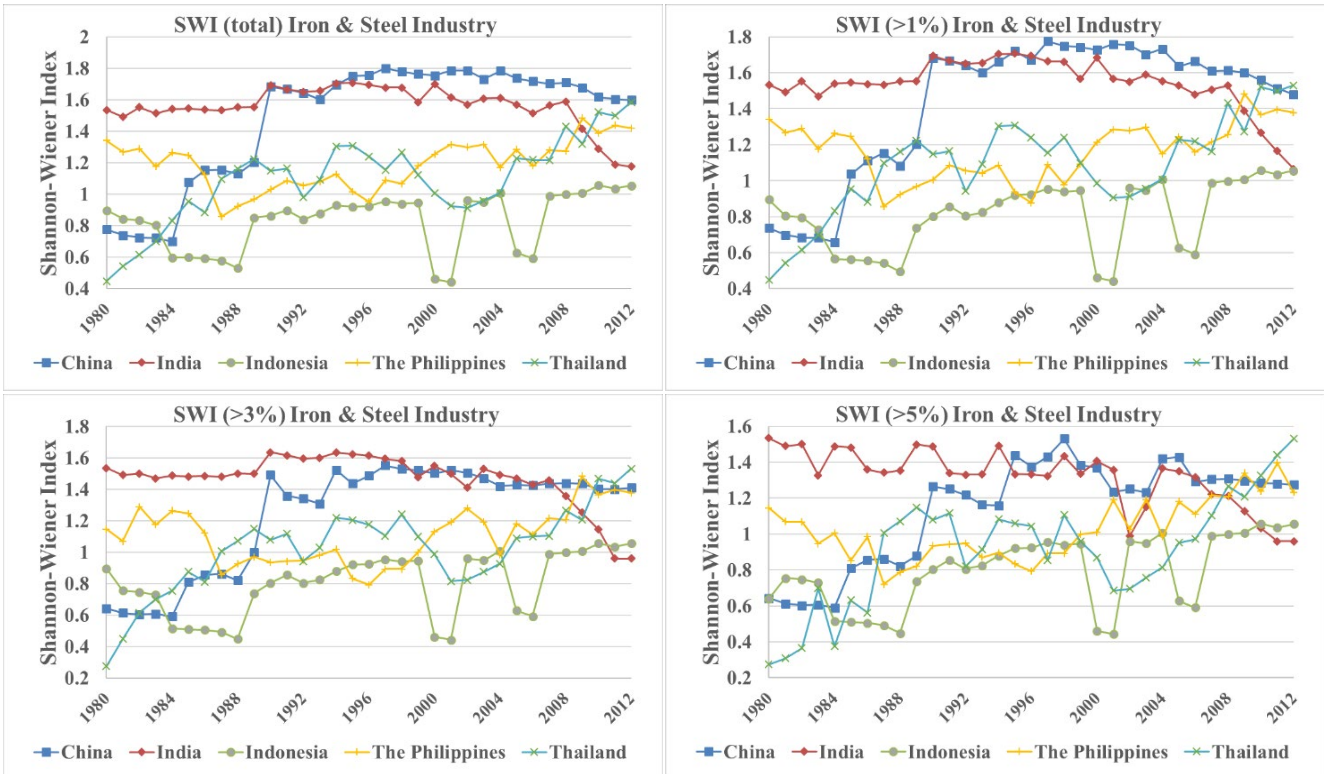


Figure 6.29-6.32 Iron and Steel industrial fuel mix diversity measured with SWI for the 1980-2012 timeline

The fuel mix concentration of the Iron & Steel industry follows reverse trends between India and China for all the examined option scenarios (**Figure 6.25-6.28**). India presents low concentration in comparison to the other four countries, with an increased concentration trend starting in 1999 and spiking in 2009 to 2012. Overall, HHI presents a growth trend, between 1980-2012, of approximately 93% for the all options scenario. This HHI increase is mainly attributed to the contribution of other bituminous coal in the industrial fuel mix, increasing from 13.01% in 1980 to a share of 63.86% in 2012. Reversing that contribution in the fuel mix, China presents a concentration decrease of the fuel mix between 1980-2012 of 61.15% for all options and 61.48% for options that contribute more than 5%. Other bituminous coal was the main industrial fuel in 1980 (77.58%) reduced to just 27.92% in 2012. As a result, China is the second-best performing country in HHI, as the fuel mix concentration (**HHI=2413**) is only surpassed by Thailand (**HHI=2284**). Thailand and China present the highest concentrations in 1980, with the former achieving a reduction of 71.47% during 1980-2012 due to its reduction of fuel oil which was the dominant fuel powering the sector from 1980-2004 and the introduction of natural gas between 2005-2012.

Indonesia and the Philippines have presented a reduction in their concentration indices for 1980-2012. The former presents a reduction of 26.88% for all option scenarios but >5% (-26.39%) and the latter has an average HHI reduction of 19.84% for the >5% option scenario. Indonesia is supplying its industry with only three fuel options from 1995 onwards. It achieves a lower concentration than India due to its fuel mix balance, 36.02% for fuel oil, 20.57% for gas/diesel oil and 43.41% for natural gas. However, Indonesia in years 2000-2001 and 2005-2006 presents concentration spikes as a result of the country reporting null figures natural gas, its main industry fuel.

The diversification of the Chinese fuel energy mix is reflected on the SWI (**Figure 6.29-6.32**) where an increase of 106.01% has occurred during 1980-2012 from **SWI=0.78** to approximately **SWI=1.6**. However, this growing trend has mostly occurred in a timeframe of ten years; 1980-1990, where China introduced 5 more fuels in the energy mix with a share higher than 1%. Comparing all options to those that exceed >3% and higher, shows that India becomes the least diversified country, placed lower than Indonesia, even though it has increased its fuel consumption by 3-fold during the examined timeline. India has six options that do not contribute more than 5% to the fuel mix during the latest year examined; 2012. In comparison, the country with the most diversified fuel mix, in the final year, including all options (**SWI=1.584**) is Thailand 7 fuel products. Five of them have a share greater than 5%. Thailand presents a vast improvement in its fuel mix diversification, with an increase of

254.37% during 1980-2012 for all options or a 457.08% for options >5%, the highest in comparison to all other countries.

6.3.3 Chemical & Petrochemical Industry

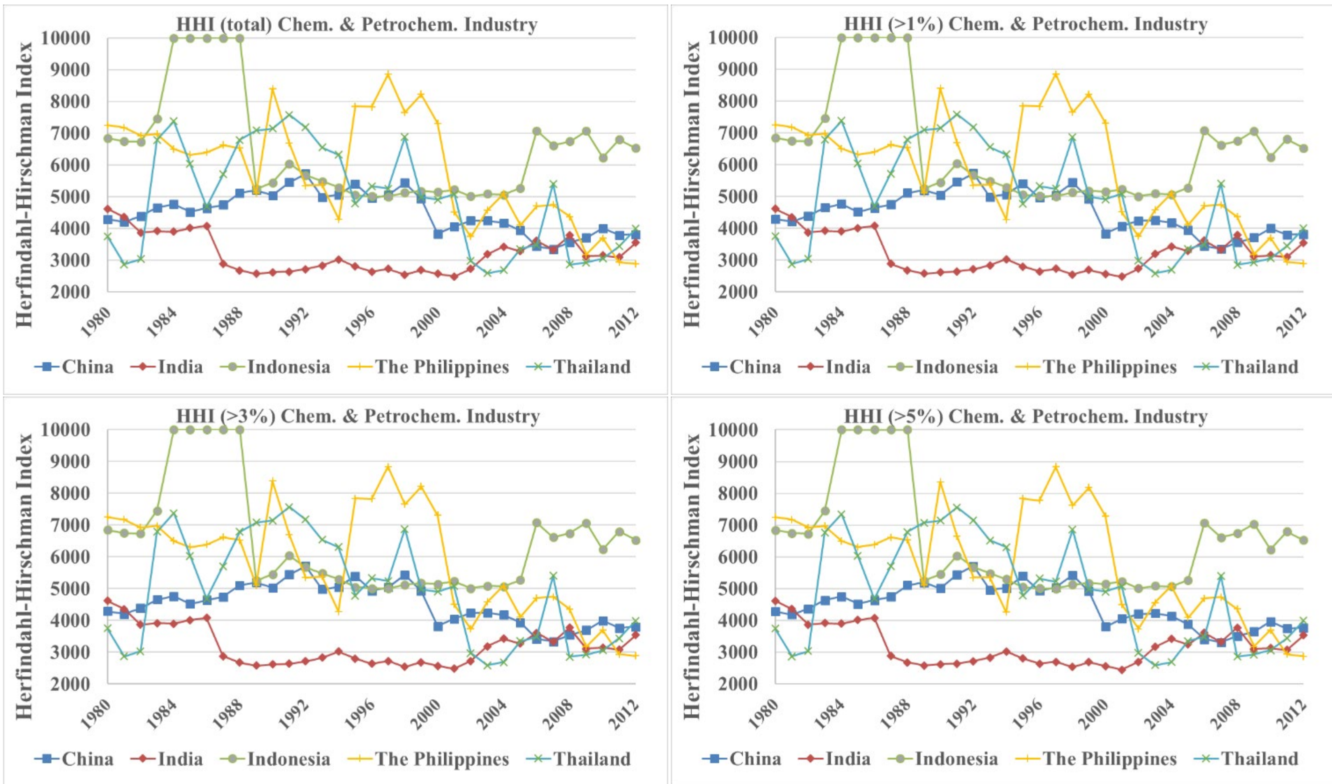


Figure 6.33-6.36 Chemical and Petrochemical fuel mix concentration measured with HHI for the 1980-2012 timeline

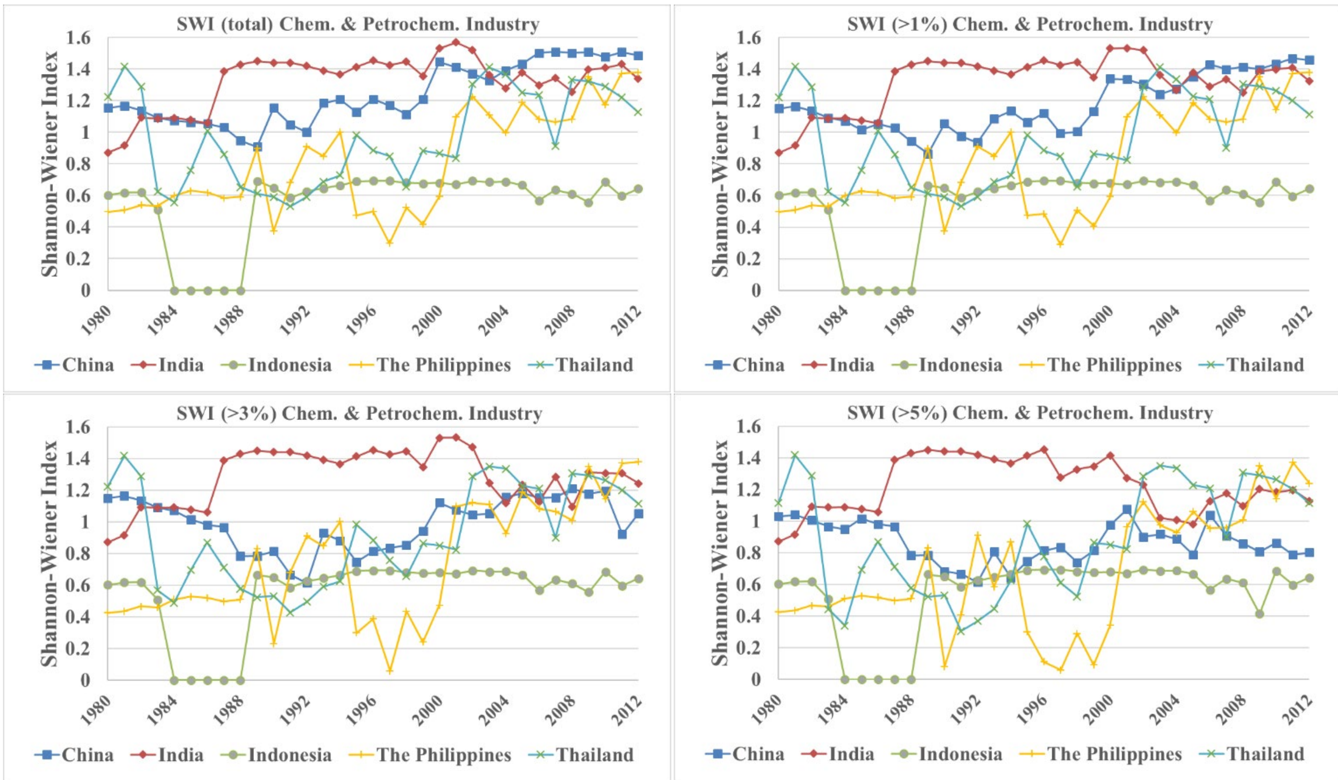


Figure 6.37-6.40 Chemical and Petrochemical industrial fuel mix diversity measured with SWI for the 1980-2012 timeline

Looking the Chemical & Petrochemical industry indices, Indonesia presents the highest concentration in the most recent years. From 1984 to 1988, the country relied on one fuel option, Gas/diesel oil reflected in both HHI and SWI indices (**HHI=10000, SWI=0**). The introduction of additional fuel options resulted, as expected, to concentration decrease and diversity increase. The introduction of Natural Gas from 2006 onwards, replaced oil as major fuel in the energy mix with an average share of 80%. This is reflected as a deterioration of the concentration (**Figures 6.33-6.36**) and diversity indices alike (**Figure 6.37-6.40**).

Looking at all options in the diversity index, China is the best performer from 2006 to 2012. The country introduced a plethora of fuel options, however excluding options that contribute less than 3% and 5% presents the country as the second worst performer following Indonesia. China has 13 fuel options from 2004 to 2012, but this number is limited to a maximum of four for options that exceed 5%. Other bituminous coal holds a major share in the energy mix with 59.23% in the last year examined, highlighting the high concentration for the 5% option scenario (**Figure 6.36**). India presents a well-balanced fuel mix; out of the 7 options used in its energy mix from 2007 to 2012, 5 contribute more than 3% and 4 contribute more than 5%. As a result, the country performs well alongside the Philippines and Thailand, with 23.11%

improvement in concentration for 1980-2012 and 53.74% in diversity when assessing all options.

Thailand presents a mixed output regarding HHI and SWI results of the total timeline. While HHI is increasing for 1980-2012 at 6.39%, the SWI presents a decrease of 7.83% for the same period. This improvement of SWI is nullified for options that contribute more than 5% in the fuel mix, as the improvement becomes insignificant at 0.18%. HHI for the same options remains approximately stable at 6.66%. Thailand has effectively replaced Fuel Oil with Natural Gas and LPG as the main industrial fuel from 2002 onwards, enhancing its HHI performance. This fuel switch has not taken place in the Philippines. The country presents a low concentration / high diversity energy mix compared to the other four, with an improvement of 60.22% and 177.92% respectively, however, by using various oil products as a main fuel source.

6.3.4 Non-metallic minerals Industry

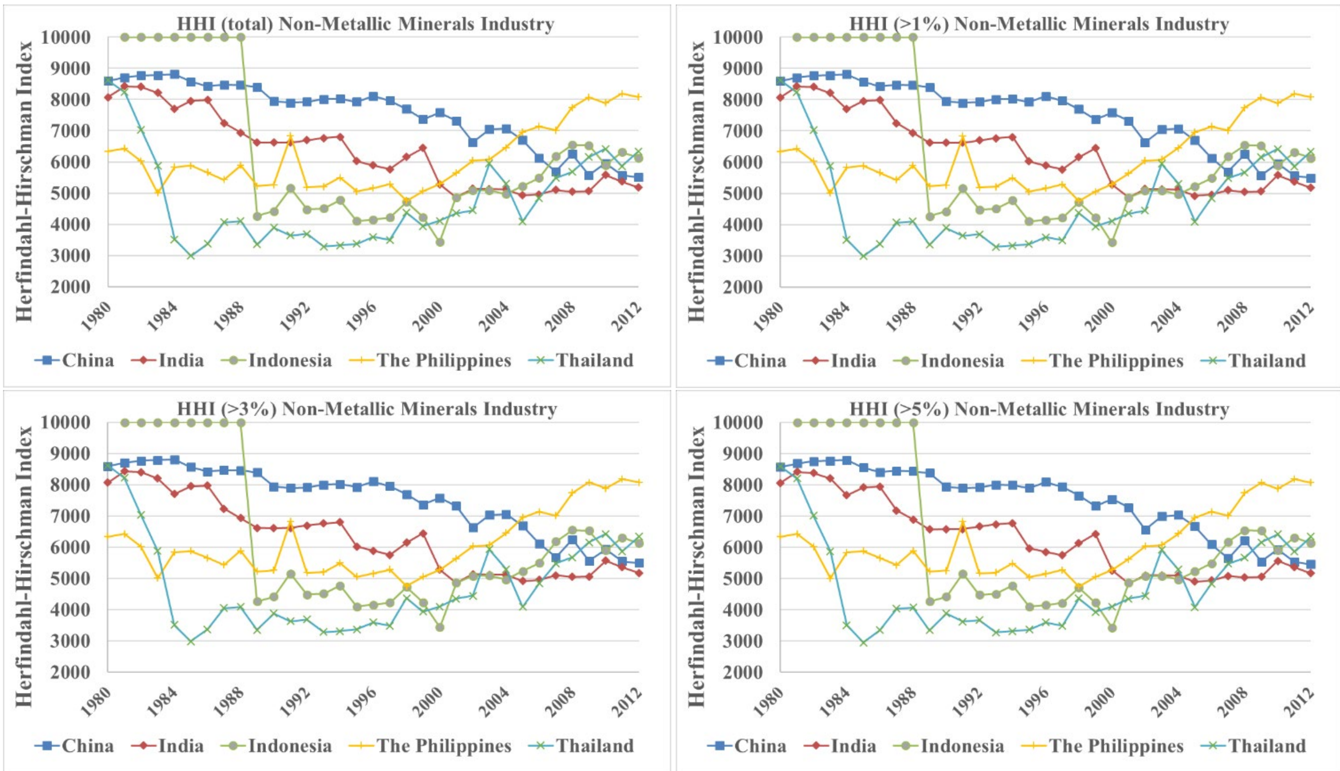


Figure 6.41-6.44 Non-metallic minerals industrial fuel mix concentration measured with HHI for the 1980-2012 timeline

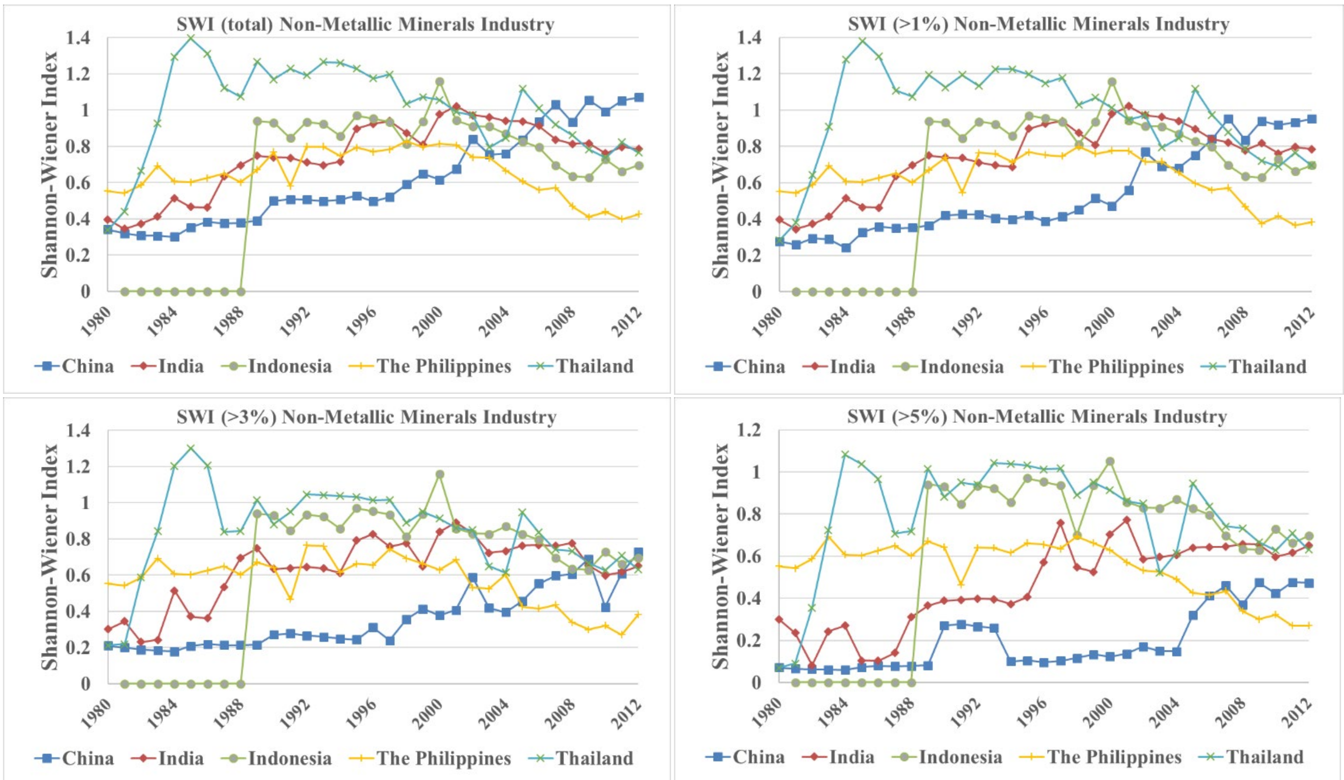


Figure 6.45-6.48 Non-metallic minerals industrial fuel mix diversity measured with SWI for the 1980-2012 timeline

In the Non-metallic Minerals industry, China presents a similar HHI and SWI trend, to that observed in the Chemical & Petrochemical industry (see previous section). China started as the second worst performer and had the second most diverse fuel mix from 2006 onwards when all the options are included. Excluding options that contribute less or equal to 5%, this trend is reversed, with China reverting to having one of the worst diversity indices between the compared countries only second to that of the Philippines. However, China presents an improved diversity with its SWI growth by 14.21% for all options and by 15.21% for >5% options (2006-2012) and satisfies the energy requirements of the Non-metallic Minerals industry with12 fuel options. This is reflected on the concentration index which was improved by 36.1% (1980-2012) on average for all option scenarios. This highlights the Chinese capacity for further improvement as its reliance on other bituminous coal is diminishing and undergoing a phase out process.

India is the country with the best performing concentration index for 2012 (**HHI=5179**), including all options, with no significant variation existing between the additional option scenarios (**HHI >5%=5173**). While India presents the lowest concentration, generally HHI presents a highly concentrated market in each of the examined countries. India has only 2 fuel options contributing higher than 5% in the fuel mix, other bituminous coal and petroleum coke. India's lower concentration (HHI) is the result of a balanced mix for each of those fuels, 64.1% and 32.63% respectively. Indonesia does not present any industrial activity in this sector, until 1988. From 1989 onwards, the country satisfied its energy requirements by using three fuel options in its energy mix, all exceeding 5%; fuel oil, gas/diesel oil and natural gas. From 2000 to 2012 as the available data suggest, Indonesia has undergone a process of gradually phasing out natural gas as a fuel source and additionally reduced the contribution of oil, effectively replacing them both with sub-bituminous coal. The share of sub-bituminous coal increased from 45.96% (1989) to 76.19% in 2012. That switch in fuel options was reflected in the concentration index, following an increasing path of 78.99% and a reduction of diversity by 33.83% when examining the higher than 5% option contribution scenario (**Figures 6.41-6.48**).

The Philippines present the highest concentration in every scenario assessed. The concentration during the examined timeline increased by 27.4% for all options and 27.22% for options higher than 5% of the total. These figures are the result of the country's energy supply over-reliance on sub-bituminous coal for up to 89.6% having phased out fuel oil between 1980-2012. Those two fuel options (sub-bituminous coal and fuel oil) are the only ones that present a contribution higher than 5% across the timeline. Other bituminous coal is the major fuel source in Thailand since its introduction in 1989, up to the final year where data have been available; 2012. This fuel option contributes 78.54% of the total, with 2 additional options contributing more than >5%, natural gas and lignite. Thailand presents an HHI decrease, during the examined timeline, by 26.28% and an increase in diversity of 126.29% when all fuel options are considered.

6.3.5 Machinery Industry

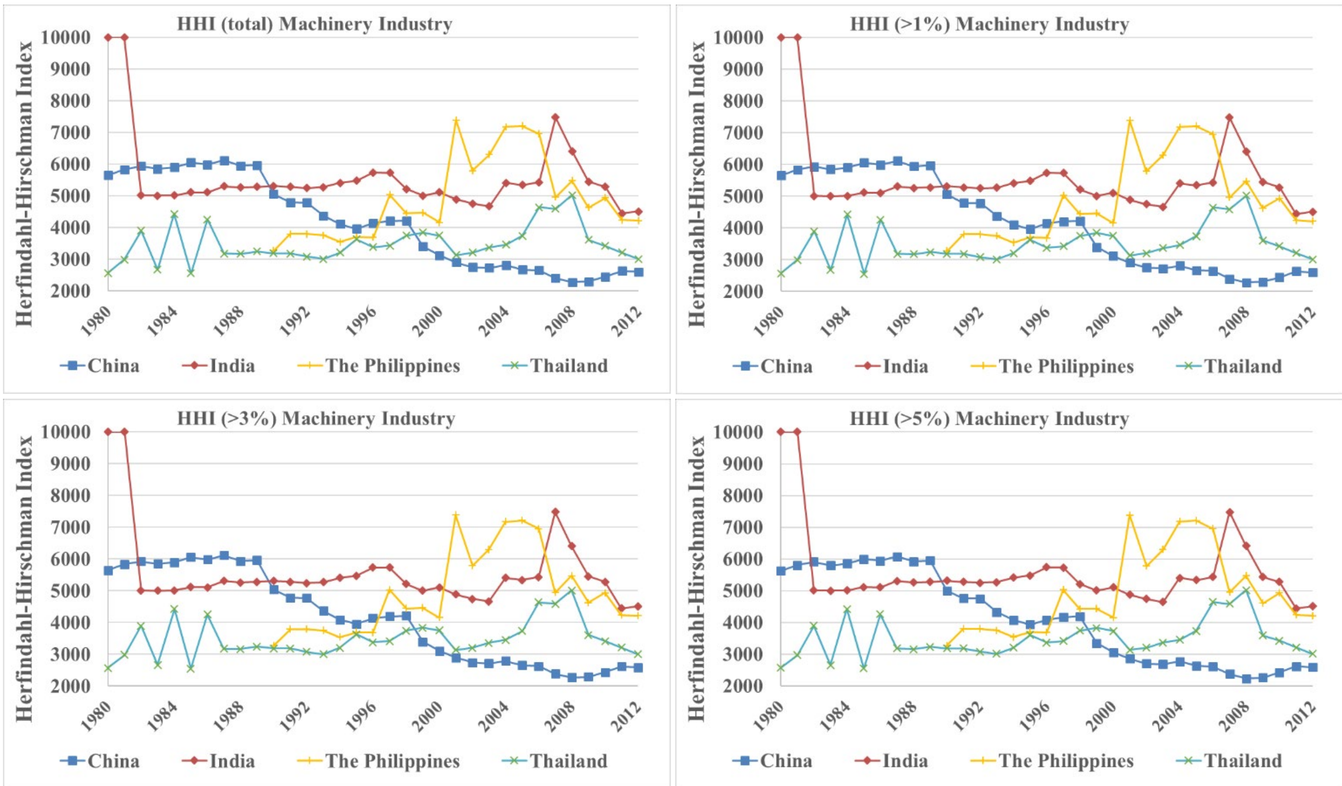


Figure 6.49-6.52 Machinery industrial fuel mix concentration measured with HHI for the 1980-2012 timeline.

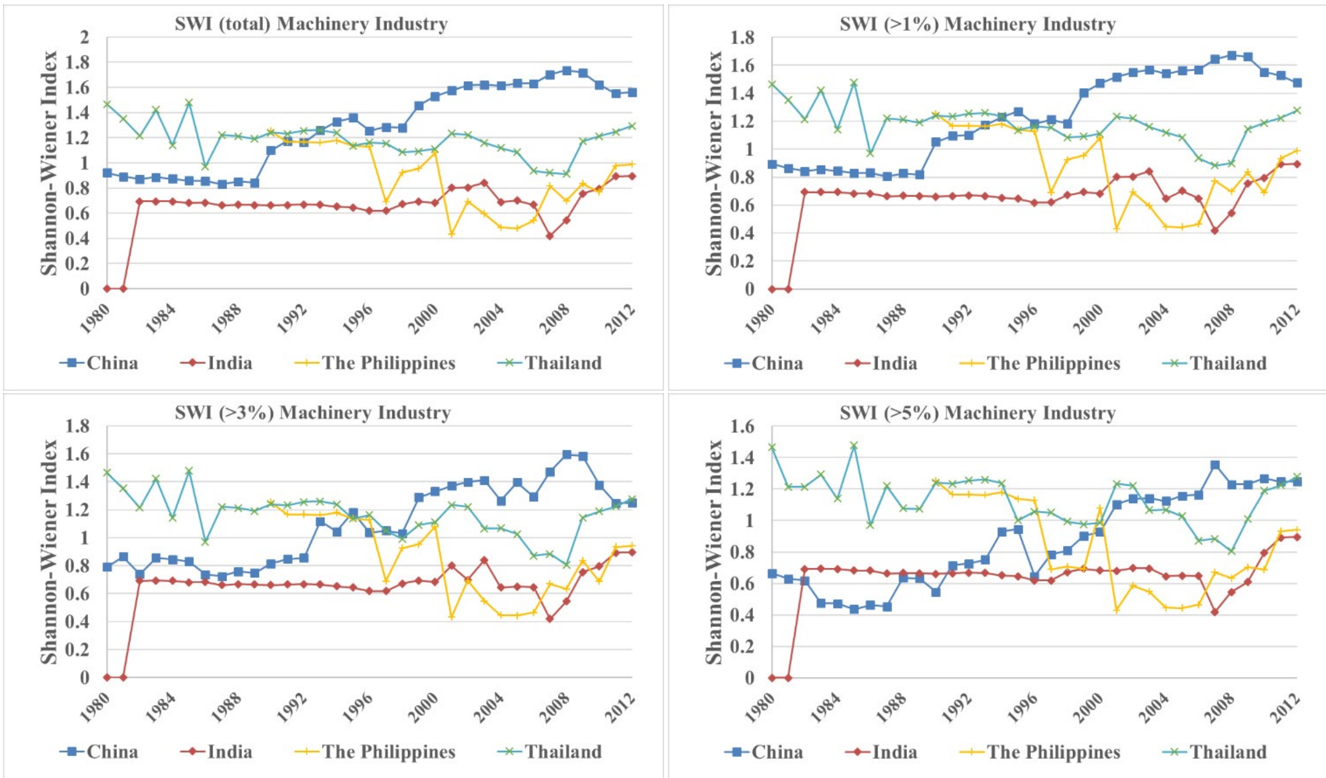


Figure 6.53-6.56 Machinery industrial fuel mix diversity measured with SWI for the 1980-2012 timeline

In the machinery industry, Indonesia does not present any activity until 1988. Since that point it uses one fuel option (gas/diesel oil) only. Therefore, the country is not included in the HHI and SWI metrics, as it presents the lowest concentration and highest diversity values across the range (**HHI=10000**, **SWI=0**), effectively limiting any further insights.

India's machinery industrial activity has only been fuel by fuel oil in 1980 and 1981. Two more options were introduced in the energy mix, gas/diesel oil in 1982 and LPG during 2001-2006 and 2009-2012, with the former being an option with significant weight in the fuel mix. Due to the limited options used in the industry, India presents the highest HHI and lowest SWI than the rest of the countries which are included in this study, with all fuels contributing higher than 5% of the total in the fuel mix. A shared balance of the fuel options shows India improving its HHI and SWI during the period of 2008-2012 by 29.66% and 64.3% respectively.

China demonstrates a diverse fuel mix as reflected in the results from 1996 onwards. It uses at least 10 options since 1990 with no less than 4 having a share greater than 5% since 2001. As a result, China in the latest year examined, is classified as the country with the lowest concentration (**HHI=2590.55**) and the highest diversity (**SWI=1.25**) in the sector (**Figures 6.49-6.56**) for every fuel option scenario. The Chinese machinery industry, presents an increasing consumption of natural gas as a fuel source, effectively replacing coal products.

The activity level of Thailand is dwarfed by that of China but remains comparable to that of India. Thailand presents low concentration and high diversity levels throughout the timeline. From 2008 to 2012 the country's industry is using 5 fuel options in its fuel mix with at least 3 having a share greater than 5%. Oil products and natural gas are the main fuels used by Thailand's industry, showing an improvement of 40.11% and 41.91% in HHI and SWI respectively. The Philippines did not present or report any activity in the machinery sector up to 1989. From 1990 onwards, the country presents increased concentration with a similar fuel pattern to that observed in the non-metallic minerals sector i.e. based on gas/diesel oil and fuel oil products. The concentration grows and the diversity decreases throughout 1990-2012.

6.3.6 Food & Tobacco Industry

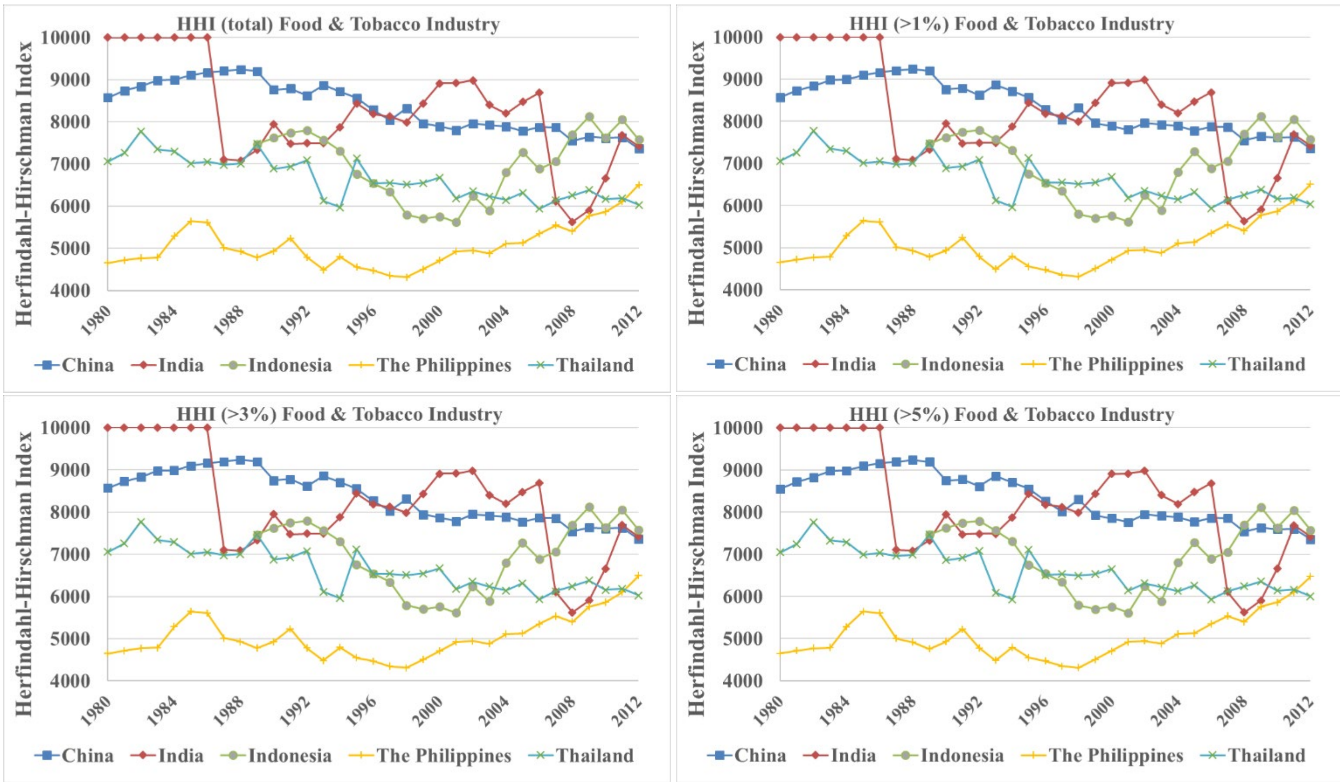


Figure 6.57-6.60 Food & Tobacco industrial fuel mix concentration measured with HHI for the 1980-2012 timeline

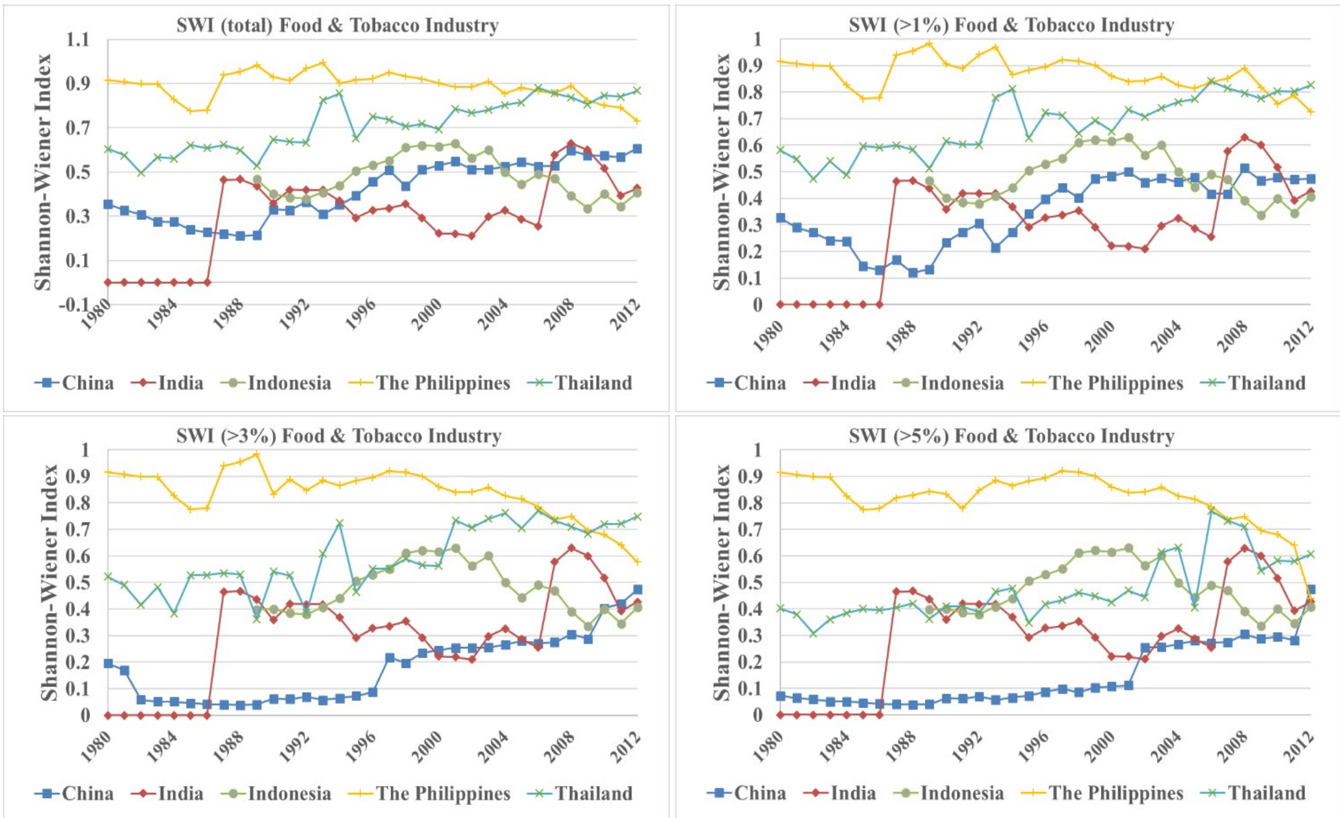


Figure 6.61-6.64 Food & Tobacco industrial fuel mix diversity measured with SWI for the 1980-2012 timeline

In the Food & Tobacco (F&T) industry, India has significantly improved its diversity by 92.9% for all option scenarios since 2000 but that improvement presents a decelerating trend, during 2008-2011, from 37.63% to 8.6%. Overall, China produces a higher diversity index, with Thailand and the Philippines showing an improved performance, when examining the last three years. However, in absolute terms all countries present low diversity with SWI below 1. Discussing India, the low diversity that the country presents is attributed to its over-reliance on fuel oil exceeding 70% during the timeline, while the country uses only two fuel options in total.

Thailand has the most improved concentration and diversity rates from 1980 to 2012, at 14.62% and 43.76% respectively when all options have been included. The country has 4 out of its 7 fuel options contributing more than 3% in the fuel mix, but a further improvement in the sector diversity is hindered, as the fuel mix is dominated throughout the timeline by primary solid biofuels, with a share of 76.64% (2012). Indonesia uses 2 fuel options from 1990 onwards showing an insignificant increase in HHI (1.42%) but a considerable decrease in diversity (12.81%). China is demonstrating a leap in improving its fuel mix diversity, by achieving a 70.95% improvement, or a staggering 556.88% for fuel options that exceed 5% of the total contribution. The Chinese F&T industry uses a total of 10 fuel options, but only 3 exceed a contribution greater than 1% for the last year examined, with other bituminous coal holding a major share at 85.34%.

The concentration figures of all the five countries compared, exceed HHI=4000 throughout the examined timeline, demonstrating the urgency and challenges that the industry is facing for diversifying or even balancing the fuel mix (Ministry of Economic Trade and Industry, 2015). The Philippines decreasing diversification in the latest years of the examined period, is attributed to an increasing share of primary solid biofuels in the energy mix, at 79.53% for 2012, substituting various oil products that the industry consumes.

6.3.7 Paper, Pulp and Print Industry

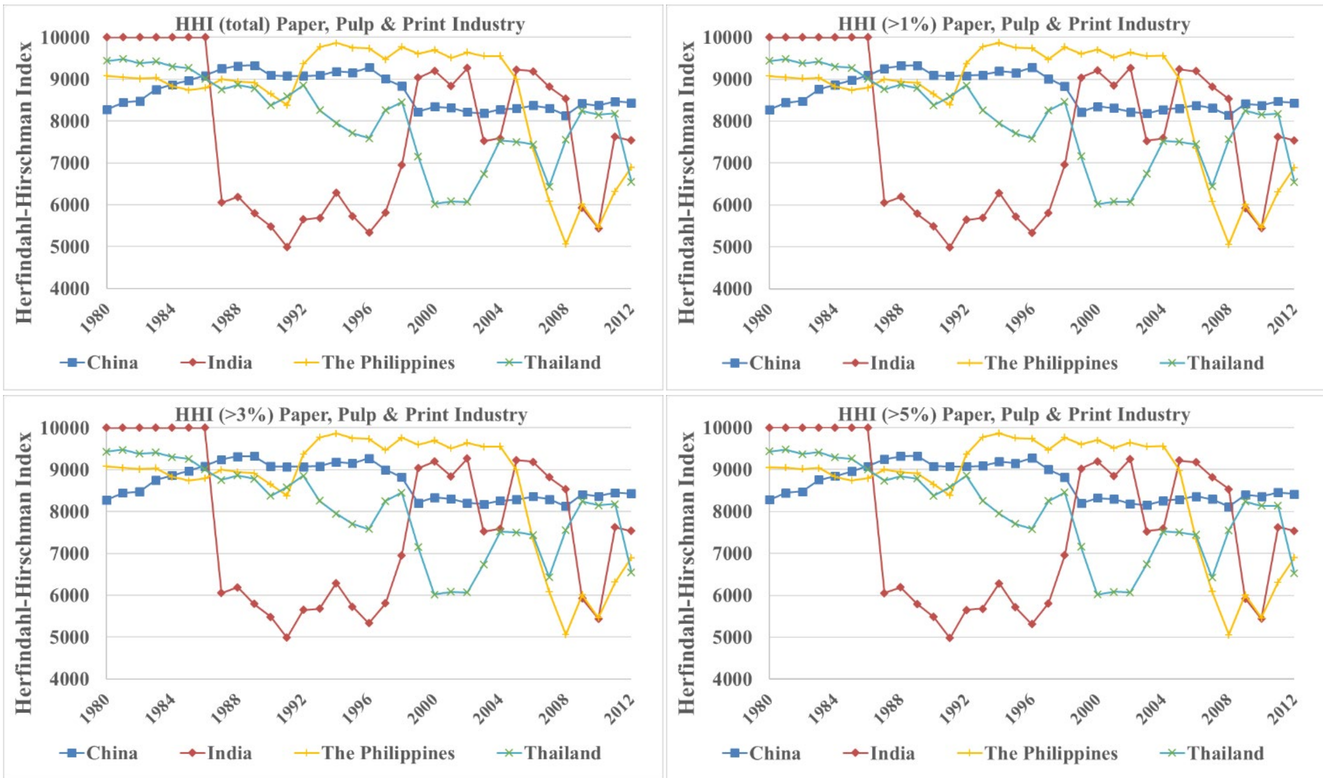


Figure 6.65-6.68 Paper, pulp and print industrial fuel mix concentration measured with HHI for the 1980-2012 timeline

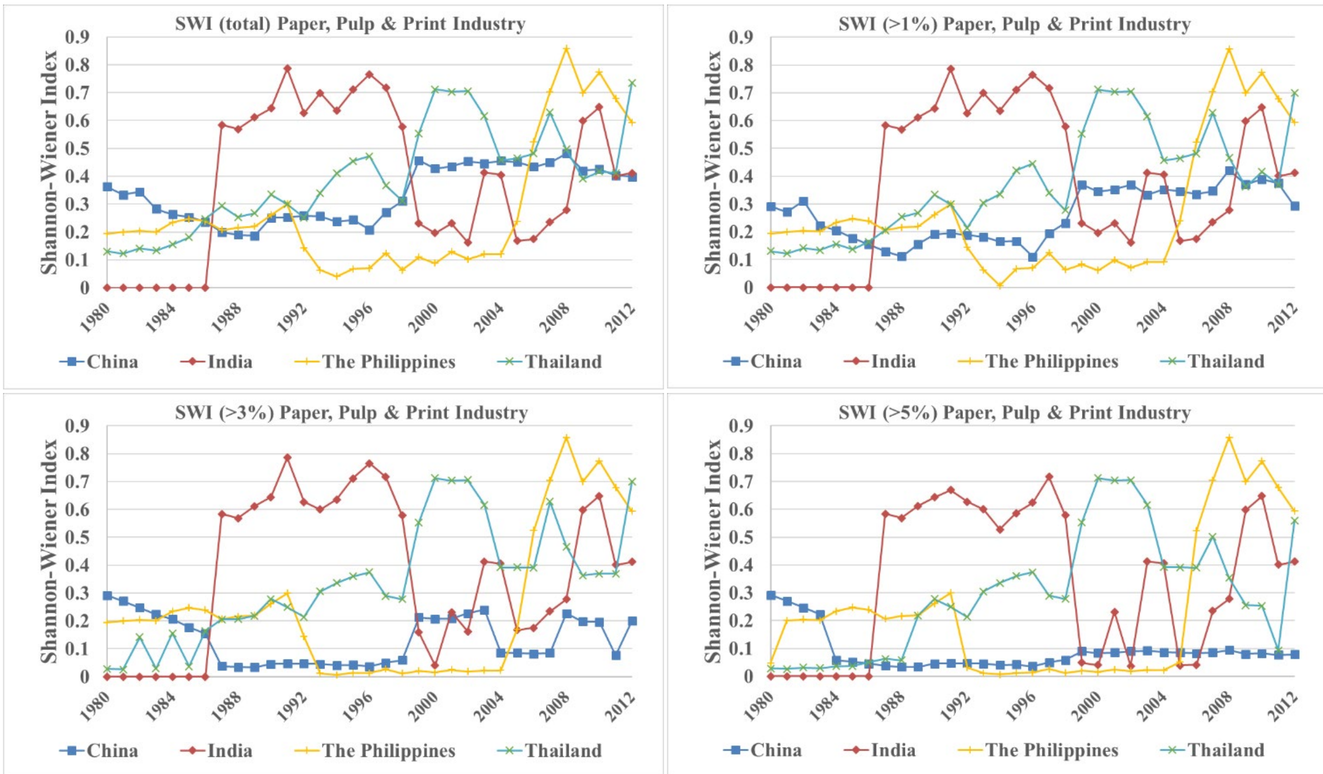


Figure 6.69-6.72 Paper, pulp and print industrial fuel mix diversity measured with SWI for the 1980-2012 timeline

Examining the Paper, Pulp & Print industry, both the concentration and diversity indices are characterized by large variations, which can be mainly attributed to fuels entering or being phased out of the fuel mix. India presents the most pronounced variance in its fuel mix diversity and concentration for the timeline duration. Since 1980 to 1986, the country satisfies the energy requirements of the paper, pulp and print industrial sector by using only one fuel; other bituminous coal. The introduction of coking coal; 1987, and lignite; 1991, has not been crucial in decreasing concentration. Other bituminous coal held a 95.89% share in the fuel mix in 2000. However, as coking coal was phased out of the industry from 2001 onwards, an improved balance ratio between the two remaining coal products, is critical in increasing diversity by 109.78% for 2000-2012 for all fuel options considered.

Similarly, as concluded in previously examined industries, Indonesia reports as using only one fuel option for paper, pulp and print industry for the duration of the timeline examined. As a result, both HHI and SWI indicators present their maximum and lowest index values respectively and are not included in **Figures 6.65-6.72**.

China presents an increase in HHI by 1.92% during 1980 to 2012. The Chinese fuel mix is characterised consistently by a low diversity index. The SWI reaches its lowest value when the only options contributing higher than 5% are accounted. China has a fuel consumption greater than the other countries in this study combined and has 10 fuel options in the energy mix. However, China uses other bituminous coal to meet 90% of the total across the timeline.

Thailand and the Philippines present an improvement in SWI and a reduction in the HHI that is rated at 30.62% and 24.03% respectively. Thailand has effectively substituted fuel oil for natural gas starting from 2008 and up to the latest year examined. The country is using four fuel options at a rate higher than 5%, reflected in an improved diversity index, when compared to the Philippines. Following a similar trend to that observed in the SWI of Thailand, the Philippines has phased imported fuel oil out (Montefrio and Sonnenfeld, 2011), replacing it with sub-bituminous coal, starting from 2009 up to 2012.

6.3.8 Wood & Wood Products Industry

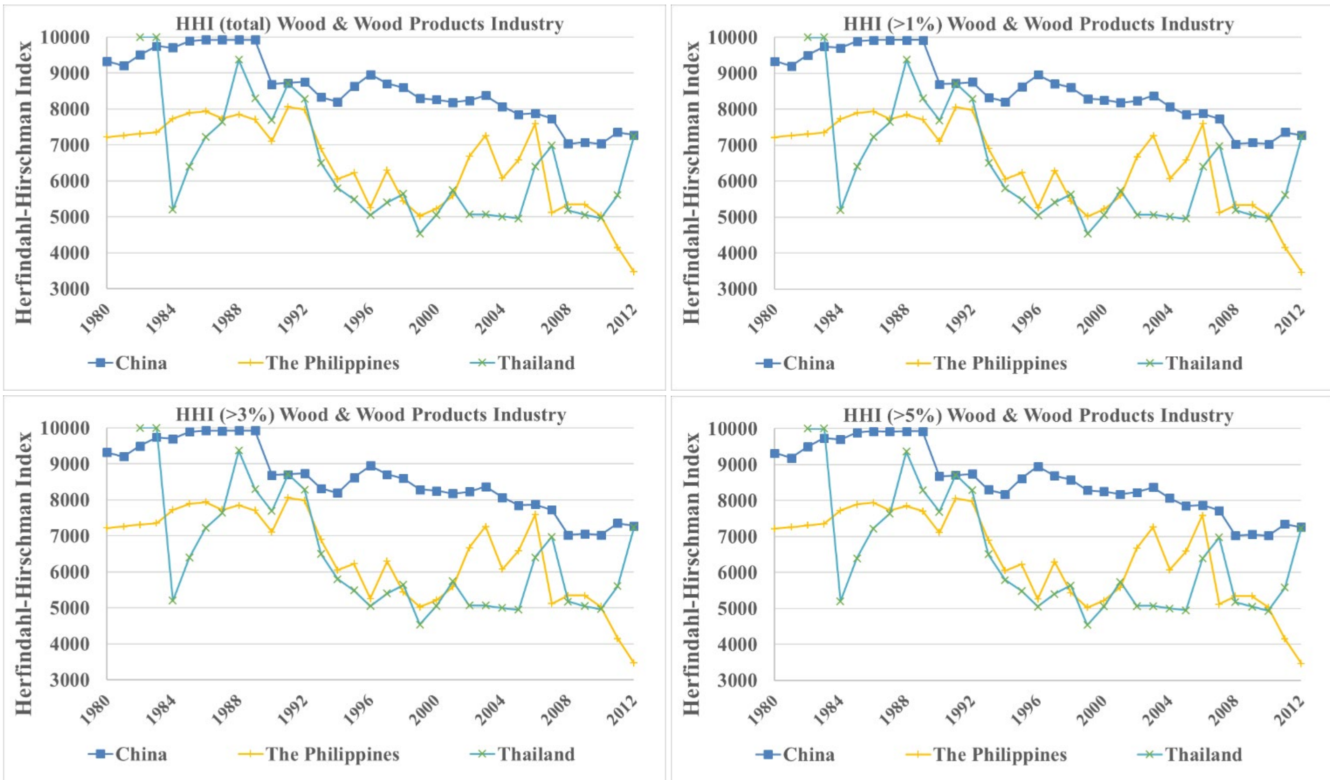


Figure 6.73-6.76 Wood and wood products industrial fuel mix concentration measured with HHI for the 1980-2012 timeline

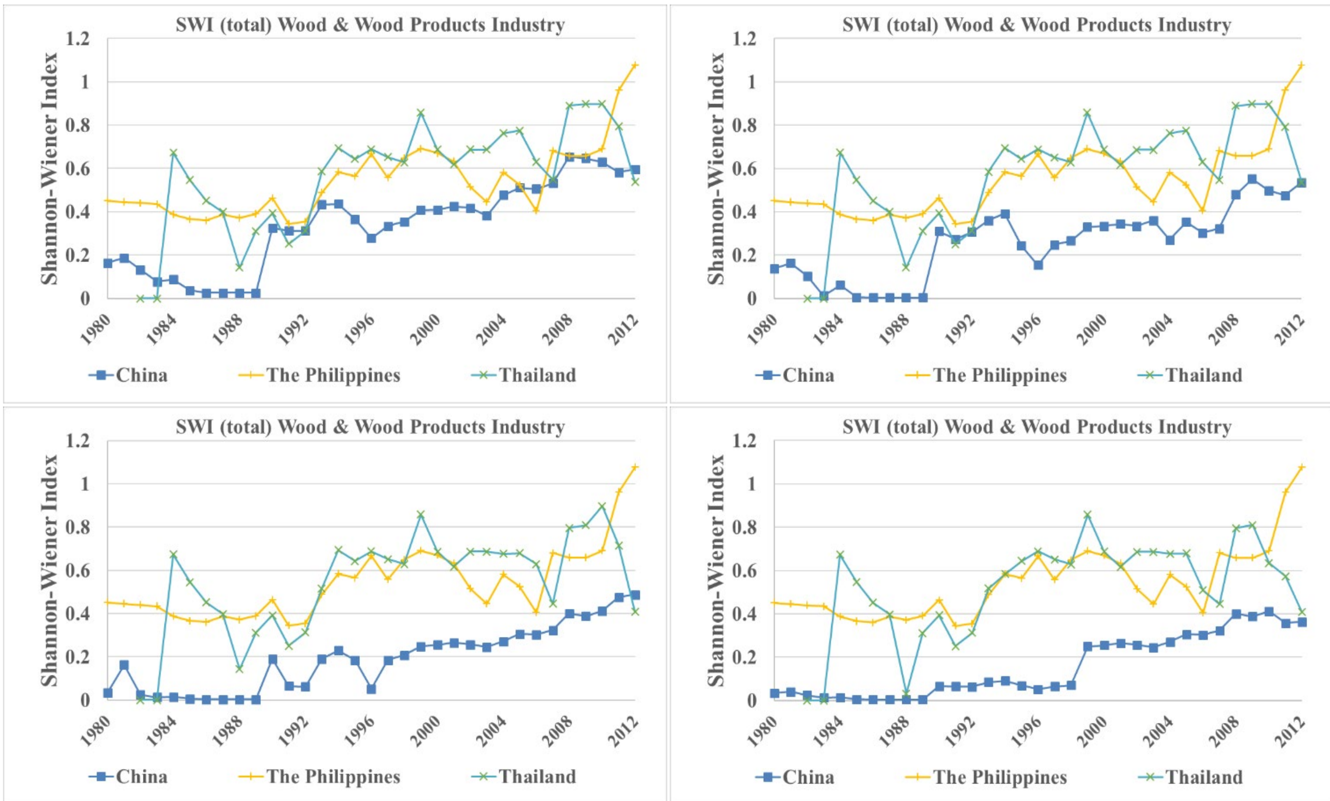


Figure 6.77-6.80 Wood and wood products fuel mix diversity measured with SWI for the 1980-2012 timeline

The Wood & Wood Products industry (W&WP) contains plots for only three countries out of the five examined in this chapter. India and Indonesia do not produce any activity levels according to the data reported to IEA. However, both countries include those data, as part of the non-specified industries. This is a common practice applied by countries that have difficulties in reporting their industrial breakdown of fuels (International Energy Agency, 2015e).

Complete data are reported by China, the Philippines and Thailand, with the latter not presenting activity levels for the first two years of the examined timeline, 1980 and 1981. China has a low diversity fuel mix, however, improving its concentration for all options by 22.02% and diversity by 262.2% during 1980-2012. Two fuels out of the 8 used in the latest year; 2012, contribute more than 5% of the total. Other bituminous coal is the main fuel of that industrial sector, from 96.55% from 1980 to 84.69% at 2012.

The Philippines have used 2 fuel options between the period of 1980 to 2010. For the two final years, the country has gradually reduced the share of the used oil products; fuel and gas/diesel oils, effectively replacing it with LPG. As a result, the Philippines has improved its fuel mix diversity by 138.8%, lowering the concentration for the same period by 51.94%. Due to all options having a share greater than 5%, the resulting plots (**Figures 6.73-6.80**) present identical output. Thailand presents lower diversity levels for the last two years examined, 2011 and 2012, by 45.88% due to gas/diesel oil holding a major share in the fuel mix, at 84.11% while LPG and fuel oil have been decreasing their contribution.

6.3.9 Textile and Leather Industry

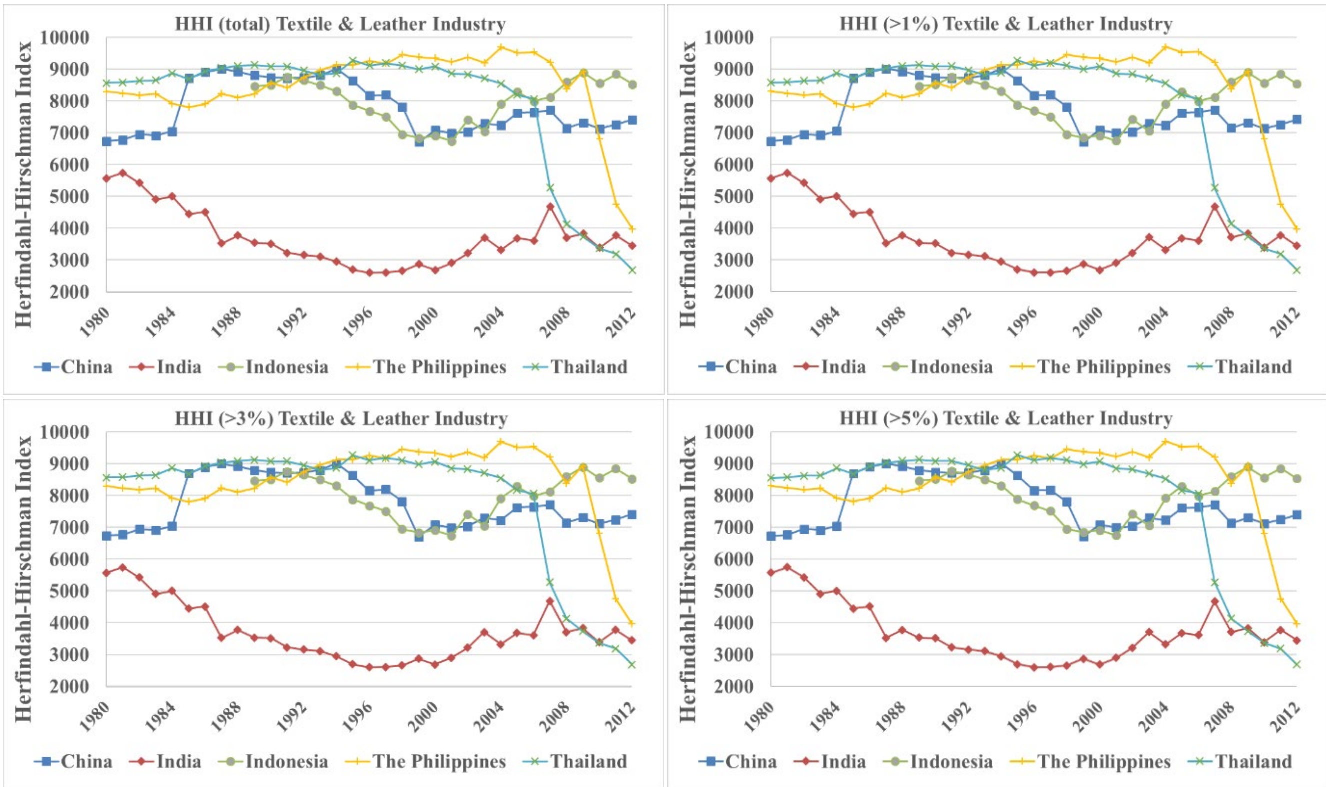


Figure 6.81-6.84 Textile and leather industrial fuel mix concentration measured with HHI for the 1980-2012 timeline

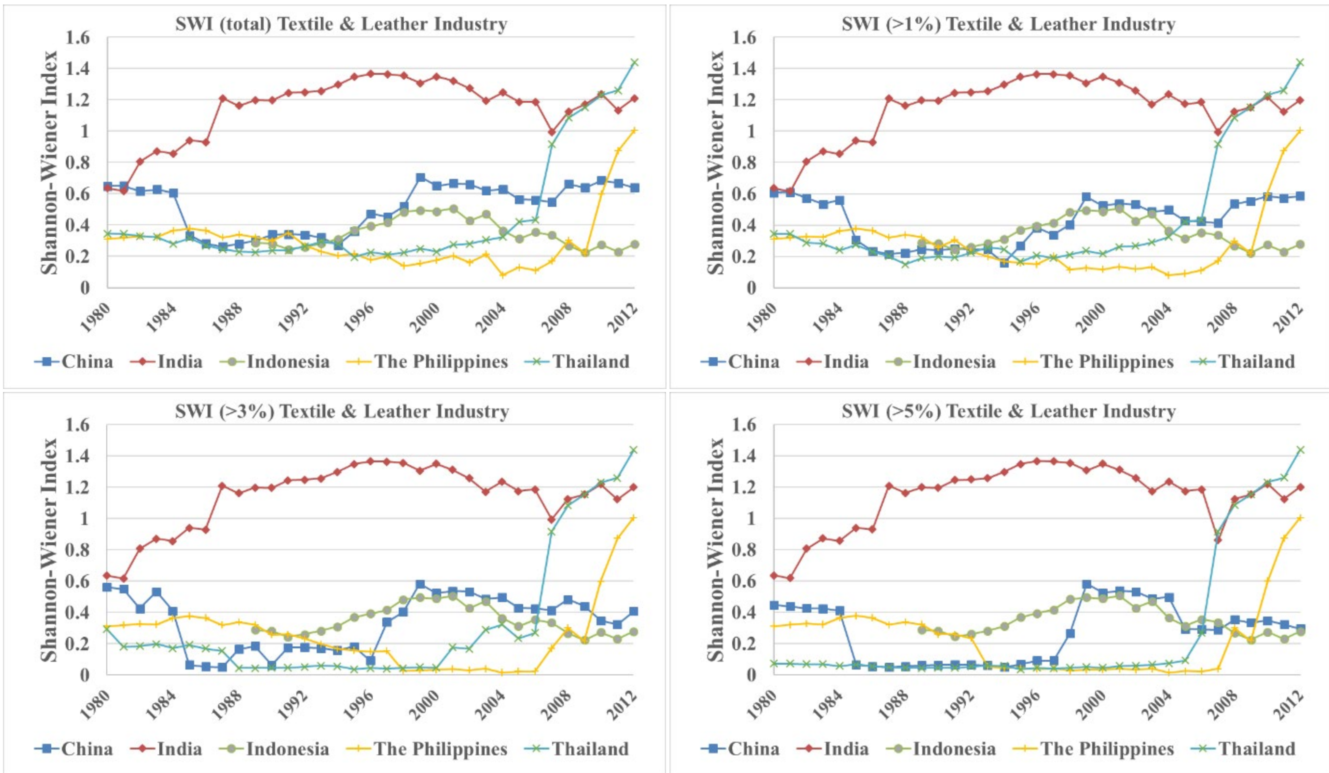


Figure 6.85-6.88 Textile and leather industrial fuel mix diversity measured with SWI for the 1980-2012 timeline

Examining the HHI for the Textile & Leather industry (**Figures 6.81-6.84**), shows that India demonstrates consistently low fuel mix concentration, surpassed only by Thailand during the last two years. Four out of the five options in India's industrial fuel mix present a contribution accounted higher than 5% of the total energy consumption. Nevertheless, due to the negligible contribution of LPG, all option scenarios present identical results. India demonstrates with improved fuel diversity, over the period of 1980-2012, accounted at 90.29% for all options, or 88.84% for options higher than 5% of the total. Its concentration presents an improvement of 38.11% for the same period.

China presents high concentration and low diversity despite reaching 11 fuel options for the latest year examined since only three contribute more than 3%, and only two more than 5%. China relies by over 80% on other bituminous coal throughout 1980-2012 resulting in concentration increase by 10.05% and diversity decrease by 1.66%. Indonesia is the worst performer from 2010-2012 compared to the other countries on a comparison basis. The concentration has risen by 23.49% between 2000 to 2012. The diversity index has decreased by 42.93%, as the industry mainly satisfied its energy requirements with gas/diesel oil.

Thailand presents a concentration index improvement over the examined timeline by 68.66% for all options. The country uses a total of 6 products but no more than 5 are used simultaneously over any annual period. A balanced fuel mix found during 2012 and a further growth of natural gas as a fuel source, have been critical for the country producing improved concentration. Similar to Thailand, the introduction of LPG in the Philippines from 2010 phasing out fuel oil resulting in improved diversity by 24.77% during that period.

6.3.10 Mining Industry

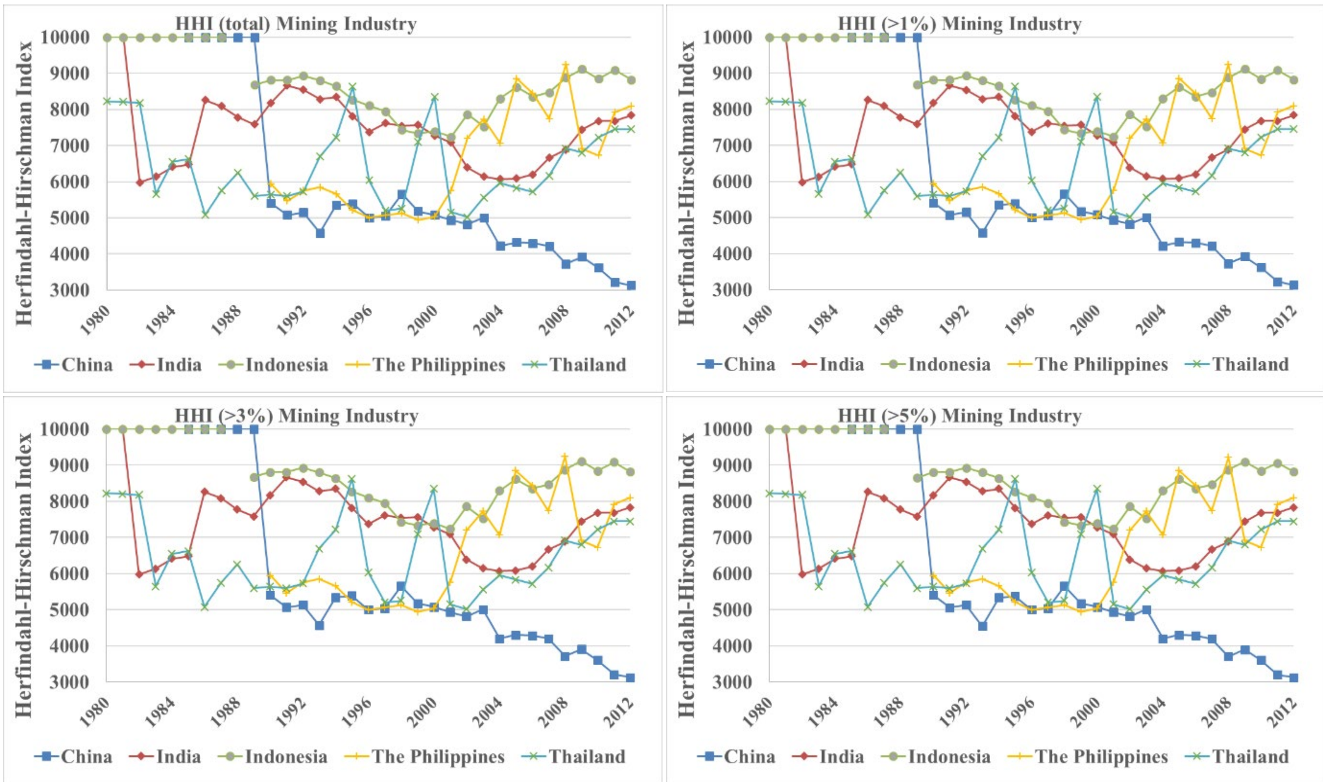


Figure 6.89-6.92 Mining industrial fuel mix concentration measured with HHI for the 1980-2012 timeline

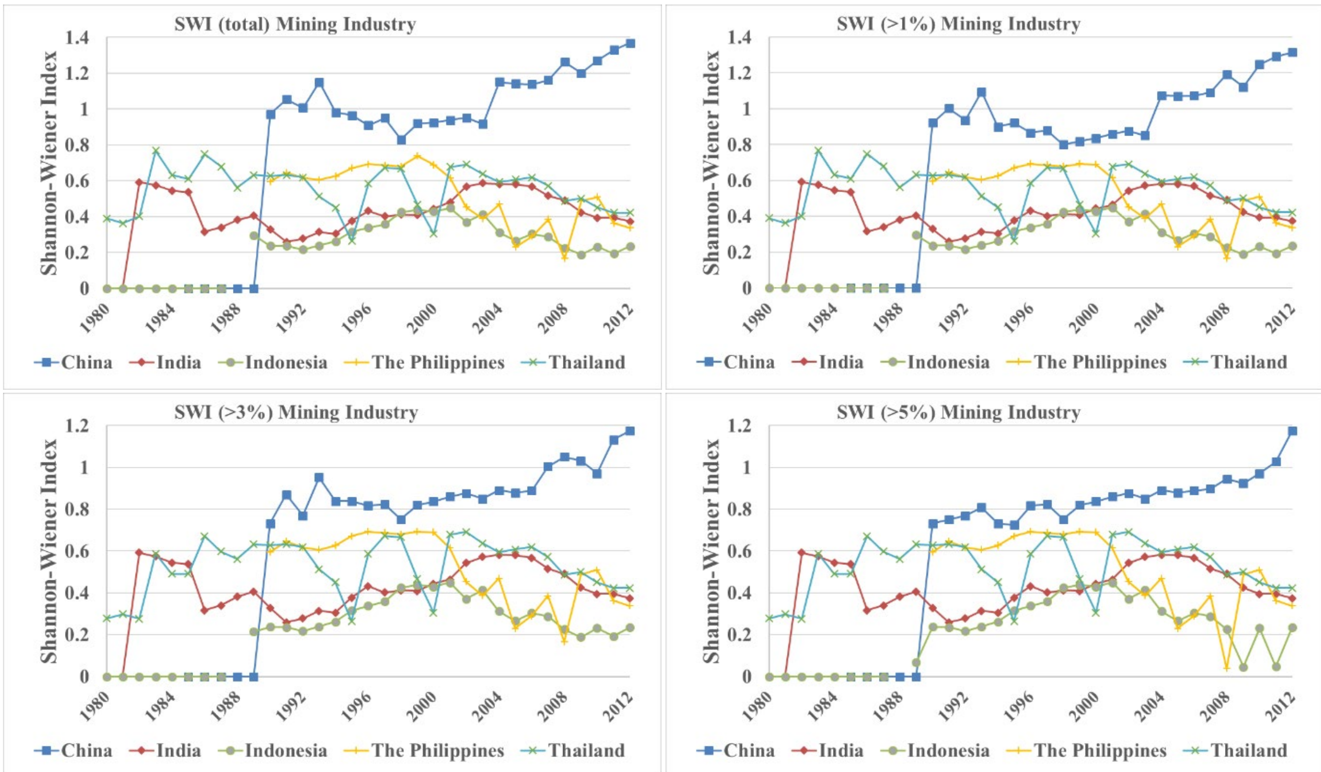


Figure 6.93-6.96 Mining industrial fuel mix diversity measured with SWI for the 1980-2012 timeline

For the mining industry, China presents lower concentration and higher diversity than the other four countries for all option fuel mix scenarios considered (**Figures 6.89-6.96**). Chinese activity level shows a diverse mix of fuels reported from 1990 onwards, with the improvement during the 1990-2012 reaching 42.1% for concentration and 40.89% for diversity for all options. Four out of eleven fuel options hold a share higher than 5% of the total energy consumption with other bituminous coal (36.85%) and gas/diesel oil (39.5%) having the highest fuel mix contribution.

Indonesia presents the highest concentration and lowest diversity reporting more than one product in its energy mix only after 1999 replacing other bituminous coal with fuel and gas/diesel oils. Concentration is high since gas/diesel oils remain the main energy source (93.7%) for covering the industrial energy requirements until the final year examined, 2012. From 2000 to 2012, Indonesia has increased its fuel mix concentration by 19.27%, decreasing its diversity by 45.28%. The same pattern is evident for the Philippines which only started reporting on this industrial sector in 1990, with fuel and gas/diesel oil entering the fuel mix. By 2012, gas/diesel oil had become the main fuel source with 89.38% of the total, presenting a concentration increase for the 1990-2012 period by 36.2%. India follows a similar pattern regarding the fuels used but reporting data from 1982 to 2012.

Thailand is consistently reporting since 1980, with five fuel options being available during the period of 1980 to 1987. From 1988 onwards, the pattern observed in the Philippines, Indonesia and India is repeated with fuel and gas/diesel being the only two options available for consumption. This trend is common for several industries in Thailand where the country relies increasingly on oil and NG (Selvakkumaran and Limmeechokchai, 2013). The fuel mix concentration was reduced overall by 9.4% and the diversity increased by 8.42% for all options considered. Gas/diesel oil in the final year examined, holds a share of 85.01% in the mining industry fuel mix of the country.

6.3.11 Non-Specified Industry

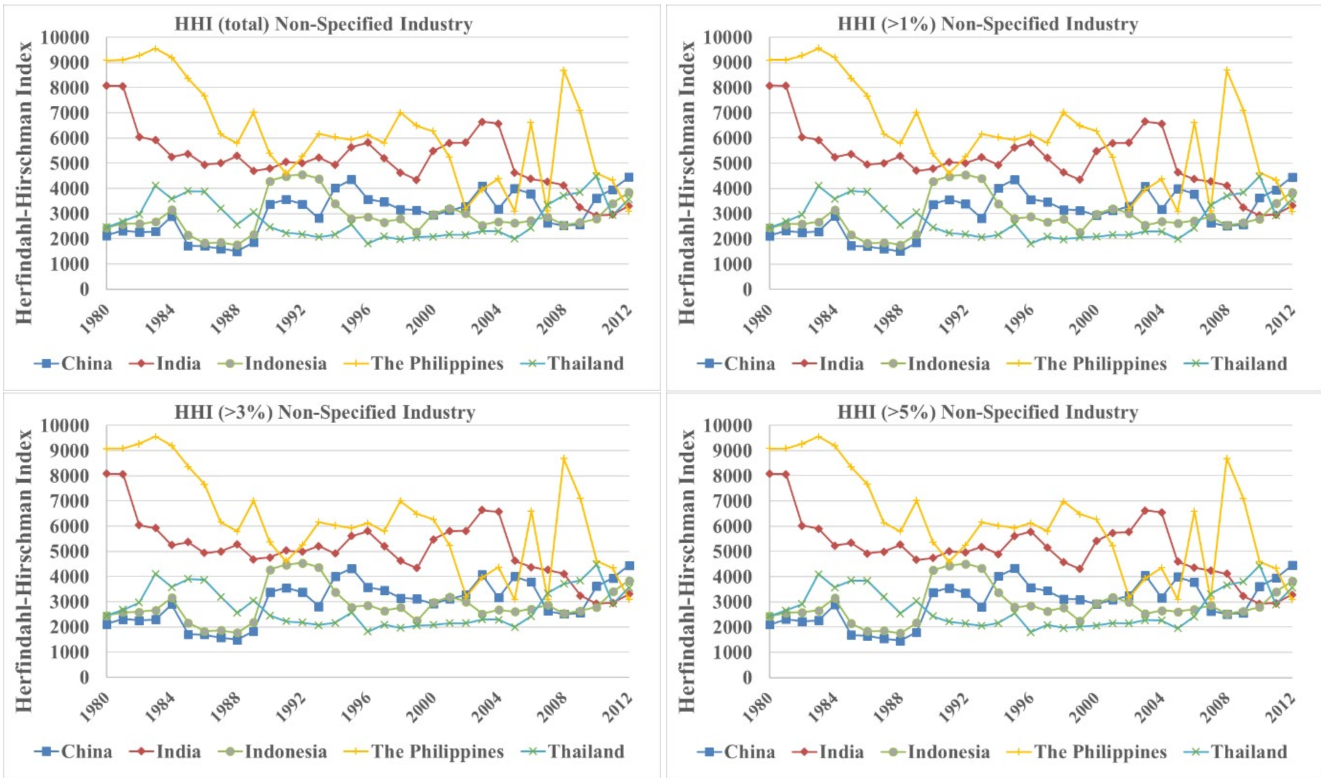


Figure 6.97-6.100 Non-specified industry fuel mix concentration measured with HHI for the 1980-2012 timeline

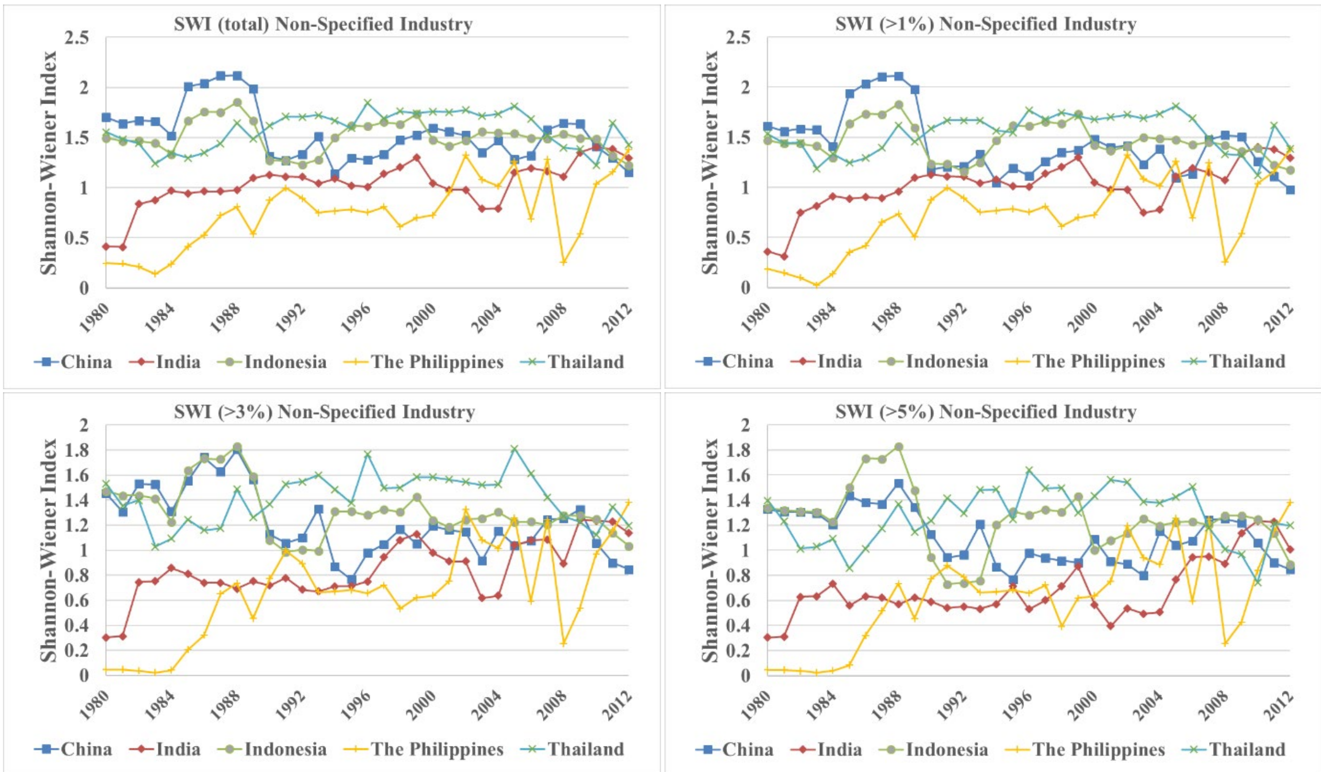


Figure 6.101-6.104 Non-specified industry fuel mix diversity measured with SWI for the 1980-2012 timeline

The non-specified industry includes all industries that are part of the total but are not specifically included in other categories of IEA due to country-specific disaggregation limitations. Therefore, as a common practice in such cases, an aggregation in the non-specified industry category takes place, by industries that are not reported in an individual basis in the set IEA categories. India aggregates the wood & wood products in the non-specified industrial sector. Sectors contained in the non-specified category as set by IEA include transport and medical equipment, recycling, furniture manufacturing, rubber & plastics.

Examining the fuel mix concentration of the non-specified industry (**Figures 6.97-6.100**) shows that the Philippines has the lowest HHI. All the fuels used by the industry in 2012 exceed the 5% option scenario set. Therefore, the concentration remains identical for all fuel option scenarios that are considered (**HHI=3087.6**). The concentration index presents an improvement over the timeline is estimated at 66.04%. Thailand presents a concentration increase of 45.88%, but this is attributed to a spike in HHI output during 1980-1983. Examining the concentration improvement trend from 1984-2012, there is an insignificant decrease by 0.38%. The HHI spike is the result of other bituminous coal presenting a rapid growth from 1980 to 1983, raising its share from 21.69% to 45.17% respectively, but dropping to 13.89% the following year; 1984. Thailand uses 5 out of the available 8 options at a higher than 5% of the total, with primary solid biofuels holding the largest share.

India improved its concentration by 58.99% for all options or 59.31% when the highest than 5% options are considered (**Figures 6.101-6.104**). This spike in consumption is the result of primary solid biofuels replacing coking coal. India has increasingly been using natural gas from 2008 to 2012.

China presents the highest concentration (**HHI=4453**) and lowest diversity (**SWI=1.15**) for 2012. The country is following an increasing concentration path between 1980-2012 at a level of 109.3% increase, with diversity diminishing at 32.54% for all options. China, starting from 2004, introduced other oil products to cover its industrial energy requirements, increasing its share in the fuel mix, and by 2012 this reached a 61.86% share. Out of the 17 options available at the last year examined, only three contributed more than 3% to the fuel mix. This is reflected in different option scenarios (**Figures 6.101-6.104**), where the country presents diminished diversity for the same year when increasing the fuel mix accounting threshold from including all to those holding a share greater than 5%.

Fuel mix diversity in Indonesia is reduced from 2008 to 2012 by 30.07% for all options accounted. The country was effectively replacing sub-bituminous coal for natural gas as a main fuel source. Natural gas held a share of 53.78% at the latest year examined with three of the total 10 options holding a contribution share higher than 5% in the fuel mix.

6.5 Discussion

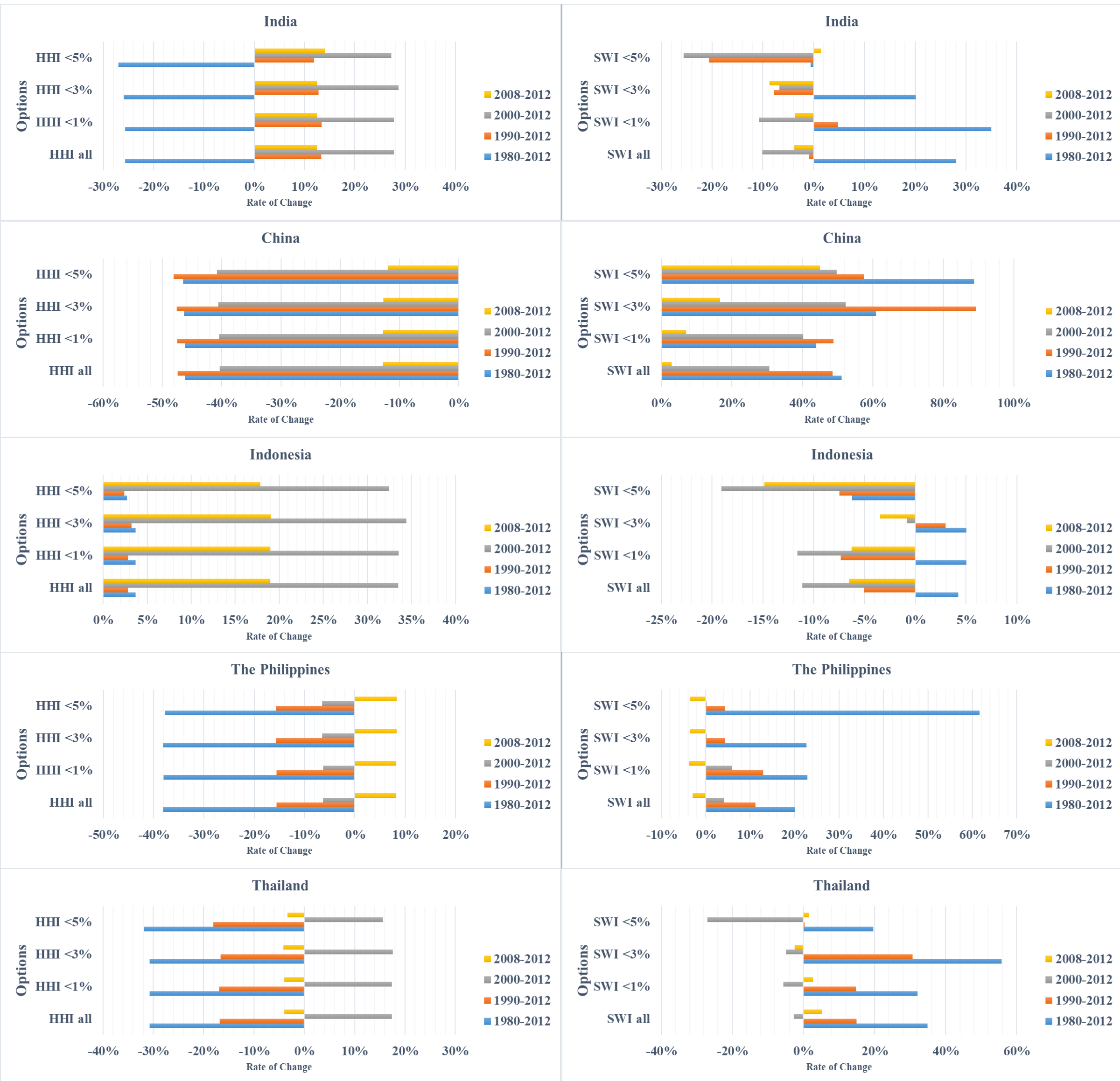


Figure 6.105-6.114. Comparison of HHI and SWI change rate (%) of the total industry between selected time periods and 2012 (base year) for India, China, Indonesia, The Philippines and Thailand.

HHI is evaluated for ASEAN countries as an indicator of high concentration in the total fuel mix when having a value greater than 2500 and presenting an unconcentrated market for values under HHI=1500 (Kanchana and Unesaki, 2014). Examining the assessed countries under that prism, and including India and China in that benchmark, it can be conclusive that none of the studied countries presents an unconcentrated fuel supply in the total or specific industrial sectors (**Figure 6.115-6.124**). However, India for options that contribute higher than 5% and

Thailand for all options, do not exceed the value set for a highly concentrated market. India has performed better in the past but has reversed that improvement from 2007 onwards as it shifts its industrial fuel supply mix towards a higher contribution originating from other bituminous coal. As India has not been a member of IEA until 2017 (IEA, 2017b), it had limited contingency plans or energy security policies to avert vulnerability to supply disruptions (Sharma, 2007). This fact can be deemed as a cause for an increasing shift towards the usage of indigenous coal products in favour of oil and gas imports. However, even though indigenous coal is offering the country the access to a secure source of energy (Narula et al., 2017) with over a 55% share of the total commercial energy consumption (Kuntala Lahiri-Dutt, 2016), India starts to form a strategic capacity for limiting its reliance on indigenous coal as a main fuel source in the energy mix. This shift is deemed as a possible pathway for India, mainly due to the success of several renewable energy projects that have been undertaken in the country (Mohan and Topp, 2018), presenting a greater capacity for policy innovation by the central government which would lead subsequently to the fuel mix diversification.

Discussing the steps that India has taken steps in improving its fuel mix concentration and diversity, the rate of improvement is evident only in relation to the HHI and SWI compared against 1980 under a timeline assessment, as set by the present research. Dissecting this, it becomes essential to distinguish the industrial sectors that have not improved their performance during that timeline. The Iron & Steel sector in India is the largest energy consumer in the country's total industry. It holds approximately a 25% energy consumption share of the total found in the manufacturing industry (Bali et al., 2019). Among the examined sectors, it presents the worst performance between the disaggregated industrial sectors that comprise the total. Iron and steel industries of the country present a concentration increase from 1990 to the final year examined and a diversity decrease from 1980 to 2012 when assessing options that contribute higher than 5% in the fuel mix (**Figures 6.115-6.116; 6.130-6.131**).

China presents a fuel mix originating from numerous options used in the country's total industry. China is using 18 available options in the total industry but only five contribute higher than 5%. This highlights a decrease in diversity, additionally underlining increased concentration in the fuel mix. Indeed, the country can be classified as having a highly concentrated fuel mix, that exceeds the benchmark set of HHI being higher than 2500 (**Figures 6.117-6.118**). However, the country is taking continuous steps that point towards improvement as every HHI and SWI comparison performed between 2012 and previous years highlights a difference of the index between 40% to 50% for HHI for all fuel options, towards lower concentration. Determining diversity by using Shannon-Wiener methodology, the index varies presenting an increase more prominent in options that contribute higher than 5%. Under that last scenario and comparing 1980 to 2012 diversity figures, that increase exceeds 80% (**Figure 6.107**) highlighting the emphasis that China puts in diversifying its energy mix (**Figure 6.107**).

Benchmarking the countries included in this study on individual industrial sectors, it is evident that Food and Tobacco, Paper, Pulp and Print and the Textiles and Leather, are sectors which present an urgency for further diversification through the introduction of a further number of options or balancing out the options contribution. Distinguishing the difference in concentration and diversification of fuel sources in the energy mix, between all options and options that exceed 5% for selected years (**Figure 6.125-6.129**), HHI does not present a value that exceeds a 3.09% accounted difference in index, as found for the total industry of China in 2010. The Philippines do not exceed that difference between the fuel option scenarios, by more than 1% at peak, as this is valid for the Iron and Steel industry in 2012.

What can be determined as a minimal index difference for the HHI in the comparison of the five-country group, is not valid for the different option scenarios examined in the application of SWI in selected years. As demonstrated by the present study (**Figures 6.130-6.139; 6.140-6.141**), the difference between the all and >5% scenarios, can extend up to an index difference of 485.1% as found in the Philippines PP&P industry in 2000. China presents a consistent gap between SWI in 1990, 2000, 2010 and 2012 in the PP&P industry, and shows similar deviations ranging from 350% to 400% for the F&T and T&L industries. The T&L industry presents similar deviation for Thailand during 1980, 1990 and 2000 exceeding 400% for the latter.

While Indonesia does not present a similar varied fuel mix in terms of the number of available options, as found in major economies of the region, e.g. China, the options used in the country's fuel mix have a high contribution rate. Therefore, the country does perform adequately when compared to the other countries in the concentration index for all the examined scenarios, but not for all the industries that comprise the total. Regarding diversity though, for the scenario that exceeds 5%, the diversity of the industries present decreased rates. This agrees with conclusions reached by international literature, in regard to China being a country that needs to improve the diversification of its fuel supply (Geng and Ji, 2014) in addition to its increasing energy efficiency performance from 2005 onwards.

Indonesia is determined by the data reports, to have only one option used in the fuel mix, for satisfying the energy requirements of the Machinery and Paper, Pulp & Print industrial sectors, exposing those sectors to unsustainable risk (Bishop et al., 2008). A diverse fuel mix pattern is also observed in Thailand and the Philippines, but that mix is utilising fewer options to be used by specific industrial sectors, not only in comparison to India and China, but additionally to that of Indonesia. In the Philippines' case, the country experiences a continuous trend pointing towards diversification increase, highlighted when taking account all fuel options, even though following a diminished rate (**Figures 6.111-6.112**). That diversification improvement though is nullified when options than contribute higher than 5% in the fuel mix, are accounted, highlighting an urgent requirement for further increase of fuel sources used to satisfy the requirements set by the industry, with the option of prioritizing the use of indigenous fuels to achieve that target (La Viña et al., 2018).

Indonesia, Philippines and Thailand are countries with increased fossil fuel production activity (Thomson, 2006), but have been highly dependent on imported crude oil, with the two latter also presenting high dependence on coal products (British Petroleum, 2015). Therefore, to achieve energy security through sustainable energy consumption means, this country group needs to diversify the industrial energy mix by further increasing the share of domestically produced resources. Even though the countries that belong in the ASEAN group had successfully adopted strategies for diversifying their primary energy supply as part of a broader energy security strategy, the data results suggest that this does not apply in the industrial sector when examining fuel options that exceed 5 per cent contribution (**Figures 6.135; 6.137; 6.139**) (Kanchana and Unesaki, 2015). However, energy security is expected to improve in future terms at least in the case of Indonesia, as the country has set policies of decreasing its dependence on coal by 33%, natural gas by 30% and oil by 20% by 2025 in favour of renewable energy solutions (Mujiyanto and Tiess, 2013), but that reduction remains to be reflected in the industrial energy mix. The countries showcase high reserves to production ratio in natural gas when discussing Indonesia and coal products examining the Philippines and Thailand (BP, 2018).

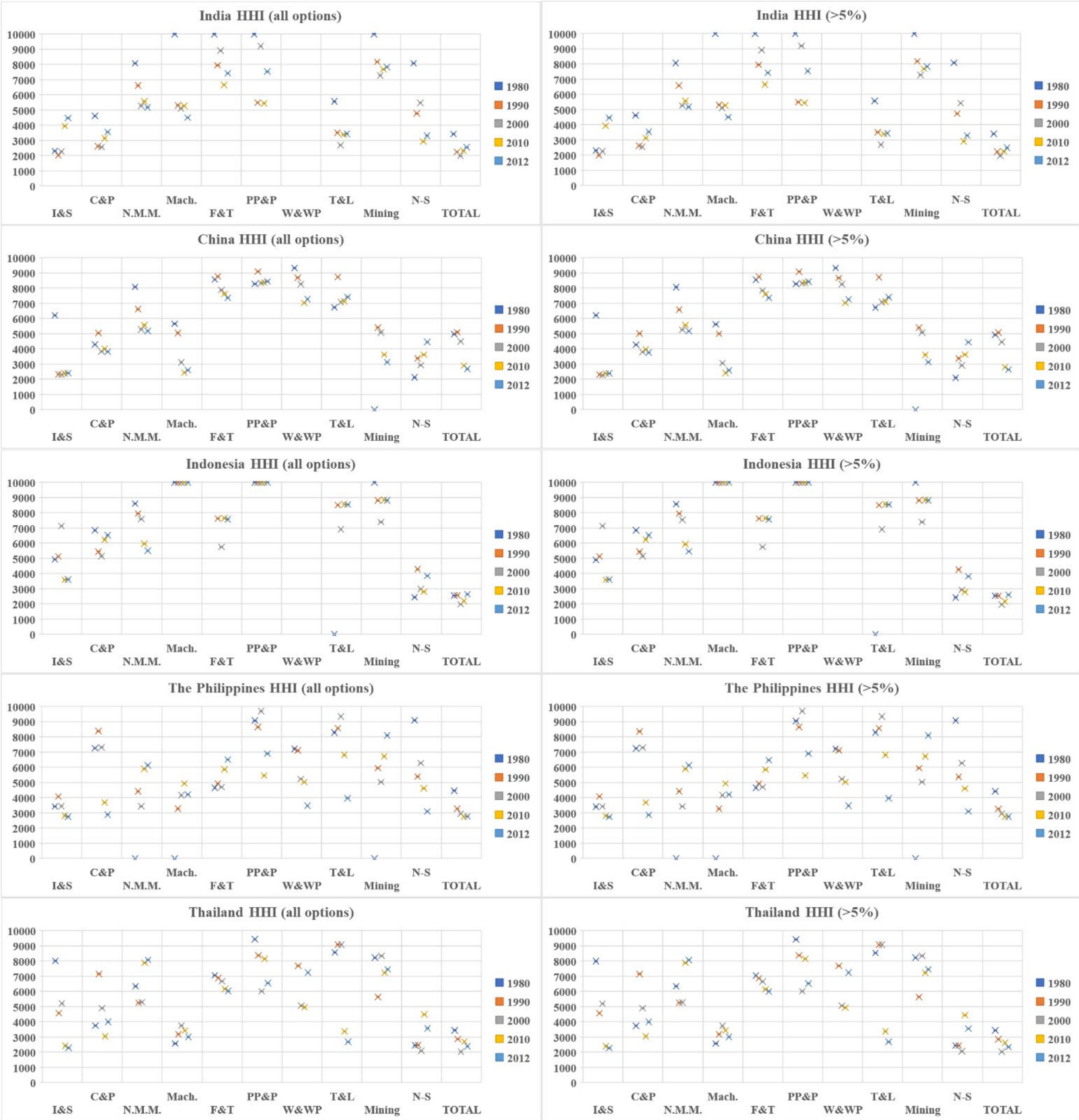


Figure 6.115-6.124 HHI performance per country for all and >5% of the fuel options; total and each industrial sector of selected years 1980, 1990, 2000, 2010, 2012.

Figures 6.125-6.129 Comparison between HHI of all fuel options and > 5% for the total and each industrial sector of selected years 1980, 1990, 2000, 2010, 2012

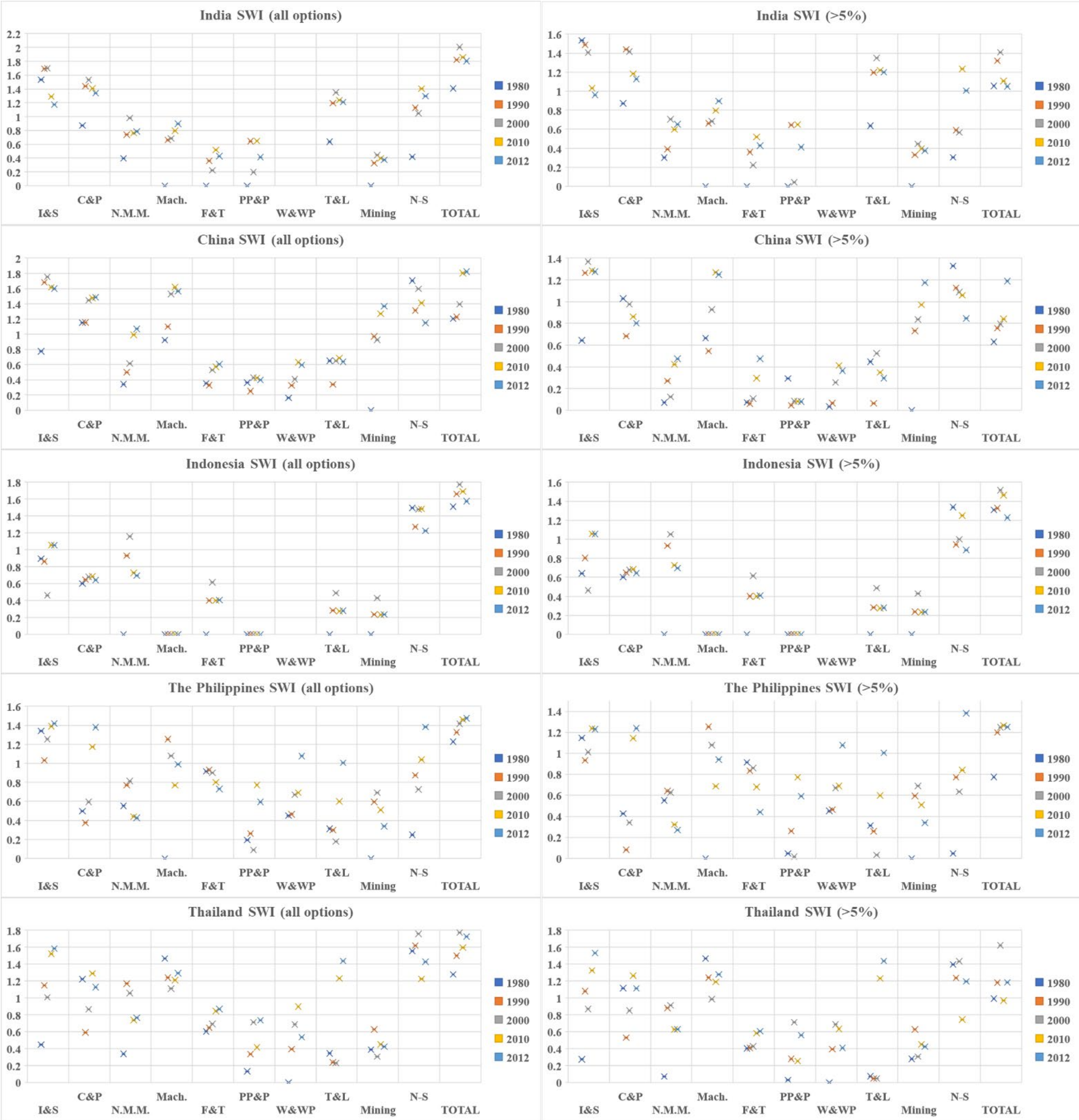


Figure 6.130-6.139 SWI performance per country for all and >5% of the fuel options; total and each industrial sector of selected years 1980, 1990, 2000, 2010, 2012

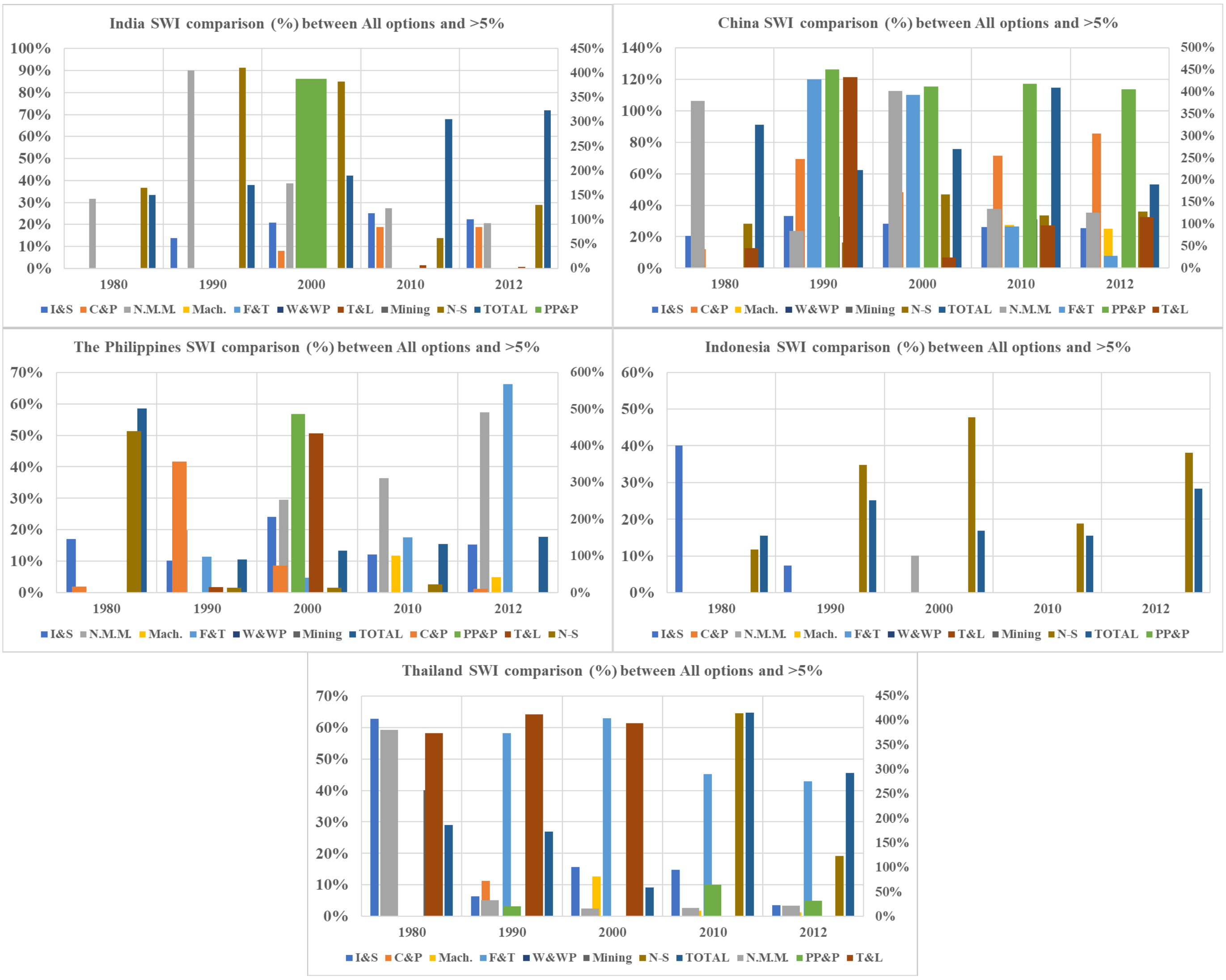


Figure 6.140-6.144 Comparison between SWI of all fuel options and > 5% for the total and each industrial sector of selected years 1980, 1990, 2000, 2010, 2012. (Wider bars refer to the secondary axis).

Focusing the discussed results, it is evident that a mixed output regarding concentration and diversity indices of the energy supply mix, that is used by the industry of India, China, Indonesia, the Philippines and Thailand, exists. Responding to the hypotheses posed in **section 6.2** of the present chapter, this study can conclude as following:

H1a: Concentration indices of the total Indian industry have improved from 1980 to 2012. However, the I&S sector presents an increase in concentration. As a result, the hypothesis is partially accepted.

H1b: Diversity indices for the total Indian industry have improved from 1980 to 2012. Examining specific industries, the I&S sector presents a diversity decrease between the same period. Therefore, this hypothesis is partially accepted.

H1c: Diversity, marginally, and concentration of India’s total industry for options >5% between 1980 present an improvement. However, the I&S sector does not improve its performance, resulting in this hypothesis being partially accepted.

H2a: Concentration indices of China’s total industry have improved from 1980 to 2012. However, the index of the Paper, Pulp & Print, Textile & Leather, Mining and Non-Specified industries sectors present an increase in concentration. As a result, the hypothesis is only partially accepted.

H2b: The diversity index for the total Chinese industry sector has improved from 1980 to 2012. Examining specific industries, the T&L, even marginally, and the N-S sector present a diversity decrease for the same period. Therefore, this hypothesis is partially accepted.

H2c: Concentration of China’s total industry for options >5% between 1980 presents an improvement. However, the PP&P, T&L, Mining and N-S sector does not improve its concentration for the same options. Diversity presents a decrease for N-S, T&L, PP&P and C&P for options >5%. As a result, this hypothesis is partially accepted.

H3a: Concentration indices of Indonesia’s total industry have marginally increased from 1980 to 2012 (**Figure 6.120**). Therefore, this hypothesis is rejected before the individual assessment of industrial sectors.

H3b: The diversity index for the total Indonesian industry sector has improved from 1980 to 2012. Examining specific industrial sectors, the N-S industrial sector presents a diversity decrease between 1980 and 2012. As a result, this hypothesis is only partially accepted.

H3c: Concentration of Indonesia’s total industry for options >5% between 1980 and 2012 presents a marginal increase. Examining diversity for the same options contribution threshold in the fuel mix, diversity has decreased during the same period. As a result, this hypothesis is partially accepted.

H4a: Concentration indices of the Philippines’ total industry presents improvement comparing 1980 to 2012 (**Figure 6.122**). However, for the N.M.M., Machinery, Food & Tobacco and Mining, concentration has increased, effectively only partially accepting this hypothesis.

H4b: The diversity index for the Philippines’ total industry presents an improvement comparing the timeline points set; 1980 and 2012. Examining specific industrial sectors, the F&T industrial sector presents a definitive diversity decrease between 1980 and 2012. As a result, this hypothesis is partially accepted.

H4c: Concentration of Indonesia’s total industry for options >5% between 1980 and 2012 presents an improvement, following the performance set when accounting all options.

Examining diversity for the same options contribution threshold in the fuel mix, diversity has increased during the same period. However, the N-S industrial sector presents a diversity decrease, while the F&T, N.M.M, Machinery and Mining present a concentration increase. As a result, this effectively leads to only partially accepting this hypothesis.

H5a: Concentration indices of Thailand's total industry present improved performance comparing 1980 to the final year examined; 2012. However, the concentration index for C&P, N.M.M., Machinery and N-S industries sectors show a concentration increase. This results in the hypothesis being partially accepted.

H5b: The diversity index for the total Thai industry sector has improved from 1980 to 2012. Examining specific industries, the C&P, Machinery and N-S industries present a diversity decrease for that period defined. As a result, this hypothesis is partially accepted.

H5c: Concentration of Thailand's total industry for options >5% between 1980 and 2012 is improved. However, the C&P, N.M.M., Machinery and N-S sectors do not present improved concentration for the same options in the fuel mix. Diversity is increased for the total industry for the same options scenario but for C&P, even marginally, Machinery, N-S is decreased. Therefore, this hypothesis according to the conditions set, is partially accepted.

6.6 Conclusions

Achieving energy security by increasing the diversification and reducing the concentration of fuel resources comprising the industrial energy mix, is of foremost importance regarding countries that have their economic growth coupled with energy demand. Those included in the present research do follow that pattern and either lead the global economy, in the case of China, have the capacity to do so in the future; India, or present high economic growth figures and are projected to perform similarly in the future.

Energy security can additionally be realised through increasing energy efficiency, effectively reducing the consumption of energy resources. As decreasing energy intensity in China and India is identified as a major factor for decoupling economic and emission growth (Wang et al., 2018) countries take steps towards that direction as part of energy policies to avoid the scenario of energy supply shocks damaging their economies (Shahbaz et al., 2017). Adding to that context, Indonesia plans to increase energy efficiency by 1% per annum up to 2025 (Dutu, 2016; Erdiwansyah et al., 2019), Thailand proclaimed its intention, through policy introduction, to reduce its energy intensity levels by 30% up to 2036 in comparison to the 2010 levels (Meangbua et al., 2019), while the Philippines also plan on a respective 40% reduction during the set period 2010-2030 (Mondal et al., 2018). In addition to national commitments towards the reduction of GHG emissions, amounting at a rate of 70% in the case of Philippines from 2010 to 2030 (Cenia et al., 2018), those policies point towards an alternative fuel mix in relation to the presently used, essentially diversifying energy supply towards sustainable or renewable solutions which would further enhance the projected HHI and SWI.

With the present study, five major or fast-growing economies of the Asian region are evaluated, under four different energy supply contribution scenarios, regarding the underexplored theme of concentration and diversity of the industrial total and ten disaggregated industrial sectors' fuel mix. However, despite an extensive database assembled and modelled for producing results according to the HHI and SWI methodology, this research presents specific limitations. These include a limited availability of data that extend no further than 2012 due to some of the countries reporting schedule in a non-periodic manner and secondly, due to the data modelling focus, fuel imports as part of the total consumption, are disregarded in the model. Future research can further explore the energy security concept of the examined sectors, additionally integrating imports and extending the assessed timeline, by connecting the fuel options trajectories against the national commitments that aim to satisfy the sustainability criteria as set by the INDCs for achieving the COP21 goals where appropriate.

7. Conclusions

7.1 Contribution of the Thesis

The potential relocation of industrial activities from China, the origin country, to India and the examined SE Asian countries will alter the emissions output and energy demand, as the result of various factors depending on the industrial sector in focus. This thesis focuses on the impact of this industrial production shift on regional emissions and energy requirements, identifying suitable and unsuitable industries for relocating. In doing so it does not disregard the potential impacts of relocation between any combination of the examined countries. The actual intensity, pace and extent of the industrial relocation practice taking place among the studied countries has not been the focus of this work. As discussed in **Chapter 1**, the aim of this thesis is to study the necessary parameters that determine the direct results of that potential shift from an energy and emissions standpoint.

As cost or environmental sensitive firms seek to relocate the newfound potential for an industrial cross-country shift is expected to generate profound impacts on energy demand and environmental emissions. The regional reporting authorities present accounting inconsistencies and performing comparisons with international reports shows a mismatch of raw materials consumption and as a result, emissions estimations. The generated emission uncertainties pose a risk when setting feasible emission targets that are expected to comply with proclaimed INDCs towards the Paris Agreement. The present study locates and highlights those gaps in accounting emissions, for a major economy that acts as a potential industrial host, through a set of attractive factors and policies, for attracting manufacturing production and carries the risk of affecting global emissions estimates as stated in the Paris Agreement; India. The work of this research quantifies those generated uncertainties, starting from the primary level; raw materials and the generated heat from consumption, up to the generated carbon emissions emitted. Upon studying and presenting the accounted uncertainties between international reporting authorities, combining emission factors used by those reporting authorities generates new streams of accounted carbon emissions, demonstrating the risk for further unaccounted resulting uncertainties. Concluding, inconsistencies that occur between those quantified streams of carbon and emission factors become available, bringing carbon emissions and accounting gaps where those exist under the spotlight. This approach presents the impacting magnitude that the emissions uncertainties carry, against existing accounting estimation systems, standards and reported CO_2 emissions, eventually questioning the existence of an accurate carbon estimate for the country.

As a result, this study locates significant uncertainties between all the generated emission scenarios of India's industrial sector. Setting a benchmark gap, the average emissions accounted produce significantly different CO_2 outputs compared to the mean published estimates. Between the published CO_2 estimations, these can differ as high as 284.74MtCO_2 as found for 2008, or at a rate of 26.75% as accounted for 1982. Combining the emission factors used by authorities to generate the scenarios utilised by this thesis presents uncertainties that are accounted at 32.22% or 226.98MtCO_2 on average, while the net scenarios based on IPCC and IEA emission factors has an uncertainty rate of 14.69% across the examined timelines.

Highlighting this emissions uncertainty, presents an existing urgency for reporting authorities to unify their carbon emissions factors and standards. It points towards the requirement for establishing unified databases between local, regional, and international reporting authorities, using agreed metrics and utilising local emission factors to account and produce carbon estimates. Applying such a practice, will provide the necessary means for setting realistic emissions targets and in extent, form policy making and an effective pathway to sustainable development. Following that recommendation, India's MOSPI proclamation of a unification of its accounting standards with those of IEA, as an effort commencing in 2017 is a required step towards the direction argued by the present thesis. However, increased effort is required to adjust inconsistencies found in reporting energy and raw materials consumption levels, emissions factors between regions and the resulting accumulated carbon emissions over time.

Expanding the research theme for a broader but regional group of countries, the energy and carbon intensity industrial levels are investigated. This requires an expansion of country focus to include candidate industrial host countries. Starting from India, included to that group are Indonesia, Thailand and the Philippines. Examining China serves the purpose of performing the necessary comparisons and setting a benchmark between the manufacturing origin country against the four-country group of hosts while remaining open to alternative combinations. A range of seven industrial segments have been accounted to reach conclusions regarding the potential industrial shift; energy usage versus the economic output and the subsequent emissions output versus energy and economic output. This approach can reach conclusions upon examining the countries' performance in the event of an industrial relocation shift, following the total and industrial sectoral basis.

Energy and carbon intensity produce varied results on a per country and per industrial sector basis. A confirmed convergence of the energy intensity indicators is pointing to similar energy requirements for producing a set economic output for each of the countries examined. However, host countries show an increased energy intensity requirement for specific industries when compared to the country of origin; Thailand for PP&P or Indonesia for the chemical and petrochemical industries. The research effectively concludes towards a range of findings regarding energy and emissions intensity. Energy intensity of the examined countries' total and individual industrial sectors has significantly different output, but it demonstrates convergence over time. India's two-fold higher energy intensity output of the total industry compared to China, is mainly attributed to the iron and steel and non-metallic minerals sectors. The latter sector compared to China, produces similar results for the rest of the countries examined. The CO_2 emissions intensity of the total industry is higher in India, Indonesia, the Philippines and Thailand, compared to that of China. Highlighting specific findings regarding the examined industrial sectors, the Indian and Indonesian CO_2 emissions intensity of the non-metallic minerals industry is three-fold and two-fold higher respectively than that of China. For the iron and steel industry, CO_2 emissions intensity in India is two-times higher than that of China.

Decarbonisation remains a desirable result for host countries, as the carbon produced per energy input requires improvement in the total and several of the industries examined, underlining a potential emissions spike in the event of relocation from the origin to the host countries. The high reliance on coal products and technological lag in relation to China, except for the PP&P industries, highlights the requirement for fuel substitutes or introducing optimisation to achieve output convergence. This will satisfy the environmental and sustainability standards that the countries are committed to achieve. However, the research findings are conclusive towards the argument that industrial relocation for most industrial sectors, will result in the Paris Agreement INDC commitments to be challenged.

Focusing further on the host countries CO_2 emissions and examining any available capacity for further improvement, requires the disaggregation of carbon emissions by specified driving factors (EI, CI, LP, IS) as indicated in **Chapter 5**. Using the additive index decomposition analysis tool, this thesis can allocate the drivers' effect on carbon emissions change for eleven three-year time periods. This breakdown, that covers 1980 to 2012, is the tool for providing an elevated level of detail of studying each driver's effect on CO_2 emissions. The exclusion of Thailand at this part of the research is a conscious choice as several primary data reports, required for executing the chosen additive LMDI-I model, are not available.

While the improvement of carbon intensity is deemed as essential for promoting economic sustainability in the developing countries examined, labour productivity and industrial scale are on par with energy intensity in their contribution levels in driving CO_2 emissions for countries such as India and Indonesia. The introduction of efficient production processes through automation, is determined as a feasible solution for improving several industrial sectors CO_2 emissions performance. Choosing this technological improvement pathway would lower the effect that industrial scale and labour productivity produce historically in driving CO_2 in the three examined countries. Highlighted simultaneously, according to the research findings, is the requirement for that proposed automation should be integrated through energy efficiency or a low-carbon fuel mix, otherwise automation may have adverse effects on CO_2 emissions. Focusing on the Philippines, the introduction of low carbon content fuel resources used for satisfying industrial energy requirements, is expected to have a direct result in decreasing the effect of carbon intensity; a significant aggregator in the country's industrial CO_2 emissions output.

Overall, each country experiences a different significance rate for each of the chosen factors that contribute to CO_2 emissions. This observation is valid for either across the timeline in the examined country or between those examined countries. However, controlling the contribution of the examined factors, except for the effect of carbon intensity, in most country cases would result in increased control over the CO_2 emissions change. The change of CO_2 emissions is not driven by carbon intensity in many countries of South Asia, including India, an argument that is confirmed by the most recent IDA studies (Gupta, 2019). This finding becomes valid for all the countries examined by the present research but the Philippines. The effect of carbon intensity is a non-significant contributor in the examined industrial sectors. This low contribution rate of CI in driving emissions, is mainly the result of a fixed fuel mix used by the examined countries for the duration of the studied periods.

In most of the industrial sector cases, decreased carbon intensity found in host countries compared to that of China, is effectively cancelled by the increased energy intensity levels. Energy intensity upon LMDI decomposition is identified as the most prominent factor of increasing CO_2 emissions (Ma et al., 2019). As a result, a transfer of industries from China to host countries would result in elevated CO_2 emissions due to the existing energy requirements for achieving a fixed economic output. Neutralising this expected output would require structural change to the industrial energy input (Li and Qin, 2019). Increased energy intensity leading to increased CO_2 output neutralising the carbon intensity effect, becomes pronounced when approaching the Philippines as a total industry host. Disaggregating this further, this performance is validated for the paper pulp and print sector in the Philippines, the textile and leather and chemical & petrochemical sectors in Indonesia and the iron and steel sector in India.

In all cases, a transfer of the non-metallic minerals sector to the examined host countries will result in significant CO_2 emissions increase due to the higher energy and carbon intensity indicator levels. However, a transfer of the machinery sector from China to any host country would result in significant CO_2 emissions decrease due to the lower energy and carbon intensity levels. Significant emissions decrease is also expected for a transfer of the iron and steel sectors from China to Indonesia and Thailand. The expected emissions output however, is dependent on the effect of industrial scale and labour productivity.

With only limited data available for Thailand, the potential CO_2 emissions decrease suggested as part of a production shift, cannot be confirmed. In contrast, confirming the benefit of an iron and steel production shift to Indonesia, increased industrial scale would not contribute towards increasing CO_2 emissions. The contribution of the chosen factors on CO_2 suggest that for the most recent periods, such a shift would be environmentally beneficial, with only labour productivity presenting a positive link to CO_2 increase. That paradigm can be confirmed for the machinery sector only when examining India as a host country. In the Indian case all factors are found to contribute negatively towards carbon dioxide emissions in the latter period examined. For Indonesia and the Philippines, labour productivity and industrial scale produce a positive link on CO_2 emissions, suggesting that increasing the number of employees would result in a significant increase of CO_2 emissions.

Energy security is a critical topic for policy makers. Initially serving the methodological means for exploring the access to finite fuel resources, e.g. fossil fuels. It is transformed by the present global standards and market requirements, as the additional means for considering environmental and climate change issues. The high-growth GDP country group that this thesis focused on has its rate of growth coupled with industrial output. Determining the diversification and concentration indices of industrial fuel mix portfolios, is critical for showcasing the foundations of that economic growth, exposing vulnerabilities either present or eliminated over the examined timeline.

Further discussing the industrial production and economic growth coupling, a concentrated fuel mix is identified as a threat to the chosen developmental pathway. Exploring energy security indicators as such, Indonesia is found to have decreased concentration-high diversity in its total industrial fuel mix. This is mainly attributed to the output index of the industries included in the non-specified category. Contrasting that picture, India has experienced increased concentration in its energy supply for the most recent examined periods. The country is found to be an average performer regarding its concentration and diversity indices, a conclusion confirmed by the most updated relevant research comparisons (Hou et al., 2019). The iron and steel industry, a major industrial sector that reflects on the total, has the highest concentration index compared to the rest of the host countries. Therefore, India effectively faces an urgency for a fuel mix diversification, especially in light of setting ambitious policy initiatives of sustaining its economic growth for the following forty years (Mehra and Bhattacharya, 2019; Mukherjee, 2019). Improving the diversification index, serves the aim of reducing any risks that may arise, effectively sustaining its economic development and decoupling energy and emissions in India and the ASEAN group (Chontanawat, 2019). Despite the discussed trend observed in India, all countries present similar concentration indices to that of China in the latest examined periods. Comparing all countries and examining industrial sectors, finds the Philippines offering consistent diversified energy supply across the timeline range. The Philippines present higher diversity than that of China for the food and tobacco, paper pulp and print, textiles and leather. It is the only country between origin and hosts, that is identified as consistently reducing its fuel mix concentration across the timeline for the total industry.

7.2 Policy Recommendations

According to the findings, an industrial production shift to the selected host countries; India, Indonesia, the Philippines and Thailand requires actions from policymakers and industries alike. It is essential that emissions control is being approached predominantly within the industrial and energy sectors. Lacklustre control of emissions deriving from primary energy provision, can generate negative impacts for transport electrification, as it can mitigate the environmental benefits (Hofmann et al., 2016). While China acts as a benchmark for this research, its industrial energy consumption is found to play a significant role in decoupling of energy and emissions (Liang et al., 2019), highlighting the benefit of setting relevant policies in the host countries as well.

This thesis explores and applies the methodological means required and evidences an enhanced view regarding the performance of the industry. This quantified performance shows the produced emission levels versus the economic output, presenting existing energy requirements and investigating the driving effect for achieving a meaningful exploration of sustainable future pathways. The carbon dioxide levels emitted by manufacturing activities in

India and other rapid economic growth countries of SE Asia are either higher than China or follow trajectories that are alarming in a world that aims to reach carbon neutrality for combatting climate change (Allen et al., 2019). Indicators such as energy efficiency are facing a critical implementation junction considering the economic sustainability and environmental commitments that respective governments are committed to satisfying. Considering the current industrial growth scale, this commitment becomes increasingly urgent.

The industry experiences the formation of a relocation pattern following established theories, as the introduction discusses. These are additionally confirmed by historical patterns found in the geographical region of Asia. The relocation of manufacturing hubs is the logically expected outcome as China becomes the lead goose in the region (Wang et al., 2020). The policies that the assessed countries have set in attracting Chinese based industries aim in accelerating that pattern, for claiming a larger share against competing countries, aiding the growth of their economy and, looking at the bigger picture, strengthening their geopolitical importance in the region.

However, this transition is not an issue that concerns the national economic growth or corporate profit margins exclusively. The monetary impact that climate change generates is a realised risk (Debelle, 2019). The wellbeing of future generations is jeopardised, with the expected impact on societies, in terms of equity and equality adding pressure on governments to form climate policies that address and reduce vulnerability created by climate change (Huynh and Stringer, 2018). As such, it urges national authorities, looking from a financial standpoint, to now act and commit to introducing policies which include mitigation strategies for reducing the environmental burden and deriving impacts. Discussing the industry, those targets must include the industrial energy consumption levels as a critical contributing factor to CO_2. Set commitments can be jeopardised if policies are weak, either by design or application, sometimes subject to a prioritisation of short-term financial gains. Following the example set by the EU-28, with energy consumption decoupled to economic growth (Pao and Chen, 2019), the policies set must aim at being ambitious. Energy innovation policies can not only bring energy efficiency convergence of the host countries with that of their western counterparts but R&D capacity as that found in India can generate a desired technological frog-leap that puts the country ahead of the curve.

However, aside from introducing innovation at the production level in-house, policies that favour technological transfer should be implemented as a logical step to make the learning curves of the host countries steeper, essentially helping the host countries gain a competitive edge (K.S. Sekhara and V. Sri, 2017). Policies aimed at technological transfer can be introduced at either in forms of absorptive capacity, investment incentives or FDI facilitation. Aiding multinational companies in transferring their expertise to their new manufacturing hubs, by accelerating or eliminating bureaucratic procedures and adding process transparency, is a crucial factor for the technology transfer to occur (Andrenelli et al., 2019). Lifting existing barriers is an issue widely addressed in the international literature, either in terms of using national systems of innovation (Ockwell and Byrne, 2016), employing the effect of FDI (Sikdar and Mukhopadhyay, 2020) or determining drivers of low carbon technology transfer between nations (Kirchherr and Urban, 2018).

Examining the application of innovative production means in the examined countries, policies targeted towards the development of energy innovation are necessary steps for the formulation of a sustainable pathway. This action will contribute in sustaining the current high rates of economic growth, which will be less suspect to risk susceptible to energy supply and price fluctuations. Policies aimed at creating and facilitating innovation in the energy field, are dependent on parameters such as regional politics, resource access and trajectories of socio-technical nature, among others (Chalvatzis and Rubel, 2015). Since the 1990s, there have been governmental actions of linking the science and business sectors. This has been conducted by providing incentives for relevant activities and balancing of imported technology and indigenous R&D production.

The national innovative capacity concept is measured as a nation's ability to produce and commercialize a flow of innovative technology in a long term basis (Furman et al., 2002). That innovative capacity is dependent on the strength of the common innovation infrastructure of a country, the innovation environment in the industrial clusters and finally, the linkages that exist between these two factors. Innovation capacity has been a significant contributor to the economic growth of major developing countries such as China and India. Both countries invest heavily in R&D activities, to obtain gains in patents and high-tech and service exports (Fan, 2011). Focusing on India, the country has to rely on innovation to a greater extent, in order to sustain its growing economy and decouple growth from energy (Kumar and Chakraborty, 2013). This requirement, however, is a debatable target, for India. Thornton (2013) has found India to hold great innovation potential, while Nair et al. (2015) claim that the country suffers from a lack of infrastructure for technological and policy innovation. Despite the current debate, a characteristic of India is its strong educational system and a robust software and information technology services sector that enable the country to follow an innovation-based development path, differentiating India from other developing economies (Cooper, 2009). Confirming that capacity for technological innovation, foreign multinational companies are the leaders in India's R&D activity, offering frugal innovation or creating patents for products that are aimed towards the international markets (Krishnan and Prashantham, 2019). The spill-over of these activities is now realised by Indian start-up companies invested at frugal innovation, pointing towards more efficient production means (Assisi et al., 2019).

Aiming at increasing the industry's competitiveness, Indonesia issued a long-term plan named "Making Indonesia 4.0" for the adoption of Industry 4.0 (Hidayatno et al., 2019). Through the implementation of the plan, the country aims to optimise the energy use of its T&L, food, chemical, machinery and automotive industry, increasing efficiency and lowering consumption, as contributing factors to the country aspiring to be in the world's top 10 countries by GDP terms. However, Indonesia, in contrast to India, is lacking in infrastructure that can facilitate innovation, risking the country's target (Gupta et al., 2019). A fiscal policy such as the introduction of tax exemption for R&D activities, in addition to the inflow of human capital, can produce results in a short-term scenario.

Aiming at the same target for increasing industrial competitiveness in a global context, Thai manufacturing companies are adopting a governmental initiative on the implementation of Industry 4.0, named "Industry 4.0 in Thailand 4.0" with a focus in innovation aimed at automation. A closed loop of a fuel mix high in carbon content aimed at using automation, hence higher energy input, can signal an increase in carbon emissions. However, achieving increased efficiency in production can result in a similar or lower emissions output, making the transition to Industry 4.0 the desired outcome (Salam, 2019). In December 2019, the Philippines' Department of Trade and Industry had taken the initiative, through signing MoUs with the Department of Labour and Employment and the Technical Education and Skills Development Authority, for the country's manufacturing transition to Industry 4.0 (Umali, 2019). The policy initiative aims at enhancing workforce skills or retrain, investing in upgrading its labour productivity.

The impact of climate change provides a boost to extended development and integration of low carbon technology innovation through the introduction of mitigation policies and regulations (Nuttall and Manz, 2008). The concept of decarbonizing the economy through innovation by various policy incentives has also been a matter of research on socio-economic transitions (Murphy, 2014). Numerous studies both in conceptual and practical terms have assessed this eco-innovation for sectors such as transport (Banister et al., 2011), energy production (Jeffrey et al., 2013), building construction (Lai et al., 2016) and were the subject of research both for commercial and industrial applications and management methods (Carrillo-Hermosilla et al., 2010; Ekins, 2010; Pujari, 2006; Rennings, 2000). Carbon tax and subsidies for low-carbon technologies as well as public expenditure on technology research and development are considered the two most effective instruments for low-carbon technological innovation (Aghion, 2009; Aghion et al., 2009). This innovation pathway can be stimulated by the introduction of regional low carbon management establishments, e.g. the Low Carbon Trust (LCT) organization, which supports and influences the integration of low-carbon innovation technologies globally (Kern, 2012). Attracting or establishing organisations that aid in relevant policymaking can further aid the accelerated adoption and development of energy efficiency measures, closing the gap between the industrial hosts and the origin country.

The technological innovation applications must be evaluated for their environmental, security and affordability performance that will affect their wide-scale adoptability either by the state or private investors. These terms aim to establish a solid framework for evaluating policy innovation and enable the "invention" of alternate scenarios to be followed. The purpose of the pathways under examination, follow the scenario of developing the host countries examined, India, Indonesia, the Philippines, and Thailand to maintain their industrial production output. At the same time, their carbon emissions are mitigated, following a declining trend. While conceptual efforts were recently conducted in other innovation thematic areas such as agriculture with ecological aspects (Ramani and Thutupalli, 2015), India is found to suffer from a lack of infrastructure (Nair et al., 2015), discussing technological and policy innovation.

The levels of energy and carbon intensity and their contributing effect is added to the effect that labour productivity and industrial scale have on carbon emissions. Determining the effect of those four factors enables the provision of enhanced clarity for introducing policy recommendations. Those recommendations focus on policies aimed at technology, economic growth and environmental protection.

Policies assisting the technological upgrade of the industry is a requirement for mitigating carbon emissions effectively. Under that prism, the priority would be to disconnect labour productivity and CO_2 emissions growth. Emphasis is placed in heavy industries, which are subject to high energy intensity when obsolete technologies are still utilised in production. Economic policy aimed at higher fuel tax or environmental financial penalties can act as an inhibiting factor to heavy and high polluting industries, pushing towards lower energy consumption. The utilisation of energy-efficient production means can accelerate a technological upgrade or technological transfer, for the affected industries to benefit from other advantages of the host country (i.e. lower wages, land value). Nevertheless, the industrial energy mix in its current utilisation status is still highly dependent on coal and oil products. Restructuring the fuel mix towards fuels with lower carbon content must be a priority, as the environmental cost of using indigenous fuel resources can outweigh the direct financial benefits (Ferroukhi et al., 2016).

India has introduced several actions that would mitigate GHG emissions through its Integrated Energy Policy (IEP) of 2006 (Government Of India, 2010). Governmental actions relevant to the industry are additionally described in the country's INDC to the Paris Agreement but the historical results included in the present research, fail to demonstrate an improvement in the energy and carbon efficiency of the industry up to 2012. Other actions such as the "India GHG Programme" shows the initiative to conduct a voluntary programme for industries to measure their specific carbon footprints.

In addition, the host country governments should continue their ambitious programmes of regulatory reforms that will trigger more robust private investment in renewables and energy storage (Zafirakis et al., 2016). Concluding, as electrification in the domestic sector expands to an ever-increasing number of homes, such as in the case of India, the host countries must consider public engagement with issues of domestic energy efficiency, which can have a significant impact on sustainable growth (Pothitou et al., 2016).

7.3 Research Limitations

The research was subject to limitations related to data, in terms of availability and concision and the analytical methods that were used. These are analysed and presented in demarcated subsections to enhance clarity for the reader and the consideration of future researchers.

7.3.1 Data Limitations

In terms of data, difficulties were widely present during the collection process. This research relies exclusively to secondary data that are sourced by the IEA and UNIDO. As discussed throughout this thesis, the IEA and UNIDO were selected due to the level of detail they provide. The industry sector and sub-sector breakdown when publishing and organising data output of raw materials consumption is unparalleled by other databases at the time of data collection. However, the data in many cases, both for IEA and UNIDO were not complete with annual output left blank for specific countries. This is a lesser problem when approaching India and becomes more significant when examining the other host countries included in this research. Data limitations present in the IEA database show net calorific values per fuel not subject to yearly variations, as realistically expected. This expected NCV variation is evident only between generic NCVs and the industry. Gap years or gap periods exist in the data collected in cases pointed out in the relevant research chapters. In addition, carbon emission factors use standard values as provided by IEA or the IPCC. As Dabo et al. (2012) demonstrate, this presents a significant limitation to the real carbon output of a country and the present research acknowledges that limitation. The first research chapter (**Ch. 3**) places specific emphasis on that limitation, and the research aim is to add to the discourse of the scientific community, regarding that problematic area. However, the utilised accounting methods, remain subject to the problematic data reporting and the standardised emission factors. These act as a loop, making the research subject to that limitation when striving to achieve higher accuracy. Access to primary data, and enhancement of the quality of the historical data present in the database or upgrading the quality of data reporting are key to surpassing those limitations.

In terms of data availability, it is considered that during the term where this research was performed for this thesis, the data extracted and used from UNIDO and the INDSTAT2 database, were not available for years later than 2012. UNIDO annual data output for the following years became available in late stages of this thesis, at the thesis post-submission stage, in October 2019. Due to the complex methodological procedures described in the relevant chapters 4 and 5, for communicating IEA and UNIDO data by ISIC standards, the usage of another UNIDO database (INDSTAT4) was not an option that provided a comparable level of output accuracy in a plug 'n' play basis. Moreover, IEA has not provided finalised data for years later than 2012 when the research methods and results produced by the thesis were accounted. It is due to that fact that later years than 2012 are not accounted when working with data extracted exclusively from the IEA.

Summarising the limited reported data effect, for each research chapter, the main points are present on the following **Table 7.3.**

Table 7.3 Data limitations and effect on the accounting output per thesis' chapter.

Chapter	Data limitation	Effect
3	• Generic emissions factors per fuel. • NCVs differentiate between general and industry or between long periods. • IEA non-provisional data not available for years later than 2012 at the time of collection (2015-early 2016)	• Accuracy in country-specific carbon emissions is potentially limited. • Discrepancies studied up to 2012.
4	• Raw materials present gap years • NCVs differentiate between general and industry only or between long periods. • IEA does not breakdown industrial sectors to the detail provided by UNIDO for the countries examined. • UNIDO INDSTAT2 data not available for years later than 2013. The following years	• Gap years use median values where appropriate. • The industry is not broken down for all active economic sectors. It is limited to the sectors that IEA publishes. • Precision in country-specific carbon emissions is potentially limited. • Energy intensity and carbon intensity accounted for 1980 to 2012.

	became available in October 2019.	
5	• Economic output presents gap years with numerous sectors not producing adequate data to perform a decomposition across the timeline. • UNIDO INDSTAT2 data not available for years later than 2013. The following years became available in October 2019.	• Thailand is excluded from the decomposition due to poor data availability. • Decomposition performed in set periods from 1980 up to 2012.
6	IEA does not publish activity levels of raw materials in specific industrial sub-sectors of India and Indonesia.	• The **HHI** and **SWI** for the Wood & Wood Products industry of India cannot be examined. • The **HHI** and **SWI** for the Wood & Wood Products and Paper, Pulp and Print, and Machinery industries of Indonesia cannot be examined.

7.3.2 Analytical Limitations

The analytical methods applied do not present variations in applied models when calculating heat derived from various fuels or carbon emissions. The variation exists within the factors as long as the carbon emissions are calculated as production-based. This approach is the common standard in carbon emissions accounting as adopted by the IPCC guidelines (2006). This is the methodology utilised by the present research and presented in **Chapter 2** as primary data are widely available through international databases. In contrast to the consumption-based approach, the production-based method holds greater certainty in its accounted output but at the cost of not covering the embodied CO_2 emissions, i.e. those emitted by international trade activities. The present research aims to the acquisition of a full total, sectoral and sub-sectoral data-coverage to produce the desired accounting outcome. Thus, it is subject to production-based model analytical limitations. The production-based approach is the root for calculating all the produced heat and in extent, carbon, CO_2 estimates and effect of their derivative factors, utilised by the present research.

Energy and carbon intensity levels present high research interest on a standalone basis as the present study shows. However, they are required factors when performing an index decomposition analysis (IDA). Decomposing the carbon emissions of the examined countries' industrial sectors, results to quantifying the effect that carbon and energy intensity have in driving emissions change, among others.

The chosen methodology for performing the decomposition of carbon emissions has been the additive LMDI-I, measuring absolute carbon changes, as this is described in the methodology found in **Chapter 2**. The methodological chapter also contains the supporting arguments for adopting this approach. However, while LMDI-I achieves perfect decomposition, it is subject to specific limitations when considering the produced output. As the decomposition method is using a base and target year for studying the factors' effect, errors in the interpretation of results are possible when large discontinuities or gaps in the indicators are evident. This research counteracts this limitation of LMDI-I by decomposing the examined 32 years long time-series, in three-year rolling periods with each period having the base and closing year. As such, the decomposition analysis according to Ang and Liu (2007) and Kim (2017) reveals the underlying factors for such a change with no analytical limitations evident in the applied method as it achieves perfect decomposition with no residual effects. The limitations will remain linked with the quality of the input data.

The HHI or SWI results exclusively use the number of different fuels present in the fuel mix to apply the methodological steps for examining energy security. The application of those indicators does not account for the effect that other factors have, such as political, environmental or social. Additionally, discussing energy, the indices do not capture the national import dependency of the fuel mix, due to residual values producing unrealistic figures found in the primary data collection, early in the research phase. It is due to that erroneous data that the research focuses on the concentration (HHI) or diversity (SWI) of fuel activity levels present in the industrial energy mix. The impact of that analytical approach is that it does not capture the broader effect that the utilised fuel mix generates, either in energy security or environmental terms. An examined country can be found to utilise a diverse fuel mix, but energy security can be at risk due to a high import dependency of those fuels. As such, this approach is unable to make direct suggestions on a broader policy context by using this quantified output. The research relies on the further review of existing literature, to establish that diversity producing high security of supply. It is through the HHI and SWI results, that the research later recommends areas for improvement or greater focus, for achieving sustainable pathways for the nations' industrial sector and in extent their economic growth. The strong coupling of economic growth and energy activity levels, present in the discussed developing countries, highlights that approach as necessary.

7.3 Future Research

This thesis establishes the foundations for future research that expands further from the fields that this research is addressing. It provides the methodological means and calculation steps, to reach credible accounting results in a multitude of previously underexplored thematic areas and research fields when discussing the selection of host countries. The produced research output that derives from energy consumption and carbon emissions output can be relevant to future researchers for discussing the thematic areas of business competitiveness, economic development, and technological change. The conclusions point towards a formed urgency, for limiting or reversing the generated negative environmental impacts that the total economic and industrial activity levels are producing. Future research output that further aids the set of policies relevant to the themes mentioned will enable the mitigation of negative impacts produced by the rapid economic development that the region experiences. The coupling effect observed, for economic growth and energy consumption, becomes profound and requires increased future research output to be addressed and recommend decoupling pathways.

The carbon discrepancies accounting model discussed in **Chapter 3** can be a valuable asset for future research as the produced results highlight significant implications, not only for the environment but additionally for India's economic activity levels. The accounted discrepancy margins that this research produces highlight the severity of the emissions uncertainty when approaching a more significant scope and discussing global emissions. As India is the world's 3rd largest carbon emitter, those discrepancies cause concern in the current global emissions output field. This uncertainty in carbon emissions can impact the output accuracy of predicting models, thus hindering the accurate allocation of carbon emissions responsibilities and mitigation targets set by policies and international treaties. Policy makers are denied the accuracy required for setting effective policies. Therefore a pragmatic, or regionally adjusted, approach in carbon emissions accounting factors is a matter of utmost importance.

This research aims to highlight the existing discrepancies in carbon emissions through a set timeline; 1980 to 2012. However, as the problem is located and quantified, it points towards the path that future research should follow to produce high impact research output. This pragmatic approach for determining the realistic output of CO_2 emissions is a recommended pathway involving several areas of focus that hold academic interest for producing further research. The deep reform of the current carbon accounting factors is necessary. Revisiting the current coal statistics widely becomes a requirement, with a high degree of detail equalling the extensive breakdown of fuels, as these comprise the fuel mix utilised by the total and manufacturing sectors. Defining the real carbon emissions levels will minimize discrepancies. A method to achieve that outcome is to use in-situ measurements of carbon emission factors of coal, gas and oil products used in India's energy mix, in the same methodological and accounting patterns demonstrated by Dabo et al. (2012) and the present research. Determining the actual carbon content, net calorific values, oxidisation rate, and utilising the methodology demonstrated in **Chapter 2**, are the required steps for improving and updating the quality of the statistical output while producing high impact research. In the same vein, determining the energy efficiency of industrial technologies, currently mainstreamed in Indian factories, can produce higher accuracy levels that enhance the accuracy of energy intensity predicting models.

Assessing the total industry and industrial sub-sectors of the examined countries, the energy and carbon intensity indicators presented in **Chapter 4**, historically present varied output per industrial sector. The higher levels of the indicators present in the host countries and the existing positive relationship of economic growth and energy consumption highlights the existing urgency towards the increase of FDI or domestic investment to achieve a structural transformation of the industry. Investment channels can be either governmental or private, pointed towards a shift in increasing the share of renewable energy production or the introduction of more efficient technologies in manufacturing. The exploration of those developmental pathways either by modelling simulation or approaching this from a business/social perspective to locate factors that present higher positive impact for raising industrial efficiency are subjects that can produce large research volume. Examining the technological innovation required for the manufacturing process of each industrial sub-sector, effectively lowering the energy and carbon intensity levels, is a promising field for future research output. The thesis findings act as major contributors towards this path, as insight and evidence are provided for those indicators when examining each industrial sector on a per-country basis. This approach enables future researchers to focus on the specific sectors that require urgent attention in addressing the energy consumption and carbon emissions output. Manufacturers or investors gain insight regarding the sectors that require an influx of capital to remain competitive or gain a competitive edge.

The data sources, methodologies, results and areas of concern that this thesis provides are essential tools for producing future research that expands to other developing countries than those included here. Expanding on the industry and industrial sectors of an increased country sample can provide further insight on the intensity, efficiency, scale, and security indicators as well as compare the uncertainty margins. The thesis provides the necessary methodological means, including error handling, regarding addressing the existing data limitations. In the same vein, as the statistical authorities of the examined countries are upgrading their data collection and quality procedures, as experienced with India establishing an associate relationship with the IEA, the continuous update of the data and further breakdown to a larger sample of industrial sectors will be a feasible research field. This is an exciting prospect for updating the findings, following new trends, examining industrial development, primarily producing a continuous research output in a high esteemed topic of the international literature.

The Divisia index and its LMDI-I analytical framework provide the methodological foundations to decompose the effect that a range of factors have, in driving carbon emissions of industries as these are based in the examined countries. The choice of the factors was finalised in accordance to previous work, as this was found in the international literature, aided by the fact that two of the four, energy intensity and carbon intensity, have been used in **Chapter 5** of this thesis. However, decomposition using LMDI-I is not locked within that set range of factors. A broader or alternate thematic set of factors can be chosen, using the same methodology, additionally given a choice to perform the additive decomposition as it is methodologically established in this research. As such, the research can extend further than what is accounted for in the thesis. Extending or replacing the included environmental or productivity factors that define the effect in driving carbon emissions change is feasible. Indicators can be selected from the field of business, economics social studies and innovation with minor adjustments to the methodology provided that they follow a time series reporting structure. As such there a realised opportunity exists for conducting impactful future research on a variety of different disciplines.

This thesis establishes future research opportunities without deviating from the chosen methodology. Data availability during the collection process has prohibited the research from extending to more recent time periods. As the required data for performing an LMDI-I decomposition are now available, future research can include increased time periods with the possibility for extended industrial sectors. Locating further variations, regarding the effect of the indicators chosen, will provide a high impact to environmental policy targets and push further towards energy efficiency and technological innovation in manufacturing.

Following the findings presented in **Chapter 6**, the thesis demonstrates the diversity and concentration of the fuels present in the industrial energy mix consumed for manufacturing products. These indicators, characterised as HHI and SWI, are essential for highlighting existing risks. The research output can point towards a created urgency for further diversification that alleviates the risk in sustaining production levels, especially in light of decarbonisation that the industry is now facing, following the targets set by national pledges towards the Paris climate agreement. Future research can update the timelines that this research is producing due to increasing data availability. The required structural change for the industry to utilise an increased number of fuel resources, introduce fuels lower in carbon content, as well as the existing or future capacity for using renewable energy in production can be investigated. This research can be used as the required benchmark that measures and quantifies change. Further research output can focus on establishing a relationship between the decision factors weight for businesses that seek to relocate to countries that present competitive advantages but low fuel diversity, such as those found in the present assessed group. The output of this research can act as the necessary background for setting benchmarks, with elevated research value when including fuel import data when these become available.

A critical field for future research is the study of the effect that COVID-19 crisis will have on the indicator levels that contribute or are causally linked with carbon emissions. A lengthy lockdown imposed among significant economies globally, for controlling the spread of the disease, has impacted energy consumption, with oil at the time of writing being at a historical low (Kelly, 2020). Updated carbon emissions research estimates show a significant mean drop of 17% in daily global emitted CO_2 output when compared to 2019 (Quéré et al., 2020). As such, modelled projections for the year 2020, before the crisis, are effectively cancelled. The increased data volume, available from a short to mid-term future, depending on the country of choice, can present variations that do not fall within any of the previously expected projections. Oil prices have explored negative sell price territory (-$37.93) in April 2020 (Kumar, 2020).

This price trend can hinder the adaptation of renewable energy in developing countries as the economic incentives for adopting RES promoting policies are neutralised. Produced reports that become increasingly available expect a decline in RES capacity net addition by 13% when compared to 2019 (IEA, 2020). As such, future research that utilises a similar methodological approach can update the data, findings and conclusions. New research following the newly established trends, can demonstrate the imposed impact on national and global energy strategy, environmental policy, and technological development, making practical proposals that account for that new-formed reality.

Reference List

Aalto, P., 2015. Institutions in European and Asian energy markets : A methodological overview. Energy Policy 74, 4–15. doi:10.1016/j.enpol.2014.08.022

ADBI, 2014. ASEAN 2030: Borderless Economic Community, ADB Institute.

Aghion, P., 2009. Cold Start for the Green Innovation Machine. Bruegel Policy Contrib.

Aghion, P., Hemous, D., Veugelers, R., 2009. No green growth without innovation. Bruegel Policy Br. 1–8.

Ahearne, A.G., Fernald, J.G., Loungani, P., Schindler, J.W., 2008. Flying geese or sitting ducks: China's impact on the trading fortunes of other Asian economies. China Asia Econ. Financ. Interact. 7–25. doi:10.4324/9780203886397

Akamatsu, K., 1962. A HISTORICAL PATTERN OF ECONOMIC GROWTH IN DEVELOPING COUNTRIES. Dev. Econ. doi:10.1111/j.1746-1049.1962.tb01020.x

Alam, M.M., Murad, M.W., Noman, A.H.M., Ozturk, I., 2016. Relationships among carbon emissions, economic growth, energy consumption and population growth: Testing Environmental Kuznets Curve hypothesis for Brazil, China, India and Indonesia. Ecol. Indic. 70, 466–479. doi:10.1016/j.ecolind.2016.06.043

Allen, M., Antwi-Agyei, P., Aragon-Durand, F., Babiker, M., Bertoldi, P., Bind, M., Brown, S., Buckeridge, M., Camilloni, I., Cartwright, A., 2019. Technical Summary: Global warming of 1.5° C. An IPCC Special Report on the impacts of global warming of 1.5° C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the thre.

Alon, I., Wang, H., Shen, J., Zhang, W., 2014. Chinese state-owned enterprises go global. J. Bus. Strategy. doi:10.1108/jbs-12-2013-0118

Ambec, S., Cohen, M.A., Elgie, S., Lanoie, P., 2013. The porter hypothesis at 20: Can environmental regulation enhance innovation and competitiveness? Rev. Environ. Econ. Policy. doi:10.1093/reep/res016

Anbumozhi, V., Yao, X., 2017. Remaking Energy Policies for Global Sustainability: The Case of Flying Geese Model and Path Dependencies in East Asia 26.

Andrenelli, A., Gourdon, J., Moïsé, E., 2019. International Technology Transfer Policies. doi:https://doi.org/https://doi.org/10.1787/7103eabf-en

Andres, R., Boden, T., Higdon, D., 2014. A new evaluation of the uncertainty associated with CDIAC estimates of fossil fuel carbon dioxide emission. Int. Meteorol. Inst. Stock. 1, 1–15.

Ang, B.W., 2015. LMDI decomposition approach: A guide for implementation. Energy Policy 86, 233–238. doi:10.1016/j.enpol.2015.07.007

Ang, B.W., 2005. The LMDI approach to decomposition analysis: A practical guide. Energy Policy 33, 867–871. doi:10.1016/j.enpol.2003.10.010

Ang, B.W., 2004. Decomposition analysis for policymaking in energy: Which is the preferred method? Energy Policy 32, 1131–1139. doi:10.1016/S0301-4215(03)00076-4

Ang, B.W., Choong, W.L., Ng, T.S., 2015a. Energy security: Definitions, dimensions and indexes. Renew. Sustain. Energy Rev. 42, 1077–1093. doi:10.1016/j.rser.2014.10.064

Ang, B.W., Huang, H.C., Mu, A.R., 2009. Properties and linkages of some index decomposition analysis methods. Energy Policy 37, 4624–4632.

Ang, B.W., Liu, N., 2007. Handling zero values in the logarithmic mean Divisia index decomposition approach. Energy Policy 35, 238–246. doi:10.1016/j.enpol.2005.11.001

Ang, B.W., Wang, H., 2015. Index decomposition analysis with multidimensional and multilevel energy data. Energy Econ. 51, 67–76. doi:10.1016/j.eneco.2015.06.004

Ang, B.W., Xu, X.Y., Su, B., 2015b. Multi-country comparisons of energy performance: The index decomposition analysis approach. Energy Econ. 47, 68–76. doi:10.1016/j.eneco.2014.10.011

Apergis, N., Tang, C.F., 2013. Is the energy-led growth hypothesis valid? New evidence from a sample of 85 countries. Energy Econ. doi:10.1016/j.eneco.2013.02.007

Arce, G., López, L.A., Guan, D., 2016. Carbon emissions embodied in international trade: The post-China era. Appl. Energy 184, 1063–1072. doi:10.1016/j.apenergy.2016.05.084

Assisi, C., Raghava, A., Ramnath, N.S., 2019. The rise of the Indian start-up ecosystem. Commun. ACM 62, 82–87.

Aye, G.C., Edoja, P.E., 2017. Effect of economic growth on CO2 emission in developing countries: Evidence from a dynamic panel threshold model. Cogent Econ. Financ. 5, 1–22. doi:10.1080/23322039.2017.1379239

Azam, M., Khan, A.Q., Abdullah, H.B., Qureshi, M.E., 2016. The impact of CO2 emissions on economic growth: evidence from selected higher CO2 emissions economies. Environ. Sci. Pollut. Res. 1–14. doi:10.1007/s11356-015-5817-4

Azam, M., Khan, A.Q., Bakhtyar, B., Emirullah, C., 2015. The causal relationship between energy consumption and economic growth in the ASEAN-5 countries. Renew. Sustain. Energy Rev. 47, 732–745. doi:10.1016/j.rser.2015.03.023

Baek, J., 2016. A new look at the FDI-income-energy-environment nexus: Dynamic panel data analysis of ASEAN. Energy Policy 91, 22–27. doi:10.1016/j.enpol.2015.12.045

Balasubramanyam, V.N., Wei, Y., 2015. A Comparative Analysis of the Manufacturing Sectors in India and China. Rev. Dev. Chang. 20, 35–58. doi:10.1177/0972266120150203

Baldwin, R.E., Okubo, T., 2005. Heterogeneous firms, agglomeration and economic geography: spatial selection and sorting. J. Econ. Geogr. 6, 323–346.

Bali, N., Panta, M.P., Antelo, M., 2019. Sustainable performance-oriented production practices in the Indian iron and steel industry: An empirical investigation. J. Clean. Prod. doi:10.1016/j.jclepro.2019.03.252

Banister, D., Anderton, K., Bonilla, D., Givoni, M., Schwanen, T., 2011. Transportation and the Environment. Annu. Rev. Environ. Resour. 36, 247–270. doi:10.1146/annurev-environ-032310-112100

Bassi, A.M., Yudken, J.S., Ruth, M., 2009. Climate policy impacts on the competitiveness of energy-intensive manufacturing sectors. Energy Policy 37, 3052–3060. doi:10.1016/j.enpol.2009.03.055

Bataille, C., Åhman, M., Neuhoff, K., Nilsson, L.J., Fischedick, M., Lechtenböhmer, S., Solano-Rodriquez, B., Denis-Ryan, A., Stiebert, S., Waisman, H., Sartor, O., Rahbar, S., 2018. A review of technology and policy deep decarbonization pathway options for making energy-intensive industry production consistent with the Paris Agreement. J. Clean. Prod. 187, 960–973. doi:10.1016/j.jclepro.2018.03.107

Bazilian, M., Roques, F., 2008. Analytical Methods For Energy Diversity And Security, Analytical Methods for Energy Diversity and Security. doi:10.1016/B978-0-08-056887-4.X0001-7

Bhattacharya, M., Bhattacharya, S.N., 2014. Economic growth and Energy consumption nexus in Developing World : The case of China and India 4, 150–167.

Bhattacharyya, S.C., 2009. Fossil-fuel dependence and vulnerability of electricity generation: Case of selected European countries. Energy Policy 37, 2411–2420. doi:10.1016/j.enpol.2009.02.031

Bildirici, M.E., Bakirtas, T., 2014. The relationship among oil, natural gas and coal consumption and economic growth in BRICTS (Brazil, Russian, India, China, Turkey and South Africa) countries. Energy. doi:10.1016/j.energy.2013.12.006

Bishop, J.D.K., Amaratunga, G.A.J., Rodriguez, C., 2008. Using strong sustainability to optimize electricity generation fuel mixes. 2008 IEEE Int. Conf. Sustain. Energy Technol. ICSET 2008 502–507. doi:10.1109/ICSET.2008.4747060

Blair, J.P., Premus, R., 1987. Major Factors in Industrial Location: A Review. Econ. Dev. Q. 1, 72–85. doi:10.1177/089124248700100109

Blomstrom, M., Lipsey, R.E., Zejan, M., 2006. Is Fixed Investment the Key to Economic Growth? Q. J. Econ. doi:10.2307/2946665

Boqiang, L., Liu, K., 2017. Using LMDI to Analyze the Decoupling of Carbon Dioxide Emissions from China's Heavy Industry. Sustainability 9, 1198. doi:10.3390/su9071198

Boulhol, H., Fontagne, L., 2011. Deindustrialisation and the Fear of Relocations in the Industry. SSRN Electron. J. doi:10.2139/ssrn.1243522

BP, 2018. BP Statistical Review of World Energy 2018, BP p.l.c.

Brahim, S.P., 2014. Renewable energy and energy security in the Philippines. Energy Procedia 52, 480–486. doi:10.1016/j.egypro.2014.07.101

Brautigam, D., Xiaoyang, T., Xia, Y., 2018. What kinds of Chinese "geese" are flying to Africa? Evidence from Chinese manufacturing firms. J. Afr. Econ. doi:10.1093/jae/ejy013

British Petroleum, 2016. Statistical Review of World Energy 2016 - data workbook.

British Petroleum, 2015. BP Statistical Review of World Energy June 2015 48. doi:bp.com/statisticalreview

Brown, T., Florin, N., Fennell, P., 2012. Briefing Paper No. 7: Reducing CO2 emissions from heavy industry: a review of technologies and considerations for policy makers. Grantham Inst. Clim. Chang. Brief. Pap. 32.

Bureau of Labor Statistics, 2016. CPI Inflation Calculator [WWW Document]. Databases, Tables Calc. by Subj. URL http://www.bls.gov/data/inflation_calculator.htm (accessed 9.11.16).

Byer, H.B., 1937. Labor Involved in Industrial Production. Mon. Labor Rev. 45, 579–582.

Calkins, S., 2006. The New Merger Guidelines and the Herfindahl-Hirschman Index. Calif. Law Rev. 71, 402. doi:10.2307/3480160

Carbon Dioxide Information Analysis Centre (CDIAC), 2015. Fossil Fuel CO2 emissions.

Carrillo-Hermosilla, J., Del Río, P., Könnölä, T., 2010. Diversity of eco-innovations: Reflections from selected case studies. J. Clean. Prod. 18, 1073–1083. doi:10.1016/j.jclepro.2010.02.014

Cenia, M.C.B., Tamayao, M.A.M., Soriano, V.J., Gotera, K.M.C., Custodio, B.P., 2018. Life cycle energy use and CO2 emissions of small-scale gold mining and refining processes in the Philippines. Int. J. Life Cycle Assess. 23, 1928–1939. doi:10.1007/s11367-017-1425-5

Central Electricity Authority, 2016. All India installed capacity (in MW) of power stations - As of 31.01.2016 (Utilities) [WWW Document]. Gov. India - Minist. Power. URL http://www.cea.nic.in/reports/monthly/installedcapacity/2016/installed_capacity-01.pdf (accessed 2.25.16).

Central Statistics Office, 2016. Statistical Year Book India 2016 - Energy [WWW Document]. Minist. Stat. Program. Implement. URL http://mospi.nic.in/Mospi_New/upload/SYB2016/index.html (accessed 2.25.16).

Chalvatzis, K.J., 2009. Electricity generation development of Eastern Europe: A carbon technology management case study for Poland. Renew. Sustain. Energy Rev. 13, 1606–1612. doi:10.1016/j.rser.2008.09.019

Chalvatzis, K.J., Ioannidis, A., 2017. Energy supply security in the EU: Benchmarking diversity and dependence of primary energy. Appl. Energy 207, 465–476. doi:10.1016/j.apenergy.2017.07.010

Chalvatzis, K.J., Ioannidis, A., 2016. Energy Supply Security in Southern Europe and Ireland. Energy Procedia 105, 3656–3662. doi:10.1016/j.egypro.2017.03.660

Chalvatzis, K.J., Rubel, K., 2015. Electricity portfolio innovation for energy security: The case of carbon constrained China. Technol. Forecast. Soc. Change 100, 267–276. doi:10.1016/j.techfore.2015.07.012

Chang, G., Jiang, C., Chang, K., Alam, B., 2013. Land Prices and Intracountry Industrial Relocation in China. Chinese Econ. 46, 54–73. doi:10.2753/CES1097-1475460203

Checchi, A., Behrens, A., Egenhofer, C., 2009. Long-Term Energy Security Risks for Europe: A Sector-Specific Approach, SSRN. doi:10.2139/ssrn.1334620

Chen, J., Cheng, S., Song, M., Wang, J., 2016. Interregional differences of coal carbon dioxide emissions in China. Energy Policy 96, 1–13. doi:10.1016/j.enpol.2016.05.015

Chen, Z.M., Chen, G.Q., Zhou, J.B., Jiang, M.M., Chen, B., 2010. Ecological input–output modeling for embodied resources and emissions in Chinese economy 2005. Commun. Nonlinear Sci. Numer. Simul. 15, 1942–1965.

Chester, L., 2010. Conceptualising energy security and making explicit its polysemic nature. Energy Policy. doi:10.1016/j.enpol.2009.10.039

Chester, L., 2009. Does the polysemic nature of energy security make it a ‘wicked’ problem?

Int. Conf. Energy, Environ. Sustain. Dev.

Chiou-Wei, S.Z., Chen, C.-F., Zhu, Z., 2008. Economic growth and energy consumption revisited — Evidence from linear and nonlinear Granger causality. Energy Econ. 30, 3063–3076. doi:10.1016/j.eneco.2008.02.002

Chiu, C.Y., Lin, C.C., Yang, C.H., 2019. Technological catching-up between two ASEAN members and China: A metafrontier approach. China Econ. Rev. 54, 12–25. doi:10.1016/j.chieco.2018.09.012

Chomik, R., Piggott, J., 2015. Population Ageing and Social Security in Asia. Asian Econ. Policy Rev. 10, 199–222. doi:10.1111/aepr.12098

Chomik, R., Piggott, J., 2013. Asia in the ageing century: Part I – Population trends 1–18.

Chontanawat, J., 2019. Driving forces of energy-related CO2 emissions based on expanded IPAT decomposition analysis: Evidence from ASEAN and four selected countries. Energies. doi:10.3390/en12040764

Chu, K., 2013. China Manufacturers Survive by Moving to Asian Neighbors - WSJ [WWW Document]. Wall Str. J. URL https://www.wsj.com/articles/SB10001424127887323798104578453073103566416 (accessed 4.29.17).

Chuang, M.C., Ma, H.W., 2013. Energy security and improvements in the function of diversity indices-Taiwan energy supply structure case study. Renew. Sustain. Energy Rev. 24, 9–20. doi:10.1016/j.rser.2013.03.021

Clapp, J., 1998. Foreign direct investment in hazardous industries in developing countries: rethinking the debate. Env. Polit. 7, 92–113. doi:10.1080/09644019808414424

Cohen, G., Joutz, F., Loungani, P., 2011. Measuring energy security: Trends in the diversification of oil and natural gas supplies. Energy Policy. doi:10.1016/j.enpol.2011.06.034

Cole, M.A., Elliott, R.J.R., 2005. FDI and the Capital Intensity of “Dirty” Sectors: A Missing Piece of the Pollution Haven Puzzle. Rev. Dev. Econ. 9, 530–548. doi:10.1111/j.1467-9361.2005.00292.x

Cole, M.A., Elliott, R.J.R., Strobl, E., 2008. The environmental performance of firms: The role of foreign ownership, training, and experience. Ecol. Econ. doi:10.1016/j.ecolecon.2007.07.025

Cook, S.E.K., 1976. Quest for an index of community structure sensitive to water pollution. Environ. Pollut. 11, 269–288. doi:10.1016/0013-9327(76)90067-7

Cooper, R.G., 2009. The State of Product Development. Res. Manag. 52, 6.

Csereklyei, Z., Rubio-varas, M.M., Stern, D.I., 2016. Energy and Economic Growth : The Stylized Facts 37, 223–256.

CSI/ECRA, 2009. Development of State of the Art-Techniques in Cement Manufacturing: Trying to look ahead. Technol. Pap. 99.

Dai, S., Zhang, M., Huang, W., 2016. Decomposing the decoupling of CO2emission from economic growth in BRICS countries. Nat. Hazards 84, 1055–1073. doi:10.1007/s11069-016-2472-0

De Felice, F., Petrillo, A., Silvestri, A., 2015. Offshoring: Relocation of production processes towards low-cost countries through the project management & process reengineering performance model. Bus. Process Manag. J. 21, 379–402. doi:10.1108/BPMJ-01-2014-0008

de Vera, B.O., 2014. More firms relocating to Philippines, M'sia, Indonesia - Business - The Jakarta Post [WWW Document]. Jakarta Post. URL http://www.thejakartapost.com/news/2014/08/28/more-firms-relocating-philippines-msia-indonesia.html (accessed 4.29.17).

Debelle, G., 2019. Climate change and the economy, in: Public Forum Hosted by the Centre for Policy Development, Sydney.

Deesomsak, R., Paudyal, K., Pescetto, G., 2009. Debt maturity structure and the 1997 Asian financial crisis. J. Multinatl. Financ. Manag. doi:10.1016/j.mulfin.2008.03.001

Denyer, S., 2015. China's 'Black Monday' spreads stock market fears worldwide [WWW Document]. Washington Post.

Department of Energy, n.d. Energy Intensity Indicators: Terminology and Definitions [WWW Document]. Off. Energy Effic. Renew. Energy. URL http://energy.gov/eere/analysis/energy-intensity-indicators-terminology-and-definitions (accessed 9.10.16a).

Department of Energy, n.d. Energy Intensity Indicators: Terminology and Definitions [WWW Document]. Off. Energy Effic. Renew. Energy.

Department of Industrial Policy and Promotion, 2011. Report of the Working Group on Cement Industry for XII Five Year Plan. Minist. Commer. Ind. 176.

Destek, M.A., Okumus, I., 2019. Does pollution haven hypothesis hold in newly industrialized countries? Evidence from ecological footprint. Environ. Sci. Pollut. Res. 23689–23695. doi:10.1007/s11356-019-05614-z

Di Bitetti, M.S., 2000. The distribution of grooming among female primates: Testing hypotheses with the shannon-wiener diversity index. Behaviour. doi:10.1163/156853900502709

Donaldson, J., 1931. International Industrial Relations: Migration of Enterprise and Policies Affecting It, in: Proceedings of the Forty-Third Annual Meeting of the American Economic Association. American Economic Association.

Donaldson, T., 2016. China Factory Owners Look to India for Relocation as Costs Rise - Sourcing Journal [WWW Document]. Sourc. J. URL https://sourcingjournalonline.com/china-factory-owners-look-india-relocation-costs-rise/ (accessed 4.29.17).

Dorfman, R., 1979. A Formula for the Gini Coefficient. Rev. Econ. Stat. 61, 146–149. doi:10.2307/1924845

Dorian, J.P., Franssen, H.T., Simbeck, D.R., 2006. Global challenges in energy. Energy Policy 34, 1984–1991. doi:10.1016/j.enpol.2005.03.010

Dou, J., Han, X., 2019. How does the industry mobility affect pollution industry transfer in China: Empirical test on Pollution Haven Hypothesis and Porter Hypothesis. J. Clean. Prod. 217, 105–115. doi:10.1016/j.jclepro.2019.01.147

Dowling, M., Cheang, C.T., 2000. Shifting comparative advantage in Asia: new tests of the “flying geese” model. J. Asian Econ. doi:10.1016/s1049-0078(00)00070-1

Duan, H., Mo, J., Fan, Y., Wang, S., 2018. Achieving China’s energy and climate policy targets in 2030 under multiple uncertainties. Energy Econ. 70, 45–60. doi:10.1016/j.eneco.2017.12.022

Dubash, N.K., Khosla, R., Rao, N.D., Bhardwaj, A., 2018. Corrigendum: India’s energy and emissions future: an interpretive analysis of model scenarios (2018 Environ. Res. Lett. 13 074018) . Environ. Res. Lett. 13, 089501. doi:10.1088/1748-9326/aad506

Dubey, R., Gunasekaran, A., Childe, S.J., Wamba, S.F., Papadopoulos, T., 2016. The impact of big data on world-class sustainable manufacturing. Int. J. Adv. Manuf. Technol. doi:10.1007/s00170-015-7674-1

Duflou, J.R., Sutherland, J.W., Dornfeld, D., Herrmann, C., Jeswiet, J., Kara, S., Hauschild, M., Kellens, K., 2012. Towards energy and resource efficient manufacturing: A processes and systems approach. CIRP Ann. - Manuf. Technol. doi:10.1016/j.cirp.2012.05.002

Duggan, J., 2015. Chinese stock markets continue to nosedive as regulator warns of panic [WWW Document]. Guard.

Dutu, R., 2016. Challenges and policies in Indonesia’s energy sector. Energy Policy 98, 513–519. doi:10.1016/j.enpol.2016.09.009

Eichhammer, W., Walz, R., 2011. Industrial energy efficiency and competitiveness, Development Policy, Statistics and Resaeerch Branch Working Paper 05/2011.

Ekins, P., 2010. Eco-innovation for environmental sustainability: Concepts, progress and policies. Int. Econ. Econ. Policy 7, 267–290. doi:10.1007/s10368-010-0162-z

Erdiwansyah, Mamat, R., Sani, M.S.M., Sudhakar, K., 2019. Renewable energy in Southeast Asia: Policies and recommendations. Sci. Total Environ. 670, 1095–1102. doi:10.1016/j.scitotenv.2019.03.273

ESMAP, 2011. Energy Intensive Sectors of the Indian Economy -Path to Low Carbon Development-. Brief. note-Low carbon growth Ctry. Stud. Progr. 006/10.

European Comission Joint Research Center (JRC), 2014. Emission database for global atmospheric research (EDGAR).

European Environment Agency, 2015. Energy intensity.

Faisal, F., Andiningtyas, E.D., Achmad, T., Haryanto, H., Meiranto, W., 2018. The content and determinants of greenhouse gas emission disclosure: Evidence from Indonesian companies. Corp. Soc. Responsib. Environ. Manag. 25, 1397–1406. doi:10.1002/csr.1660

Falkner, R., 2016. The Paris Agreement and the new logic of international climate politics. Int. Aff. 92, 1114–1115.

Fan, P., 2011. Innovation capacity and economic development: China and India. Econ. Chang. Restruct. 44, 49–73. doi:10.1007/s10644-010-9088-2

Fan, P., 2010. Innovation capacity and economic development: China and India. Econ. Chang. Restruct. 44, 49–73. doi:10.1007/s10644-010-9088-2

Fan, R., Luo, M., Zhang, P., 2016. A study on evolution of energy intensity in China with heterogeneity and rebound effect. Energy 99, 159–169. doi:http://dx.doi.org/10.1016/j.energy.2016.01.041

Ferris, D., 2014. Indian Microgrids Aim to Bring Millions Out of Darkness by David Ferris: Yale Environment 360 [WWW Document]. Yale Environ. 360. URL http://e360.yale.edu/feature/indian_microgrids_aim_to_bring_millions_out_of_darkness/2729/ (accessed 2.24.16).

Ferroukhi, R., Lopez-Peña, A., Kieffer, G., Nagpal, D., Hawila, D., Khalid, A., El-Katiri, L., Vinci, S., Fernandez, A., 2016. Renewable Energy Benefits: Measuring the Economics. IRENA Int. Renew. Energy Agency 92.

Fingar, C., 2016. India knocks China from top of FDI league table - FT.com. Financ. Times.

Forin, S., Radebach, A., Steckel, J.C., 2017. The effect of industry delocalization on global energy use: A global sectoral perspective Silvia. Energy Econ. 70, 233–243. doi:10.1016/j.eneco.2017.12.031

Furman, J.L., Porter, M.E., Stern, S., 2002. The determinants of national innovative capacity. 2Research Policy 31, 899–933. doi:10.5465/APBPP.2000.5536001

Gadonneix, P., Kim, Y.D., Birnbaum, L., Meyers, K., Ward, G., Frei, C., 2013. World Energy Trilemma. London.

Gallagher, K., 2010. Handbook on Trade and the Environment, Elgar Original Reference Series. Edward Elgar Publishing.

Gambhir, A., Napp, T.A., Emmott, C.J.M., Anandarajah, G., 2014. India’s CO2 emissions pathways to 2050: Energy system, economic and fossil fuel impacts with and without carbon permit trading. Energy 77, 791–801. doi:10.1016/j.energy.2014.09.055

Ganguli, S., 2016. Energy Interdependence as a Strategic Factor in the Post Cold War Context. Strateg. Anal. 0161. doi:10.1080/09700161.2016.1165468

Gao, X., 2018. Measuring the Generalized Global Industry Relocation.

Garg, A., Shukla, P.R., Kankal, B., Mahapatra, D., 2017. CO2emission in India: trends and management at sectoral, sub-regional and plant levels. Carbon Manag. 8, 111–123. doi:10.1080/17583004.2017.1306406

Gazheli, A., Van Den Bergh, J., Antal, M., 2016. How realistic is green growth? Sectoral-level carbon intensity versus productivity. J. Clean. Prod. 129, 449–467. doi:10.1016/j.jclepro.2016.04.032

Ge, Y., 2009. Globalization and Industry Agglomeration in China. World Dev. 37, 550–559. doi:10.1016/j.worlddev.2008.07.005

Geng, J.B., Ji, Q., 2014. Multi-perspective analysis of China’s energy supply security. Energy 64, 541–550. doi:10.1016/j.energy.2013.11.036

Gianino, M.M., Lenzi, J., Bonaudo, M., Fantini, M.P., Siliquini, R., Ricciardi, W., Damiani, G., 2018. Organized screening programmes for breast and cervical cancer in 17 EU countries: trajectories of attendance rates. BMC Public Health 18, 1236.

Gini, C., 1912. Variabilità e mutabilità, Memorie di metodologica statistica. doi:Cited By (since 1996) 41\rExport Date 21 September 2011

Ginzburg, A., Simonazzi, A., 2005. Patterns of industrialization and the flying geese model: The case of electronics in East Asia. J. Asian Econ. 15, 1051–1078. doi:10.1016/j.asieco.2004.11.003

Gómez, D.R., Watterson, J.D., Americanohia, B.B., Ha, C., Marland, G., Matsika, E., Namayanga, L.N., Osman-Elasha, B., Saka, J.D.K., Treanton, K., 2006. Chapter 2: Stationary Combustion. 2006 IPCC Guidel. Natl. Greenh. Gas Invent. 47. doi:10.1016/S0166-526X(06)47021-5

Government Of India, 2010. National Action Plan on Climate Change. J. Sch. Health. doi:10.1111/j.1746-1561.1993.tb06065.x

Graaf, T. Van De, Sovacool, B.K., 2014. Thinking big : Politics , progress , and security in the management of Asian and European energy megaprojects. Energy Policy 74, 16–27. doi:10.1016/j.enpol.2014.06.027

Greening, L.A., Davis, W.B., Schipper, L., Khrushch, M., 1997. Comparison of six decomposition methods: application to aggregate energy intensity for manufacturing in 10 OECD countries. Energy Econ. 19, 375–390.

Grether, J.-M., de Melo, J., 2003. Globalization and Dirty Industries: Do Pollution Havens Matter? Cambridge, MA. doi:10.3386/w9776

Grinin, L., Tsirel, S., Korotayev, A., 2014. Will the explosive growth of China continue? Technol. Forecast. Soc. Change 95, 297. doi:10.1016/j.techfore.2014.06.023

Groot, L., 2010. Carbon Lorenz curves. Resour. Energy Econ. 32, 45–64.

Grossman, G.M., Krueger, A.B., 1995. Economic Growth and the Environment. Q. J. Econ. 110, 353–377. doi:10.2307/2118443

Grubb, M., Butler, L., Feldman, O., 2004a. Analysis of the Relationship between Growth in Carbon Dioxide Emissions and Growth in Income.

Grubb, M., Butler, L., Twomey, P., 2006. Diversity and security in UK electricity generation: The influence of low-carbon objectives. Energy Policy 34, 4050–4062. doi:10.1016/j.enpol.2005.09.004

Grubb, M., Muller, B., Butter, L., 2004b. The relationship between carbon dioxide emissions and economic growth. Univ. Cambridge Appl. Econ. 1–19.

Guan, D., Liu, Z., Geng, Y., Lindner, S., Hubacek, K., 2012. The gigatonne gap in China's carbon dioxide inventories. Nat. Clim. Chang. 2, 672–675. doi:10.1038/nclimate1560

Gunatilake, H., Roland-Holst, D., Sugiyarto, G., 2014. Energy security for India: Biofuels, energy efficiency and food productivity. Energy Policy. doi:10.1016/j.enpol.2013.10.050

Gupta, K., Vierke, I., Ibrahim, A., Suwandi, J., Selowidodo, A., 2019. Boosting global competitiveness in Indonesia: Is Industry 4.0 the answer?, in: Global Competitiveness: Business Transformation in the Digital Era: Proceedings of the First Economics and Business Competitiveness International Conference (EBCICON 2018), September 21-22, 2018, Bali, Indonesia. Routledge, p. 205.

Gupta, M., 2019. Decomposing the Role of Different Factors in CO 2 Emissions Increase in South Asia. Stud. Bus. Econ. 14, 72–86. doi:10.2478/sbe-2019-0006

Haque, S.M.I., Thaku, I.A., 2015. Development of Textile Industry of India and China : Flying

Geese Model Revisited. Pacific Bus. Rewiew Int. 8, 68–75.

Harrison, A., 1994. The role of multinationals in economic development: The benefits of FDI. Columbia J. World Bus. 29, 6–11. doi:https://doi.org/10.1016/0022-5428(94)90028-0

Hasanbeigi, A., Menke, C., Therdyothin, A., 2010. The use of conservation supply curves in energy policy and economic analysis: The case study of Thai cement industry. Energy Policy 38, 392–405. doi:10.1016/j.enpol.2009.09.030

Hausman, J.A., Sidak, J.G., Market, E., 2007. EVALUATING MARKET POWER USING COMPETITIVE BENCHMARK PRICES INSTEAD OF THE HERFINDAHL-HIRSCHMAN INDEX. ANTITRUST L.J. 1.

Heckscher, E., 1919. The Effect of Foreign Trade on the Distribution of Income. Ekon. Tidskr.

Heip, C., 1974. A new index measuring evenness. J. Mar. Biol. Assoc. United Kingdom 54, 555–557.

Henderson, S., Upchurch, M.L., 1943. Relocation of Manpower and Zoning. J. L. Public Util. Econ. 19, 3–17.

Hidayatno, A., Rahman, I., Irminanda, K.R., 2019. A conceptualization of industry 4.0 adoption on textile and clothing sector in Indonesia, in: ACM International Conference Proceeding Series. doi:10.1145/3364335.3364351

Hiley, M., 1999. Industrial restructuring in ASEAN and the role of Japanese foreign direct investment. Eur. Bus. Rev. 99, 80–90. doi:10.1108/09555349910256827

HKTDC Research, 2013a. The search for low-cost production bases in Southeast Asia | Hong Kong Means Business [WWW Document]. URL http://hkmb.hktdc.com/en/1X09U0V5/hktdc-research/The-search-for-low-cost-production-bases-in-Southeast-Asia (accessed 1.20.17).

HKTDC Research, 2013b. The search for low-cost production bases in Southeast Asia | Hong Kong Means Business [WWW Document].

Hofmann, J., Guan, D., Chalvatzis, K., Huo, H., 2016. Assessment of electrical vehicles as a successful driver for reducing CO2 emissions in China. Appl. Energy. doi:10.1016/j.apenergy.2016.06.042

Hoover, E.M.J., 1937. LOCATION THEORY AND THE SHOE AND LEATHER INDUSTRIES. Harvard University Press.

Hou, Y., Iqbal, W., Muhammad Shaikh, G., Iqbal, N., Ahmad Solangi, Y., Fatima, A., 2019. Measuring Energy Efficiency and Environmental Performance: A Case of South Asia. Process. . doi:10.3390/pr7060325

Hsiao, F.S.T., Hsiao, M.C.W., 2006. FDI, exports, and GDP in East and Southeast Asia-Panel data versus time-series causality analyses. J. Asian Econ. 17, 1082–1106. doi:10.1016/j.asieco.2006.09.011

Hu, J., Liu, Yanfang, Fang, J., Jing, Y., Liu, Yaolin, Liu, Yi, 2019. Characterizing pollution-intensive industry transfers in China from 2007 to 2016 using land use data. J. Clean. Prod. 223, 424–435. doi:10.1016/j.jclepro.2019.03.139

Hu, Y., Guo, D., Wang, M., Zhang, X., Wang, S., 2015. The Relationship between Energy Consumption and Economic Growth: Evidence from China's Industrial Sectors 9392–

9406. doi:10.3390/en8099392

Huang, C., Sharif, N., 2009. Manufacturing dynamics and spillovers: The case of Guangdong Province and Hong Kong, Macau, and Taiwan (HKMT). Res. Policy. doi:10.1016/j.respol.2008.12.010

Hung, T.Y., Hsiao, Y.J., Wu, S.W., 2014. Advantage management strategy in competition via technological race perspective: Empirical evidence from the Taiwanese manufacturing industry. Sci. World J. 2014. doi:10.1155/2014/843436

Hunt, V., Layton, D., Prince, S., 2015. Diversity Matters: Study on the relationship between levels of gender and ethic diversity in leadership and financial performance. McKinsey Co. doi:10.1001/archneurol.2012.77

Huynh, L.T.M., Stringer, L.C., 2018. Multi-scale assessment of social vulnerability to climate change: An empirical study in coastal Vietnam. Clim. Risk Manag. doi:10.1016/j.crm.2018.02.003

IEA, 2020. Renewable energy market update. Paris.

IEA, 2017a. Southeast Asia Energy Outlook 2017, Southeast Asia Energy Outlook 2017. doi:10.1787/9789264285576-en

IEA, 2017b. India joins IEA family, a major milestone for global energy governance [WWW Document]. URL https://www.iea.org/newsroom/news/2017/march/india-joins-iea-family-a-major-milestone-for-global-energy-governance.html (accessed 7.15.19).

IEA, 2016. Statistics: CO2 emissions from fuel combustion highlights (2016 edition).

IMF, 2019. World Economic Outlook (April, 2019) Growth Slowdown, Precarious Recovery. doi:10.18356/6d35867e-en

IMF, 2018a. 2018 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for Philippines; IMF Country Report No. 18/287; September 2018.

IMF, 2018b. World Economic Outlook Update - An update of the key WEO projections. Davos.

IMF, 2017. World Economic Outlook: Gaining Momentum?, World Economic Outlook April 2017. International Monetary Fund, Washington, DC.

IMF, 2016a. 2016 Article IV Consultation — Press Release; Staff Report; and Statement By the Executive Director for Thailand, IMF Country Report.

IMF, 2016b. Philippines: Staff Report for the 2016 Article IV Consultation.

IMF, 2016c. Subdued Demand, Diminished Prospects, World Economic Outlook Update [WWW Document]. URL http://www.imf.org/external/pubs/ft/weo/2016/update/01/pdf/0116.pdf

IMF Communications Department, 2016a. IMF Staff Completes 2016 Article IV Mission to Indonesia.

IMF Communications Department, 2016b. IMF Staff Completes 2016 Article IV Mission to Indonesia.

Indian Ministry of Statistics and Programme Implementation, 2015a. India Energy Statistics 2015. India Stat. Yearb. doi:Twenty first issue

Indian Ministry of Statistics and Programme Implementation, 2015b. Energy Statistics 2015. New Delhi.

Intergovernmental Panel on Climate Change, 2014. Climate Change 2014 Synthesis Report - IPCC, Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. doi:10.1017/CBO9781107415324

International Atomic Energy Agency, 2005. Energy indicators for sustainable development, IAEA. Vienna.

International Energy Agency, 2016. India (key partner country) [WWW Document]. Non-Member Ctries. URL https://www.iea.org/countries/non-membercountries/india/ (accessed 9.12.16).

International Energy Agency, 2015a. World energy outlook 2015 (executive summary). doi:10.1787/weo-2005-en

International Energy Agency, 2015b. CO2 Emissions from Fuel Combustion: CO2 Indicators - Energy Intensity Index TPES / GDP & Carbon Intensity Index: ESCII CO2 / TPES. doi:http://dx.doi.org/10.5257/iea/co2/2015

International Energy Agency, 2015c. Key World Energy Statistics 2015 81. doi:10.1787/9789264039537-en

International Energy Agency, 2015d. IEA Statistics. CO2 Emissions From Fuel Combustion: Highlights. doi:http://dx.doi.org/10.5257/iea/co2/2015

International Energy Agency, 2015e. Balance Definitions. Statistics (Ber). doi:10.1210/jc.2010-0606

International Energy Agency, 2014a. Energy Statistics of Non OECD Countries. Conversion Factors 1971-2013 [WWW Document]. UK Data Serv. doi:http://dx.doi.org/10.5257/iea/esnon/2014

International Energy Agency, 2014b. Summary Energy Balances: World Energy Balances, 1960-2013. doi:http://dx.doi.org/10.5257/iea/web/2014

International Energy Agency, 2014c. Energy Statistics of Non OECD Countries. Energy Statistics 1971-2013 [WWW Document]. UK Data Serv. doi:http://dx.doi.org/10.5257/iea/esnon/2014

International Energy Agency, 2013. Coal Information 2013, IEA Statistics. doi:10.1787/coal-2012-en

International Energy Agency, 2012a. Iea Statistics, CO2 Emissions From Fuel Combustion. International Energy Agency.

International Energy Agency, 2012b. Energy Technology Perspectives 2012, Energy Technology Perspectives 2012. doi:10.1787/energy_tech-2012-en

International Institute for Sustainable Development, 2009. Earth Negotiations Bulletin Vol 12 No 459, COP-15: summary, 7-19 December 2009. Earth Negot. Bull. 12, 1–30.

International Monetary Fund, 2019. World Economic Outlook (April 2019 Edition). doi:http://dx.doi.org/10.5257/imf/weo/2019-04

Ioannidis, A., Chalvatzis, K.J., Li, X., Notton, G., Stephanides, P., 2019. The case for islands' energy vulnerability: Electricity supply diversity in 44 global islands. Renew. Energy 143, 440–452. doi:10.1016/j.renene.2019.04.155

IPCC, 2007. Mitigation of climate change: Contribution of working group III to the fourth assessment report of the Intergovernmental Panel on Climate Change, Intergovernmental Panel on Climate Change.

IPCC, 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Main 2, 12. doi:http://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/2_Volume2/V2_3_Ch3_Mobile_Combustion.pdf

Isard, W., 1951. Interregional and Regional Input-Output Analysis: A Model of a Space-Economy. Rev. Econ. Stat. 33, 318–328. doi:10.2307/1926459

Isard, W., 1948. Some Locational Factors in the Iron and Steel Industry since the Early Nineteenth Century. J. Polit. Econ. 56, 203–217. doi:10.1086/256673

Ivanic, M., Martin, W., 2018. Sectoral Productivity Growth and Poverty Reduction: National and Global Impacts. World Dev. 109, 429–439. doi:10.1016/j.worlddev.2017.07.004

Iyengar, R., 2015. India Has Overtaken the U.S. and China to Top Spot in a Key World Foreign Investment Table. Time.

Jafari, Y., Othman, J., Nor, A.H.S.M., 2012. Energy consumption, economic growth and environmental pollutants in Indonesia. J. Policy Model. doi:10.1016/j.jpolmod.2012.05.020

Jaffe, A.B., Palmer, K., 1997. Environmental Regulation and Innovation: A Panel Data Study. Rev. Econ. Stat. 79, 610–619. doi:10.1162/003465397557196

Jamel, L., Abdelkader, D., 2016. Do energy consumption and economic growth lead to environmental degradation? Evidence from Asian economies. Cogent Econ. Financ. 4, 1–19. doi:10.1080/23322039.2016.1170653

Jänicke, M., Binder, M., Mönch, H., 1997. "Dirty industries": Patterns of change in industrial countries. Environ. Resour. Econ. 9, 467–491. doi:10.1007/BF02441762

Javorcik, B.S., Wei, S.-J., 2005. Pollution Havens and Foreign Direct Investment: Dirty Secret or Popular Myth? Contrib. Econ. Anal. Policy. doi:10.2202/1538-0645.1244

Jeffrey, H., Jay, B., Winskel, M., 2013. Accelerating the development of marine energy: Exploring the prospects, benefits and challenges. Technol. Forecast. Soc. Change 80, 1306–1316. doi:10.1016/j.techfore.2012.03.004

Jhingran, V.G., Ahmad, S.H., Singh, A.K., 1989. Application of Shannon-Weiner index as a measure of pollution of River Ganga at Patna, Bihar, India. Curr. Sci.

Jian, J.I.N., Jianxiang, W., Xiaoyi, M.A., Yuding, W., Renyong, L.I., 2015. Equality of medical health resource allocation in China based on the Gini coefficient method. Iran. J. Public Health 44, 445.

Jiang, X., Guan, D., 2016. Determinants of global CO2 emissions growth. Appl. Energy 1–10. doi:10.1016/j.apenergy.2016.06.142

Jonas, M., Marland, G., Winiwarter, W., White, T., Nahorski, Z., Bun, R., Nilsson, S., 2010. Benefits of dealing with uncertainty in greenhouse gas inventories: Introduction. Clim.

Change 103, 3–18.

Jönsson, J., Algehed, J., 2010. Pathways to a sustainable European kraft pulp industry: Trade-offs between economy and CO2 emissions for different technologies and system solutions. Appl. Therm. Eng. 30, 2315–2325. doi:10.1016/j.applthermaleng.2010.01.025

Jun, E., Kim, W., Chang, S.H., 2009. The analysis of security cost for different energy sources. Appl. Energy 86, 1894–1901. doi:10.1016/j.apenergy.2008.11.028

K.S. Sekhara, R., V. Sri, D., 2017. Technology Transfer in India: A Facet of Manufacturing Industries. i-manager's J. Manag. 12, 15. doi:10.26634/jmgt.12.1.13566

Kaldellis, J., Spyropoulos, G., Chalvatzis, K., 2004. The impact of greek electricity generation sector on the national air pollution problem. Fresenius Environ. Bull. 13, 647–656.

Kaldellis, J.K., Chalvatzis, K.J., 2005. Environment and Industrial Development: Sustainability and Development, in: Air Pollution. Stamoulis Publications, Athens.

Kaldor, N., 1976. Inflation and Recession in the World Economy. Econ. J. 86, 703–714. doi:10.2307/2231447

Kanchana, K., Unesaki, H., 2015. Assessing Energy Security Using Indicator-Based Analysis: The Case of ASEAN Member Countries. Soc. Sci. 4, 1269–1315. doi:10.3390/socsci4041269

Kanchana, K., Unesaki, H., 2014. ASEAN energy security: An indicator-based assessment. Energy Procedia 56, 163–171. doi:10.1016/j.egypro.2014.07.145

Kasahara, S., 2013. The Asian Developmental State and the Flying Geese Paradigm. United Nations.

Keeble, D.E., 1980. Industrial Decline, Regional Policy and the Urban—Rural Manufacturing Shift in the United Kingdom. Environ. Plan. A Econ. Sp. 12, 945–962. doi:10.1068/a120945

Kelly, S., 2020. Oil price crashes into negative territory for the first time in history amid pandemic - Reuters [WWW Document]. Reuters. URL https://uk.reuters.com/article/uk-global-oil/oil-price-crashes-into-negative-territory-for-the-first-time-in-history-amid-pandemic-idUKKBN2210VU (accessed 5.24.20).

Kenderdine, T., 2018. Death of the East Asian Goose and the Rise of China's Geoindustrial Policy. J. Chinese Polit. Sci. 23, 437–453. doi:10.1007/s11366-018-9551-x

Kern, F., 2012. Using the multi-level perspective on socio-technical transitions to assess innovation policy. Technol. Forecast. Soc. Change 79, 298–310. doi:10.1016/j.techfore.2011.07.004

Keylock, C.J., Lane, W., 2005. Simpson diversity and the Shannon-Wiener index as special cases of a generalized entropy. Oikos 109, 203–207. doi:https://doi-org.ueaezproxy.uea.ac.uk:2443/10.1111/j.0030-1299.2005.13735.x

Kim, S., 2017. LMDI decomposition analysis of energy consumption in the Korean manufacturing sector. Sustain. 9. doi:10.3390/su9020202

Kim, Y.H., 2007. Impacts of regional economic integration on industrial relocation through FDI in East Asia. J. Policy Model. 29, 165–180. doi:10.1016/j.jpolmod.2006.04.008

Kirchherr, J., Urban, F., 2018. Technology transfer and cooperation for low carbon energy technology: Analysing 30 years of scholarship and proposing a research agenda. Energy Policy 119, 600–609. doi:10.1016/j.enpol.2018.05.001

Kojima, K., 2000. The "flying geese" model of Asian economic development: Origin, theoretical extensions, and regional policy implications. J. Asian Econ. 11, 375–401. doi:10.1016/S1049-0078(00)00067-1

Korhonen, P., 1994. The Theory of the Flying Geese Pattern of Development and Its Interpretations. J. Peace Res. doi:10.1177/0022343394031001008

Krishnan, R.T., Prashantham, S., 2019. Innovation in and from India: The who, where, what, and when. Glob. Strateg. J. doi:10.1002/gsj.1207

Kumar, A., Chakraborty, D., 2013. Unraveling the success of India's IT-ITES industry: Can India sustain this success? J. Inf. Technol. Theory Appl. 14.

Kumar, D.R., 2018. FDI Promotions and Advancement through Make in India Programme. Int. J. Eng. Technol. Sci. Res. 5, 535–538.

Kumar, K.D., 2020. A month after negative oil prices, U.S. crude contract expiry looms - Reuters [WWW Document]. Reuters. URL https://uk.reuters.com/article/us-usa-oil-trading/a-month-after-negative-oil-prices-u-s-crude-contract-expiry-looms-idUKKBN22T0D6 (accessed 5.24.20).

Kumar, S., 2016. Assessment of renewables for energy security and carbon mitigation in Southeast Asia: The case of Indonesia and Thailand. Appl. Energy 163, 63–70. doi:10.1016/j.apenergy.2015.11.019

Kuramochi, T., 2016. Assessment of midterm CO2 emissions reduction potential in the iron and steel industry: a case of Japan. J. Clean. Prod. 132, 81–97. doi:10.1016/j.jclepro.2015.02.055

Kuznets, S., 1963. Quantitative Aspects of the Economic Growth of Nations: VIII. Distribution of Income by Size. Econ. Dev. Cult. Change 11, 1–80. doi:10.1086/450006

Kwon, W.Y., 1981. A Study of the Economic Impact of Industrial Relocation: The Case of Seoul. Urban Stud. 18, 73–90. doi:10.1080/00420988120080061

La Viña, A.G., Tan, J.M., Guanzon, T.I.M., Caleda, M.J., Ang, L., 2018. Navigating a trilemma: Energy security, equity, and sustainability in the Philippines' low-carbon transition. Energy Res. Soc. Sci. 35, 37–47. doi:10.1016/j.erss.2017.10.039

Lahiri-Dutt, K, 2016. The Coal Nation: Histories, Ecologies and Politics of Coal in India. Taylor & Francis.

Lahiri-Dutt, Kuntala, 2016. The diverse worlds of coal in India: Energising the nation, energising livelihoods. Energy Policy 99, 203–213. doi:10.1016/j.enpol.2016.05.045

Lai, X., Liu, J., Georgiev, G., 2016. Low carbon technology integration innovation assessment index review based on rough set theory – an evidence from construction industry in China. J. Clean. Prod. 126, 88–96. doi:10.1016/j.jclepro.2016.03.035

Lanoie, P., Laurent-Lucchetti, J., Johnstone, N., Ambec, S., 2011. Environmental policy, innovation and performance: New insights on the porter hypothesis. J. Econ. Manag. Strateg. doi:10.1111/j.1530-9134.2011.00301.x

Le Quéré, C., Andrew, R., Friedlingstein, P., Sitch, S., Hauck, J., Pongratz, J., Pickers, P., Ivar Korsbakken, J., Peters, G., Canadell, J., Arneth, A., Arora, V., Barbero, L., Bastos, A., Bopp, L., Ciais, P., Chini, L., Ciais, P., Doney, S., Gkritzalis, T., Goll, D., Harris, I., Haverd, V., Hoffman, F., Hoppema, M., Houghton, R., Hurtt, G., Ilyina, T., Jain, A., Johannessen, T., Jones, C., Kato, E., Keeling, R., Klein Goldewijk, K., Landschützer, P., Lefèvre, N., Lienert, S., Liu, Z., Lombardozzi, D., Metzl, N., Munro, D., Nabel, J., Nakaoka, S.I., Neill, C., Olsen, A., Ono, T., Patra, P., Peregon, A., Peters, W., Peylin, P., Pfeil, B., Pierrot, D., Poulter, B., Rehder, G., Resplandy, L., Robertson, E., Rocher, M., Rödenbeck, C., Schuster, U., Skjelvan, I., Séférian, R., Skjelvan, I., Steinhoff, T., Sutton, A., Tans, P., Tian, H., Tilbrook, B., Tubiello, F., Van Der Laan-Luijkx, I., Van Der Werf, G., Viovy, N., Walker, A., Wiltshire, A., Wright, R., Zaehle, S., Zheng, B., 2018. Global Carbon Budget 2018. Earth Syst. Sci. Data 10, 2141–2194. doi:10.5194/essd-10-2141-2018

Lean, H.H., Smyth, R., 2010. CO2emissions, electricity consumption and output in ASEAN. Appl. Energy 87, 1858–1864. doi:10.1016/j.apenergy.2010.02.003

Lefèvre, N., 2010. Measuring the energy security implications of fossil fuel resource concentration. Energy Policy 38, 1635–1644. doi:10.1016/j.enpol.2009.02.003

Leontief, W., 2008. Input-output analysis. Springer.

Leontief, W., 1974. Sructure of the world economy: outline of a simple input-output formulation. Am. Econ. Rev. 64, 823–834.

Leontief, W., Chenery, H., Clark, P., 1953. Studies in the Structure of the American Economy. qje.oxfordjournals.org.

Li, H., Qin, Q., 2019. Challenges for China's carbon emissions peaking in 2030: A decomposition and decoupling analysis. J. Clean. Prod. doi:10.1016/j.jclepro.2018.10.043

Li, J.S., Chen, G.Q., 2013. Energy and greenhouse gas emissions review for Macao. Renew. Sustain. Energy Rev. 22, 23–32. doi:10.1016/j.rser.2012.11.072

Li, Y., Sun, L., Zhang, H., Liu, T., Fang, K., 2018. Does industrial transfer within urban agglomerations promote dual control of total energy consumption and energy intensity? J. Clean. Prod. 204, 607–617. doi:10.1016/j.jclepro.2018.08.342

Li, Z., Sun, Z., Chen, Y., Li, C., Pan, Z., Harby, A., Lv, P., Chen, D., Guo, J., 2020. The net GHG emissions of the China Three Gorges Reservoir: I. Pre-impoundment GHG inventories and carbon balance. J. Clean. Prod. doi:10.1016/j.jclepro.2020.120635

Liang, W., Gan, T., Zhang, W., 2019. Dynamic evolution of characteristics and decomposition of factors influencing industrial carbon dioxide emissions in China: 1991–2015. Struct. Chang. Econ. Dyn. 49, 93–106. doi:10.1016/j.strueco.2018.09.009

Lieberman, D., Jonas, M., Nahorski, Z., Nilsson, S., 2007. Accounting for climate change: Uncertainty in greenhouse gas inventories - Verification, compliance, and trading, Accounting for Climate Change: Uncertainty in Greenhouse Gas Inventories - Verification, Compliance, and Trading. Springer Netherlands.

Lima, F., Nunes, M.L., Cunha, J., Lucena, A.F.P., 2017. Driving forces for aggregate energy consumption: A cross-country approach. Renew. Sustain. Energy Rev. 68, 1033–1050. doi:10.1016/j.rser.2016.08.009

Lima, F., Nunes, M.L., Cunha, J., Lucena, A.F.P., 2016. A cross-country assessment of energy-related CO2 emissions: An extended Kaya Index Decomposition Approach. Energy 115, 1361–1374. doi:10.1016/j.energy.2016.05.037

Lin, B., Tan, R., 2017. Sustainable development of China's energy intensive industries: From the aspect of carbon dioxide emissions reduction. Renew. Sustain. Energy Rev. 77, 386–394. doi:10.1016/j.rser.2017.04.042

Lisienko, V.G., Chesnokov, Y.N., Lapteva, A. V., Noskov, V.Y., 2016. Types of greenhouse gas emissions in the production of cast iron and steel. IOP Conf. Ser. Mater. Sci. Eng. 150. doi:10.1088/1757-899X/150/1/012023

Liu, H., Kim, H., 2018. Ecological footprint, foreign direct investment, and gross domestic production: Evidence of Belt & Road Initiative countries. Sustain. 10. doi:10.3390/su10103527

Liu, L.C., Fan, Y., Wu, G., Wei, Y.M., 2007. Using LMDI method to analyze the change of China's industrial CO2 emissions from final fuel use: An empirical analysis. Energy Policy 35, 5892–5900. doi:10.1016/j.enpol.2007.07.010

Liu, X., Da, W., Martin, G.F., Liu, K., 2019. Regional income mobility in large cities throughout China. Appl. Econ. Lett. 26, 1322–1327. doi:10.1080/13504851.2018.1558333

Liu, Z., Feng, K., Hubacek, K., Liang, S., Anadon, L.D., Zhang, C., Guan, D., 2015a. Four system boundaries for carbon accounts. Ecol. Modell. 318, 118–125. doi:10.1016/j.ecolmodel.2015.02.001

Liu, Z., Guan, D., Wei, W., Davis, S.J., Ciais, P., Bai, J., Peng, S., Zhang, Q., Hubacek, K., Marland, G., Andres, R.J., Crawford-Brown, D., Lin, J., Zhao, H., Hong, C., Boden, T.A., Feng, K., Peters, G.P., Xi, F., Liu, J., Li, Y., Zhao, Y., Zeng, N., He, K., 2015b. Reduced carbon emission estimates from fossil fuel combustion and cement production in China. Nature 524, 335–8. doi:10.1038/nature14677

Löschel, A., Moslener, U., Rübbelke, D.T.G., 2010. Indicators of energy security in industrialised countries. Energy Policy. doi:10.1016/j.enpol.2009.03.061

Luo, le, Tang, Q., Lan, Y.C., 2013. Comparison of propensity for carbon disclosure between developing and developed countries: A resource constraint perspective. Account. Res. J. doi:10.1108/ARJ-04-2012-0024

Ma, X., Wang, C., Dong, B., Gu, G., Chen, R., Li, Y., Zou, H., Zhang, W., Li, Q., 2019. Carbon emissions from energy consumption in China: Its measurement and driving factors. Sci. Total Environ. doi:10.1016/j.scitotenv.2018.08.183

MacLachlan, S., 2016. COP21 was decades in the making, so how do we make future decades work for climate? [WWW Document]. OECD Insights Blog. URL http://oecdinsights.org/2016/01/21/cop21-was-decades-in-the-making-so-how-do-we-make-future-decades-work-for-climate/ (accessed 5.10.16).

Malekpoor, H., Chalvatzis, K., Mishra, N., Dubey, R., Zafeirakis, D., 2017. Integrated Grey Relational Analysis and Multi Objective Grey Linear Programming for Sustainable Electricity Generation Planning. Ann. Oper. Res.

Månsson, A., Johansson, B., Nilsson, L.J., 2014. Assessing energy security: An overview of commonly used methodologies. Energy 73, 1–14. doi:10.1016/j.energy.2014.06.073

Marland, G., 2008. Uncertainties in accounting for CO2 from fossil fuels. J. Ind. Ecol. 12, 136–139. doi:10.1111/j.1530-9290.2008.00014.x

Marland, G., Brenkert, A., Olivier, J., 1999. CO2 from fossil fuel burning: a comparison of ORNL and EDGAR estimates of national emissions. Environ. Sci. Policy 2, 265–273. doi:10.1016/S1462-9011(99)00018-0

Martchamadol, J., Kumar, S., 2012. Thailand's energy security indicators. Renew. Sustain. Energy Rev. 16, 6103–6122. doi:10.1016/j.rser.2012.06.021

Mathiesen, L., Mœstad, O., 2004. Climate policy and the steel industry: Achieving global emission reductions by an incomplete climate agreement. Energy J. doi:10.5547/ISSN0195-6574-EJ-Vol25-No4-5

Matsumoto, A., Merlone, U., Szidarovszky, F., 2012. Some notes on applying the Herfindahl-Hirschman index. Appl. Econ. Lett. 19, 181–184. doi:10.1080/13504851.2011.570705

Mattila, L., Strandell, A.-C., 2006. Defining and measuring relocation and outsourcing of production. Swedish Inst. Growth Policy Stud.

Meangbua, O., Dhakal, S., Kuwornu, J.K.M., 2019. Factors influencing energy requirements and CO 2 emissions of households in Thailand: A panel data analysis. Energy Policy 129, 521–531. doi:10.1016/j.enpol.2019.02.050

Mehra, M., Bhattacharya, G., 2019. Energy Transitions in India Implications for Energy Access, Greener Energy, and Energy Security.

Meng, J., Mi, Z., Guan, D., Li, J., Tao, S., Li, Y., Feng, K., Liu, J., Liu, Z., Wang, X., Zhang, Q., Davis, S.J., 2018. The rise of South-South trade and its effect on global CO2 emissions. Nat. Commun. doi:10.1038/s41467-018-04337-y

Merican, Y., Yusop, Z., Mohd Noor, Z., Siong Hook, L., 2007. Foreign direct investment and the pollution in Five ASEAN nations. Int. J. Econ. Manag.

Ministry of Economic Trade and Industry, 2015. Promoting Energy Efficiency in Small and Medium Sized Enterprises (SMEs) and Waste Heat Recovery Measures in India, in: 6th Workshop for Energy Management and Action Network (EMAK). New Delhi.

Mishra, A., 2009. Assessment of Coal Quality of Some Indian Coals 45.

Mohan, A., Topp, K., 2018. India's energy future: Contested narratives of change. Energy Res. Soc. Sci. 44, 75–82. doi:10.1016/j.erss.2018.04.040

Mohan, C., 2019. India's budget opens up to more FDI - Locations - fDiIntelligence.com [WWW Document]. fDiIntelligence.com. URL https://www.fdiintelligence.com/Locations/Asia-Pacific/India/India-s-budget-opens-up-to-more-FDI (accessed 8.7.19).

Mondal, M.A.H., Rosegrant, M., Ringler, C., Pradesha, A., Valmonte-Santos, R., 2018. The Philippines energy future and low-carbon development strategies. Energy 147, 142–154. doi:10.1016/j.energy.2018.01.039

Montefrio, M.J.F., Sonnenfeld, D.A., 2011. Forests, fuel, or food? competing coalitions and biofuels policy making in the philippines. J. Environ. Dev. 20, 27–49. doi:10.1177/1070496510394321

Montes, M.F., Cruz, J., 2019. The political economy of foreign investment and industrial development: the Philippines, Malaysia and Thailand in comparative perspective. J. Asia Pacific Econ. 0, 1–24. doi:10.1080/13547860.2019.1577207

Morrow, W.R., Hasanbeigi, A., Sathaye, J., Xu, T., 2014a. Assessment of energy efficiency improvement and CO2 emission reduction potentials in India's cement and iron & steel industries. J. Clean. Prod. 65, 131–141. doi:10.1016/j.jclepro.2013.07.022

Morrow, W.R., Hasanbeigi, A., Sathaye, J., Xu, T., 2014b. Assessment of energy efficiency improvement and CO2 emission reduction potentials in India's cement and iron & steel industries. J. Clean. Prod. 65, 131–141. doi:10.1016/j.jclepro.2013.07.022

MOSPI, 2019. PRESS NOTE ON FIRST ADVANCE ESTIMATES OF NATIONAL INCOME 2018-19 CENTRAL STATISTICS OFFICE MINISTRY OF STATISTICS PROGRAMME IMPLEMENTATION GOVERNMENT OF INDIA.

Moya, J.A., 2017. Where diffusion of clean technologies and barriers to innovation clash: Application to the global diffusion of the electrical arc furnace. Energies 10. doi:10.3390/en10010109

Mueller, E., Morgan, J.N., 1962. Location Decisions of Manufacturers. Am. Econ. Rev. 52, 204–217.

Mujiyanto, S., Tiess, G., 2013. Secure energy supply in 2025: Indonesia's need for an energy policy strategy. Energy Policy. doi:10.1016/j.enpol.2013.05.119

Mukherjee, S., 2019. Exploring Low-Carbon Energy Security Path for India: Role of Asia-Pacific Energy Cooperation.

Mulder, P., 2015. International specialization, sector structure and the evolution of Manufacturing energy intensity in OECD countries. Energy J. 36, 111–136. doi:10.5547/01956574.36.3.4

Murphy, R., 2014. The emerging hypercarbon reality, technological and post-carbon utopias, and social innovation to low-carbon societies. Curr. Sociol. 63, 317–338. doi:10.1177/0011392114551757

Murthy, K. V, Gambhir, S., 2018. Analyzing Environmental Kuznets Curve and Pollution Haven Hypothesis in India in the Context of Domestic and Global Policy Change. Australas. Accounting, Bus. Financ. J. 12, 134–156. doi:10.14453/aabfj.v12i2.9

Musa, C., Licheri, R., Locci, A.M., Orrù, R., Cao, G., Rodriguez, M.A., Jaworska, L., 2009. Energy efficiency during conventional and novel sintering processes: the case of Ti-Al2O3-TiC composites. J. Clean. Prod. 17, 877–882. doi:10.1016/j.jclepro.2009.01.012

Nair, A., Guldiken, O., Fainshmidt, S., Pezeshkan, A., 2015. Innovation in India: A review of past research and future directions. Asia Pacific J. Manag. 32, 925–958. doi:10.1007/s10490-015-9442-z

Nam, W.C., Nam, S., Steinhoff, P., 2017. Modi's 'Make in India' Industrial Reform Policy and East Asian Flying-Geese Paradigm, CESIFO WORKING PAPER NO. 6431.

Narayan, S., 2016a. Predictability within the energy consumption – economic growth nexus : Some evidence from income and regional groups. Econ. Model. 54, 515–521. doi:10.1016/j.econmod.2015.12.037

Narayan, S., 2016b. Predictability within the energy consumption–economic growth nexus:

Some evidence from income and regional groups. Econ. Model. 54, 515–521. doi:10.1016/j.econmod.2015.12.037

Narula, K., Sudhakara Reddy, B., Pachauri, S., Mahendra Dev, S., 2017. Sustainable energy security for India: An assessment of the energy supply sub-system. Energy Policy 103, 127–144. doi:10.1016/j.enpol.2017.01.001

National Development and Reform Commission of China, 2015. Enhanced Actions on Climate Change: China's intended nationally determined contributions. Unfccc 36. doi:http://www4.unfccc.int/submissions/INDC/Published%20Documents/China/1/China's%20INDC%20-%20on%2030%20June%202015.pdf

Nejat, P., Jomehzadeh, F., Taheri, M.M., Gohari, M., Muhd, M.Z., 2015. A global review of energy consumption, CO2 emissions and policy in the residential sector (with an overview of the top ten CO2 emitting countries). Renew. Sustain. Energy Rev. 43, 843–862. doi:10.1016/j.rser.2014.11.066

Newbold, S.C., Daigneault, A., 2009. Climate Response Uncertainty and the Benefits of Greenhouse Gas Emissions Reductions. Environ. Resour. Econ. 44, 351–377.

Nijkamp, P., 1986. Infrastructure and regional development: A multidimensional policy analysis. Empir. Econ. 11, 1–21. doi:10.1007/BF01978142

Noorzoy, M.S., 1979. Flows of direct investment and their effects on investment in Canada. Econ. Lett. 2, 257–261. doi:https://doi.org/10.1016/0165-1765(79)90032-6

North, D.C., 1955. Location Theory and Regional Economic Growth. J. Polit. Econ. 63, 243–258. doi:10.1086/257668

Nurdiawansyah, Lindianasari, Komalasari, A., 2018. Carbon Emission Issues in Indonesia. Rev. Integr. Bus. Econ. Res. 7, 20–33.

Nuttall, W.J., Manz, D.L., 2008. A new energy security paradigm for the twenty-first century. Technol. Forecast. Soc. Change 75, 1247–1259. doi:10.1016/j.techfore.2008.02.007

Ockwell, D., Byrne, R., 2016. Improving technology transfer through national systems of innovation: climate relevant innovation-system builders (CRIBs). Clim. Policy 16, 836–854. doi:10.1080/14693062.2015.1052958

OECD, 2017. Industrial production (indicator) [WWW Document]. doi:10.1787/39121c55-en

OECD Development Centre, 2015. Economic Outlook for Southeast Asia 3. doi:10.1787/saeo-2015-en

Office of Natural Resources and Environmental Policy, 2015. Thailand ' s Intended Nationally Determined Contribution (INDC), UNFCC.

Okubo, T., Tomiura, E., 2012. Industrial relocation policy, productivity and heterogeneous plants: Evidence from Japan. Reg. Sci. Urban Econ. 42, 230–239. doi:10.1016/j.regsciurbeco.2011.09.004

Okubo, T., Tomiura, E., 2010. Industrial relocation policy and heterogeneous plants sorted by productivity: Evidence from Japan. RIETI Discuss. Pap. 10016.

Olivier, J.G.J., Muntean, M., Peters, J.A.H.W., 2015. Trends in global CO2 emissions: 2015 report. PBL Netherlands Environ. Assess. Agency Eur. Comm. Jt. Res. Cent. 1–78.

Ouyang, X., Lin, B., 2015. An analysis of the driving forces of energy-related carbon dioxide emissions in China's industrial sector. Renew. Sustain. Energy Rev. 45, 838–849. doi:10.1016/j.rser.2015.02.030

Ozawa, T., 2015. Next Great Industrial Transmigration : Relocating China's Factories to Sub-Saharan Africa , Flying-Geese Style?

Ozawa, T., Bellak, C., 2011. Will the world bank's vision materialize? Relocating China's factories to sub-Saharan Africa, flying-geese style. Glob. Econ. J. doi:10.2202/1524-5861.1764

Özokcu, S., Özdemir, Ö., 2017. Economic growth, energy, and environmental Kuznets curve. Renew. Sustain. Energy Rev. 72, 639–647. doi:10.1016/j.rser.2017.01.059

Pal, P., Gupta, H., Kapur, D., 2016. Carbon mitigation potential of Indian steel industry. Mitig. Adapt. Strateg. Glob. Chang. 21, 391–402. doi:10.1007/s11027-014-9605-0

Pani, R., Mukhopadhyay, U., 2010. Identifying the major players behind increasing global carbon dioxide emissions: A decomposition analysis. Environmentalist 30, 183–205. doi:10.1007/s10669-010-9256-y

Pao, H.-T., Chen, C.-C., 2019. Decoupling strategies: CO2 emissions, energy resources, and economic growth in the Group of Twenty. J. Clean. Prod. 206, 907–919.

Pappas, D., Chalvatzis, K.J., 2016. Energy and Industrial Growth in India : The Next Emissions Superpower ? Energy Procedia 00, 3656–3662. doi:10.1016/j.egypro.2017.03.842

Pappas, D., Chalvatzis, K.J., Guan, D., Ioannidis, A., 2018. Energy and carbon intensity : A study on the cross-country industrial shift from China to India and SE Asia. Appl. Energy 225, 183–194. doi:10.1016/j.apenergy.2018.04.132

Pappas, D., Chalvatzis, K.J., Guan, D., Li, X., 2017. Industrial Relocation and CO 2 Emission Intensity: Focus on the Potential Cross-Country Shift from China to India and SE Asia. Energy Procedia 142, 2898–2904. doi:10.1016/j.egypro.2017.12.414

Pearce, F., 2016. Can We Reduce CO2 Emissions And Grow the Global Economy? [WWW Document]. Yale Environ. 360. URL http://e360.yale.edu/feature/can_we_reduce_co2_emissions_and_grow_global_economy/2983/ (accessed 5.10.16).

Pennings, E., Sleuwaegen, L., 2000. International relocation: Firm and industry determinants. Econ. Lett. 67, 179–186. doi:10.1016/S0165-1765(99)00269-4

Perloff, H.S., EE, L., RF, K., 1960. Regions, resources, and economic growth. Reg. Resour. Econ. growth.

Policy Department Economic and Scientific Policy, 2006a. Relocation of EU Industry An Overview of Literature Background Note.

Policy Department Economic and Scientific Policy, 2006b. Relocation of EU Industry An Overview of Literature Background Note, DG Internal Policies of the Union.

Porter, M.E., Van der Linde, C., 1995. Toward a New Conception of the Environment-Competitiveness Relationship. J. Econ. Perspect. 9, 97–118. doi:10.1257/jep.9.4.97

Pothitou, M., Hanna, R.F., Chalvatzis, K.J., 2017. ICT entertainment appliances' impact on domestic electricity consumption. Renew. Sustain. Energy Rev. 69, 843–853.

doi:http://dx.doi.org/10.1016/j.rser.2016.11.100

Pothitou, M., Hanna, R.F., Chalvatzis, K.J., 2016. Environmental knowledge, pro-environmental behaviour and energy savings in households: An empirical study. Appl. Energy 184, 1217–1229. doi:10.1016/j.apenergy.2016.06.017

Pourebadollahan Covich, M., Panahi, H., Shahbazy Homonlo, S., Salehi, K., 2016. Decomposing influencing factors of energy consumption changes in the iranian industrial subsectors: The comparison of laspeyres and divisia methods. Q. J. Appl. Theor. Econ. 2, 49–70.

Pujari, D., 2006. Eco-innovation and new product development: Understanding the influences on market performance. Technovation 26, 76–85. doi:10.1016/j.technovation.2004.07.006

PwC, 2014. Future of India - The Winning Leap, The Winning Leap.

PWC, 2017. The Long View. How will the global economic order change by 2050? Price Waterhouse and Coopers Februrary, 1–72.

Qu, Y., Cai, F., Zhang, X., 2013. Has the “flying geese” paradigm occurred in China. China Econ. 8, 18–31.

Quéré, C. Le, Jackson, R.B., Jones, M.W., Smith, A.J.P., Abernethy, S., Andrew, R.M., De-gol, A.J., Willis, D.R., Shan, Y., Canadell, J.G., Friedlingstein, P., Creutzig, F., Peters, G.P., 2020. during the COVID-19 forced confinement 1–8. doi:10.1038/s41558-020-0797-x

Ralph, N., Hancock, L., 2019. Energy security, transnational politics, and renewable electricity exports in Australia and South east Asia. Energy Res. Soc. Sci. 49, 233–240. doi:10.1016/j.erss.2018.10.023

Ramani, S. V., Thutupalli, A., 2015. Emergence of controversy in technology transitions: Green Revolution and Bt cotton in India. Technol. Forecast. Soc. Change 100, 198–212. doi:10.1016/j.techfore.2015.06.018

Rathje, K.J., 1974. Causes and consequences of industrial relocation: a case study 1–37.

Ray, S., 2011. Econometric Analysis of Efficiency in Indian Cement Industry 1, 11–23.

Raymond Vernon, 1966. International Investment and International Trade in the Product Life Cycle. Q. J. Econ.

Reinert, E., Ghosh, J., Kattel, R., Alacevich, M., 2016. Albert O. Hirschman, in: Handbook of Alternative Theories of Economic Development. doi:10.4337/9781782544685.00031

Rennings, K., 2000. Redefining innovation - Eco-innovation research and the contribution from ecological economics. Ecol. Econ. 32, 319–332. doi:10.1016/S0921-8009(99)00112-3

Republic of Indonesia, 2015. Intended National Determined Contribution to the UNFCC.

Republic of the Philippines, 2015. REPUBLIC OF THE PHILIPPINES Intended Nationally Determined Contributions 1–6.

Resosudarmo, B.P., Alisjahbana, A., Nurdianto, D.A., 2012. Energy Security in Indonesia, in: Anceschi, L., Symons, J. (Eds.), Energy Security in the Era of Climate Change: The Asia-

Pacific Experience. Palgrave Macmillan UK, London, pp. 161–179. doi:10.1057/9780230355361_10

Riley, C., Yan, S., 2015. China's stock market crash...in 2 minutes [WWW Document]. CNN Bus.

Ruan, J., Zhang, X., 2014. "Flying geese" in China: The textile and apparel industry's pattern of migration. J. Asian Econ. 34, 79–91. doi:10.1016/j.asieco.2014.06.003

Rubashkina, Y., Galeotti, M., Verdolini, E., 2015. Environmental regulation and competitiveness: Empirical evidence on the Porter Hypothesis from European manufacturing sectors. Energy Policy 83, 288–300. doi:10.1016/j.enpol.2015.02.014

Rutter, R., Chalvatzis, K.J., Roper, S., Lettice, F., 2017. Branding Instead of Product Innovation: A Study on the Brand Personalities of the UK's Electricity Market. Eur. Manag. Rev. doi:10.1111/emre.12155

Sadorsky, P., 2013. Do urbanization and industrialization affect energy intensity in developing countries? Energy Econ. 37, 52–59. doi:10.1016/j.eneco.2013.01.009

Saidi, K., Hammami, S., 2015. The impact of CO2 emissions and economic growth on energy consumption in 58 countries. Energy Reports 1, 62–70. doi:10.1016/j.egyr.2015.01.003

Salam, M.A., 2019. Analyzing manufacturing strategies and Industry 4.0 supplier performance relationships from a resource-based perspective. Benchmarking. doi:10.1108/BIJ-12-2018-0428

Sanstad, A.H., Roy, J., Sathaye, J.A., 2006. Estimating energy-augmenting technological change in developing country industries. Energy Econ. 28, 720–729. doi:10.1016/j.eneco.2006.07.005

Sasana, H., Aminata, J., 2019. Energy Subsidy , Energy Consumption , Economic Growth , and Carbon Dioxide Emission : Indonesian Case Studies. Int. J. Energy Econ. Policy 9, 117–122.

Selvakkumaran, S., Limmeechokchai, B., 2013. Energy security and co-benefits of energy efficiency improvement in three Asian countries. Renew. Sustain. Energy Rev. 20, 491–503. doi:10.1016/j.rser.2012.12.004

Shaban, S.A., 2018. Applications in Industry, in: Lognormal Distributions. Routledge, pp. 267–285.

Shahbaz, M., Hoang, T.H. Van, Mahalik, M.K., Roubaud, D., 2017. Energy consumption, financial development and economic growth in India: New evidence from a nonlinear and asymmetric analysis. Energy Econ. doi:10.1016/j.eneco.2017.01.023

Shahbaz, M., Nasreen, S., Abbas, F., Anis, O., 2015. Does foreign direct investment impede environmental quality in high-, middle-, and low-income countries? Energy Econ. doi:10.1016/j.eneco.2015.06.014

Shan, J., 2002. A VAR approach to the economics of FDI in China. Appl. Econ. doi:10.1080/00036840110058941

Shan, Y., Guan, D., Zheng, H., Ou, J., Li, Y., Meng, J., Mi, Z., Liu, Z., Zhang, Q., 2018. China CO 2 emission accounts 1997-2015. Sci. Data. doi:10.1038/sdata.2017.201

Shan, Y., Huang, Q., Guan, D., Hubacek, K., 2020. China CO2 emission accounts 2016–2017.

Sci. Data. doi:10.1038/s41597-020-0393-y

Shan, Y., Liu, J., Liu, Z., Xu, X., Shao, S., Wang, P., Guan, D., 2016a. New provincial CO2 emission inventories in China based on apparent energy consumption data and updated emission factors. Appl. Energy 184, 742–750. doi:10.1016/j.apenergy.2016.03.073

Shan, Y., Liu, J., Liu, Z., Xu, X., Shao, S., Wang, P., Guan, D., 2016b. New provincial CO2 emission inventories in China based on apparent energy consumption data and updated emission factors. Appl. Energy. doi:10.1016/j.apenergy.2016.03.073

Shannon, C.E., 1948. A Mathematical Theory of Communication (Part I). Bell Syst. Tech. J. doi:10.1002/j.1538-7305.1948.tb01338.x

Sharifuddin, S., 2014. Methodology for quantitatively assessing the energy security of Malaysia and other southeast asian countries. Energy Policy 65, 574–582. doi:10.1016/j.enpol.2013.09.065

Sharma, A., 2007. India and Energy Security. Asian Aff. (Lond). 38, 158–172. doi:10.1080/03068370701349110

Shen, J., Wei, Y.D., Yang, Z., 2017. The impact of environmental regulations on the location of pollution-intensive industries in China. J. Clean. Prod. 148, 785–794. doi:10.1016/j.jclepro.2017.02.050

Shimoda, M., Watanabe, T., Ye, Z., Fujikawa, K., 2008. An empirical study on interdependency of environmental load and international IO structure in the Asia-Pacific region, in: International Input-Output Meeting on Managing the Environment. Seville, Spain.

Sikdar, C., Mukhopadhyay, K., 2020. Technology Transfer And Productivity Growth-Evidence From Indian Manufacturing Industries. J. Dev. Areas 54. doi:10.1353/jda.2020.0046

Silberglitt, R., Kimmel, S., 2015. Energy scenarios for Southeast Asia. Technol. Forecast. Soc. Change 101, 251–262. doi:10.1016/j.techfore.2015.04.010

Singh, N., Jain, S., Sharma, P., 2016. Environmental benchmarking practices in Indian industries: Evidences from an empirical study. Benchmarking 23, 1132–1146. doi:10.1108/BIJ-08-2014-0079

Singh, R.K., Modgil, S., Tiwari, A.A., 2018. Identification and evaluation of determinants of sustainable manufacturing: a case of Indian cement manufacturing. Meas. Bus. Excell. doi:10.1108/MBE-08-2018-0056

Singla, A., Ahuja, I.S., Sethi, A.P.S., 2018. Technology push and demand pull practices for achieving sustainable development in manufacturing industries. J. Manuf. Technol. Manag. doi:10.1108/JMTM-07-2017-0138

Skea, J., 2010. Valuing diversity in energy supply. Energy Policy 38, 3608–3621. doi:10.1016/j.enpol.2010.02.038

Smith, R. V., 2003. Industry Cluster Analysis: Inspiring a Common Strategy for Community Development. Cent. Pennsylvania Work. Dev. Corp. Rep. 296.

Soni, V., Singh, S.P., Banwet, D.K., 2015. Sustainable coal consumption and energy production in India using life cycle costing and real options analysis. Sustain. Prod.

Consum. 6, 26–37. doi:10.1016/j.spc.2015.12.002

Sovacool, B.K., 2013. Assessing energy security performance in the Asia Pacific, 1990-2010. Renew. Sustain. Energy Rev. 17, 228–247. doi:10.1016/j.rser.2012.09.031

Sovacool, B.K., 2011. Evaluating energy security in the Asia pacific: Towards a more comprehensive approach. Energy Policy 39, 7472–7479. doi:10.1016/j.enpol.2010.10.008

Sovacool, B.K., Mukherjee, I., 2011. Conceptualizing and measuring energy security: A synthesized approach. Energy 36, 5343–5355. doi:10.1016/j.energy.2011.06.043

Spyropoulos, G., Chalvatzis, K., Paliatsos, A., Kaldellis, J.K., 2005. Sulphur Dioxide Emissions Due to Electricity Generation in the Aegean Islands: Real Threat or Overestimated Danger?, in: 9th International Conference on Environmental Science and Technology.

Srinivasan, P., 2015. Causality among Energy Emission , Economic Growth and Trade : A Case of India. doi:10.1177/0015732515589441

Steiner, G.A., 1938. THE TAX SYSTEM AND INDUSTRIAL DEVELOPMENT. Bull. Natl. Tax Assoc. 23, 98–110.

Steininger, K.W., Lininger, C., Meyer, L.H., Munoz, P., Schinko, T., 2016. Multiple carbon accounting to support just and effective climate policies. Nat. Clim. Chang. 6, 35–41. doi:10.1038/nclimate2867

Stern, D.I., 2004. The Rise and Fall of the Environmental Kuznets Curve. World Dev. 32, 1419–1439. doi:10.1016/j.worlddev.2004.03.004

Stilwell, F.J.B., 1969. Regional growth and structural adaptation. Urban Stud. 6, 162–178.

Stirling, A., 1998. On the economics and analysis of diversity. Electron. Work. Pap. Ser. no 28 28.

Stirling, A., 1994. Diversity and ignorance in electricity supply investment. Addressing the solution rather than the problem. Energy Policy. doi:10.1016/0301-4215(94)90159-7

Suryahadi, A., Suryadarma, D., Sumarto, S., 2009. The effects of location and sectoral components of economic growth on poverty: Evidence from Indonesia. J. Dev. Econ. 89, 109–117. doi:10.1016/j.jdeveco.2008.08.003

Tamazian, A., Chousa, J.P., Vadlamannati, K.C., 2009. Does higher economic and financial development lead to environmental degradation: Evidence from BRIC countries. Energy Policy. doi:10.1016/j.enpol.2008.08.025

Tan, R., Lin, B., 2018. What factors lead to the decline of energy intensity in China's energy intensive industries? Energy Econ. 71, 213–221. doi:10.1016/j.eneco.2018.02.019

Tan, Z.A., 2002. Product cycle theory and telecommunications industry - Foreign direct investment, government policy, and indigenous manufacturing in China. Telecomm. Policy 26, 17–30. doi:10.1016/S0308-5961(01)00051-9

Tang, S., Selvanathan, E.A., Selvanathan, S., 2008. Foreign direct investment, domestic investment and economic growth in China: A time series analysis. World Econ. 31, 1292–1309. doi:10.1111/j.1467-9701.2008.01129.x

The World Economic Forum, 2015. Global Energy Architecture Performance Index Report 2015 Methodological Addendum.

Thomson, E., 2006. ASEAN and Northeast Asian energy security: Cooperation or competition? East Asia 23, 67–90. doi:10.1007/s12140-006-0011-4

Thornton, I., 2013. The fruits of frugal innovation. Green Futur. Mag.

Tian, Y., Xiong, S., Ma, X., 2017. Analysis of the potential impacts on China's industrial structure in energy consumption. Sustain. 9. doi:10.3390/su9122284

Timilsina, G.R., Shrestha, A., 2009. Transport sector CO2 emissions growth in Asia: Underlying factors and policy options. Energy Policy 37, 4523–4539. doi:10.1016/j.enpol.2009.06.009

Tongsopit, S., Kittner, N., Chang, Y., Aksornkij, A., Wangjiraniran, W., 2016. Energy security in ASEAN: A quantitative approach for sustainable energy policy. Energy Policy 90, 60–72. doi:10.1016/j.enpol.2015.11.019

Torrie, R.D., Stone, C., Layzell, D.B., 2016. Understanding Energy Systems Change in Canada: 1. Decomposition of Total Energy Intensity. Energy Econ. 56, 101–106. doi:10.1016/j.eneco.2016.03.012

Tung, A.C., 2003. Beyond flying geese: The expansion of East Asia's electronics trade. Ger. Econ. Rev. doi:10.1111/1468-0475.00072

Turnquist, R., 1964. Industrial mobilization and its importance to industry. Boston University.

U.S. Energy Information Administration (EIA), 2018. Energy implications of faster growth in India with different economic compositions. Int. Energy Outlook 2018 9.

Umali, T., 2019. The Philippines' Department of Trade and Industry Signs MoUs for Industry 4.0 [WWW Document]. OpenGovAsia. URL https://www.opengovasia.com/the-philippines-department-of-trade-and-industry-signs-mous-for-industry-4-0/ (accessed 5.17.20).

UNDP, 2011. UNDP and Energy Access for the Poor: Energizing the Millennium Development Goals. Environ. Energy, United Nations Dev. Program.

UNFCCC, 2015. India's Intended National Determined Contributions 1–38.

UNIDO, 2016. SUMMARY TABLES, in: International Yearbook of Industrial Statistics 2016. doi:10.4337/9781785364938.00011

United Nations, 2015. Adoption of the Paris Agreement. Conf. Parties its twenty-first Sess. 21932, 32.

United Nations Industrial Development Organization, 2016. INDSTAT2 Industrial Statistics Database (Edition: 2016). UK Data Service. doi:http://dx.doi.org/10.5257/unido/indstat2/2016

United Nations Industrial Development Organization, 2010. Compilation of energy statistics for economic analysis, UNIDO.

United Nations Sustainable Development Division, 2005a. Intensity of Energy Use, Total and by Economic Activity.

United Nations Sustainable Development Division, 2005b. Intensity of Energy Use, Total and by Economic Activity.

US Energy Information Administration, 2016. International Energy Statistics.

Voigt, S., De Cian, E., Schymura, M., Verdolini, E., 2014. Energy intensity developments in 40 major economies: Structural change or technology improvement? Energy Econ. 41, 47–62. doi:10.1016/j.eneco.2013.10.015

Von Hippel, D., Suzuki, T., Williams, J.H., Savage, T., Hayes, P., 2011. Energy security and sustainability in Northeast Asia. Energy Policy 39, 6719–6730. doi:10.1016/j.enpol.2009.07.001

Wang, C., 2013. Changing energy intensity of economies in the world and its decomposition. Energy Econ. 40, 637–644. doi:10.1016/j.eneco.2013.08.014

Wang, C., Chen, J., Zou, J., 2005. Decomposition of energy-related CO2emission in China: 1957-2000. Energy 30, 73–83. doi:10.1016/j.energy.2004.04.002

Wang, F., Xia, J., Xu, J., 2020. To upgrade or to relocate? Explaining heterogeneous responses of Chinese light manufacturing firms to rising labor costs. China Econ. Rev. 60, 101333.

Wang, H., Chen, W., 2019. Modelling deep decarbonization of industrial energy consumption under 2-degree target: Comparing China, India and Western Europe. Appl. Energy 238, 1563–1572. doi:10.1016/j.apenergy.2019.01.131

Wang, L.N., Ma, D., Chen, W.Y., 2013. A New Improved Decomposition Model Based on Laspeyres Index: A Case of CO2 Emission in China from 1996-2011, in: Advanced Materials Research. Trans Tech Publ, pp. 1797–1803.

Wang, P., Jiang, Z., Geng, X., Hao, S., Zhang, X., 2014. Quantification of Chinese steel cycle flow: Historical status and future options. Resour. Conserv. Recycl. 87, 191–199. doi:10.1016/j.resconrec.2014.04.003

Wang, Q., Li, R., 2016. Drivers for energy consumption: A comparative analysis of China and India. Renew. Sustain. Energy Rev. 62, 954–962. doi:10.1016/j.rser.2016.04.048

Wang, Q., Su, M., Li, R., 2018. Toward to economic growth without emission growth: The role of urbanization and industrialization in China and India. J. Clean. Prod. 205, 499–511. doi:10.1016/j.jclepro.2018.09.034

Wang, Y., Zhu, Zhiwei, Zhu, Zhaoge, Liu, Z., 2019. Analysis of China’s energy consumption changing using the Mean Rate of Change Index and the logarithmic mean divisia index. Energy. doi:10.1016/j.energy.2018.10.177

Wang, Z., Chen, S., Cui, C., Liu, Q., Deng, L., 2019. Industry relocation or emission relocation? Visualizing and decomposing the dislocation between China’s economy and carbon emissions. J. Clean. Prod. 208, 1109–1119. doi:10.1016/j.jclepro.2018.10.166

Wen, Z., Meng, F., Chen, M., 2014. Estimates of the potential for energy conservation and CO2 emissions mitigation based on Asian-Pacific Integrated Model (AIM): The case of the iron and steel industry in China. J. Clean. Prod. 65, 120–130. doi:10.1016/j.jclepro.2013.09.008

WEO, 2014. World Energy Outlook. Int. Energy Agency 690 pp. doi:10.1787/20725302

Winiwarter, W., Rypdal, K., 2001. Assessing the uncertainty associated with national greenhouse gas emission inventories: Atmos. Environ. 35, 5425–5440.

doi:10.1016/S1352-2310(01)00171-6

World Bank, 2016. Poverty Overview [WWW Document]. World Bank.

Wright, D.J., 1975. The natural resource requirements of commodities. Appl. Econ. 7, 31–39.

Wright, D.J., 1974. 3. Good and services: an input-output analysis. Energy Policy 2, 307–315.

WSA, 2016. Steel Statistical Yearbook 2016. WorldSteel Assoc. 128.

Wu, A., Li, G., Sun, T., Liang, Y., 2014. Effects of industrial relocation on Chinese regional economic growth disparities: Based on system dynamics modeling. Chinese Geogr. Sci. 24, 706–716. doi:10.1007/s11769-014-0664-7

Wu, A., Sun, T., Li, G., 2013. Spatial agglomeration and regional shift of textile and garment industry in China. Acta Geogr. Sin. 68, 775–790.

Wu, J., Wei, Y.D., Chen, W., Yuan, F., 2019. Environmental regulations and redistribution of polluting industries in transitional China: Understanding regional and industrial differences. J. Clean. Prod. 206, 142–155. doi:10.1016/j.jclepro.2018.09.042

Wu, K., 2014. China's energy security: Oil and gas. Energy Policy 73, 4–11. doi:10.1016/j.enpol.2014.05.040

Wu, L., Liu, S., Liu, D., Fang, Z., Xu, H., 2015. Modelling and forecasting CO2 emissions in the BRICS (Brazil, Russia, India, China, and South Africa) countries using a novel multi-variable grey model. Energy 79, 489–495. doi:10.1016/j.energy.2014.11.052

Wübbeke, J., Heroth, T., 2014. Challenges and political solutions for steel recycling in China. Resour. Conserv. Recycl. 87, 1–7. doi:10.1016/j.resconrec.2014.03.004

Xia, X.H., Huang, G.T., Chen, G.Q., Zhang, B., Chen, Z.M., Yang, Q., 2011. Energy security, efficiency and carbon emission of Chinese industry. Energy Policy 39, 3520–3528. doi:10.1016/j.enpol.2011.03.051

Xu, J., Hubbard, P., 2018. A flying goose chase: China's overseas direct investment in manufacturing (2011–2013). China Econ. J. 11, 91–107. doi:10.1080/17538963.2018.1449445

Xu, L., Chen, N., Chen, Z., 2017. Will China make a difference in its carbon intensity reduction targets by 2020 and 2030? Appl. Energy 203, 874–882. doi:10.1016/j.apenergy.2017.06.087

Yadav, A.K., Joseph, J., 2018. Growth and structural changes in Indian economy-an analysis, Reflecting on India's Development: Employment, Skill and Health. Springer Singapore. doi:10.1007/978-981-13-1414-8_3

Yang, C., 2016. Relocating labour-intensive manufacturing firms from China to Southeast Asia: a preliminary investigation. Bandung J. Glob. South 3, 3. doi:10.1186/s40728-016-0031-4

Yang, J., Guo, H., Liu, B., Shi, R., Zhang, B., Ye, W., 2018. Environmental regulation and the Pollution Haven Hypothesis: Do environmental regulation measures matter? J. Clean. Prod. 202, 993–1000. doi:10.1016/j.jclepro.2018.08.144

Yao, L., Chang, Y., 2014. Energy security in China: A quantitative analysis and policy implications. Energy Policy 67, 595–604. doi:10.1016/j.enpol.2013.12.047

Yellishetty, M., Mudd, G.M., Ranjith, P.G., Tharumarajah, A., 2011. Environmental life-cycle comparisons of steel production and recycling: Sustainability issues, problems and prospects. Environ. Sci. Policy 14, 650–663. doi:10.1016/j.envsci.2011.04.008

Yin, J., Zheng, M., Li, X., 2016. Interregional transfer of polluting industries: A consumption responsibility perspective. J. Clean. Prod. 112, 4318–4328. doi:10.1016/j.jclepro.2015.07.103

Yuan, P., Cheng, S., 2011. Determinants of carbon emissions growth in China: A structural decomposition analysis. Energy Procedia 5, 169–175. doi:10.1016/j.egypro.2011.03.030

Zafirakis, D., Chalvatzis, K.J., 2014. Wind energy and natural gas-based energy storage to promote energy security and lower emissions in island regions. Fuel 115, 203–219. doi:10.1016/j.fuel.2013.06.032

Zafirakis, D., Chalvatzis, K.J., Baiocchi, G., 2015. Embodied CO2 emissions and cross-border electricity trade in Europe: Rebalancing burden sharing with energy storage. Appl. Energy 143, 283–300. doi:10.1016/j.apenergy.2014.12.054

Zafirakis, D., Chalvatzis, K.J., Baiocchi, G., Daskalakis, G., 2016. The value of arbitrage for energy storage: Evidence from European electricity markets. Appl. Energy. doi:10.1016/j.apenergy.2016.05.047

Zafirakis, D., Elmasides, C., Sauer, D.U., Leuthold, M., Merei, G., Kaldellis, J.K., Vokas, G., Chalvatzis, K.J., 2014. The multiple role of energy storage in the industrial sector: Evidence from a Greek industrial facility. Energy Procedia 46, 178–185. doi:10.1016/j.egypro.2014.01.171

Zarsky, L., 1999. Havens, Halos and Spaghetti: Uuntangling The Evidence About Forein Direct Investment and the Environment, in: Foreign Direct Investment and the Environment. OECD Publishing.

Zhai, W., Sun, S., Zhang, G., 2016. Reshoring of American manufacturing companies from China. Oper. Manag. Res. 9, 62–74. doi:10.1007/s12063-016-0114-z

Zhang, B., Qiao, H., Chen, Z.M., Chen, B., 2016. Growth in embodied energy transfers via China's domestic trade: Evidence from multi-regional input–output analysis. Appl. Energy 184, 1093–1105.

Zhang, G., Liang, Q., 2010. The Study of Industry Transfer and the Spacial Allocative Effect of Resources. Rev. Ind. Econ. 3.

Zhao, Y., Nielsen, C.P., Lei, Y., McElroy, M.B., Hao, J., 2011. Quantifying the uncertainties of a bottom-up emission inventory of anthropogenic atmospheric pollutants in China. Atmos. Chem. Phys. doi:10.5194/acp-11-2295-2011

Zheng, D., Shi, M., 2017. Multiple environmental policies and pollution haven hypothesis: Evidence from China's polluting industries. J. Clean. Prod. 141, 295–304. doi:10.1016/j.jclepro.2016.09.091

Zhou, Y., Shan, Y., Liu, G., Guan, D., 2018. Emissions and low-carbon development in Guangdong-Hong Kong-Macao Greater Bay Area cities and their surroundings. Appl. Energy. doi:10.1016/j.apenergy.2018.07.038

Zhu, H., Duan, L., Guo, Y., Yu, K., 2016. The effects of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5: Evidence from panel quantile regression.

Econ. Model. 58, 237–248. doi:10.1016/j.econmod.2016.05.003

Ziesemer, T., 2016. Gini Coefficients of Education for 146 Countries, 1950-2010. Bull. Appl. Econ. 3, 1–8.

Zweig, D., Jianhai, B., 2005. China’s global hunt for energy. Foreign Aff.

APPENDIX I

Carbon content stored per fuel

Fuel carbon stored (kt/PJ)	Default	Low	High
Crude Oil	73.3	71.1	75.5
Natural Gas Liquids	64.2	58.3	70.4
Motor Gasoline	69.3	67.5	73
Aviation Gasoline	70	67.5	73
Jet Gasoline	70	67.5	73
Jet Kerosene	71.5	69.7	74.4
Other Kerosene	71.9	70.8	73.7
Shale Oil	73.3	67.8	79.2
Gas/Diesel Oil	74.1	72.6	74.8
Residual Fuel Oil	77.4	75.5	78.8
Liquified Petroleum Gases	63.1	61.6	65.6
Ethane	61.6	56.5	68.6
Naphtha	73.3	69.3	76.3
Bitumen	80.7	73	89.9
Lubricants	73.3	71.9	75.2
Petroleum Coke	97.5	82.9	115
Refinery Feedstocks	73.3	68.9	76.6
Refinery Gas	57.6	48.2	69
Paraffin Waxes	73.3	72.2	74.4
Other Petroleum Products	73.3	72.2	74.4
Anthracite	98.3	94.6	101
Coking Coal	94.6	87.3	101
Other Bitumiunus Coal	94.6	89.5	99.7
Sub-bituminous coal	96.1	92.8	100
Lignite	101	90.9	115
Oil Shale and Tar Sands	107	90.2	125
Brown Coal Briquettes	97.5	87.3	109
Patent Fuel	97.5	87.3	109
Coke Oven Coke	107	95.7	119
Gas Coke	107	95.7	119
Coal Tar	80.7		
Gas Works Gas	44.4	37.3	54.1
Coke oven Gas	44.4	37.3	54.1
Blast Furnace Gas	260	219	308
Oxygen Steel Furnace Gas	182	145	202
Natural Gas	56.1	54.3	58.3
Municipal Wastes	91.7	73.3	121
Industrial Wastes	143	110	183
Waste Oils	73.3	72.2	74.4

Peat	106	100	108
Wood/Wood Waste	112	95	132
Other Primary Solid Biomass	100	84.7	117
Charcoal	112	95	132
Biogasoline	70.8	59.8	84.3
Biodiesels	70.8	59.8	84.3
Other Liquid Biofuels	79.6	67.1	95.3
Other Biogas	54.6	46.2	66
Municipal Wastes (biomass function)	100	84.7	117

Carbon content (carbon emitted from carbon stored)

Fuel CC	Default	Low	High
Crude Oil	20	19.4	20.6
Natural Gas Liquids	22	20.0	24.1
Motor Gasoline	18.9	18.4	19.9
Aviation Gasoline	18.9	18.2	19.7
Jet Gasoline	18.9	18.2	19.7
Jet Kerosene	19.5	19.0	20.3
Other Kerosene	20	19.7	20.5
Shale Oil	20	18.5	21.6
Gas/Diesel Oil	20.2	19.8	20.4
Residual Fuel Oil	21.1	20.6	21.5
Liquified Petroleum Gases	17.2	16.8	17.9
Ethane	16.8	15.4	18.7
Naphtha	20	18.9	20.8
Bitumen	22	19.9	24.5
Lubricants	20	19.6	20.5
Petroleum Coke	27.5	23.4	32.4
Refinery Feedstocks	20	18.8	20.9
Refinery Gas	18.2	15.2	21.8
Paraffin Waxes	20	19.7	20.3
Other Petroleum Products	20	19.7	20.3
Anthracite	26.8	25.8	27.5
Coking Coal	25.8	23.8	27.5
Other Bitumiunus Coal	25.8	24.4	27.2
Sub-bituminous coal	26.2	25.3	27.3
Lignite	27.6	24.8	31.4
Oil Shale and Tar Sands	20	16.9	23.4
Brown Coal Briquettes	20	17.9	22.4
Patent Fuel	20	17.9	22.4
Coke Oven Coke	29.5	26.4	32.8
Gas Coke	29.5	26.4	32.8
Coal Tar			

Gas Works Gas	13	10.9	15.8
Coke oven Gas	13	10.9	15.8
Blast Furnace Gas	66	55.6	78.2
Oxygen Steel Furnace Gas	66	52.6	73.3
Natural Gas	15.3	14.8	15.9
Municipal Wastes	29.9	23.9	39.5
Industrial Wastes	29.9	23.0	38.3
Waste Oils	20	19.7	20.3
Peat	29.9	28.2	30.5
Wood/Wood Waste	29.9	25.4	35.2
Other Primary Solid Biomass	29.9	25.3	35.0
Charcoal	29.9	25.4	35.2
Biogasoline	30.6	25.8	36.4
Biodiesels	20	16.9	23.8
Other Liquid Biofuels	20	16.9	23.9
Other Biogas	30.6	25.9	37.0
Municipal Wastes (biomass function)	20	16.9	23.4

APPENDIX II

UNIDO NUMBER OF PERSONS EMPLOYED

India	TOTAL	Iron&Steel	Chemical& Petrochemical	Non-metallic minerals	Machinery	Textiles&Leather	Paper, Pulp and Print
1980	6801000	578000	529000	347000	909000	1717000	273000
1981	6850819	590000	528844	366193	917029	1655176	289127
1982	7025816	604000	562419	406307	964765	1723577	303031
1983	6778561	618000	550699	426770	968833	1682795	299025
1984	6759142	669000	556179	411639	979319	1696135	290985
1985	6468964	596000	585816	426484	976758	1544982	277102
1986	6419606	615000	567311	415931	910540	1543577	271684
1987	6709047	617000	603697	422989	1011702	1544000	290250
1988	6731446	618000	621724	428209	1027690	1505853	271094
1989	7115437	590461	616910	434823	1041828	1619168	272782
1990	7184394	622372	605554	431006	1078670	1593639	284641
1991	7236878	595799	633463	454049	1082198	1551232	288789
1992	7716627	661886	702827	455944	1132289	1623785	301576
1993	7698146	625355	708640	440783	1105876	1698845	301184
1994	7987515	631304	744053	444396	1138904	1752409	319362
1995	8776820	736457	835936	481267	1269815	1960728	355928
1996	8670087	659104	836682	460195	1273024	1899291	333511
1997	8716713	666591	853361	442791	1190024	1922379	336664
1998	7939537	620431	830072	430709	1204268	1733184	285154

1999	7903693	630106	889232	451074	1126932	1701530	290274
2000	7753732	563730	867242	443861	1084303	1757842	297610
2001	7453098	539315	826078	459024	1011906	1637330	277683
2002	7638178	531752	821238	590028	1030490	1650577	291625
2003	7569359	536698	810954	447859	1010222	1726122	284911
2004	8114719	574526	860604	515572	1113035	1855436	290144
2005	8736589	640891	906811	569258	1241524	2035729	309451
2006	9637176	765646	963035	654618	1392762	2282120	331033
2007	10027104	806708	998099	662962	1576503	2290890	392872
2008	10847877	895440	1068946	769052	1836528	2438828	357173
2009	11307840	891473	1122217	789076	2000446	2495863	359332
2010	12156472	1009748	1211864	894088	2118121	2610110	405830
2011	12809570	1084055	1329145	925927	2148284	2673253	423202
2012	12307025	1014578	1262703	875828	2046487	2608683	399752

Indonesia	TOTAL	Iron&Steel	Chemical&Petrochemical	Non-metallic minerals	Machinery	Textiles&Leather	Paper, Pulp and Print
1980	963000	8800		46400	90100	256000	31800
1981	1004896	9500		49800	95200	262900	34300
1982	1059831	10100		52600	93900	264100	37000
1983	1112355	12900		55500	94800	262900	36700
1984	1190421	14000		55000	92100	284000	35400
1985	1671990	15600		87600	119066	378100	56300

1986	1679260	16900		79800	113700	385700	62100
1987	1776710	16800		81300	116000	415700	61600
1988	2058250	19600		95800	129700	480600	68100
1989	2247108	21200		107700	144900	556200	72700
1990	2649439	32717	135419	112875	170674	728217	86609
1991	2981126	37498	138642	128551	201859	903617	102132
1992	3298122	40020	149206	135236	237801	1075855	118518
1993	3559378	43512	161078	148362	261078	1184755	122817
1994	3798606	46700	170648	155365	311515	1251832	132107
1995	4156980	47602	186364	177852	355389	1308520	148662
1996	4196494	50385	188554	188020	374262	1350133	164942
1997							
1998	4106843	55269	241804		329773	1224078	171588
1999	4216865	56542	197954		376587	1349910	153103
2000	4350461	59972	200873		384890	1418647	164596
2001	4385923	61019	224703		379118	1368185	161692
2002	4364869	53509	174222		357478	1294625	147786
2003	4273880	59373	215322	165755	382564	1242901	172162
2004	4324979	58967	208402	165413	416655	1212809	168024
2005	4226572	56411	213824	165056	426860	1227740	168840
2006	4735619	65035	213996	188927	440373	1388376	191631
2007	4608728	64233	219462	176321	445761	1286729	192824
2008	4457932	64099	206717	176459	431899	1200042	185948
2009	4345174	60632	218378	175127	411791	1181853	180981
2010	4501145	68623	221985	168868	478159	1245715	169096

2011	4729153	64678	237963	174811	592374	1286721	177256
2012	4928839	60430	255169	193136	510515	1338958	181506

Philippines	TOTAL	Iron&Steel	Chemical& Petrochemical	Non-metallic minerals	Machinery	Textiles&Leather	Paper, Pulp and Print
1980	948700	22500	52700	31300	113900	252600	39500
1981	970500	21800	45700	32900	122500	258000	39500
1982	968600	22100	45400	30900	117200	262800	43100
1983	696003	20900	37153	28600	89249	172480	28150
1984	639000	19800	33400	25360	82550	162800	24900
1985	618400	18300	35273	21100	66000	159880	24600
1986	630140	18300	36000	20800	69400	172300	27700
1987	671000	17000	36500	21200	74490	187300	28400
1988	845100	18100	43500	27600	95000	243100	35200
1989	940300	20200	45300	30700	103700	309000	37300
1990	1108500	22100	46500	42700	137000	304300	44000
1991	1105700	22300	48000	43400	155100	298000	46400
1992	958800	23000	46700	42200	151100	278200	41300
1993	900600	22200	45900	35000	149000	247400	41900
1994	887100	25100	45900	36200	160200	229400	39600
1995	903400	27000	47300	32700	191200	221200	41700
1996	1052000	36600	57900	44300	213800	243300	50000
1997	1097200	37400	59800	46400	231100	247500	51900
1998	1153500	39200	57900	47300	272000	252600	53700

1999	1084200	35600	48000	49800	279500	228500	47200
2000							
2001	932400	27100	46400	27300	260400	206000	38500
2002							
2003	983886	27786	45176	29593	303627	201926	40831
2004							
2005	1022114	24980	51410	26578	317828	214296	41568
2006	989401	23613	40960	28750	337886	185669	38947
2007							
2008	886973	21101	39670	22910	284847	136356	29297
2009	839663	20455	41754	22597	244973	120478	27712
2010	871195	20527	39739	22644	280038	120759	29740
2011							
2012	1045677	20485	53065	32579	324962	148296	35144

UNIDO INDUSTRIAL VALUE ADDED

India	TOTAL	Iron&Steel	Chemical&Petrochemical	Non-metallic minerals	Machinery	Textiles&Leather	Paper, Pulp and Print
1980	31010855085	3.72E+09	5.2E+09	1.22E+09	6.19E+09	6611795545	1.31E+09
1981	29893897556	4.35E+09	5.13E+09	1.2E+09	5.73E+09	5315412468	1.33E+09
1982	29935980045	3.86E+09	5.56E+09	1.58E+09	5.93E+09	4659553085	1.06E+09
1983	31574007575	3.97E+09	5.61E+09	1.62E+09	6.11E+09	5097623718	1.08E+09
1984	29510646258	3.08E+09	4.93E+09	1.65E+09	6.3E+09	4689074259	1.22E+09
1985	28178968289	3.46E+09	5.16E+09	1.64E+09	5.69E+09	4220887929	9.3E+08
1986	29048326684	3.1E+09	5.32E+09	1.43E+09	5.55E+09	4547357111	1.12E+09
1987	31520125754	3.41E+09	6.87E+09	1.48E+09	6.41E+09	4300072923	1.14E+09
1988	35007269472	4.87E+09	7.02E+09	1.52E+09	6.83E+09	4451393972	1.12E+09
1989	35848306241	4.21E+09	6.94E+09	1.58E+09	6.91E+09	5335918939	1.29E+09
1990	37514939891	4.79E+09	7.02E+09	1.92E+09	6.93E+09	5691537327	1.37E+09
1991	29755190641	2.58E+09	5.56E+09	2.07E+09	6.1E+09	4179238385	1.17E+09
1992	31474224157	3.46E+09	7.54E+09	1.41E+09	6.05E+09	3956807203	1.13E+09
1993	32990676464	3.62E+09	7.89E+09	1.35E+09	5.35E+09	5104931780	1.26E+09
1994	38793181518	4.52E+09	8.82E+09	1.6E+09	7E+09	5688995830	1.43E+09
1995	46499528845	5.52E+09	1.18E+10	2.28E+09	8.29E+09	5192198771	1.84E+09
1996	42877412575	4.86E+09	1.02E+10	1.71E+09	7.32E+09	5146828897	1.38E+09
1997	42437347914	6.64E+09	8.66E+09	1.86E+09	7.14E+09	5181488169	1.17E+09
1998	47227038722	6.09E+09	1.32E+10	1.97E+09	7.66E+09	5812582656	1.35E+09
1999	50680635397	6.31E+09	1.34E+10	2.64E+09	7.32E+09	6172326545	1.58E+09

2000	44493721799	4.77E+09	1.16E+10	2.5E+09	6.75E+09	6061800523	1.9E+09
2001	41856471978	4.03E+09	1.12E+10	2.41E+09	6.46E+09	4993984073	1.47E+09
2002	46912730655	5.6E+09	1.39E+10	2.23E+09	6.54E+09	5431369330	1.7E+09
2003	55108638729	7.85E+09	1.64E+10	2.44E+09	7.47E+09	5889957586	1.78E+09
2004	69017826373	1.31E+10	1.94E+10	3.45E+09	8.59E+09	6423095219	1.82E+09
2005	81101179138	1.16E+10	2.39E+10	3.6E+09	1.19E+10	7521510662	2.39E+09
2006	95737310985	1.56E+10	2.61E+10	5.37E+09	1.46E+10	9143932805	2.5E+09
2007	1.21949E+11	2.27E+10	3.28E+10	8.26E+09	1.91E+10	9652696855	3.32E+09
2008	1.22575E+11	1.77E+10	3.49E+10	8.63E+09	2.27E+10	9514475129	2.75E+09
2009	1.23926E+11	1.7E+10	3.25E+10	8.67E+09	2.34E+10	10306286332	2.58E+09
2010	1.52479E+11	1.99E+10	3.99E+10	8.31E+09	2.9E+10	13957734167	4E+09
2011	1.70069E+11	3.06E+10	4.28E+10	9.77E+09	2.92E+10	13268084109	3.71E+09
2012	1.50154E+11	1.63E+10	4.41E+10	8.54E+09	2.65E+10	14634927713	3.21E+09

Indonesia	TOTAL	Iron&Steel	Chemical& Petrochemical	Non-metallic minerals	Machinery	Textiles&Leather	Paper, Pulp and Print
1980	8.03E+09	2.53E+08	9.15E+08	5.77E+08	8.32E+08	1.1E+09	2.22E+08
1981	9.22E+09	2.7E+08	1.22E+09	6.49E+08	8.64E+08	1.08E+09	1.98E+08
1982	9.09E+09	2.08E+08	1.22E+09	5.63E+08	1.07E+09	1.2E+09	2.33E+08
1983	7.29E+09	4.33E+08	8.63E+08	4.7E+08	7.27E+08	9.16E+08	1.57E+08
1984	8.2E+09	9.03E+08	9.6E+08	4.38E+08	7.07E+08	1.24E+09	1.81E+08
1985	1.18E+10	8.51E+08	1.48E+09	6.98E+08	1.09E+09	1.52E+09	3.66E+08
1986	1.16E+10	9.87E+08	1.25E+09	6.37E+08	9.12E+08	1.76E+09	3.93E+08
1987	1.06E+10	1.08E+09	1.09E+09	5.11E+08	8.29E+08	1.41E+09	4E+08

1988	1.23E+10	1.03E+09	1.28E+09	4.85E+08	1.09E+09	1.57E+09	5.77E+08
1989	1.5E+10	1.25E+09	1.31E+09	4.82E+08	1.54E+09	2.41E+09	5.76E+08
1990	2.04E+10	1.84E+09	1.84E+09	7.71E+08	1.46E+09	2.98E+09	9.37E+08
1991	2.2E+10	1.26E+09	2.49E+09	1E+09	1.82E+09	3.3E+09	1.21E+09
1992	2.84E+10	1.76E+09	2.64E+09	1.08E+09	2.72E+09	4.72E+09	1.37E+09
1993	3.09E+10	2.07E+09	2.74E+09	1.35E+09	2.5E+09	6.23E+09	1.32E+09
1994	3.65E+10	2.56E+09	3.36E+09	1.42E+09	3.21E+09	7.79E+09	1.69E+09
1995	3.82E+10	2.89E+09	3.3E+09	1.43E+09	4.25E+09	7.2E+09	1.92E+09
1996	4.52E+10	4.98E+09	4.31E+09	1.53E+09	6.05E+09	8.07E+09	2.44E+09
1997							
1998	1.77E+10	7.03E+08	2.42E+09		1.79E+09	3.11E+09	1.09E+09
1999	2.69E+10	1.1E+09	3.11E+09		2.91E+09	5.26E+09	1.66E+09
2000	3.03E+10	1.13E+09	3.26E+09		4.44E+09	5.08E+09	1.99E+09
2001	2.76E+10	1.44E+09	3.03E+09		3.72E+09	3.47E+09	1.85E+09
2002	3.34E+10	1.32E+09	2.98E+09		3.28E+09	4.81E+09	2.03E+09
2003	4.04E+10	1.46E+09	4.84E+09	1.69E+09	4.11E+09	5.49E+09	3.34E+09
2004	4.15E+10	1.49E+09	3.98E+09	1.92E+09	4.7E+09	5.27E+09	3.37E+09
2005	4.08E+10	1.45E+09	4.54E+09	1.98E+09	4.21E+09	4.71E+09	3E+09
2006	5.44E+10	2.13E+09	6.16E+09	2E+09	5.36E+09	7.12E+09	3.94E+09
2007	6.16E+10	2.55E+09	4.32E+09	2.47E+09	5.62E+09	7.19E+09	4.13E+09
2008	6.39E+10	2.91E+09	1.16E+10	2.34E+09	6.71E+09	6.25E+09	4.02E+09
2009	6.69E+10	2.37E+09	1.17E+10	2.59E+09	7.14E+09	7.31E+09	4.78E+09
2010	8.41E+10	3.09E+09	1.2E+10	3.21E+09	9.28E+09	8.43E+09	5.26E+09
2011	1.01E+11	3.78E+09	1.4E+10	3.66E+09	1.11E+10	1.01E+10	6.78E+09
2012	1.04E+11	3.52E+09	1.29E+10	4.12E+09	1.28E+10	1.07E+10	5.66E+09

Philippines	TOTAL	Iron&Steel	Chemical&Petrochemical	Non-metallic minerals	Machinery	Textiles&Leather	Paper, Pulp and Print
1980	1.15E+10	3.15E+08	2.41E+09	3.26E+08	1.15E+09	1.47E+09	5.15E+08
1981	1.05E+10	2.41E+08	2.18E+09	2.97E+08	8.79E+08	1.52E+09	4.32E+08
1982	7.71E+09	1.87E+08	1.74E+09	2E+08	9.08E+08	8.08E+08	2.5E+08
1983	8.82E+09	7.93E+08	2.07E+09	2.87E+08	7.92E+08	8.02E+08	3.62E+08
1984	6.93E+09	6.06E+08	1.24E+09	2.66E+08	7.66E+08	6.96E+08	2.87E+08
1985	6.26E+09	3.48E+08	1.86E+09	1.75E+08	4.27E+08	4.11E+08	2.6E+08
1986	6.95E+09	1.83E+08	1.98E+09	1.37E+08	4.71E+08	4.76E+08	3.48E+08
1987	7.02E+09	2.75E+08	1.56E+09	2.27E+08	5.64E+08	5.63E+08	2.73E+08
1988	9.4E+09	5.79E+08	1.76E+09	3.62E+08	7.17E+08	1.01E+09	3.74E+08
1989	1.05E+10	3.82E+08	1.75E+09	4.73E+08	9.87E+08	1.47E+09	4.08E+08
1990	1.32E+10	5.27E+08	2.3E+09	5.31E+08	1.52E+09	1.41E+09	4.61E+08
1991	1.31E+10	4.76E+08	2.76E+09	5.39E+08	1.82E+09	1.43E+09	4.51E+08
1992	1.47E+10	6.4E+08	3.32E+09	6.64E+08	1.81E+09	1.46E+09	5.63E+08
1993	1.49E+10	8.25E+08	2.77E+09	6.15E+08	1.8E+09	1.52E+09	5.52E+08
1994	1.62E+10	9.15E+08	3.43E+09	7.52E+08	2.1E+09	1.6E+09	5.72E+08
1995	1.96E+10	1.03E+09	4.36E+09	9.03E+08	2.89E+09	1.64E+09	6.69E+08
1996	2.37E+10	9.68E+08	5.82E+09	1.13E+09	3.89E+09	1.58E+09	8.3E+08
1997	2.31E+10	9.14E+08	5.25E+09	1.05E+09	4.21E+09	1.59E+09	7.69E+08
1998	1.96E+10	6.17E+08	3.46E+09	7.65E+08	4.27E+09	1.33E+09	6.7E+08
1999	2.04E+10	7.54E+08	3.87E+09	8.48E+08	4.94E+09	1.39E+09	7.36E+08
2000		0	0	0	0	0	0

2001	1.33E+10	4.1E+08	2.18E+09	4.07E+08	3.81E+09	9.92E+08	4.36E+08
2002		0	0	0	0	0	0
2003	1.13E+10	3.36E+08	2.51E+09	4.27E+08	2.91E+09	7.37E+08	3.76E+08
2004		0	0	0	0	0	0
2005	1.24E+10	3.97E+08	2.68E+09	4.9E+08	3.33E+09	7.68E+08	3E+08
2006	1.27E+10	6.56E+08	2.04E+09	4.52E+08	4.45E+09	6.25E+08	3.05E+08
2007		0	0	0	0	0	0
2008	1.69E+10	6.78E+08	4.55E+09	6.4E+08	3.84E+09	5.32E+08	2.88E+08
2009	1.9E+10	8.12E+08	4.09E+09	6.69E+08	6.41E+09	5E+08	3.12E+08
2010	1.99E+10	8.64E+08	5.28E+09	7.84E+08	4.93E+09	5.02E+08	3.5E+08
2011		0	0	0	0	0	0
2012	2.28E+10	3.97E+08	1.67E+09	8.96E+08	1.03E+10	6.25E+08	2.94E+08

APPENDIX III

Year	vs IEA (%)	vs EDGAR (%)	vs BP (%)	vs EIA (%)	vs CDIAC (%)
1980	11.15%	-11.39%	-9.51%	0.73%	-7.23%
1981	13.60%	-10.02%	-8.24%	-2.39%	-3.04%
1982	13.39%	-10.54%	-3.61%	0.35%	-2.89%
1983	10.63%	-12.47%	-4.54%	-0.47%	-6.76%
1984	8.87%	-12.62%	-2.79%	-6.59%	-2.83%
1985	10.24%	-11.96%	-2.93%	-6.75%	-6.24%
1986	7.86%	-12.83%	-3.53%	-5.93%	-6.58%
1987	2.98%	-10.59%	-8.26%	-5.76%	-9.99%
1988	3.57%	-16.15%	-9.67%	-6.77%	-11.47%
1989	1.83%	-17.42%	-12.57%	-7.05%	-14.46%
1990	-1.63%	-20.32%	-9.63%	-9.21%	-16.14%
1991	-5.44%	-22.85%	-11.63%	-12.86%	-19.18%
1992	-7.10%	-24.29%	-14.36%	-15.53%	-21.60%
1993	-10.51%	-27.35%	-17.19%	-19.75%	-24.88%
1994	-10.98%	-27.40%	-16.17%	-20.73%	-25.17%
1995	-14.40%	-30.03%	-20.82%	-31.09%	-27.39%
1996	-15.18%	-30.94%	-23.37%	-22.43%	-30.52%
1997	-14.37%	-29.89%	-21.24%	-21.72%	-29.24%
1998	-15.94%	-30.29%	-22.89%	-24.52%	-30.65%
1999	-11.77%	-26.81%	-15.82%	-20.49%	-27.14%
2000	-6.78%	-21.49%	-12.72%	-16.09%	-22.76%
2001	-7.99%	-22.06%	-12.62%	-17.53%	-23.26%
2002	-6.53%	-21.48%	-12.74%	-12.77%	-21.03%
2003	-4.99%	-21.21%	-12.90%	-11.33%	-22.04%
2004	-7.47%	-22.88%	-14.31%	-14.68%	-21.81%
2005	-7.76%	-22.13%	-15.07%	-15.17%	-21.72%
2006	-5.07%	-20.43%	-11.88%	-14.23%	-19.52%
2007	-7.46%	-20.66%	-12.68%	-14.23%	-19.84%
2008	-5.93%	-19.17%	-12.60%	-12.88%	-22.40%
2009	-2.09%	-11.45%	-5.69%	-9.85%	-16.95%
2010	-1.11%	-10.39%	-3.72%	-7.92%	-10.78%
2011	0.73%	-7.59%	-1.89%	-4.60%	-11.15%
2012	1.90%	-8.06%	-2.21%	-0.92%	

APPENDIX IEA vs Emission inventories (reference to Figure 3.41

Year	vs IEA (%)	vs EDGAR (%)	vs BP (%)	vs EIA (%)	vs CDIAC (%)	Average
1980	21.95%	-2.77%	-0.71%	10.53%	1.79%	6.16%
1981	24.49%	-1.39%	0.56%	6.98%	6.27%	7.38%
1982	23.55%	-2.52%	5.03%	9.35%	5.81%	8.24%
1983	20.41%	-4.73%	3.90%	8.33%	1.48%	5.88%
1984	19.05%	-4.46%	6.30%	2.15%	6.25%	5.86%
1985	19.02%	-4.94%	4.80%	0.68%	1.23%	4.16%
1986	15.65%	-6.54%	3.44%	0.87%	0.17%	2.72%
1987	9.83%	-4.64%	-2.15%	0.51%	-4.00%	-0.09%
1988	10.76%	-10.33%	-3.40%	-0.30%	-5.33%	-1.72%
1989	8.31%	-12.17%	-7.01%	-1.14%	-9.02%	-4.20%
1990	5.14%	-14.83%	-3.41%	-2.96%	-10.37%	-5.29%
1991	1.27%	-17.37%	-5.35%	-6.67%	-13.43%	-8.31%
1992	-0.81%	-19.17%	-8.56%	-9.82%	-16.29%	-10.93%
1993	-4.92%	-22.81%	-12.02%	-14.73%	-20.19%	-14.93%
1994	-5.33%	-22.79%	-10.84%	-15.70%	-20.42%	-15.01%
1995	-9.49%	-26.01%	-16.28%	-27.14%	-23.22%	-20.43%
1996	-10.41%	-27.06%	-19.07%	-18.08%	-26.62%	-20.25%
1997	-9.51%	-25.91%	-16.77%	-17.27%	-25.22%	-18.94%
1998	-11.80%	-26.85%	-19.09%	-20.80%	-27.23%	-21.15%
1999	-7.82%	-23.53%	-12.04%	-16.93%	-23.88%	-16.84%
2000	-3.17%	-18.45%	-9.34%	-12.84%	-19.77%	-12.71%
2001	-4.36%	-18.98%	-9.17%	-14.27%	-20.22%	-13.40%
2002	-2.32%	-17.94%	-8.82%	-8.85%	-17.48%	-11.08%
2003	-0.86%	-17.78%	-9.11%	-7.47%	-18.65%	-10.77%
2004	-3.20%	-19.32%	-10.36%	-10.75%	-18.21%	-12.37%
2005	-3.11%	-18.20%	-10.79%	-10.89%	-17.77%	-12.15%
2006	-0.20%	-16.34%	-7.36%	-9.83%	-15.38%	-9.82%
2007	-2.93%	-16.77%	-8.41%	-10.03%	-15.92%	-10.81%
2008	-0.66%	-14.64%	-7.70%	-8.00%	-18.05%	-9.81%
2009	4.08%	-5.87%	0.25%	-4.17%	-11.72%	-3.49%
2010	4.96%	-4.89%	2.19%	-2.27%	-5.30%	-1.06%
2011	6.85%	-1.98%	4.07%	1.19%	-5.75%	0.88%
2012	7.92%	-2.64%	3.56%	4.92%		3.44%

APPENDIX IPCC vs Emission inventories (reference to Figure 3.42)

APPENDIX IV

	BKB	diff (%)			Other Bituminous Coal	diff (%)
NCVIPCCLOW_CO2LOW	662.8585	0.116838		NCV IEA_CO2LOW	261311.2	0.056983
NCVIPCCLOW_CO2NET	740.3058	0.117949		NCV IEA_CO2NET	276201.6	0.019669
NCVIPCCLOW_CO2HIGH	827.624	0.060818		NCVIPCCLOW_CO2LOW	281634.2	0.033582
NCV IEA_CO2LOW	877.9582	0.035		NCV IEA_CO2HIGH	291091.9	0.022641
NCVIPCCNET_CO2LOW	908.6868	0.079071		NCVIPCCLOW_CO2NET	297682.6	0.053911
NCV IEA_CO2NET	980.5375	0.035		NCVIPCCLOW_CO2HIGH	313731	0.163843
NCVIPCCNET_CO2NET	1014.856	0.080144	0.093885	NCVIPCCNET_CO2LOW	365133.7	0.056983
NCV IEA_CO2HIGH	1096.191	0.035		NCVIPCCNET_CO2NET	385940.3	0.053911
NCVIPCCNET_CO2HIGH	1134.557	0.238133		NCVIPCCNET_CO2HIGH	406746.8	0.061226
NCVIPCCHIGH_CO2LOW	1404.733	0.116838		NCVIPCCHIGH_CO2LOW	431650.4	0.056983
NCVIPCCHIGH_CO2NET	1568.86	0.117949		NCVIPCCHIGH_CO2NET	456247.2	0.053911
NCVIPCCHIGH_CO2HIGH	1753.905			NCVIPCCHIGH_CO2HIGH	480844	
	Coke Oven Coke	diff (%)			Sub-Bituminous Coal	diff (%)
NCVIPCCLOW_CO2LOW	10859.13	0.118077		NCVIPCCLOW_CO2LOW	85322.88	0.03556
NCVIPCCLOW_CO2NET	12141.35	0.004855		NCVIPCCLOW_CO2NET	88356.99	0.040583
NCV IEA_CO2LOW	12200.3	0		NCV IEA_CO2LOW	91942.76	0.525148
NCVIPCCNET_CO2LOW	12200.3	0.070922		NCVIPCCNET_CO2LOW	140226.3	0
NCVIPCCHIGH_CO2LOW	13065.57	0.033479		NCVIPCCLOW_CO2HIGH	140226.3	0.03556
NCVIPCCLOW_CO2HIGH	13502.99	0.010211		NCV IEA_CO2NET	145212.8	0
NCV IEA_CO2NET	13640.88	0		NCVIPCCNET_CO2NET	145212.8	0.040583

NCVIPCCNET_CO2NET	13640.88	0.070922		NCV IEA_CO2HIGH	151105.9	0
NCVIPCCHIGH_CO2NET	14608.31	0.038497		NCVIPCCNET_CO2HIGH	151105.9	0.276614
NCV IEA_CO2HIGH	15170.69	0		NCVIPCCHIGH_CO2LOW	192903.9	0.03556
NCVIPCCNET_CO2HIGH	15170.69	0.070922		NCVIPCCHIGH_CO2NET	199763.6	0.040583
NCVIPCCHIGH_CO2HIGH	16246.63			NCVIPCCHIGH_CO2HIGH	207870.6	
	Coking Coal	diff (%)			Biodiesels	diff (%)
NCVIPCCLOW_CO2LOW	17968.87	0.011792		NCVIPCCLOW_CO2LOW	52.19232	0.183946
NCV IEA_CO2LOW	18180.75	0.070991		NCVIPCCLOW_CO2NET	61.79292	0.190678
NCVIPCCLOW_CO2NET	19471.42	0.011792		NCVIPCCLOW_CO2HIGH	73.57547	0.408311
NCV IEA_CO2NET	19701.02	0.055211		NCVIPCCNET_CO2LOW	103.6171	0.183946
NCVIPCCLOW_CO2HIGH	20788.72	0.011792		NCVIPCCNET_CO2NET	122.6771	0.151203
NCV IEA_CO2HIGH	21033.86	0.003783		NCV IEA_CO2LOW	141.2263	0.03429
NCVIPCCNET_CO2LOW	21113.42	0.08362	0.03756	NCVIPCCNET_CO2HIGH	146.0689	0.144695
NCVIPCCNET_CO2NET	22878.92	0.014462		NCV IEA_CO2NET	167.2044	0.190678
NCVIPCCHIGH_CO2LOW	23209.79	0.052433		NCV IEA_CO2HIGH	199.0866	0.040925
NCVIPCCNET_CO2HIGH	24426.75	0.029633		NCVIPCCHIGH_CO2LOW	207.2342	0.183946
NCVIPCCHIGH_CO2NET	25150.58	0.067653		NCVIPCCHIGH_CO2NET	245.3542	0.190678
NCVIPCCHIGH_CO2HIGH	26852.1			NCVIPCCHIGH_CO2HIGH	292.1379	
	Lignite	diff (%)			Biogases	diff (%)
NCVIPCCLOW_CO2LOW	3388.073	0.111111		NCV IEA_CO2LOW	1504.518	0
NCVIPCCLOW_CO2NET	3764.525	0.138614		NCVIPCCNET_CO2LOW	1504.518	0
NCVIPCCLOW_CO2HIGH	4286.341	0.371907		NCVIPCCLOW_CO2LOW	1504.518	0
NCV IEA_CO2LOW	5880.463	0.111111		NCVIPCCHIGH_CO2LOW	1504.518	0.181818

NCV IEA_CO2NET	6533.847	0.121936		NCV IEA_CO2NET	1778.066	0
NCVIPCCNET_CO2LOW	7330.558	0.014865		NCVIPCCNET_CO2NET	1778.066	0
NCV IEA_CO2HIGH	7439.529	0.094836		NCVIPCCLOW_CO2NET	1778.066	0
NCVIPCCNET_CO2NET	8145.064	0.138614		NCVIPCCHIGH_CO2NET	1778.066	0.208791
NCVIPCCNET_CO2HIGH	9274.083	0.434739		NCV IEA_CO2HIGH	2149.311	0
NCVIPCCHIGH_CO2LOW	13305.89	0.111111		NCVIPCCNET_CO2HIGH	2149.311	0
NCVIPCCHIGH_CO2NET	14784.32	0.138614		NCVIPCCLOW_CO2HIGH	2149.311	0
NCVIPCCHIGH_CO2HIGH	16833.63			NCVIPCCHIGH_CO2HIGH	2149.311	

	Biogasoline	diff (%)			Crude Oil	diff (%)
NCVIPCCLOW_CO2LOW	311.6892	0.183946		NCVIPCCLOW_CO2LOW	624859.6	0.030942
NCVIPCCLOW_CO2NET	369.0233	0.190678		NCVIPCCLOW_CO2NET	644194.2	0.023203
NCVIPCCLOW_CO2HIGH	439.3879	0.397879		NCVIPCCNET_CO2LOW	659141.2	0.006657
NCV IEA_CO2LOW	614.2111	0.007463		NCVIPCCLOW_CO2HIGH	663528.8	0.004871
NCVIPCCNET_CO2LOW	618.7947	0.175177		NCV IEA_CO2LOW	666761	0.019161
NCV IEA_CO2NET	727.193	0.007463		NCVIPCCNET_CO2NET	679536.5	0.01156
NCVIPCCNET_CO2NET	732.6198	0.181858		NCV IEA_CO2NET	687392.2	0.015574
NCV IEA_CO2HIGH	865.8527	0.007463		NCVIPCCHIGH_CO2LOW	698097.5	0.002628
NCVIPCCNET_CO2HIGH	872.3143	0.418743		NCVIPCCNET_CO2HIGH	699931.9	0.01156
NCVIPCCHIGH_CO2LOW	1237.589	0.183946		NCV IEA_CO2HIGH	708023.3	0.01649
NCVIPCCHIGH_CO2NET	1465.24	0.190678		NCVIPCCHIGH_CO2NET	719698.3	0.030014
NCVIPCCHIGH_CO2HIGH	1744.629			NCVIPCCHIGH_CO2HIGH	741299	

	Bitumen	diff (%)			Fuel Oil	diff (%)
NCVIPCCLOW_CO2LOW	11378.75	0.105479		NCVIPCCLOW_CO2LOW	19984.51	0.01005
NCVIPCCLOW_CO2NET	12578.97	0.053099		NCV IEA_CO2LOW	20185.36	0.004975
NCV IEA_CO2LOW	13246.9	0.030769		NCVIPCCNET_CO2LOW	20285.78	0.00994
NCVIPCCNET_CO2LOW	13654.5	0.024876		NCVIPCCLOW_CO2NET	20487.43	0.01005
NCVIPCCHIGH_CO2LOW	13994.16	0.001347		NCV IEA_CO2NET	20693.33	0.004975
NCVIPCCLOW_CO2HIGH	14013	0.045042		NCVIPCCNET_CO2NET	20796.28	0.002968
NCV IEA_CO2NET	14644.17	0.030769	0.038765	NCVIPCCLOW_CO2HIGH	20858	0.003861
NCVIPCCNET_CO2NET	15094.76	0.024876		NCVIPCCHIGH_CO2LOW	20938.54	0.006165
NCVIPCCHIGH_CO2NET	15470.26	0.054517		NCV IEA_CO2HIGH	21067.63	0.004975
NCV IEA_CO2HIGH	16313.65	0.030769		NCVIPCCNET_CO2HIGH	21172.44	0.01384
NCVIPCCNET_CO2HIGH	16815.6	0.024876		NCVIPCCHIGH_CO2NET	21465.47	0.018088
NCVIPCCHIGH_CO2HIGH	17233.9			NCVIPCCHIGH_CO2HIGH	21853.74	
	Blast Furnace Gas	diff (%)			Gas works Gas	diff (%)
NCV IEA_CO2LOW	53208.29	0		NCV IEA_CO2LOW	34.49488	85322.88
NCVIPCCNET_CO2LOW	53208.29	0		NCVIPCCNET_CO2LOW	34.49488	88356.99
NCVIPCCLOW_CO2LOW	53208.29	0		NCVIPCCLOW_CO2LOW	34.49488	91942.76
NCVIPCCHIGH_CO2LOW	53208.29	0.187215		NCVIPCCHIGH_CO2LOW	34.49488	140226.3
NCV IEA_CO2NET	63169.66	0		NCV IEA_CO2NET	41.06093	140226.3
NCVIPCCNET_CO2NET	63169.66	0		NCVIPCCNET_CO2NET	41.06093	145212.8
NCVIPCCLOW_CO2NET	63169.66	0	0.033803	NCVIPCCLOW_CO2NET	41.06093	145212.8
NCVIPCCHIGH_CO2NET	63169.66	0.184615		NCVIPCCHIGH_CO2NET	41.06093	151105.9
NCV IEA_CO2HIGH	74831.75	0		NCV IEA_CO2HIGH	50.03144	151105.9

NCVIPCCNET_CO2HIGH	74831.75	0		NCVIPCCNET_CO2HIGH	50.03144	192903.9
NCVIPCCLOW_CO2HIGH	74831.75	0		NCVIPCCLOW_CO2HIGH	50.03144	199763.6
NCVIPCCHIGH_CO2HIGH	74831.75			NCVIPCCHIGH_CO2HIGH	50.03144	
	Coke oven Gas	diff (%)			Gas/diesel oil excl. biofuels	diff (%)
NCV IEA_CO2LOW	1868.686	0		NCVIPCCLOW_CO2LOW	189325.5	0.020661
NCVIPCCNET_CO2LOW	1868.686	0		NCVIPCCLOW_CO2NET	193237.2	0.009447
NCVIPCCLOW_CO2LOW	1868.686	0		NCVIPCCLOW_CO2HIGH	195062.6	0.008099
NCVIPCCHIGH_CO2LOW	1868.686	0.190349		NCVIPCCNET_CO2LOW	196642.4	0.006977
NCV IEA_CO2NET	2224.388	0		NCV IEA_CO2LOW	198014.3	0
NCVIPCCNET_CO2NET	2224.388	0		NCVIPCCHIGH_CO2LOW	198014.3	0.01359
NCVIPCCLOW_CO2NET	2224.388	0	0.037165	NCVIPCCNET_CO2NET	200705.3	0.006977
NCVIPCCHIGH_CO2NET	2224.388	0.218468		NCV IEA_CO2NET	202105.5	0
NCV IEA_CO2HIGH	2710.346	0		NCVIPCCHIGH_CO2NET	202105.5	0.002453
NCVIPCCNET_CO2HIGH	2710.346	0		NCVIPCCNET_CO2HIGH	202601.3	0.006977
NCVIPCCLOW_CO2HIGH	2710.346	0		NCV IEA_CO2HIGH	204014.8	0
NCVIPCCHIGH_CO2HIGH	2710.346			NCVIPCCHIGH_CO2HIGH	204014.8	

	Kerosene	diff (%)			Municipal Waste (non-renewable)	diff (%)
NCVIPCCLOW_CO2LOW	4625.095	0.025825		NCV IEA_CO2LOW	941.0892	0
NCVIPCCLOW_CO2NET	4744.538	0.023566		NCVIPCCNET_CO2LOW	941.0892	0
NCVIPCCNET_CO2LOW	4856.349	0.011338		NCVIPCCLOW_CO2LOW	941.0892	0

NCV IEA_CO2LOW	4911.41	0.005205		NCVIPCCHIGH_CO2LOW	941.0892	0.251023
NCVIPCCLOW_CO2HIGH	4936.973	0.003744		NCV IEA_CO2NET	1177.324	0
NCVIPCCHIGH_CO2LOW	4955.459	0.005308		NCVIPCCNET_CO2NET	1177.324	0
NCVIPCCNET_CO2NET	4981.764	0.011338	0.012304	NCVIPCCLOW_CO2NET	1177.324	0
NCV IEA_CO2NET	5038.247	0.008969		NCVIPCCHIGH_CO2NET	1177.324	0.31952
NCVIPCCHIGH_CO2NET	5083.433	0.019748		NCV IEA_CO2HIGH	1553.503	0
NCVIPCCNET_CO2HIGH	5183.822	0.011338		NCVIPCCNET_CO2HIGH	1553.503	0
NCV IEA_CO2HIGH	5242.595	0.008969		NCVIPCCLOW_CO2HIGH	1553.503	0
NCVIPCCHIGH_CO2HIGH	5289.614			NCVIPCCHIGH_CO2HIGH	1553.503	
	LPG	diff (%)			Naphtha	diff (%)
NCVIPCCLOW_CO2LOW	42999.22	0.024351		NCVIPCCLOW_CO2LOW	34753.21	0.05772
NCVIPCCLOW_CO2NET	44046.27	0.030705		NCVIPCCLOW_CO2NET	36759.17	0.006498
NCV IEA_CO2LOW	45398.72	0		NCVIPCCNET_CO2LOW	36998.03	0.011236
NCVIPCCNET_CO2LOW	45398.72	0.008649		NCV IEA_CO2LOW	37413.74	0.022716
NCVIPCCLOW_CO2HIGH	45791.37	0.015567		NCVIPCCLOW_CO2HIGH	38263.63	0.010381
NCV IEA_CO2NET	46504.21	0		NCVIPCCHIGH_CO2LOW	38660.87	0.012227
NCVIPCCNET_CO2NET	46504.21	0.03962	0.019924	NCVIPCCNET_CO2NET	39133.56	0.011236
NCV IEA_CO2HIGH	48346.69	0		NCV IEA_CO2NET	39573.26	0.029362
NCVIPCCNET_CO2HIGH	48346.69	0.036302		NCVIPCCNET_CO2HIGH	40735.21	0.003858
NCVIPCCHIGH_CO2LOW	50101.76	0.024351		NCVIPCCHIGH_CO2NET	40892.37	0.007349
NCVIPCCHIGH_CO2NET	51321.77	0.03962		NCV IEA_CO2HIGH	41192.91	0.033333
NCVIPCCHIGH_CO2HIGH	53355.13			NCVIPCCHIGH_CO2HIGH	42566	
		Lubricants	diff (%)		Natural Gas	

NCVIPCCLOW_CO2LOW	6465.798	85322.88	0.03556	NCVIPCCLOW_CO2LOW	66131	0
NCVIPCCLOW_CO2NET	6591.697	88356.99	0.040583	NCVIPCCLOW_CO2NET	66131	0
NCV IEA_CO2LOW	6762.559	91942.76	0.525148	NCV IEA_CO2LOW	66131	0
NCVIPCCNET_CO2LOW	7758.957	140226.3	0	NCVIPCCNET_CO2LOW	66131	0.033149
NCVIPCCLOW_CO2HIGH	7910.036	140226.3	0.03556	NCVIPCCLOW_CO2HIGH	68323.19	0
NCV IEA_CO2NET	8106.373	145212.8	0	NCV IEA_CO2NET	68323.19	0
NCVIPCCNET_CO2NET	8115.071	145212.8	0.040583	NCVIPCCNET_CO2NET	68323.19	0
NCV IEA_CO2HIGH	8164.276	151105.9	0	NCV IEA_CO2HIGH	68323.19	0.039216
NCVIPCCNET_CO2HIGH	8264.217	151105.9	0.276614	NCVIPCCNET_CO2HIGH	71002.53	0
NCVIPCCHIGH_CO2LOW	8323.247	192903.9	0.03556	NCVIPCCHIGH_CO2LOW	71002.53	0
NCVIPCCHIGH_CO2NET	8478.432	199763.6	-1	NCVIPCCHIGH_CO2NET	71002.53	0
NCVIPCCHIGH_CO2HIGH	8538.993			NCVIPCCHIGH_CO2HIGH	71002.53	
	Motor Gasoline	diff (%)			Natural Gas Liquids	diff (%)
NCVIPCCLOW_CO2LOW	45135.11	0.026667		NCVIPCCLOW_CO2LOW	13524.08	0.051296
NCVIPCCLOW_CO2NET	46338.71	0.015279		NCV IEA_CO2LOW	14217.81	0.027955
NCVIPCCNET_CO2LOW	47046.71	0.011287		NCVIPCCNET_CO2LOW	14615.26	0.018984
NCV IEA_CO2LOW	47577.71	0		NCVIPCCLOW_CO2NET	14892.73	0.041317
NCVIPCCHIGH_CO2LOW	47577.71	0.015208		NCVIPCCHIGH_CO2LOW	15508.05	0.009583
NCVIPCCNET_CO2NET	48301.29	0.01059		NCV IEA_CO2NET	15656.66	0.027955
NCVIPCCLOW_CO2HIGH	48812.78	0.00069	0.012058	NCVIPCCNET_CO2NET	16094.34	0.014702
NCV IEA_CO2NET	48846.45	0		NCVIPCCLOW_CO2HIGH	16330.96	0.045712
NCVIPCCHIGH_CO2NET	48846.45	0.041634		NCVIPCCHIGH_CO2NET	17077.48	0.00534
NCVIPCCNET_CO2HIGH	50880.15	0.011287		NCV IEA_CO2HIGH	17168.67	0.027955

NCV IEA_CO2HIGH	51454.41	0		NCVIPCCNET_CO2HIGH	17648.62	0.061086
NCVIPCCHIGH_CO2HIGH	51454.41			NCVIPCCHIGH_CO2HIGH	18726.7	

	Other Kerosene	diff (%)			Primary solid biofuels	diff (%)
NCVIPCCLOW_CO2LOW	22950.78	0.015537		NCV IEA_CO2LOW	673096	0
NCVIPCCLOW_CO2NET	23307.36	0.017215		NCVIPCCNET_CO2LOW	673096	0
NCV IEA_CO2LOW	23708.59	0		NCVIPCCLOW_CO2LOW	673096	0
NCVIPCCNET_CO2LOW	23708.59	0.007688		NCVIPCCHIGH_CO2LOW	673096	0.180638
NCVIPCCLOW_CO2HIGH	23890.86	0.007789		NCV IEA_CO2NET	794682.5	0
NCV IEA_CO2NET	24076.95	0		NCVIPCCNET_CO2NET	794682.5	0
NCVIPCCNET_CO2NET	24076.95	0.016175		NCVIPCCLOW_CO2NET	794682.5	0
NCVIPCCHIGH_CO2LOW	24466.4	0.008718		NCVIPCCHIGH_CO2NET	794682.5	0.17
NCV IEA_CO2HIGH	24679.71	0		NCV IEA_CO2HIGH	929778.5	0
NCVIPCCNET_CO2HIGH	24679.71	0.006759		NCVIPCCNET_CO2HIGH	929778.5	0
NCVIPCCHIGH_CO2NET	24846.53	0.025035		NCVIPCCLOW_CO2HIGH	929778.5	0
NCVIPCCHIGH_CO2HIGH	25468.56			NCVIPCCHIGH_CO2HIGH	929778.5	
	Other oil products	diff (%)			Refinery gas	diff (%)
NCVIPCCLOW_CO2LOW	12681.16	0.015235		NCVIPCCLOW_CO2LOW	43896.31	0.012632
NCVIPCCLOW_CO2NET	12874.36	0.015007		NCV IEA_CO2LOW	44450.79	0.029106
NCVIPCCLOW_CO2HIGH	13067.57	0.151846		NCVIPCCNET_CO2LOW	45744.57	0.022222
NCV IEA_CO2LOW	15051.82	0.005		NCVIPCCHIGH_CO2LOW	46761.12	0.121808
NCVIPCCNET_CO2LOW	15127.08	0.010185		NCVIPCCLOW_CO2NET	52457	0.012632
NCV IEA_CO2NET	15281.14	0.005		NCV IEA_CO2NET	53119.61	0.029106

NCVIPCCNET_CO2NET	15357.55	0.009957		NCVIPCCNET_CO2NET	54665.72	0.022222
NCV IEA_CO2HIGH	15510.46	0.005		NCVIPCCHIGH_CO2NET	55880.51	0.124527
NCVIPCCNET_CO2HIGH	15588.02	0.163551		NCVIPCCLOW_CO2HIGH	62839.11	0.012632
NCVIPCCHIGH_CO2LOW	18137.44	0.015235		NCV IEA_CO2HIGH	63632.87	0.029106
NCVIPCCHIGH_CO2NET	18413.78	0.015007		NCVIPCCNET_CO2HIGH	65484.97	0.022222
NCVIPCCHIGH_CO2HIGH	18690.11			NCVIPCCHIGH_CO2HIGH	66940.19	
	Parafin Waxes					
NCVIPCCLOW_CO2LOW	746.8091	0.015235				
NCVIPCCLOW_CO2NET	758.1871	0.015007				
NCVIPCCLOW_CO2HIGH	769.5651	0.151846				
NCV IEA_CO2LOW	886.4203	0.005				
NCVIPCCNET_CO2LOW	890.8524	0.010185				
NCV IEA_CO2NET	899.9253	0.005				
NCVIPCCNET_CO2NET	904.425	0.009957				
NCV IEA_CO2HIGH	913.4304	0.005				
NCVIPCCNET_CO2HIGH	917.9975	0.163551				
NCVIPCCHIGH_CO2LOW	1068.136	0.015235				
NCVIPCCHIGH_CO2NET	1084.41	0.015007				
NCVIPCCHIGH_CO2HIGH	1100.684					
	Petroleum Coke	diff (%)				
NCVIPCCLOW_CO2LOW	25311	0.077441				
NCV IEA_CO2LOW	27271.11	0.015625				
NCVIPCCNET_CO2LOW	27697.22	0.074789				
NCVIPCCLOW_CO2NET	29768.67	0.077441				

NCV IEA_CO2NET	32073.98	0.015 625				
NCVIPCCNET_CO 2NET	32575.14	0.077 87				
NCVIPCCLOW_CO 2HIGH	35111.76	0.016 984				
NCVIPCCHIGH_C O2LOW	35708.11	0.059 447				
NCV IEA_CO2HIGH	37830.85	0.015 625				
NCVIPCCNET_CO 2HIGH	38421.96	0.093 043				
NCVIPCCHIGH_C O2NET	41996.87	0.179 487				
NCVIPCCHIGH_C O2HIGH	49534.77					