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

© Dimitrios Pappas

"This copy of the thesis has been supplied on condition that anyone who consults it is understood to recognise that its copyright rests with the author and that use of any information derived therefrom must be in accordance with current UK Copyright Law. In addition, any quotation or extract must include full attribution."
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


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 CO₂ 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 CO₂ 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.
Access Condition and Agreement

Each deposit in UEA Digital Repository is protected by copyright and other intellectual property rights, and duplication or sale of all or part of any of the Data Collections is not permitted, except that material may be duplicated by you for your research use or for educational purposes in electronic or print form. You must obtain permission from the copyright holder, usually the author, for any other use. Exceptions only apply where a deposit may be explicitly provided under a stated licence, such as a Creative Commons licence or Open Government licence.

Electronic or print copies may not be offered, whether for sale or otherwise to anyone, unless explicitly stated under a Creative Commons or Open Government license. Unauthorised reproduction, editing or reformatting for resale purposes is explicitly prohibited (except where approved by the copyright holder themselves) and UEA reserves the right to take immediate 'take down' action on behalf of the copyright and/or rights holder if this Access condition of the UEA Digital Repository is breached. Any material in this database has been supplied on the understanding that it is copyright material and that no quotation from the material may be published without proper acknowledgement.
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

Abstract ................................................................................................................................. 4  
Acknowledgments .................................................................................................................. 5  
Table of Contents .................................................................................................................. 7  
List of Tables .......................................................................................................................... 10  
List of Figures ......................................................................................................................... 11  

1. **Introduction** .................................................................................................................... 20  
   1.1 The Industrial Relocation Issue .................................................................................... 20  
   1.2 Theoretical Concepts of Industrial Relocation ............................................................. 21  
   1.3 Industrial Relocation Metrics ...................................................................................... 27  
   1.4 Conclusions and Research Aims .................................................................................. 30  

2. **Methodology** .................................................................................................................. 33  
   2.1 Discrepancies methodology ....................................................................................... 37  
   2.2 Intensity methodology ............................................................................................... 42  
      2.2.1 Data .................................................................................................................... 42  
      2.2.2 Energy Intensity ................................................................................................. 44  
      2.2.3 Carbon Intensity ............................................................................................... 45  
   2.3 Additive Log Mean Divisia Index (LMDI-I) Methodology ............................................ 46  
      2.3.1 CO2 Index Decomposition Analysis Rationale ..................................................... 46  
      2.3.2 Energy Emissions Intensity ................................................................................. 49  
      2.3.3 Carbon Emissions Intensity .............................................................................. 49  
      2.3.4 Labour Productivity and Industrial Scale ............................................................. 50  
   2.4 Methodology for estimating the fuel mix concentration and diversity by using the Hirschman-Herfindahl Index (HHI) and the Shannon-Wiener Index (SWI) ........................................................................ 50  
      2.4.1 Hirschman-Herfindahl Index (HHI) .................................................................... 52  
      2.4.2 Shannon-Wiener Index ...................................................................................... 53  

3. **Emissions Discrepancies** ................................................................................................ 55  
   3.1 Introduction ................................................................................................................... 55  
   3.2 Previous Research and Hypotheses Building ............................................................... 57  
   3.3 Conceptual Framework ............................................................................................... 63  
   3.4 Results ......................................................................................................................... 64  
      3.4.1 Total Final Consumption Discrepancies .............................................................. 64  
      3.4.2 Industrial Discrepancies ...................................................................................... 68  
      3.4.3 Iron and Steel Discrepancies .............................................................................. 72  
      3.4.4 Chemical and Petrochemical Discrepancies ...................................................... 75
3.4.5 Non-metallic Minerals Discrepancies ................................................................. 78
3.5 Discussion of the Results and Further Analysis. .................................................... 82
3.6 Conclusions ............................................................................................................ 92

4. Energy and carbon intensity: The challenge of a cross-country industrial shift from
China to India and SE Asia ........................................................................................... 94

4.1 Introduction .............................................................................................................. 94
4.2 Conceptual Framework ........................................................................................... 97
4.3 Results ..................................................................................................................... 99
  4.3.1 Energy Intensity ................................................................................................ 99
  4.3.2 Carbon Intensity ............................................................................................... 103
4.4 Discussion of the Results ....................................................................................... 108
  4.4.1 Energy intensity results ..................................................................................... 108
  4.4.2 Carbon intensity results .................................................................................... 110
4.5 Conclusions .......................................................................................................... 112

5. Decomposing the Total and Sectoral Industrial CO\textsubscript{2} Emissions through the
application of Additive Log Mean Divisia Index Analysis. ......................................... 115

5.1 Introduction ............................................................................................................ 115
5.2 Conceptual Framework ......................................................................................... 119
5.3 Results .................................................................................................................... 120
  5.3.1 Total Industry .................................................................................................. 120
  5.3.2 Iron and Steel Industry .................................................................................... 123
  5.3.3 Chemical and Petrochemical Industry ............................................................. 126
  5.3.4 Non-metallic minerals Industry ..................................................................... 129
  5.3.5 Machinery Industry ......................................................................................... 132
  5.3.6 Textiles & Leather Industry ............................................................................ 135
  5.3.7 Paper Pulp & Print industrial sector ................................................................. 138
5.4 Discussion ............................................................................................................... 140
  5.4.1 Total and Sectoral Industry Decomposition Analysis of India ....................... 140
  5.4.2 Total and Sectoral Industry Decomposition Analysis of Indonesia ............... 143
  5.4.3 Total and Sectoral Industry Decomposition Analysis of the Philippines ....... 147
5.5 Results - Conclusions ............................................................................................ 150

6. Industrial Fuel Mix Concentration & Diversity ..................................................... 153

6.1 Introduction ............................................................................................................ 153
6.2 Research Background – Building Hypotheses ..................................................... 157
6.3 Conceptual Framework ......................................................................................... 160
6.4 Results .................................................................................................................... 161
List of Tables

Table 2. Common accounted factors between the themes included in the present thesis......36
Table 2.1.1. Different accounting factors for calculating Carbon Dioxide Discrepancies .....38
Table 2.1.2. Typical sample of coal NCV values and carbon contents applied for Indian coal by different authorities and actual measurements..........................................................39
Table 2.1.3. Fraction of Net Carbon Content used for India’s total fuel mix. .......................41
Table 2.2.1. Breakdown of products used as input per industrial sector of India, China, Indonesia, the Philippines and Thailand. .................................................................42
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. ........................................44
Table 2.3.1. LMDI-I factors meaning and abbreviations......................................................48
Table 3.11. CO2 output difference of final energy consumption between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher) ......................68
Table 3.18. CO2 output difference of the total industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher) ............................71
Table 3.25. CO2 output difference of the I&S industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher) ............................75
Table 3.32. CO2 output difference of the C&P industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher) ............................78
Table 3.39. CO2 output difference of the C&P industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher) ............................81
List of Figures

Figure 2.4.1 HHI concentration performance per number of equal weighted fuel options in the energy mix .................................................................................................................. 52

Figure 2.4.2 SWI diversity performance per number of equal weighted fuel options in the energy mix ....................................................................................................................... 53

Figure 3.1. India’s domestic supply fuel mix in 2012. Data Source: International Energy Agency (2015) ................................................................................................................. 56

Figure 3.2. India’s domestic supply coal mix in 2012. Data Source: International Energy Agency (2015) ................................................................................................................. 57

Figure 3.2. India’s total CO₂ 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 Commission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016) ................................ 59

Figure 3.4. India’s total CO₂ 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 Commission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016). ............................... 60

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) ................................................... 61


Figure 3.7 Emissions discrepancy calculation process. .......................................................... 63

Figure 3.8 Indian CO₂ 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. .............................................................................. 65

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........... 66

Figure 3.10 CO₂ emissions discrepancies (kt) of final consumption for year 2012 under the various net calorific values and carbon content scenarios. ..................................................... 67

Figure 3.12. Indian total industrial CO₂ emissions during 1980-2012 under different Indian NCV and carbon content values provided by IEA (standardized NCV) and IPCC on low-net-high scenarios. .......................................................... 68

Figure 3.13. Indian total industrial CO₂ emissions (Gt) attributed per fuel during the 1980-2012 specified timeline. .................................................................................................. 69

Figures 3.14-3.17. Periodic snapshot of Indian CO₂ emissions share attributed to the fuel mix of the total industry. ........................................................................................................... 70

Figure 3.19. Indian Iron and Steel industrial CO₂ emissions during 1980-2012 under different Indian NCV and carbon content values provided by IEA (standardized NCV) and IPCC on low-net-high scenarios. ............................................................. 72

Figure 3.20. Indian Iron and Steel industrial CO₂ emissions (Gt) attributed per fuel during the 1980-2012 specified timeline. .......................................................................................... 73
Figures 3.21-3.24. Periodic snapshot of Indian CO₂ emissions share attributed to the fuel mix of the Iron & Steel sector. ................................................................. 74
75
Figure 3.26. Indian Chemical & Petrochemical industrial CO₂ emissions during 1980-2012 under different Indian NCV and carbon content values provided by IEA (standardized NCV) and IPCC on low-net-high scenarios. ................................................................. 75
Figure 3.27. Indian Chemical & Petrochemical industrial CO₂ emissions (Gt) attributed per fuel during the 1980-2012 specified timeline. ................................................ 76
Figure 3.28-3.31. Periodic snapshot of Indian CO₂ emissions share attributed to the fuel mix of the Chemicals & Petrochemicals sector. ......................................................... 77
Figure 3.33. Indian Non-Metallic Minerals industrial CO₂ emissions during 1980-2012 under different Indian NCV and carbon content values provided by IEA (standardized NCV) and IPCC on low-net-high scenarios. ......................................................... 78
Figure 3.34. Indian Non-Metallic Minerals industrial CO₂ emissions (Gt) attributed per fuel during the 1980-2012 specified timeline. ......................................................... 79
Figures 3.35-3.38. Periodic snapshot of Indian CO₂ emissions share attributed to the fuel mix of the Non-Metallic Minerals sector. ................................................................. 80
Figure 3.40. India’s total CO₂ 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 Commission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016). ................................................................. 82
Figure 3.41. Range of India’s total CO₂ 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 Commission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016). ......................................................... 84
Figure 3.42. Discrepancy between minimum and maximum output of official published CO₂ 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 Commission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016). ......................................................... 85
Figure 3.43. Discrepancy between selected high-low CO₂ 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 Commission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016). ......................................................... 85
Figure 3.44. Comparison of official and research scenario averages for India’s total CO₂ 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 Commission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016). ......................................................... 87
Figure 3.45 Discrepancy for the average of the emission scenarios generated from 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).

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.

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.

Figure 4.1 Energy intensity calculation process.

Figure 4.2 Carbon intensity per TPES calculation process.

Figure 4.3 Carbon intensity per economic output calculation process.


Figure 5.1. Total industrial scale (employment) of India, Indonesia and the Philippines 1980-2012 (United Nations Industrial Development Organization, 2016)................................................................................. 116

Figure 5.2. Total industrial labour productivity of India, Indonesia and the Philippines 1980-2012 (thousand const. 2005 US$ per employee). ......................................................................................... 117

Figure 5.3. Index decomposition analysis process followed per country and industrial sector. ............................................................................................................................. 119

Figure 5.4. India total industrial CO$_2$ emissions decomposition analysis .................................... 120

Figure 5.5. Indonesia total industrial CO$_2$ emissions decomposition analysis. .......................... 121

Figure 5.6. The Philippines total industrial CO$_2$ emissions decomposition analysis. ................. 122

Figure 5.7. India CO$_2$ emissions decomposition analysis of Iron & Steel industrial sector. ........ 123

Figure 5.8. Indonesian CO$_2$ emissions decomposition analysis of Iron & Steel industrial sector. ............................................................................................................................. 124

Figure 5.9. The Philippines CO$_2$ emissions decomposition analysis of Iron & Steel industrial sector. ............................................................................................................................. 125

Figure 5.10. India CO$_2$ emissions decomposition analysis of Chemical & Petrochemical industrial sector................................................................. 125

Figure 5.11. Indonesia CO$_2$ emissions decomposition analysis of Chemical & Petrochemical industrial sector. ............................................................................................................................. 127
Figure 5.12. The Philippines CO₂ emissions decomposition analysis of Chemical & Petrochemical industrial sector. ................................................................. 128
Figure 5.13. India CO₂ emissions decomposition analysis of non-metallic minerals (cement) industrial sector. ................................................................. 129
Figure 5.14. Indonesia CO₂ emissions decomposition analysis of Non-metallic Minerals (cement) industrial sector. ................................................................. 130
Figure 5.15. The Philippines CO₂ emissions decomposition analysis of Non-metallic Minerals (cement) industrial sector. ................................................................. 131
Figure 5.16. India CO₂ emissions decomposition analysis of Machinery industrial sector. ................................................................. 132
Figure 5.17. Indonesia CO₂ emissions decomposition analysis of Machinery industrial sector. ................................................................. 133
Figure 5.18. The Philippines CO₂ emissions decomposition analysis of Machinery industrial sector. ................................................................. 134
Figure 5.19. India CO₂ emissions decomposition analysis of Textiles & Leather industrial sector. ................................................................. 135
Figure 5.20. Indonesia CO₂ emissions decomposition analysis of Textile & Leather industrial sector. ................................................................. 136
Figure 5.21. The Philippines CO₂ emissions decomposition analysis of Textile & Leather industrial sector. ................................................................. 137
Figure 5.22. India CO₂ emissions decomposition analysis of Paper Pulp & Print industrial sector. ................................................................. 138
Figure 5.23. Indonesia CO₂ emissions decomposition analysis of Paper Pulp & Print industrial sector. ................................................................. 139
Figure 5.24. The Philippines CO₂ emissions decomposition analysis of Paper Pulp & Print industrial sector. ................................................................. 140
Figure 5.25. India average CO₂ contribution of drivers per industry (%) for the 1980-2012 timeline. ................................................................. 141
Figure 5.26. India CO₂ contribution of drivers per industry (%) as for the cumulative ΔC for the 1980-2012 timeline. ................................................................. 142
Figure 5.27. India cumulative effect of drivers on ΔC per industrial sector (MtCO₂) for the 1980-2012 timeline. ................................................................. 143
Figure 5.28. Indonesia average CO₂ contribution of drivers per industry (%) for the 1980-2012 timeline. ................................................................. 144
Figure 5.29. Indonesia CO₂ contribution of drivers per industry (%) for the cumulative ΔC of the 1980-2012 timeline. ................................................................. 145
Figure 5.30. Indonesia cumulative effect of drivers on ΔC per industrial sector (MtCO₂) for the 1980-2012 timeline. ................................................................. 146
Figure 5.31. The Philippines average CO₂ contribution of drivers per industry (%) for the 1980-2012 timeline. ................................................................. 147
Figure 5.32. The Philippines CO₂ contribution of drivers per industry (%) as for the cumulative ΔC for the 1980-2012 timeline. ................................................................. 148
Figure 5.33. The Philippines cumulative effect of drivers on ΔC per industrial sector (MtCO₂) for the 1980-2012 timeline. ................................................................. 149
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) ................................................................. 155

Figure 6.6-6.9 Industrial output in billion USS (current prices) comparison of India, China, Indonesia, The Philippines and Thailand per ten-year periods covering 1982-2012. Source: (UNIDO, 2016) ........................................................................................................ 156

Figure 6.10 Total Industrial output index comparison of India, China, Indonesia, The Philippines and Thailand 1998-2015. ........................................................................................................ 156

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) ........................................................................ 157

Figure 6.16. Concentration (HHI) and Diversity (SWI) calculation process for the selected country examined. ................................................................................................................ 160

Figure 6.21-6.24 Total industry fuel mix diversity measured with SWI for the 1980-2012 timeline ................................................................. 162

Figure 6.25-6.28 Iron and Steel industrial fuel mix concentration measured with HHI for the 1980-2012 timeline ........................................................................ 165

Figure 6.29-6.32 Iron and Steel industrial fuel mix diversity measured with SWI for the 1980-2012 timeline ........................................................................ 165

Figure 6.33-6.36 Chemical and Petrochemical fuel mix concentration measured with HHI for the 1980-2012 timeline ........................................................................ 167

Figure 6.37-6.40 Chemical and Petrochemical industrial fuel mix diversity measured with SWI for the 1980-2012 timeline ........................................................................ 168

Figure 6.41-6.44 Non-metallic minerals industrial fuel mix concentration measured with HHI for the 1980-2012 timeline ........................................................................ 170

Figure 6.45-6.48 Non-metallic minerals industrial fuel mix diversity measured with SWI for the 1980-2012 timeline ........................................................................ 170

Figure 6.49-6.52 Machinery industrial fuel mix concentration measured with HHI for the 1980-2012 timeline ........................................................................ 172

Figure 6.53-6.56 Machinery industrial fuel mix diversity measured with SWI for the 1980-2012 timeline ........................................................................ 173

Figure 6.57-6.60 Food & Tobacco industrial fuel mix concentration measured with HHI for the 1980-2012 timeline ........................................................................ 175

Figure 6.61-6.64 Food & Tobacco industrial fuel mix diversity measured with SWI for the 1980-2012 timeline ........................................................................ 175

Figure 6.65-6.68 Paper, pulp and print industrial fuel mix concentration measured with HHI for the 1980-2012 timeline ........................................................................ 177

Figure 6.69-6.72 Paper, pulp and print industrial fuel mix diversity measured with SWI for the 1980-2012 timeline ........................................................................ 177

Figure 6.73-6.76 Wood and wood products industrial fuel mix concentration measured with HHI for the 1980-2012 timeline ........................................................................ 179

Figure 6.77-6.80 Wood and wood products fuel mix diversity measured with SWI for the 1980-2012 timeline ........................................................................ 179

Figure 6.81-6.84 Textile and leather industrial fuel mix concentration measured with HHI for the 1980-2012 timeline ........................................................................ 181

Figure 6.85-6.88 Textile and leather industrial fuel mix diversity measured with SWI for the 1980-2012 timeline ........................................................................ 181
Figure 6.89-6.92 Mining industrial fuel mix concentration measured with HHI for the 1980-2012 timeline ................................................................................................................. 183
Figure 6.93-6.96 Mining industrial fuel mix diversity measured with SWI for the 1980-2012 timeline .......................................................................................................................... 183
Figure 6.97-6.100 Non-specified industry fuel mix concentration measured with HHI for the 1980-2012 timeline ........................................................................................................ 185
Figure 6.101-6.104 Non-specified industry fuel mix diversity measured with SWI for the 1980-2012 timeline ........................................................................................................ 185
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........................................................................................................ 187
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. ............. 191
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. ................. 192
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. ............. 193
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)................................................................. 194
### List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASEAN</td>
<td>Association of Southeast Asian Nations</td>
</tr>
<tr>
<td>BLS</td>
<td>Bureau of Labour Statistics (US)</td>
</tr>
<tr>
<td>BP</td>
<td>British Petroleum</td>
</tr>
<tr>
<td>BRIC</td>
<td>Brazil Russia India China grouping</td>
</tr>
<tr>
<td>C&amp;P</td>
<td>Chemical and Petrochemical</td>
</tr>
<tr>
<td>CC</td>
<td>Carbon Content</td>
</tr>
<tr>
<td>CDIAC</td>
<td>Carbon Dioxide Information Analysis Center</td>
</tr>
<tr>
<td>COP21</td>
<td>The 2015 United Nations Climate Change Conference</td>
</tr>
<tr>
<td>EDGAR</td>
<td>Emission Database for Global Atmospheric Research</td>
</tr>
<tr>
<td>EIA</td>
<td>Environmental Information Administration</td>
</tr>
<tr>
<td>EKC</td>
<td>Environmental Kuznets Curve</td>
</tr>
<tr>
<td>EU</td>
<td>European Union</td>
</tr>
<tr>
<td>FDI</td>
<td>Foreign Direct Investment</td>
</tr>
<tr>
<td>FGP</td>
<td>Flying Geese Pattern</td>
</tr>
<tr>
<td>FTA</td>
<td>Free Trade Agreement</td>
</tr>
<tr>
<td>GDP</td>
<td>Gross Domestic Product</td>
</tr>
<tr>
<td>GHG</td>
<td>Greenhouse Gas</td>
</tr>
<tr>
<td>I&amp;S</td>
<td>Iron and Steel</td>
</tr>
<tr>
<td>I/O</td>
<td>Input-Output</td>
</tr>
<tr>
<td>IDA</td>
<td>Index Decomposition Analysis</td>
</tr>
<tr>
<td>IEA</td>
<td>International Energy Agency</td>
</tr>
<tr>
<td>INDSTAT2</td>
<td>UNIDO 2015 statistics database edition at the 2-digit level of ISIC revision 3</td>
</tr>
<tr>
<td>INDSTAT4</td>
<td>UNIDO 2015 statistics database edition at the 3- and 4-digit level of ISIC revision 3</td>
</tr>
<tr>
<td>I-O</td>
<td>Input Output</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel for Climate Change</td>
</tr>
<tr>
<td>IS</td>
<td>Industrial Scale</td>
</tr>
<tr>
<td>ISIC</td>
<td>International Standard Industrial Classification</td>
</tr>
<tr>
<td>IVA</td>
<td>Industrial Value Added</td>
</tr>
<tr>
<td>LMDI</td>
<td>Logarithmic Mean Divisia Index</td>
</tr>
<tr>
<td>LPG</td>
<td>Liquid Petroleum Gases</td>
</tr>
<tr>
<td>MOSPI</td>
<td>Ministry of Statistics and Programme Implementation (India)</td>
</tr>
<tr>
<td>MRIO</td>
<td>Multi-Regional Input Output</td>
</tr>
<tr>
<td>N.M.M</td>
<td>Non-metallic Minerals</td>
</tr>
<tr>
<td>NCV</td>
<td>Net Calorific Value</td>
</tr>
<tr>
<td>NG</td>
<td>Natural Gas</td>
</tr>
<tr>
<td>NPE</td>
<td>Number of Persons Employed</td>
</tr>
<tr>
<td>NPRD</td>
<td>Non-Pearl River Delta</td>
</tr>
<tr>
<td>N-S</td>
<td>Non-Specified</td>
</tr>
<tr>
<td>ORNL</td>
<td>Oak Ridge National Laboratory</td>
</tr>
<tr>
<td>P. P. P or PP&amp;P</td>
<td>Paper, Pulp &amp; Print</td>
</tr>
<tr>
<td>PH</td>
<td>Porter Hypothesis</td>
</tr>
<tr>
<td>PHH</td>
<td>Pollution Haven Hypothesis</td>
</tr>
<tr>
<td>PHHH</td>
<td>Pollution Halo Hypothesis</td>
</tr>
<tr>
<td>PII</td>
<td>Pollution Intensive Industries</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
</tr>
<tr>
<td>---------</td>
<td>-------------</td>
</tr>
<tr>
<td>PLC</td>
<td>Product Life Cycle</td>
</tr>
<tr>
<td>PRD</td>
<td>Pearl River Delta</td>
</tr>
<tr>
<td>SDA</td>
<td>Structural Decomposition Analysis</td>
</tr>
<tr>
<td>SSA</td>
<td>Shift Share Analysis</td>
</tr>
<tr>
<td>T&amp;L</td>
<td>Textile &amp; Leather</td>
</tr>
<tr>
<td>TPES</td>
<td>Total Primary Energy Supply</td>
</tr>
<tr>
<td>UN</td>
<td>United Nations</td>
</tr>
<tr>
<td>UNFCCC</td>
<td>United Nations Framework Convention on Climate Change</td>
</tr>
<tr>
<td>UNIDO</td>
<td>United Nations Industrial Development Organization</td>
</tr>
<tr>
<td>UNSDD</td>
<td>United Nations Sustainable Development Division</td>
</tr>
<tr>
<td>VA</td>
<td>Value Added</td>
</tr>
<tr>
<td>W&amp;WP</td>
<td>Wood and Wood Products</td>
</tr>
<tr>
<td>YRD</td>
<td>Yangtze River Delta</td>
</tr>
</tbody>
</table>

**Nomenclature**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>CI</td>
<td>Carbon Intensity</td>
</tr>
<tr>
<td>C\text{\textit{eff}}</td>
<td>Carbon Intensity Effect</td>
</tr>
<tr>
<td>CO_2</td>
<td>Carbon Dioxide</td>
</tr>
<tr>
<td>E</td>
<td>Energy expressed in heat</td>
</tr>
<tr>
<td>EI</td>
<td>Energy Intensity</td>
</tr>
<tr>
<td>E\text{\textit{eff}}</td>
<td>Energy Intensity Effect</td>
</tr>
<tr>
<td>Gt</td>
<td>Gigatonne</td>
</tr>
<tr>
<td>GW</td>
<td>Gigawatt</td>
</tr>
<tr>
<td>GWh</td>
<td>Gigawatt-hour</td>
</tr>
<tr>
<td>HHI</td>
<td>Hirschman Herfindahl Index</td>
</tr>
<tr>
<td>IS</td>
<td>Industrial Scale</td>
</tr>
<tr>
<td>I\text{\textit{eff}}</td>
<td>Industrial Scale effect</td>
</tr>
<tr>
<td>J</td>
<td>Joule</td>
</tr>
<tr>
<td>Kg</td>
<td>Kilogramme</td>
</tr>
<tr>
<td>kt</td>
<td>Kiloton</td>
</tr>
<tr>
<td>kW</td>
<td>Kilowatt</td>
</tr>
<tr>
<td>kWh</td>
<td>Kilowatt-hour</td>
</tr>
<tr>
<td>LP</td>
<td>Labour Productivity</td>
</tr>
<tr>
<td>L\text{\textit{eff}}</td>
<td>Labour Productivity effect</td>
</tr>
<tr>
<td>PJ</td>
<td>Petajoule</td>
</tr>
<tr>
<td>t</td>
<td>Tonne</td>
</tr>
<tr>
<td>TJ</td>
<td>Terajoule</td>
</tr>
<tr>
<td>TWh</td>
<td>Terawatt-hour</td>
</tr>
<tr>
<td>US$</td>
<td>United States Dollar</td>
</tr>
<tr>
<td>\Delta C</td>
<td>Carbon Change over set period</td>
</tr>
</tbody>
</table>
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 Upchuch, 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 CO2 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 (Ambee 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), CO₂ 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 (Bouthol 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 SO₂ 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 SO₂ 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 CO₂ 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 USS (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) 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; Pourebadollahian 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 CO₂. 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.

<table>
<thead>
<tr>
<th>Theme</th>
<th>Factors accounted</th>
<th>Used by a previous chapter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carbon Emissions Discrepancies</td>
<td>• Heat</td>
<td>• Heat</td>
</tr>
<tr>
<td></td>
<td>• CO₂ (India)</td>
<td>• CO₂ (India) for the IEA net scenario</td>
</tr>
<tr>
<td>Energy and Carbon Intensity</td>
<td>• Energy Intensity</td>
<td>• Energy Intensity</td>
</tr>
<tr>
<td></td>
<td>• Carbon Intensity</td>
<td>• Carbon Intensity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Energy Intensity effect</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Carbon Intensity effect</td>
</tr>
<tr>
<td>Additive Log Mean Divisia Index (LMDI-I)</td>
<td>• Labour Productivity effect</td>
<td>• Labour Productivity effect</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Industrial Scale effect</td>
</tr>
<tr>
<td></td>
<td>• SWI</td>
<td>• SWI</td>
</tr>
<tr>
<td></td>
<td>• HHI</td>
<td>• HHI</td>
</tr>
<tr>
<td>Fuel mix concentration and diversity.</td>
<td></td>
<td>Heat</td>
</tr>
</tbody>
</table>

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).

\[
\text{Carbon dioxide emission} = \text{Physical Quantity (kt)} * \text{Carbon Emission Factor} \quad (\text{a. 1})
\]

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

\[
\text{Carbon dioxide emission}_{ij} = \text{Physical Quantity}_{ij} * \text{Carbon dioxide emission factor}_{ij} \quad (\text{a. 2})
\]

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:

\[
\text{Carbon dioxide emission}_j = \sum (\text{Physical Unit}_i * \text{Carbon dioxide emission factor}_i) \quad (\text{a. 3})
\]

To calculate the total emissions from every sector

\[
\text{Carbon dioxide emission}_{\text{TOTAL}} = \sum (\text{Carbon dioxide emission}_j) \quad (\text{a. 4})
\]

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:

\[
\text{Domestic supply of energy} = \text{Indigenous production} + \text{imports} - \text{Exports} \pm \text{Stock Change} - \text{non energy use of fuels} \quad (\text{a. 5})
\]
In that context, when assessing the present research, the following order was used in order to extract carbon dioxide (CO₂) 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.

\[
H_{\text{Heat Value}} (PJ) = \text{Physical Quantity (kt)} \times \left( \text{Net Calorific Value (} \frac{PJ}{Gt} \right)/1000000 \right) \quad (a.6)
\]

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

<table>
<thead>
<tr>
<th>Physical Quantities</th>
<th>Net Calorific Value (NCV) per fuel</th>
<th>Carbon Content per fuel</th>
</tr>
</thead>
<tbody>
<tr>
<td>International Energy Agency (IEA) – India specific</td>
<td>IPCC – Low</td>
<td></td>
</tr>
<tr>
<td>IPCC – Low</td>
<td>IPCC – Net</td>
<td></td>
</tr>
<tr>
<td>IPCC – Net</td>
<td>IPCC – High</td>
<td></td>
</tr>
<tr>
<td>IPCC- High</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\[
\text{Carbon dioxide emissions (kt)} = \text{Heat Value (PJ)} \times \left( \text{Carbon content (} \frac{kt}{PJ} \right) - \text{Carbon Stored} \right) \times \text{Carbon Oxidization Rate} \times \text{CtoCO2} \quad (a.7)
\]

Carbon converted to CO₂ (CtoCO₂) always equals to 3.664191 as it is the result of dividing the molecular weight of CO₂ which is 44 to that of carbon which equals to 12. A standard carbon oxidation 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>
<thead>
<tr>
<th>Coal Net Calorific Value (kJ/kg)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>India Statistics (Indian Ministry of Statistics and Programme Implementation, 2015a)</td>
<td>19,259</td>
</tr>
<tr>
<td>IPCC (IPCC, 2006)</td>
<td>25,000</td>
</tr>
<tr>
<td>IEA (International Energy Agency, 2013)</td>
<td></td>
</tr>
<tr>
<td>Coking Coal: 24,283</td>
<td></td>
</tr>
<tr>
<td>Other Bituminous Coal: 18,464</td>
<td></td>
</tr>
<tr>
<td>Sub-Bituminous (import): 18,900</td>
<td></td>
</tr>
<tr>
<td>Sample measurements in-situ (Mishra, 2009)</td>
<td>15,056 to 19,690</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Carbon Content CC (kg/TJ)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>IPCC (IPCC, 2006)</td>
<td>27.2</td>
</tr>
<tr>
<td>BP (British Petroleum, 2015)</td>
<td>25.82</td>
</tr>
</tbody>
</table>

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:

\[
\text{Fraction of Net carbon (per fuel)} = \frac{\text{Net Carbon Emissions Factor IEA} \left(\frac{\text{kt}}{\text{p}}\right)}{\text{Carbon emissions Factor IPCC} \left(\frac{\text{kt}}{\text{p}}\right)} \quad (a.8)
\]

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.

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

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 (UNSDDD), 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)

<table>
<thead>
<tr>
<th>Country</th>
<th>Industrial Sectors</th>
<th>Anthracite</th>
<th>BK3B</th>
<th>Briquettes</th>
<th>Blast Furnace Coke oven Coke</th>
<th>Coke oven Gas</th>
<th>Coking Coal</th>
<th>Fuel Oil</th>
<th>Gas Coke</th>
<th>Gas Works Gas</th>
<th>Gasworks oil</th>
<th>Liquefied</th>
<th>LNG</th>
<th>Motor gasoline</th>
<th>Naphtha</th>
<th>Natural Gas</th>
<th>Other Bituminous Coal</th>
<th>Other Liquefied</th>
<th>Other Oil</th>
<th>Patent Fuel</th>
<th>Petroleum Coke</th>
<th>Primary Solid</th>
<th>Refinery Gas</th>
<th>Sub-bituminous coal</th>
</tr>
</thead>
</table>
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:

\[ E_{i,j,k} = E_{phy,i,j,k} \times NCV_{i,j,k} \quad (b.1) \]

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).

\[ E_k = (E_{i1980j1} + E_{i1981j1} + \ldots + E_{i2011j1}) + (E_{i1980j2} + E_{i1981j2} + \ldots + E_{i2011j2}) + \ldots + (E_{i1980jn} + E_{i1981jn} + \ldots + E_{i2011jn}) \quad (b.2) \]
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)

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

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:

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

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.

\[ E (TJ) = \frac{E (PJ)}{1000000} \quad (\text{b.4}) \]

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

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)

\[ CO_{2} (i,j,k) = Carbon \ content \left( \frac{kt}{PJ} \right) \times Carbon \ oxidation \ rate \times CtoCO_{2} \ conversion\quad (\text{b.6}) \]

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 CO₂ 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 CO₂ for all fuel products per industrial sector expressed in kt. To calculate the appropriate carbon intensity, equation (b.7) is used:

\[
\text{Carbon Intensity (CI)} = \frac{CO_2 (i,k)}{E(i,k)} (b.7)
\]

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 CO₂ Index Decomposition Analysis Rationale

The index decomposition analysis (IDA) using the logarithmic mean divisia index (LMDI-I) approach for analysing CO₂ 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 CO₂ emissions (Dai et al., 2016), against the energy consumption of developed economies (Lima et al., 2017, 2016) or LMDI decompositions of CO₂ 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 CO₂ 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; CO₂ 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 CO₂ emissions and providing an enhanced level of insight.

The LMDI-I method is following an additive formula approach, using physical units (tonnes of CO₂) 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 CO₂ emissions. These are expressed as following:

\[
CO_2^{eff} = \frac{CO_2}{total\ energy\ consumption\ (TOE)} \times \frac{TOE}{GDP} \times \frac{GDP}{Population\ (POP)} \times POP \ (c.1)
\]

The CO₂ side of the equation stands for the total amount of CO₂ 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 CO₂ emissions under the Kaya identity prism.

The characteristics of a country’s CO₂ 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.

$$\text{CO}_2\text{eff} = \frac{\text{CO}_2}{\text{EFF}} \times \frac{\text{EFF}}{\text{IVA}} \times \frac{\text{IVA}}{\text{NPE}} \times \text{NPE} = \text{CI} \times \text{EI} \times \text{LP} \times \text{IS} \ (c.2)$$

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.

$$\text{CI}_{eff} = \frac{\text{CO}_2(t) - \text{CO}_2(0)}{\ln[\text{CO}_2(t)/\text{CO}_2(0)]} \times \text{CI}(t)/\text{CI}(0) \ (c.3)$$

$$\text{EI}_{eff} = \frac{\text{CO}_2(t) - \text{CO}_2(0)}{\ln[\text{CO}_2(t)/\text{CO}_2(0)]} \times \text{EI}(t)/\text{EI}(0) \ (c.4)$$

$$\text{LP}_{eff} = \frac{\text{CO}_2(t) - \text{CO}_2(0)}{\ln[\text{CO}_2(t)/\text{CO}_2(0)]} \times \text{LP}(t)/\text{LP}(0) \ (c.5)$$

$$\text{IS}_{eff} = \frac{\text{CO}_2(t) - \text{CO}_2(0)}{\ln[\text{CO}_2(t)/\text{CO}_2(0)]} \times \text{IS}(t)/\text{IS}(0) \ (c.6)$$

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 CO2 emissions of this period, can be reached and attributed.

Table 2.3.1. LMDI-I factors meaning and abbreviations

<table>
<thead>
<tr>
<th>Factor</th>
<th>Meaning</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO2/EFF</td>
<td>The effect of carbon intensity</td>
<td>CI_{eff}</td>
</tr>
<tr>
<td>EFF/TIO</td>
<td>The effect of energy intensity</td>
<td>EI_{eff}</td>
</tr>
<tr>
<td>TIO/NPE</td>
<td>The effect of labour productivity</td>
<td>LP_{eff}</td>
</tr>
<tr>
<td>NPE</td>
<td>The effect of industrial scale</td>
<td>IS_{eff}</td>
</tr>
</tbody>
</table>
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 CO₂ 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 CO₂ per economic output, but that of CO₂ 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 CO₂ 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 CO₂ emissions per fuel. Summing the CO₂ 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.

\[
\text{Labour Productivity (LP)} = \frac{\text{Industrial Value Added (IVA)}}{\text{Number of Persons Employed (NPE)}} \quad (c. 7)
\]

\[
\text{Industrial Scale (IS)} = \text{Number of Persons Employed (NPE)} \quad (c. 8)
\]

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, where \(i\) is the fuel type and \(j\) is the sector

\[
\text{Physical Quantity}_{i,j,k}(kt) \times \left( \frac{\text{Net Calorific Value}}{\text{Gt}} \right)_{i,j,k} \times \frac{\text{Heat Value}_{i,j,k}(Pj)}{1000000} = \text{Heat Value}_{i,j,k}(Pj) \quad (d.1)
\]

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)

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).

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

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

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).

\[-\sum_{o=1}^{n} S_{i} * \ln(S_{o}) = SWI (d.3)\]

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 CO₂ 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 CO₂ 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 CO₂
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)
3.2 Previous Research and Hypotheses Building

The existing literature on India’s CO\textsubscript{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\textsubscript{2} in India. The empirical results confirmed the existence of a unidirectional causality running from energy use to CO\textsubscript{2} emissions, and in the short run from CO\textsubscript{2} to economic growth. Similarly, Wu et al. (2015) examined the relationship of parameters such as CO\textsubscript{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 2°C 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\textsubscript{2} reductions that would occur while Nejat et al. (2015) used IEA data to review the status of CO\textsubscript{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 CO₂ 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 CO₂ 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 CO₂ results published by different energy research institutes and agencies.


The highest CO₂ emissions were estimated by CDIAC with a value of 2,074,345 kt and the lowest by BP with 1,704,145 kt of CO₂ 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 CO₂, 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)

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 CO₂ 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 CO₂ uncertainties for India’s total industry between the discrepancy scenarios that are generated from selected data inventories. (H₂a)
- There are significant CO₂ 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 CO₂ 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 CO₂ 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).

![Diagram showing emissions discrepancy calculation process](image)

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 CO₂ 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 CO₂ 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 CO₂ 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):
Approaching the CO₂ discrepancies for the total final consumption of India, the amount of CO₂ that each scenario generates is distinct. The highest emitting scenario amounts to 2.23 Gt of CO₂, while the net scenarios of IEA and IPCC present an output of 1.81 Gt and 1.92 Gt of CO₂ respectively, for 2012. The lowest CO₂ emitting scenario is the product of low IPCC NCV and low carbon content, and it amounts approximately at 1.62 Gt of CO₂ for the same year. Therefore, the difference of CO₂ 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 CO₂ 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 CO₂ 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 CO₂. 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 CO₂ emissions reached approximately 189.8Mt of CO₂.

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 CO₂ or 74.09% higher result than the reference scenario which is presented in Figure 3.9.
The established pattern of differed CO₂ output per scenario, is not observed in gas fuels. Natural gas and blast furnace gas present the same CO₂ 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 CO₂ 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. CO₂ output difference of final energy consumption between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher)

<table>
<thead>
<tr>
<th>Scenarios (Final Consumption)</th>
<th>Difference (%)</th>
<th>Difference (Mt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPCC NCV_LOW + CO2LOW</td>
<td>500.40%</td>
<td>1352.29</td>
</tr>
<tr>
<td>IEA NCV + CO2LOW</td>
<td>521.77%</td>
<td>1452.03</td>
</tr>
<tr>
<td>IPCC NCV_NET + CO2LOW</td>
<td>499.89%</td>
<td>1525.68</td>
</tr>
<tr>
<td>IPCC NCV_LOW + CO2NET</td>
<td>497.34%</td>
<td>1417.35</td>
</tr>
<tr>
<td>IEA NCV + CO2NET</td>
<td>518.36%</td>
<td>1520.69</td>
</tr>
<tr>
<td>IPCC NCV_HIGH + CO2LOW</td>
<td>505.72%</td>
<td>1688.87</td>
</tr>
<tr>
<td>IPCC NCV_NET + CO2NET</td>
<td>496.81%</td>
<td>1599.15</td>
</tr>
<tr>
<td>IPCC NCV_LOW + CO2HIGH</td>
<td>495.24%</td>
<td>1487.56</td>
</tr>
<tr>
<td>IEA NCV + CO2HIGH</td>
<td>516.03%</td>
<td>1595.08</td>
</tr>
<tr>
<td>IPCC NCV_HIGH + CO2NET</td>
<td>502.79%</td>
<td>1770.85</td>
</tr>
<tr>
<td>IPCC NCV_NET + CO2HIGH</td>
<td>494.78%</td>
<td>1678.46</td>
</tr>
<tr>
<td>IPCC NCV_HIGH + CO2HIGH</td>
<td>501.03%</td>
<td>1859.64</td>
</tr>
</tbody>
</table>

3.4.2 Industrial Discrepancies

![Industrial CO₂ Emissions](image)

Figure 3.12. Indian total industrial CO₂ 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 CO₂ emissions over the examined timeline, but also increased CO₂ discrepancies following this annual timeline approach. An increased rate of CO₂ 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 CO₂ emissions output of 235.68MtCO₂. Primary Solid Biofuels still hold a significant role regarding the amount of CO₂ emissions for the last year examined with 137.37MtCO₂, while Blast Furnace Gas follows with an output of 63.17MtCO₂. It should however be highlighted that Primary Solid Biofuels are not considered in the calculations, when approaching the CO₂ emission discrepancy scenarios as those are presented in Figure 3.12 because IEA does not include the fuel in its methodologies.

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 CO₂ 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 CO₂ emissions, presenting a reduction in its share amounting to approximately 22% from 1982, placing it as the second most significant contributor of CO₂ in the total industry. Evident is also the increase of natural gas (NG), which triples its contribution towards CO₂ 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. CO₂ output difference of the total industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher)
3.4.3 Iron and Steel Discrepancies

Examine the iron and steel industry of India, the CO₂ output presents greater discrepancies when measured in weight from 2002 onwards. This output discrepancy is linked to the growth in CO₂ emissions as a result of the industrial growth that this sector presents. The highest emitting scenario, being IPCC NCV high and high CC, produces 270.36MtCO₂ in the final examined year, while the lowest, IEA NCV and low CC is rated at an output of 167.65MtCO₂ for the same year. The reference scenario shows an output of 185.28MtCO₂.

This growth amounts to 347.5% or 143.87MtCO₂ 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 95.87MtCO₂, while measured in output, the highest difference amounts to 102.7MtCO₂ for 2012. The average difference between the highest and the lowest performing scenario, across the timeline, is rated at 47.17%.

Figure 3.19. Indian Iron and Steel industrial CO₂ emissions during 1980-2012 under different Indian NCV and carbon content values provided by IEA (standardized NCV) and IPCC on low-net-high scenarios.
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.
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 in CO₂ emissions from 1982 to 2012. Blast furnace gas was effectively replaced as the main CO₂ 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 CO₂ emissions presents an approximate 2-fold CO₂ increase at 23.89% accounted between 2002 to 2012. The contribution of other bituminous coal amounts at 51.01% of the I&S total CO₂ output.
Energy and Emissions Accounting: The case of Intra-Regional Industrial Shifts in SE Asia

Table 3.25. CO₂ output difference of the I&S industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher)

<table>
<thead>
<tr>
<th>Scenarios (I&amp;S)</th>
<th>Difference (%)</th>
<th>Difference (Mt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPCC NCV_LOW + CO2LOW</td>
<td>382.73%</td>
<td>135.62</td>
</tr>
<tr>
<td>IEA NCV + CO2LOW</td>
<td>360.91%</td>
<td>131.28</td>
</tr>
<tr>
<td>IPCC NCV_NET + CO2LOW</td>
<td>432.84%</td>
<td>164.14</td>
</tr>
<tr>
<td>IPCC NCV_LOW + CO2NET</td>
<td>367.72%</td>
<td>148.40</td>
</tr>
<tr>
<td>IEA NCV + CO2NET</td>
<td>347.50%</td>
<td>143.87</td>
</tr>
<tr>
<td>IPCC NCV_HIGH + CO2LOW</td>
<td>469.54%</td>
<td>186.68</td>
</tr>
<tr>
<td>IPCC NCV_NET + CO2NET</td>
<td>414.87%</td>
<td>178.60</td>
</tr>
<tr>
<td>IPCC NCV_LOW + CO2HIGH</td>
<td>353.94%</td>
<td>162.41</td>
</tr>
<tr>
<td>IEA NCV + CO2HIGH</td>
<td>335.22%</td>
<td>157.69</td>
</tr>
<tr>
<td>IPCC NCV_HIGH + CO2NET</td>
<td>449.61%</td>
<td>202.46</td>
</tr>
<tr>
<td>IPCC NCV_NET + CO2HIGH</td>
<td>398.27%</td>
<td>194.28</td>
</tr>
<tr>
<td>IPCC NCV_HIGH + CO2HIGH</td>
<td>431.13%</td>
<td>219.46</td>
</tr>
</tbody>
</table>

3.4.4 Chemical and Petrochemical Discrepancies

Figure 3.26. Indian Chemical & Petrochemical industrial CO₂ 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 CO₂ emissions over time, as observed in other industrial sectors. While the respective CO₂ emissions have increased for the reference scenario by 12.84MtCO₂ or 165.6% during 1980-2012, they present an overall decrease from 2002-2012.
that amounts to 18.8% or 477.4ktCO₂. Additionally, in 1998-999 a steep decrease in CO₂ emissions is observed when compared to the previous year, amounting to 24.7% or 4738ktCO₂ before rebounding during the following year.

The peak of CO₂ emissions is in 2002 presenting an output of 25.37MtCO₂ under the reference scenario. For 2002, the difference between the highest and lowest CO₂ output scenarios as presented in Figure 3.26 amounts to 9.66MtCO₂ having a difference of 41.67%. The average difference between the highest and the lowest CO₂ output scenarios is 54.03% or 8178ktCO₂. The average CO₂ emissions gap between the two scenarios (IEA as reference and IPCC) is approximately 15% for 1980-2012 or 2.395MtCO₂.

The highest CO₂ 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 13.14MtCO₂.

Examining the fuels that contribute towards CO₂ 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 CO₂ emissions from its year of introduction; 2000, with 8313 ktCO₂ surpassing other bituminous coal by 2685 ktCO₂. It has remained a significant emissions contributor until the last year examined with 10,374 ktCO₂ 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 CO₂ 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 ktCO₂ for 2012.

![Fuel CO₂ Contribution for Chem. sector 1982](image1) ![Fuel CO₂ Contribution for Chem. sector 1992](image2) ![Fuel CO₂ Contribution for Chem. sector 2002](image3) ![Fuel CO₂ Contribution for Chem. sector 2012](image4)

**Figure 3.28-3.31.** Periodic snapshot of Indian CO₂ emissions share attributed to the fuel mix of the Chemicals & Petrochemicals sector.

Approaching the CO₂ 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 CO₂ 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 CO₂ 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)

<table>
<thead>
<tr>
<th>Scenarios (C&amp;P)</th>
<th>Difference (%)</th>
<th>Difference (Mt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPCC NCV_LOW + CO2LOW</td>
<td>151.75%</td>
<td>10.99</td>
</tr>
<tr>
<td>IEA NCV + CO2LOW</td>
<td>163.98%</td>
<td>12.10</td>
</tr>
<tr>
<td>IPCC NCV_NET + CO2LOW</td>
<td>128.19%</td>
<td>11.54</td>
</tr>
<tr>
<td>IPCC NCV_LOW + CO2NET</td>
<td>153.43%</td>
<td>11.66</td>
</tr>
<tr>
<td>IEA NCV + CO2NET</td>
<td>165.61%</td>
<td>12.84</td>
</tr>
<tr>
<td>IPCC NCV_HIGH + CO2LOW</td>
<td>110.76%</td>
<td>11.87</td>
</tr>
<tr>
<td>IPCC NCV_NET + CO2NET</td>
<td>129.25%</td>
<td>12.25</td>
</tr>
<tr>
<td>IPCC NCV_LOW + CO2HIGH</td>
<td>152.85%</td>
<td>12.16</td>
</tr>
<tr>
<td>IEA NCV + CO2HIGH</td>
<td>164.68%</td>
<td>13.40</td>
</tr>
<tr>
<td>IPCC NCV_HIGH + CO2NET</td>
<td>111.37%</td>
<td>12.60</td>
</tr>
<tr>
<td>IPCC NCV_NET + CO2HIGH</td>
<td>128.21%</td>
<td>12.78</td>
</tr>
<tr>
<td>IPCC NCV_HIGH + CO2HIGH</td>
<td>109.97%</td>
<td>13.14</td>
</tr>
</tbody>
</table>

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](image.png) 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 CO₂ emissions when compared to the rest that present activity within the industry. It produced a total of 59.1 MtCO₂ in 2012, the year that presents the highest emissions output in total for the industry. The CO₂ 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 CO₂ 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 32.07 MtCO₂ (Figure 3.34). Fuel oil and lignite show a negligible contribution in CO₂ 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 CO₂ 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 CO₂ 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. CO₂ output difference of the C&P industry between 1980-2012 for each of the examined NCV and CC scenarios (red: lower, green: higher)
3.5 Discussion of the Results and Further Analysis.

![India’s total CO₂ 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).](image)

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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂, 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 284.74MtCO₂ 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 82.8MtCO₂. This gap in reported CO₂ 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 CO₂ 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 CO₂ 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 192.95MtCO₂.

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 CO₂ output in weight (Figure 3.40) presents discrepancies between those scenarios of 608.28MtCO₂ 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 226.98MtCO₂ 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 CO₂ 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 Commission 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 CO₂ 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 Commission Joint Research Center (JRC), 2014), (British Petroleum, 2015), (US Energy Information Administration, 2016).

Figure 3.43 Discrepancy between selected high-low CO₂ 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 Commission 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 CO₂ 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 CO₂ 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 (MtCO₂), deviating from the comparison of output scenarios approached individually in hypothesis 1b. The average research scenario presents lower CO₂ 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 6.14MtCO₂ to 50.05MtCO₂ higher output respectively.

Comparing in share terms (%) (Figure 3.45), the results highlight the relationship between the scenarios CO₂ 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 CO₂ 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 CO₂ 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 CO₂ is 2199.38MtCO₂ 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 CO₂ 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 CO₂ 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).
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 Commission 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 23MtCO₂ to 20.8% and 92.64MtCO₂, 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 113.42MtCO₂. 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 11MtCO₂ for the IPCC net scenario, while the lowest is observed in 2008 with 24.55% or 14.13MtCO₂. 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 (NMEE). 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\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{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 CO₂ 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 CO₂ 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.](image)

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

![Total Industrial Energy Intensity](image)


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.


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.

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 CO₂ 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.

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.

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%. 


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.


### 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 Alghed, 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 CO2 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 United 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 CO2/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 2.1tCO2/t compared to 0.6tCO2/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 (CO₂/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 CO₂ 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 CO₂ emissions.
5. Decomposing the Total and Sectoral Industrial CO₂ 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).
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 CO₂ 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).
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 CO₂ emissions. Determining the relationship between CO₂ 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 CO₂ emissions by reducing high energy demand and replacing inefficient industrial processes (Brown et al., 2012).

Therefore, identifying the importance of specific factors in driving CO₂ 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 CO₂ 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 CO₂ emissions of the industrial sectors discussed. To
achieve that, an index decomposition analysis of CO₂ 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 CO₂ change. (H1)
- CO₂ emissions change has a positive relationship with industrial automation. (H2)
- CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions is performed for the three countries both for total industry and for six industrial sectors in the following sections of this chapter.

Figure 5.4. India total industrial CO₂ emissions decomposition analysis.

Indian CO₂ 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 CO₂ 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 CO₂ emissions change, amounting at 80.09 MtCO₂ and 50.06 MtCO₂ respectively towards that decreasing effect. Industrial scale expansion is found to have a significant effect on CO₂ emissions, either negative or positive. As the industrial scale effect on the change of CO₂ 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.

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).

**Figure 5.6.** The Philippines total industrial CO₂ emissions decomposition analysis.

Focusing on the total data provided by the Philippines industry, **Figure 5.6** the change of CO₂ 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 CO₂ emissions, especially in the periods 1989-1991 and 2007-2009. Examining the factors contributing to a CO₂ 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 MtCO₂ 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 CO₂ emissions change increase.
5.3.2 Iron and Steel Industry

Following up to the analysis of the drivers for India and its iron and steel industrial sector, the most significant factors of CO2 emissions change throughout the assessed timeline are energy intensity (EI) and labour productivity (LP). While the change in CO2 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 CO2 emissions change from 1983 onwards. Energy intensity (EI) presents its most significant effect regarding the overall increase of CO2 emissions change for 2007-2009 and 2010-2012. Labour productivity (LP) is underlined as the most important driving factor towards a decrease of CO2 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 CO2 emissions would be possible in comparison to that interval calculated output. This link between CO2 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 CO2. 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 CO₂ emissions throughout the examined timeline, and as a result it presents reduced significance rate.

**Figure 5.8.** Indonesian CO₂ emissions decomposition analysis of Iron & Steel industrial sector.

Approaching the Indonesian iron and steel analysis, the results demonstrate that a change in CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions change in 1989-1991 and 1995-1997 with the latter showing a contribution of 4.75 MtCO₂ of the total increase of 4.98 MtCO₂. Approaching the effect that the other examined factors have on CO₂ 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 CO₂ emissions.
Concluding with the analysis of the Philippines iron and steel sector, it does not reveal any definite trends. The CO₂ 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 CO₂ 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 MtCO₂ in 1986-1988 and it has driven emissions reduction of 1.21 MtCO₂ in 1983-1985. The increase of emitted CO₂ 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$. A similar decrease of produced CO₂ observed in the 1983-1985 interval reflects an LP decrease from 37,965.3 to 18,990.21 const.2005 US$, demonstrating a strong directional interconnection that exists between CO₂ and LP\textsuperscript{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 CO₂ 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 CO₂ increasing change rate (Figure 5.9).
5.3.3 Chemical and Petrochemical Industry

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 CO₂ 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 CO₂ 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 CO₂ 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.

Figure 5.10. India CO₂ 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 $\Delta C$ 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 $\Delta C$ (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$_2$. 

**Figure 5.11.** Indonesia CO$_2$ emissions decomposition analysis of Chemical & Petrochemical industrial sector.
The Philippines results demonstrate variable characteristics regarding CO₂ 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 CO₂ 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

The CO₂ 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 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).
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 CO2 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 CO2 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 MtCO2, in contrast to LP and IS with a 1.88 and 2.21 MtCO2 increase respectively.
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\textsubscript{2} emission changes. While EI, LP and IS present an unstable trend in their effect, they are significant in their contribution towards CO\textsubscript{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\textsubscript{2} emissions change during 2010-2012 attributed mainly to EI and LP effect. Their contribution in decreasing CO\textsubscript{2} by 1.74 and 1.59 MtCO\textsubscript{2} respectively. However, this is countered by a 2.5 MtCO\textsubscript{2} increase by industrial scale (IS), which results in a total decline of 0.82 MtCO\textsubscript{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

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 CO₂ 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 CO₂ emissions is 0.98 MtCO₂ while labour productivity (LP) and industrial scale (IS) contribute positively at a rate of 0.58 and 0.43 MtCO₂ respectively. However, energy intensity has not consistently contributed towards a decrease of CO₂ emissions change. Specifically, EI has an increasing effect on CO₂ 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 CO₂ emissions change (Figure 5.16).

![Figure 5.16. India CO₂ emissions decomposition analysis of Machinery industrial sector.](image-url)
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) decreases carbon emissions. This effect is peaking in 2010-2012 with a contribution of 0.28 MtCO₂, and carbon intensity (CI) effect follows as secondary. Contrasting to that, CI is observed to drive the increase of CO₂ emissions change during 2001-2003 and 2004-2006. An increase from 96,931 tCO₂/PJ in 2001 to 203,326 tCO₂/PJ demonstrates an established relationship regarding this effect. Labour productivity (LP) leads as a main driver increasing CO₂, found to be peaking in 1998-2000 and constantly contributing to an increase during 2001-2003, 2004-2006, 2007-2009 and 2010-2012.
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 CO₂ 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 MtCO₂. However, this is reversed on the periods that follow, with its contribution in reduction peaking in 2010-2013, driving a total reduction result of CO₂ emissions change (ΔC) of 0.088 MtCO₂. Labour productivity is the main factor driving an increase of CO₂ emissions during 2004-2006, 2007-2009 and 2010-2012.

Figure 5.18. The Philippines CO₂ emissions decomposition analysis of Machinery industrial sector.
5.3.6 Textiles & Leather Industry

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.

Figure 5.19. India CO$_2$ emissions decomposition analysis of Textiles & 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 EL_{eff} and Cl_{eff} are missing. The effect of energy intensity is a major contributor in driving CO₂ emissions change from 1992 onwards (Figure 5.20). EL has significant impact in decreasing CO₂ emissions during 1992-1994; 1998-2000; 2001-2003; and 2004-2006. During 2004-2006 EL has contributed to a reduction of CO₂ emissions by 2.77 MtCO₂ leading to a total decrease (ΔC) of 1.35 MtCO₂. Labour productivity contributes to an increase in CO₂ emissions during most of the examined intervals with its peak effect observed in 2001-2003 where it reaches 2.16 MtCO₂.
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 CO₂ 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 CO₂. However, the LP<sub>eff</sub> contributed towards an increase in emissions in 2007-2009 and added an IS<sub>eff</sub> increase in 2010-2012 (Figure 5.21) with energy and carbon intensity acting as reciprocal.

**Figure 5.21.** The Philippines CO₂ emissions decomposition analysis of Textile & Leather industrial sector.
5.3.7 Paper Pulp & Print industrial sector

Energy intensity (EI) and labour productivity (LP) were found to be the main contributors to CO₂ 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 CO₂ emissions change in 2010-2012, amounting to a decrease of 2.36 MtCO₂ (Figure 5.22).

![Figure 5.22. India CO₂ emissions decomposition analysis of Paper Pulp & Print industrial sector.](image)

![Figure 5.23. Indonesia CO₂ emissions decomposition analysis of Paper Pulp & Print industrial sector.](image)
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 CO₂ emissions results data, despite UNIDO presenting the respective number of persons employed. Additionally, the division of CO₂ to energy (PJ) from the year 2000 onwards produces the same result (96ktCO₂/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 MtCO₂ contribution in reducing CO₂ 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.

![Figure 5.24](image-url) The Philippines CO₂ 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 CO₂ emissions change. Labour productivity in 1980-1982 has caused a reduction of 0.52MtCO₂, while energy intensity caused an increase in the same period of 0.045 MtCO₂. A reduction of CO₂ 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 MtCO₂. Overall, most of the examined intervals show decreasing CO₂ emissions and 2007-2009 shows the highest increase at 0.013 MtCO₂ (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 ($\Delta C$) 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 $\Delta C$. 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 $\Delta C$, approximating 2MtCO$_2$ on average between time intervals. The average carbon emissions change amounts to an increase of 24.96MtCO$_2$ while the cumulative $\Delta C$ 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.](image)
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 $\Delta C$ 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 $\Delta C$ increase in cumulative terms, $E_{\text{eff}}$, $C_{\text{eff}}$, $I_{\text{Seff}}$ with positive contributions of 89.32MtCO$_2$, 2.28MtCO$_2$ and 17.19MtCO$_2$ respectively for 1980-2012 (Figure 5.27). However, $L_{\text{peff}}$ results in a cumulative...
decrease in emissions change for the same period, approximately at 21.39MtCO₂ or 1.94MtCO₂ 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 CO₂ 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 MtCO₂ which is attributed to labour productivity. The second is a 31.74MtCO₂ 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, $\Delta C$ presents mixed levels of output, expanded to all drivers (Figure 5.27). Energy intensity is a major contributor, driving $\Delta C$ 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 $\Delta C$ 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 $\Delta C$ 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 $\Delta C$ 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 8.8MtCO₂ on average between intervals, reaching a total contribution in reduction of 96.8MtCO₂ 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 8.68MtCO₂ 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 138.30MtCO₂ (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 6.90MtCO₂ per examined period, presenting a cumulative increase during 1980-2012 that amounts to 75.86MtCO₂.

Figure 5.28. Indonesia average CO₂ contribution of drivers per industry (%) for the 1980-2012 timeline
Focusing on sectoral index decomposition and more specifically in the iron and steel industry, energy intensity drives a $\Delta C$ increase spike during 1995-1997, with 4.75MtCO$_2$ while 1998-2000 onwards this spike is reversed by 4.49MtCO$_2$, driving a reduction in carbon emissions of 1.55MtCO$_2$, with an exception located at the 2001-2003 period (1.94MtCO$_2$). The effect of EI is also evident in its average contribution rate to $\Delta C$, amounting at 54.6% (Figure 5.28). Labour productivity presents a positive $\Delta C$ contribution performance trend from 1998 onwards averaging at cumulative contribution rate of 33.5% and 2.97MtCO$_2$ respectively.

---

**Figure 5.29.** Indonesia CO$_2$ contribution of drivers per industry (%) for the cumulative $\Delta C$ of the 1980-2012 timeline.

**Figure 5.30.** Indonesia cumulative effect of drivers on $\Delta C$ per industrial sector (MtCO$_2$) for the 1980-2012 timeline.
However, industrial scale has the highest rate towards emissions increase at 43.5% with 3.86MtCO₂ (Figures 5.29; 5.30).

The Indonesian chemical and petrochemical industrial sector presents a spike in ΔC, in 2004-2006 (8.8MtCO₂), 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 (9MtCO₂) contribution and labour productivity acting as a reciprocal with a 9.73MtCO₂ increase. The effect of labour productivity is the main contributor to cumulative carbon emissions, adding 14.86 MtCO₂, 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 3.22MtCO₂, 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 9.33MtCO₂ while IS increases ΔC by 5.08MtCO₂. 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 (0.15MtCO₂) and labour productivity (0.54MtCO₂), while energy intensity is a negative contributor in emissions with approximately 0.9MtCO₂ (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 (-0.11MtCO₂). However, the cumulative change in emissions during the timeline approaches 1.22MtCO₂, mainly attributed to the 2010-2012 interval. During that period, energy intensity is responsible for 61.1% driving emissions negative by 8.34MtCO₂. 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 CO₂ 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 unprecedented 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 0.04MtCO₂.

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 0.54MtCO₂ between time intervals, while the cumulative ΔC is 5.95MtCO₂ during the timeline. Energy intensity and labour productivity drive emissions negatively throughout 1980-2012 by 9.1MtCO₂ and 5.62MtCO₂ 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 -0.38MtCO₂ (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 CO₂ emissions, with labour productivity having the highest contribution at 54% with 0.81MtCO₂ (Figure 5.32; 5.33).
Figure 5.31. The Philippines average CO₂ contribution of drivers per industry (%) for the 1980-2012 timeline.

Figure 5.32. The Philippines CO₂ contribution of drivers per industry (%) as for the cumulative ΔC for the 1980-2012 timeline.
The chemical and petrochemical industry shows positive $\Delta C$ spikes, observed during 1989-1991 (0.82MtCO$_2$), 1995-1997 (1.04MtCO$_2$) and 1998-2000 (0.69MtCO$_2$). 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 0.87MtCO$_2$ at 67.87%. The same trend is observed for labour productivity in 2007-2009 (1.7MtCO$_2$) and 2010-2012 (-1.59MtCO$_2$). The 2007-2009 of $\Delta C$ increase is countered by energy intensity; its effect decreasing carbon emissions by 1.70MtCO$_2$. Additionally, industrial scale shows an unprecedented contribution driving positive $\Delta C$ in 2010-2012 with 2.5MtCO$_2$. Overall, carbon emissions change in cumulative terms shows an increase of 3.18MtCO$_2$ 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 0.33MtCO$_2$. 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 0.46MtCO₂ (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 0.90MtCO₂. 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂, increased capacity for a greater reduction of industrial CO₂ emissions through automation is feasible. Increased CO₂ emissions are of particular concern for Indonesia, as its CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions change.

Examining the capacity that India and the SE Asian countries have for altering industrial CO₂ 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.
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

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
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 with 12 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

Dimitrios Pappas
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 \(\text{HHI}=10000, \text{SWI}=0\), 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 \(\text{HHI}=2590.55\) and the highest diversity \(\text{SWI}=1.25\) 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 Limmeekchokchai, 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 \( \text{HHI}=3087.6 \). 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 (\( \text{HHI}=4453 \)) and lowest diversity (\( \text{SWI}=1.15 \)) 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

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

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.
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 CO₂ 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 CO₂ outputs compared to the mean published estimates. Between the published CO₂ estimations, these can differ as high as 284.74MtCO₂ 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 226.98MtCO₂ 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 CO₂ 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 CO₂ 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, CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions performance. Choosing this technological improvement pathway would lower the effect that industrial scale and labour productivity produce historically in driving CO₂ 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 CO₂ 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 CO₂ emissions output.

Overall, each country experiences a different significance rate for each of the chosen factors that contribute to CO₂ 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 CO₂ emissions change. The change of CO₂ 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 CO₂ emissions (Ma et al., 2019). As a result, a transfer of industries from China to host countries would result in elevated CO₂ 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 CO₂ 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\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{2} emissions. The contribution of the chosen factors on CO\textsubscript{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\textsubscript{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\textsubscript{2} emissions, suggesting that increasing the number of employees would result in a significant increase of CO\textsubscript{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 CO₂. 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 CO₂ 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.

<table>
<thead>
<tr>
<th>Chapter</th>
<th>Data limitation</th>
<th>Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>• Generic emissions factors per fuel.</td>
<td>• Accuracy in country-specific carbon emissions is potentially limited.</td>
</tr>
<tr>
<td></td>
<td>• NCVs differentiate between general and industry or between long periods.</td>
<td>• Discrepancies studied up to 2012.</td>
</tr>
<tr>
<td></td>
<td>• IEA non-provisional data not available for years later than 2012 at the time of collection (2015-early 2016)</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>• Raw materials present gap years</td>
<td>• Gap years use median values where appropriate.</td>
</tr>
<tr>
<td></td>
<td>• NCVs differentiate between general and industry only or between long periods.</td>
<td>• The industry is not broken down for all active economic sectors. It is limited to the sectors that IEA publishes.</td>
</tr>
<tr>
<td></td>
<td>• IEA does not breakdown industrial sectors to the detail provided by UNIDO for the countries examined.</td>
<td>• Precision in country-specific carbon emissions is potentially limited.</td>
</tr>
<tr>
<td></td>
<td>• UNIDO INDSTAT2 data not available for years later than 2013. The following years</td>
<td>• Energy intensity and carbon intensity accounted for 1980 to 2012.</td>
</tr>
</tbody>
</table>
became available in October 2019.

- 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.

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 CO₂ 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, CO₂ 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 CO₂ 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 CO₂ 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


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


Chester, L., 2009. Does the polysemic nature of energy security make it a ‘wicked’ problem?
Energy and Emissions Accounting: The case of Intra-Regional Industrial Shifts in SE Asia


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


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


Fan, R., Luo, M., Zhang, P., 2016. A study on evolution of energy intensity in China with


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


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


HKTDC Research, 2013b. The search for low-cost production bases in Southeast Asia | Hong Kong Means Business [WWW Document].


9406. doi:10.3390/en8099392


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, 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 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.


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


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.


Iyengar, R., 2015. India Has Overtaken the U.S. and China to Top Spot in a Key World Foreign Investment Table. Time.


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


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


MOSPI, 2019. PRESS NOTE ON FIRST ADVANCE ESTIMATES OF NATIONAL INCOME 2018-19 CENTRAL STATISTICS OFFICE MINISTRY OF STATISTICS PROGRAMME IMPLEMENTATION GOVERNMENT OF INDIA.


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


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., 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


Office of Natural Resources and Environmental Policy, 2015. Thailand ’ s Intended Nationally Determined Contribution ( INDC ), UNFCC.


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


Ozawa, T., 2015. Next Great Industrial Transmigration : Relocating China’s Factories to Sub-Saharan Africa , Flying-Geese Style?


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.


Republic of Indonesia, 2015. Intended National Determined Contribution to the UNFCC.


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


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


UNFCCC, 2015. India’s Intended National Determined Contributions 1–38.


United Nations Sustainable Development Division, 2005b. Intensity of Energy Use, Total and
by Economic Activity.


Wu, K., 2014. China’s energy security: Oil and gas. Energy Policy 73, 4–11. doi:10.1016/j.enpol.2014.05.040


Econ. Model. 58, 237–248. doi:10.1016/j.econmod.2016.05.003


APPENDIX I

Carbon content stored per fuel

<table>
<thead>
<tr>
<th>Fuel</th>
<th>Default</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude Oil</td>
<td>73.3</td>
<td>71.1</td>
<td>75.5</td>
</tr>
<tr>
<td>Natural Gas Liquids</td>
<td>64.2</td>
<td>58.3</td>
<td>70.4</td>
</tr>
<tr>
<td>Motor Gasoline</td>
<td>69.3</td>
<td>67.5</td>
<td>73</td>
</tr>
<tr>
<td>Aviation Gasoline</td>
<td>70</td>
<td>67.5</td>
<td>73</td>
</tr>
<tr>
<td>Jet Gasoline</td>
<td>70</td>
<td>67.5</td>
<td>73</td>
</tr>
<tr>
<td>Jet Kerosene</td>
<td>71.5</td>
<td>69.7</td>
<td>74.4</td>
</tr>
<tr>
<td>Other Kerosene</td>
<td>71.9</td>
<td>70.8</td>
<td>73.7</td>
</tr>
<tr>
<td>Shale Oil</td>
<td>73.3</td>
<td>67.8</td>
<td>79.2</td>
</tr>
<tr>
<td>Gas/Diesel Oil</td>
<td>74.1</td>
<td>72.6</td>
<td>74.8</td>
</tr>
<tr>
<td>Residual Fuel Oil</td>
<td>77.4</td>
<td>75.5</td>
<td>78.8</td>
</tr>
<tr>
<td>Liquified Petroleum Gases</td>
<td>63.1</td>
<td>61.6</td>
<td>65.6</td>
</tr>
<tr>
<td>Ethane</td>
<td>61.6</td>
<td>56.5</td>
<td>68.6</td>
</tr>
<tr>
<td>Naphtha</td>
<td>73.3</td>
<td>69.3</td>
<td>76.3</td>
</tr>
<tr>
<td>Bitumen</td>
<td>80.7</td>
<td>73</td>
<td>89.9</td>
</tr>
<tr>
<td>Lubricants</td>
<td>73.3</td>
<td>71.9</td>
<td>75.2</td>
</tr>
<tr>
<td>Petroleum Coke</td>
<td>97.5</td>
<td>82.9</td>
<td>115</td>
</tr>
<tr>
<td>Refinery Feedstocks</td>
<td>73.3</td>
<td>68.9</td>
<td>76.6</td>
</tr>
<tr>
<td>Refinery Gas</td>
<td>57.6</td>
<td>48.2</td>
<td>69</td>
</tr>
<tr>
<td>Paraffin Waxes</td>
<td>73.3</td>
<td>72.2</td>
<td>74.4</td>
</tr>
<tr>
<td>Other Petroleum Products</td>
<td>73.3</td>
<td>72.2</td>
<td>74.4</td>
</tr>
<tr>
<td>Anthracite</td>
<td>98.3</td>
<td>94.6</td>
<td>101</td>
</tr>
<tr>
<td>Coking Coal</td>
<td>94.6</td>
<td>87.3</td>
<td>101</td>
</tr>
<tr>
<td>Other Bituminus Coal</td>
<td>94.6</td>
<td>89.5</td>
<td>99.7</td>
</tr>
<tr>
<td>Sub-bituminous coal</td>
<td>96.1</td>
<td>92.8</td>
<td>100</td>
</tr>
<tr>
<td>Lignite</td>
<td>101</td>
<td>90.9</td>
<td>115</td>
</tr>
<tr>
<td>Oil Shale and Tar Sands</td>
<td>107</td>
<td>90.2</td>
<td>125</td>
</tr>
<tr>
<td>Brown Coal Briquettes</td>
<td>97.5</td>
<td>87.3</td>
<td>109</td>
</tr>
<tr>
<td>Patent Fuel</td>
<td>97.5</td>
<td>87.3</td>
<td>109</td>
</tr>
<tr>
<td>Coke Oven Coke</td>
<td>107</td>
<td>95.7</td>
<td>119</td>
</tr>
<tr>
<td>Gas Coke</td>
<td>107</td>
<td>95.7</td>
<td>119</td>
</tr>
<tr>
<td>Coal Tar</td>
<td>80.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gas Works Gas</td>
<td>44.4</td>
<td>37.3</td>
<td>54.1</td>
</tr>
<tr>
<td>Coke oven Gas</td>
<td>44.4</td>
<td>37.3</td>
<td>54.1</td>
</tr>
<tr>
<td>Blast Furnace Gas</td>
<td>260</td>
<td>219</td>
<td>308</td>
</tr>
<tr>
<td>Oxygen Steel Furnace Gas</td>
<td>182</td>
<td>145</td>
<td>202</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>56.1</td>
<td>54.3</td>
<td>58.3</td>
</tr>
<tr>
<td>Municipal Wastes</td>
<td>91.7</td>
<td>73.3</td>
<td>121</td>
</tr>
<tr>
<td>Industrial Wastes</td>
<td>143</td>
<td>110</td>
<td>183</td>
</tr>
<tr>
<td>Waste Oils</td>
<td>73.3</td>
<td>72.2</td>
<td>74.4</td>
</tr>
<tr>
<td>Energy and Emissions Accounting: The case of Intra-Regional Industrial Shifts in SE Asia</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------------------------------</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table: Energy Sources

<table>
<thead>
<tr>
<th>Description</th>
<th>Default</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peat</td>
<td>106</td>
<td>100</td>
<td>108</td>
</tr>
<tr>
<td>Wood/Wood Waste</td>
<td>112</td>
<td>95</td>
<td>132</td>
</tr>
<tr>
<td>Other Primary Solid Biomass</td>
<td>100</td>
<td>84.7</td>
<td>117</td>
</tr>
<tr>
<td>Charcoal</td>
<td>112</td>
<td>95</td>
<td>132</td>
</tr>
<tr>
<td>Biogasoline</td>
<td>70.8</td>
<td>59.8</td>
<td>84.3</td>
</tr>
<tr>
<td>Biodiesels</td>
<td>70.8</td>
<td>59.8</td>
<td>84.3</td>
</tr>
<tr>
<td>Other Liquid Biofuels</td>
<td>79.6</td>
<td>67.1</td>
<td>95.3</td>
</tr>
<tr>
<td>Other Biogas</td>
<td>54.6</td>
<td>46.2</td>
<td>66</td>
</tr>
<tr>
<td>Municipal Wastes (biomass function)</td>
<td>100</td>
<td>84.7</td>
<td>117</td>
</tr>
</tbody>
</table>

### Table: Carbon Content

<table>
<thead>
<tr>
<th>Fuel CC</th>
<th>Default</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude Oil</td>
<td>20</td>
<td>19.4</td>
<td>20.6</td>
</tr>
<tr>
<td>Natural Gas Liquids</td>
<td>22</td>
<td>20.0</td>
<td>24.1</td>
</tr>
<tr>
<td>Motor Gasoline</td>
<td>18.9</td>
<td>18.4</td>
<td>19.9</td>
</tr>
<tr>
<td>Aviation Gasoline</td>
<td>18.9</td>
<td>18.2</td>
<td>19.7</td>
</tr>
<tr>
<td>Jet Gasoline</td>
<td>18.9</td>
<td>18.2</td>
<td>19.7</td>
</tr>
<tr>
<td>Jet Kerosene</td>
<td>19.5</td>
<td>19.0</td>
<td>20.3</td>
</tr>
<tr>
<td>Other Kerosene</td>
<td>20</td>
<td>19.7</td>
<td>20.5</td>
</tr>
<tr>
<td>Shale Oil</td>
<td>20</td>
<td>18.5</td>
<td>21.6</td>
</tr>
<tr>
<td>Gas/Diesel Oil</td>
<td>20.2</td>
<td>19.8</td>
<td>20.4</td>
</tr>
<tr>
<td>Residual Fuel Oil</td>
<td>21.1</td>
<td>20.6</td>
<td>21.5</td>
</tr>
<tr>
<td>Liquified Petroleum Gases</td>
<td>17.2</td>
<td>16.8</td>
<td>17.9</td>
</tr>
<tr>
<td>Ethane</td>
<td>16.8</td>
<td>15.4</td>
<td>18.7</td>
</tr>
<tr>
<td>Naphtha</td>
<td>20</td>
<td>18.9</td>
<td>20.8</td>
</tr>
<tr>
<td>Bitumen</td>
<td>22</td>
<td>19.9</td>
<td>24.5</td>
</tr>
<tr>
<td>Lubricants</td>
<td>20</td>
<td>19.6</td>
<td>20.5</td>
</tr>
<tr>
<td>Petroleum Coke</td>
<td>27.5</td>
<td>23.4</td>
<td>32.4</td>
</tr>
<tr>
<td>Refinery Feedstocks</td>
<td>20</td>
<td>18.8</td>
<td>20.9</td>
</tr>
<tr>
<td>Refinery Gas</td>
<td>18.2</td>
<td>15.2</td>
<td>21.8</td>
</tr>
<tr>
<td>Paraffin Waxes</td>
<td>20</td>
<td>19.7</td>
<td>20.3</td>
</tr>
<tr>
<td>Other Petroleum Products</td>
<td>20</td>
<td>19.7</td>
<td>20.3</td>
</tr>
<tr>
<td>Anthracite</td>
<td>26.8</td>
<td>25.8</td>
<td>27.5</td>
</tr>
<tr>
<td>Coking Coal</td>
<td>25.8</td>
<td>23.8</td>
<td>27.5</td>
</tr>
<tr>
<td>Other Bitumiuinus Coal</td>
<td>25.8</td>
<td>24.4</td>
<td>27.2</td>
</tr>
<tr>
<td>Sub-bituminous coal</td>
<td>26.2</td>
<td>25.3</td>
<td>27.3</td>
</tr>
<tr>
<td>Lignite</td>
<td>27.6</td>
<td>24.8</td>
<td>31.4</td>
</tr>
<tr>
<td>Oil Shale and Tar Sands</td>
<td>20</td>
<td>16.9</td>
<td>23.4</td>
</tr>
<tr>
<td>Brown Coal Briquettes</td>
<td>20</td>
<td>17.9</td>
<td>22.4</td>
</tr>
<tr>
<td>Patent Fuel</td>
<td>20</td>
<td>17.9</td>
<td>22.4</td>
</tr>
<tr>
<td>Coke Oven Coke</td>
<td>29.5</td>
<td>26.4</td>
<td>32.8</td>
</tr>
<tr>
<td>Gas Coke</td>
<td>29.5</td>
<td>26.4</td>
<td>32.8</td>
</tr>
<tr>
<td>Coal Tar</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy Source</td>
<td>Value</td>
<td>Carbon</td>
<td>Oxygen</td>
</tr>
<tr>
<td>-------------------------------------</td>
<td>-------</td>
<td>--------</td>
<td>--------</td>
</tr>
<tr>
<td>Gas Works Gas</td>
<td>13</td>
<td>10.9</td>
<td>15.8</td>
</tr>
<tr>
<td>Coke oven Gas</td>
<td>13</td>
<td>10.9</td>
<td>15.8</td>
</tr>
<tr>
<td>Blast Furnace Gas</td>
<td>66</td>
<td>55.6</td>
<td>78.2</td>
</tr>
<tr>
<td>Oxygen Steel Furnace Gas</td>
<td>66</td>
<td>52.6</td>
<td>73.3</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>15.3</td>
<td>14.8</td>
<td>15.9</td>
</tr>
<tr>
<td>Municipal Wastes</td>
<td>29.9</td>
<td>23.9</td>
<td>39.5</td>
</tr>
<tr>
<td>Industrial Wastes</td>
<td>29.9</td>
<td>23.0</td>
<td>38.3</td>
</tr>
<tr>
<td>Waste Oils</td>
<td>20</td>
<td>19.7</td>
<td>20.3</td>
</tr>
<tr>
<td>Peat</td>
<td>29.9</td>
<td>28.2</td>
<td>30.5</td>
</tr>
<tr>
<td>Wood/Wood Waste</td>
<td>29.9</td>
<td>25.4</td>
<td>35.2</td>
</tr>
<tr>
<td>Other Primary Solid Biomass</td>
<td>29.9</td>
<td>25.3</td>
<td>35.0</td>
</tr>
<tr>
<td>Charcoal</td>
<td>29.9</td>
<td>25.4</td>
<td>35.2</td>
</tr>
<tr>
<td>Biogasoline</td>
<td>30.6</td>
<td>25.8</td>
<td>36.4</td>
</tr>
<tr>
<td>Biodiesels</td>
<td>20</td>
<td>16.9</td>
<td>23.8</td>
</tr>
<tr>
<td>Other Liquid Biofuels</td>
<td>20</td>
<td>16.9</td>
<td>23.9</td>
</tr>
<tr>
<td>Other Biogas</td>
<td>30.6</td>
<td>25.9</td>
<td>37.0</td>
</tr>
<tr>
<td>Municipal Wastes (biomass function)</td>
<td>20</td>
<td>16.9</td>
<td>23.4</td>
</tr>
</tbody>
</table>
APPENDIX II

UNIDO NUMBER OF PERSONS EMPLOYED

<table>
<thead>
<tr>
<th>Year</th>
<th>India</th>
<th>TOTA L</th>
<th>Iron&amp;Steel</th>
<th>Chemical&amp;Petrochemical</th>
<th>Non-metalli c minerals</th>
<th>Machine ry</th>
<th>Textiles&amp;Leather</th>
<th>Paper, Pulp and Print</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980</td>
<td>680100</td>
<td>578000</td>
<td>529000</td>
<td>347000</td>
<td>909000</td>
<td>1717000</td>
<td></td>
<td>273000</td>
</tr>
<tr>
<td>1981</td>
<td>685081</td>
<td>590000</td>
<td>528844</td>
<td>366193</td>
<td>917029</td>
<td>1655176</td>
<td></td>
<td>289127</td>
</tr>
<tr>
<td>1982</td>
<td>702581</td>
<td>604000</td>
<td>562419</td>
<td>406307</td>
<td>964765</td>
<td>1723577</td>
<td></td>
<td>303031</td>
</tr>
<tr>
<td>1983</td>
<td>677856</td>
<td>618000</td>
<td>550699</td>
<td>426770</td>
<td>968833</td>
<td>1682795</td>
<td></td>
<td>299025</td>
</tr>
<tr>
<td>1984</td>
<td>675914</td>
<td>669000</td>
<td>556179</td>
<td>411639</td>
<td>979319</td>
<td>1696135</td>
<td></td>
<td>290985</td>
</tr>
<tr>
<td>1985</td>
<td>646896</td>
<td>596000</td>
<td>585816</td>
<td>426484</td>
<td>976758</td>
<td>1544982</td>
<td></td>
<td>277102</td>
</tr>
<tr>
<td>1986</td>
<td>641960</td>
<td>615000</td>
<td>567311</td>
<td>415931</td>
<td>910540</td>
<td>1543577</td>
<td></td>
<td>271684</td>
</tr>
<tr>
<td>1987</td>
<td>670904</td>
<td>617000</td>
<td>603697</td>
<td>422989</td>
<td>1011702</td>
<td>1544000</td>
<td></td>
<td>290250</td>
</tr>
<tr>
<td>1988</td>
<td>673144</td>
<td>618000</td>
<td>621724</td>
<td>428209</td>
<td>1027690</td>
<td>1505853</td>
<td></td>
<td>271094</td>
</tr>
<tr>
<td>1989</td>
<td>711543</td>
<td>590461</td>
<td>616910</td>
<td>434823</td>
<td>1041828</td>
<td>1619168</td>
<td></td>
<td>272782</td>
</tr>
<tr>
<td>1990</td>
<td>718439</td>
<td>622372</td>
<td>605554</td>
<td>431006</td>
<td>1078670</td>
<td>1593639</td>
<td></td>
<td>284641</td>
</tr>
<tr>
<td>1991</td>
<td>723687</td>
<td>595799</td>
<td>633463</td>
<td>454049</td>
<td>1082198</td>
<td>1551232</td>
<td></td>
<td>288789</td>
</tr>
<tr>
<td>1992</td>
<td>771662</td>
<td>661886</td>
<td>702827</td>
<td>455944</td>
<td>1132289</td>
<td>1623785</td>
<td></td>
<td>301576</td>
</tr>
<tr>
<td>1993</td>
<td>769814</td>
<td>625355</td>
<td>708640</td>
<td>440783</td>
<td>1105876</td>
<td>1698845</td>
<td></td>
<td>301184</td>
</tr>
<tr>
<td>1994</td>
<td>798751</td>
<td>631304</td>
<td>744053</td>
<td>444396</td>
<td>1138904</td>
<td>1752409</td>
<td></td>
<td>319362</td>
</tr>
<tr>
<td>1995</td>
<td>877682</td>
<td>736457</td>
<td>835936</td>
<td>481267</td>
<td>1269815</td>
<td>1960728</td>
<td></td>
<td>355928</td>
</tr>
<tr>
<td>1996</td>
<td>867008</td>
<td>659104</td>
<td>836682</td>
<td>460195</td>
<td>1273024</td>
<td>1899291</td>
<td></td>
<td>333511</td>
</tr>
<tr>
<td>1997</td>
<td>871671</td>
<td>666591</td>
<td>853361</td>
<td>442791</td>
<td>1190024</td>
<td>1922379</td>
<td></td>
<td>336664</td>
</tr>
<tr>
<td>1998</td>
<td>793953</td>
<td>620431</td>
<td>830072</td>
<td>430709</td>
<td>1204268</td>
<td>1733184</td>
<td></td>
<td>285154</td>
</tr>
<tr>
<td>Year</td>
<td>TOTA L</td>
<td>Iron&amp;Steel</td>
<td>Chemical&amp;Petrochemical</td>
<td>Non-metalli c minerals</td>
<td>Machine ry</td>
<td>Textiles&amp;Lea ther</td>
<td>Paper, Pulp and Print</td>
<td></td>
</tr>
<tr>
<td>------</td>
<td>--------</td>
<td>------------</td>
<td>------------------------</td>
<td>----------------------</td>
<td>------------</td>
<td>-------------------</td>
<td>----------------------</td>
<td></td>
</tr>
<tr>
<td>1980</td>
<td>96300 0</td>
<td>8800</td>
<td></td>
<td>46400</td>
<td>90100</td>
<td>256000</td>
<td>31800</td>
<td></td>
</tr>
<tr>
<td>1981</td>
<td>10048 96</td>
<td>9500</td>
<td></td>
<td>49800</td>
<td>95200</td>
<td>262900</td>
<td>34300</td>
<td></td>
</tr>
<tr>
<td>1982</td>
<td>10598 31</td>
<td>10100</td>
<td></td>
<td>52600</td>
<td>93900</td>
<td>264100</td>
<td>37000</td>
<td></td>
</tr>
<tr>
<td>1983</td>
<td>11123 55</td>
<td>12900</td>
<td></td>
<td>55500</td>
<td>94800</td>
<td>262900</td>
<td>36700</td>
<td></td>
</tr>
<tr>
<td>1984</td>
<td>11904 21</td>
<td>14000</td>
<td></td>
<td>55000</td>
<td>92100</td>
<td>284000</td>
<td>35400</td>
<td></td>
</tr>
<tr>
<td>1985</td>
<td>16719 90</td>
<td>15600</td>
<td></td>
<td>87600</td>
<td>119066</td>
<td>378100</td>
<td>56300</td>
<td></td>
</tr>
<tr>
<td>Year</td>
<td>Energy 1</td>
<td>Energy 2</td>
<td>Energy 3</td>
<td>Energy 4</td>
<td>Energy 5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>------</td>
<td>----------</td>
<td>----------</td>
<td>----------</td>
<td>----------</td>
<td>----------</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1986</td>
<td>16792</td>
<td>16900</td>
<td>79800</td>
<td>113700</td>
<td>385700</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1987</td>
<td>17767</td>
<td>16800</td>
<td>81300</td>
<td>116000</td>
<td>415700</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1988</td>
<td>20582</td>
<td>19600</td>
<td>95800</td>
<td>129700</td>
<td>480600</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1989</td>
<td>22471</td>
<td>21200</td>
<td>107700</td>
<td>144900</td>
<td>556200</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>26494</td>
<td>32717</td>
<td>135419</td>
<td>170674</td>
<td>728217</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1991</td>
<td>29811</td>
<td>37498</td>
<td>138642</td>
<td>201859</td>
<td>903617</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td>32981</td>
<td>40020</td>
<td>149206</td>
<td>237801</td>
<td>1075855</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1993</td>
<td>35593</td>
<td>43512</td>
<td>161078</td>
<td>261078</td>
<td>1184755</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1994</td>
<td>37986</td>
<td>46700</td>
<td>170648</td>
<td>311515</td>
<td>1251832</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td>41569</td>
<td>47602</td>
<td>186364</td>
<td>355389</td>
<td>1308520</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1996</td>
<td>41964</td>
<td>50385</td>
<td>188554</td>
<td>374262</td>
<td>1350133</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>41068</td>
<td>55269</td>
<td>241804</td>
<td>329773</td>
<td>1224078</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1998</td>
<td>42168</td>
<td>56542</td>
<td>197954</td>
<td>376587</td>
<td>1349910</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1999</td>
<td>43504</td>
<td>59972</td>
<td>200873</td>
<td>384890</td>
<td>1418647</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>43859</td>
<td>61019</td>
<td>224703</td>
<td>379118</td>
<td>1368185</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2001</td>
<td>43648</td>
<td>53509</td>
<td>174222</td>
<td>357478</td>
<td>1294625</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2002</td>
<td>41068</td>
<td>55269</td>
<td>241804</td>
<td>329773</td>
<td>1224078</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2003</td>
<td>42168</td>
<td>56542</td>
<td>197954</td>
<td>376587</td>
<td>1349910</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2004</td>
<td>43504</td>
<td>59972</td>
<td>200873</td>
<td>384890</td>
<td>1418647</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2005</td>
<td>43859</td>
<td>61019</td>
<td>224703</td>
<td>379118</td>
<td>1368185</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006</td>
<td>43648</td>
<td>53509</td>
<td>174222</td>
<td>357478</td>
<td>1294625</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2007</td>
<td>42738</td>
<td>59373</td>
<td>215322</td>
<td>16575</td>
<td>382564</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td>43249</td>
<td>58967</td>
<td>208402</td>
<td>16541</td>
<td>416655</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>42265</td>
<td>56411</td>
<td>213824</td>
<td>16505</td>
<td>426860</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td>47356</td>
<td>65035</td>
<td>213996</td>
<td>18892</td>
<td>440373</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Dimitrios Pappas
<table>
<thead>
<tr>
<th>Year</th>
<th>Total Production</th>
<th>Iron &amp; Steel</th>
<th>Chemical &amp; Petrochemical</th>
<th>Non-Metallic Minerals</th>
<th>Machinery</th>
<th>Textiles &amp; Leather</th>
<th>Paper, Pulp and Print</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>47291.53</td>
<td>64678</td>
<td>237963</td>
<td>174811</td>
<td>592374</td>
<td>1286721</td>
<td>177256</td>
</tr>
<tr>
<td>2012</td>
<td>49288.39</td>
<td>60430</td>
<td>255169</td>
<td>193136</td>
<td>510515</td>
<td>1338958</td>
<td>181506</td>
</tr>
</tbody>
</table>

**Philippines**

<table>
<thead>
<tr>
<th>Year</th>
<th>Total Production</th>
<th>Iron &amp; Steel</th>
<th>Chemical &amp; Petrochemical</th>
<th>Non-Metallic Minerals</th>
<th>Machinery</th>
<th>Textiles &amp; Leather</th>
<th>Paper, Pulp and Print</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980</td>
<td>94870.00</td>
<td>22500</td>
<td>52700</td>
<td>31300</td>
<td>113900</td>
<td>252600</td>
<td>39500</td>
</tr>
<tr>
<td>1981</td>
<td>97050.00</td>
<td>21800</td>
<td>45700</td>
<td>32900</td>
<td>122500</td>
<td>258000</td>
<td>39500</td>
</tr>
<tr>
<td>1982</td>
<td>96860.00</td>
<td>22100</td>
<td>45400</td>
<td>30900</td>
<td>117200</td>
<td>262800</td>
<td>43100</td>
</tr>
<tr>
<td>1983</td>
<td>69600.03</td>
<td>20900</td>
<td>37153</td>
<td>28600</td>
<td>89249</td>
<td>172480</td>
<td>28150</td>
</tr>
<tr>
<td>1984</td>
<td>63900.00</td>
<td>19800</td>
<td>33400</td>
<td>25360</td>
<td>82550</td>
<td>162800</td>
<td>24900</td>
</tr>
<tr>
<td>1985</td>
<td>61840.00</td>
<td>18300</td>
<td>35273</td>
<td>21100</td>
<td>66000</td>
<td>159880</td>
<td>24600</td>
</tr>
<tr>
<td>1986</td>
<td>63014.00</td>
<td>18300</td>
<td>36000</td>
<td>20800</td>
<td>69400</td>
<td>172300</td>
<td>27700</td>
</tr>
<tr>
<td>1987</td>
<td>67100.00</td>
<td>17000</td>
<td>36500</td>
<td>21200</td>
<td>74490</td>
<td>187300</td>
<td>28400</td>
</tr>
<tr>
<td>1988</td>
<td>84510.00</td>
<td>18100</td>
<td>43500</td>
<td>27600</td>
<td>95000</td>
<td>243100</td>
<td>35200</td>
</tr>
<tr>
<td>1989</td>
<td>94030.00</td>
<td>20200</td>
<td>45300</td>
<td>30700</td>
<td>103700</td>
<td>309000</td>
<td>37300</td>
</tr>
<tr>
<td>1990</td>
<td>11085.00</td>
<td>22100</td>
<td>46500</td>
<td>42700</td>
<td>137000</td>
<td>304300</td>
<td>44000</td>
</tr>
<tr>
<td>1991</td>
<td>11057.00</td>
<td>22300</td>
<td>48000</td>
<td>43400</td>
<td>155100</td>
<td>298000</td>
<td>46400</td>
</tr>
<tr>
<td>1992</td>
<td>95880.00</td>
<td>23000</td>
<td>46700</td>
<td>42200</td>
<td>151100</td>
<td>278200</td>
<td>41300</td>
</tr>
<tr>
<td>1993</td>
<td>90060.00</td>
<td>22200</td>
<td>45900</td>
<td>35000</td>
<td>149000</td>
<td>247400</td>
<td>41900</td>
</tr>
<tr>
<td>1994</td>
<td>88710.00</td>
<td>25100</td>
<td>45900</td>
<td>36200</td>
<td>160200</td>
<td>229400</td>
<td>39600</td>
</tr>
<tr>
<td>1995</td>
<td>90340.00</td>
<td>27000</td>
<td>47300</td>
<td>32700</td>
<td>191200</td>
<td>221200</td>
<td>41700</td>
</tr>
<tr>
<td>1996</td>
<td>10520.00</td>
<td>36600</td>
<td>57900</td>
<td>44300</td>
<td>213800</td>
<td>243300</td>
<td>50000</td>
</tr>
<tr>
<td>1997</td>
<td>10972.00</td>
<td>37400</td>
<td>59800</td>
<td>46400</td>
<td>231100</td>
<td>247500</td>
<td>51900</td>
</tr>
<tr>
<td>1998</td>
<td>11535.00</td>
<td>39200</td>
<td>57900</td>
<td>47300</td>
<td>272000</td>
<td>252600</td>
<td>53700</td>
</tr>
<tr>
<td>Year</td>
<td>Value 1</td>
<td>Value 2</td>
<td>Value 3</td>
<td>Value 4</td>
<td>Value 5</td>
<td>Value 6</td>
<td></td>
</tr>
<tr>
<td>------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td></td>
</tr>
<tr>
<td>1999</td>
<td>1084200</td>
<td>35600</td>
<td>48000</td>
<td>49800</td>
<td>279500</td>
<td>228500</td>
<td>47200</td>
</tr>
<tr>
<td>2000</td>
<td>932400</td>
<td>27100</td>
<td>46400</td>
<td>27300</td>
<td>260400</td>
<td>206000</td>
<td>38500</td>
</tr>
<tr>
<td>2001</td>
<td>98386</td>
<td>27786</td>
<td>45176</td>
<td>29593</td>
<td>303627</td>
<td>201926</td>
<td>40831</td>
</tr>
<tr>
<td>2002</td>
<td>1022114</td>
<td>24980</td>
<td>51410</td>
<td>26578</td>
<td>317828</td>
<td>214296</td>
<td>41568</td>
</tr>
<tr>
<td>2003</td>
<td>989401</td>
<td>23613</td>
<td>40960</td>
<td>28750</td>
<td>337886</td>
<td>185669</td>
<td>38947</td>
</tr>
<tr>
<td>2004</td>
<td>886973</td>
<td>21101</td>
<td>39670</td>
<td>22910</td>
<td>284847</td>
<td>136356</td>
<td>29279</td>
</tr>
<tr>
<td>2005</td>
<td>839663</td>
<td>20455</td>
<td>41754</td>
<td>22597</td>
<td>244973</td>
<td>120478</td>
<td>27712</td>
</tr>
<tr>
<td>2006</td>
<td>871195</td>
<td>20527</td>
<td>39739</td>
<td>22644</td>
<td>280038</td>
<td>120759</td>
<td>29740</td>
</tr>
<tr>
<td>2007</td>
<td>1045677</td>
<td>20485</td>
<td>53065</td>
<td>32579</td>
<td>324962</td>
<td>148296</td>
<td>35144</td>
</tr>
</tbody>
</table>
## UNIDO INDUSTRIAL VALUE ADDED

<table>
<thead>
<tr>
<th>Year</th>
<th>India</th>
<th>TOTAL</th>
<th>Iron&amp;Steel</th>
<th>Chemical&amp;Petrochemical</th>
<th>Non-metalliferous Minerals</th>
<th>Machinery</th>
<th>Textiles&amp;Leather</th>
<th>Paper, Pulp and Print</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980</td>
<td>31010855.085</td>
<td>3.72E+09</td>
<td>5.2E+09</td>
<td>1.22E+09</td>
<td>6.19E+09</td>
<td>6611795545</td>
<td>1.31E+09</td>
<td></td>
</tr>
<tr>
<td>1981</td>
<td>29893897.556</td>
<td>4.35E+09</td>
<td>5.13E+09</td>
<td>1.2E+09</td>
<td>5.73E+09</td>
<td>5315412468</td>
<td>1.33E+09</td>
<td></td>
</tr>
<tr>
<td>1982</td>
<td>29935980.045</td>
<td>3.86E+09</td>
<td>5.56E+09</td>
<td>1.58E+09</td>
<td>5.93E+09</td>
<td>4659553085</td>
<td>1.06E+09</td>
<td></td>
</tr>
<tr>
<td>1983</td>
<td>31574007.575</td>
<td>3.97E+09</td>
<td>5.61E+09</td>
<td>1.62E+09</td>
<td>6.11E+09</td>
<td>5097623718</td>
<td>1.08E+09</td>
<td></td>
</tr>
<tr>
<td>1984</td>
<td>29510646.258</td>
<td>3.08E+09</td>
<td>4.93E+09</td>
<td>1.65E+09</td>
<td>6.3E+09</td>
<td>4689074259</td>
<td>1.22E+09</td>
<td></td>
</tr>
<tr>
<td>1985</td>
<td>28178968.289</td>
<td>3.46E+09</td>
<td>5.16E+09</td>
<td>1.64E+09</td>
<td>5.69E+09</td>
<td>4220887929</td>
<td>9.3E+08</td>
<td></td>
</tr>
<tr>
<td>1986</td>
<td>29048326.684</td>
<td>3.1E+09</td>
<td>5.32E+09</td>
<td>1.43E+09</td>
<td>5.55E+09</td>
<td>4547357111</td>
<td>1.12E+09</td>
<td></td>
</tr>
<tr>
<td>1987</td>
<td>31520125.754</td>
<td>3.41E+09</td>
<td>6.87E+09</td>
<td>1.48E+09</td>
<td>6.41E+09</td>
<td>4300072923</td>
<td>1.14E+09</td>
<td></td>
</tr>
<tr>
<td>1988</td>
<td>35007269.472</td>
<td>4.87E+09</td>
<td>7.02E+09</td>
<td>1.52E+09</td>
<td>6.83E+09</td>
<td>4451393972</td>
<td>1.12E+09</td>
<td></td>
</tr>
<tr>
<td>1989</td>
<td>35848306.241</td>
<td>4.21E+09</td>
<td>6.94E+09</td>
<td>1.58E+09</td>
<td>6.91E+09</td>
<td>5335918939</td>
<td>1.29E+09</td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>37514939.891</td>
<td>4.79E+09</td>
<td>7.02E+09</td>
<td>1.92E+09</td>
<td>6.93E+09</td>
<td>5691537327</td>
<td>1.37E+09</td>
<td></td>
</tr>
<tr>
<td>1991</td>
<td>29755190.641</td>
<td>2.58E+09</td>
<td>5.56E+09</td>
<td>2.07E+09</td>
<td>6.1E+09</td>
<td>4179238385</td>
<td>1.17E+09</td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td>31474224.157</td>
<td>3.46E+09</td>
<td>7.54E+09</td>
<td>1.41E+09</td>
<td>6.05E+09</td>
<td>3956807203</td>
<td>1.13E+09</td>
<td></td>
</tr>
<tr>
<td>1993</td>
<td>32990676.464</td>
<td>3.62E+09</td>
<td>7.89E+09</td>
<td>1.35E+09</td>
<td>5.35E+09</td>
<td>5104931780</td>
<td>1.26E+09</td>
<td></td>
</tr>
<tr>
<td>1994</td>
<td>38793181.518</td>
<td>4.52E+09</td>
<td>8.82E+09</td>
<td>1.6E+09</td>
<td>7E+09</td>
<td>5688995830</td>
<td>1.43E+09</td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td>46499528.845</td>
<td>5.52E+09</td>
<td>1.18E+10</td>
<td>2.28E+09</td>
<td>8.29E+09</td>
<td>5192198771</td>
<td>1.84E+09</td>
<td></td>
</tr>
<tr>
<td>1996</td>
<td>42877412.575</td>
<td>4.86E+09</td>
<td>1.02E+10</td>
<td>1.71E+09</td>
<td>7.32E+09</td>
<td>5146828897</td>
<td>1.38E+09</td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>42437347.914</td>
<td>6.64E+09</td>
<td>8.66E+09</td>
<td>1.86E+09</td>
<td>7.14E+09</td>
<td>5181488169</td>
<td>1.17E+09</td>
<td></td>
</tr>
<tr>
<td>1998</td>
<td>47227038.722</td>
<td>6.09E+09</td>
<td>1.32E+10</td>
<td>1.97E+09</td>
<td>7.66E+09</td>
<td>5812582656</td>
<td>1.35E+09</td>
<td></td>
</tr>
<tr>
<td>1999</td>
<td>50680635.397</td>
<td>6.31E+09</td>
<td>1.34E+10</td>
<td>2.64E+09</td>
<td>7.32E+09</td>
<td>6172326545</td>
<td>1.58E+09</td>
<td></td>
</tr>
</tbody>
</table>
### Energy and Emissions Accounting: The case of Intra-Regional Industrial Shifts in SE Asia

#### Dimitrios Pappas

<table>
<thead>
<tr>
<th>Year</th>
<th>Total Iron &amp; Steel</th>
<th>Chemical &amp; Petrochemical</th>
<th>Non-metallurgical Minerals</th>
<th>Machinery</th>
<th>Textiles &amp; Leather</th>
<th>Paper, Pulp and Print</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980</td>
<td>8.03E+09</td>
<td>2.53E+08</td>
<td>9.15E+08</td>
<td>5.77E+08</td>
<td>8.32E+08</td>
<td>1.1E+09</td>
</tr>
<tr>
<td>1981</td>
<td>9.22E+09</td>
<td>2.7E+08</td>
<td>1.22E+09</td>
<td>6.49E+08</td>
<td>8.64E+08</td>
<td>1.08E+09</td>
</tr>
<tr>
<td>1982</td>
<td>9.09E+09</td>
<td>2.08E+08</td>
<td>1.22E+09</td>
<td>5.63E+08</td>
<td>1.07E+09</td>
<td>1.2E+09</td>
</tr>
<tr>
<td>1983</td>
<td>7.29E+09</td>
<td>4.33E+08</td>
<td>8.63E+08</td>
<td>4.7E+08</td>
<td>7.27E+08</td>
<td>9.16E+08</td>
</tr>
<tr>
<td>1984</td>
<td>8.2E+09</td>
<td>9.03E+08</td>
<td>9.6E+08</td>
<td>4.38E+08</td>
<td>7.07E+08</td>
<td>1.24E+09</td>
</tr>
<tr>
<td>1985</td>
<td>1.18E+10</td>
<td>8.51E+08</td>
<td>1.48E+09</td>
<td>6.98E+08</td>
<td>1.09E+09</td>
<td>1.52E+09</td>
</tr>
<tr>
<td>1986</td>
<td>1.16E+10</td>
<td>9.87E+08</td>
<td>1.25E+09</td>
<td>6.37E+08</td>
<td>9.12E+08</td>
<td>1.76E+09</td>
</tr>
<tr>
<td>1987</td>
<td>1.06E+10</td>
<td>1.08E+09</td>
<td>1.09E+09</td>
<td>5.11E+08</td>
<td>8.29E+08</td>
<td>1.41E+09</td>
</tr>
<tr>
<td>Year</td>
<td>Electric Consumption (TWh)</td>
<td>Coal Consumption (Mt)</td>
<td>Natural Gas Consumption (Tcf)</td>
<td>Oil Consumption (Tbbl)</td>
<td>Petroleum Consumption (Tbbl)</td>
<td>LPG Consumption (Tbbl)</td>
</tr>
<tr>
<td>------</td>
<td>-----------------------------</td>
<td>----------------------</td>
<td>-------------------------------</td>
<td>------------------------</td>
<td>-----------------------------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>1988</td>
<td>1.23E+10</td>
<td>1.03E+09</td>
<td>1.28E+09</td>
<td>4.85E+08</td>
<td>1.09E+09</td>
<td>5.77E+08</td>
</tr>
<tr>
<td>1989</td>
<td>1.5E+10</td>
<td>1.25E+09</td>
<td>1.31E+09</td>
<td>4.82E+08</td>
<td>1.54E+09</td>
<td>5.76E+08</td>
</tr>
<tr>
<td>1990</td>
<td>2.04E+10</td>
<td>1.84E+09</td>
<td>7.71E+08</td>
<td>1.46E+09</td>
<td>2.98E+09</td>
<td>9.37E+08</td>
</tr>
<tr>
<td>1991</td>
<td>2.2E+10</td>
<td>1.26E+09</td>
<td>2.49E+09</td>
<td>1.82E+09</td>
<td>3.3E+09</td>
<td>1.21E+09</td>
</tr>
<tr>
<td>1992</td>
<td>2.84E+10</td>
<td>1.76E+09</td>
<td>2.64E+09</td>
<td>1.08E+09</td>
<td>2.72E+09</td>
<td>4.72E+09</td>
</tr>
<tr>
<td>1993</td>
<td>3.09E+10</td>
<td>2.07E+09</td>
<td>2.74E+09</td>
<td>1.35E+09</td>
<td>2.5E+09</td>
<td>6.23E+09</td>
</tr>
<tr>
<td>1994</td>
<td>3.65E+10</td>
<td>2.56E+09</td>
<td>3.36E+09</td>
<td>1.42E+09</td>
<td>3.21E+09</td>
<td>1.69E+09</td>
</tr>
<tr>
<td>1995</td>
<td>3.82E+10</td>
<td>2.89E+09</td>
<td>3.3E+09</td>
<td>1.43E+09</td>
<td>4.25E+09</td>
<td>1.92E+09</td>
</tr>
<tr>
<td>1996</td>
<td>4.52E+10</td>
<td>4.98E+09</td>
<td>4.31E+09</td>
<td>1.53E+09</td>
<td>6.05E+09</td>
<td>2.44E+09</td>
</tr>
<tr>
<td>1997</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1998</td>
<td>1.77E+10</td>
<td>7.03E+09</td>
<td>2.42E+09</td>
<td>1.79E+09</td>
<td>3.11E+09</td>
<td>1.09E+09</td>
</tr>
<tr>
<td>1999</td>
<td>2.69E+10</td>
<td>1.1E+09</td>
<td>3.11E+09</td>
<td>2.91E+09</td>
<td>5.26E+09</td>
<td>1.66E+09</td>
</tr>
<tr>
<td>2000</td>
<td>3.03E+10</td>
<td>1.13E+09</td>
<td>3.26E+09</td>
<td>4.44E+09</td>
<td>5.08E+09</td>
<td>1.99E+09</td>
</tr>
<tr>
<td>2001</td>
<td>2.76E+10</td>
<td>1.44E+09</td>
<td>3.03E+09</td>
<td>3.72E+09</td>
<td>3.47E+09</td>
<td>1.85E+09</td>
</tr>
<tr>
<td>2002</td>
<td>3.34E+10</td>
<td>1.32E+09</td>
<td>2.98E+09</td>
<td>3.28E+09</td>
<td>4.81E+09</td>
<td>2.03E+09</td>
</tr>
<tr>
<td>2003</td>
<td>4.04E+10</td>
<td>1.46E+09</td>
<td>4.84E+09</td>
<td>1.69E+09</td>
<td>4.11E+09</td>
<td>3.34E+09</td>
</tr>
<tr>
<td>2004</td>
<td>4.15E+10</td>
<td>1.49E+09</td>
<td>3.98E+09</td>
<td>1.92E+09</td>
<td>4.7E+09</td>
<td>3.37E+09</td>
</tr>
<tr>
<td>2005</td>
<td>4.08E+10</td>
<td>1.45E+09</td>
<td>4.54E+09</td>
<td>1.98E+09</td>
<td>4.21E+09</td>
<td>3E+09</td>
</tr>
<tr>
<td>2006</td>
<td>5.44E+10</td>
<td>2.13E+09</td>
<td>6.16E+09</td>
<td>2E+09</td>
<td>5.36E+09</td>
<td>3.94E+09</td>
</tr>
<tr>
<td>2007</td>
<td>6.16E+10</td>
<td>2.55E+09</td>
<td>4.32E+09</td>
<td>2.47E+09</td>
<td>5.62E+09</td>
<td>4.13E+09</td>
</tr>
<tr>
<td>2008</td>
<td>6.39E+10</td>
<td>2.91E+09</td>
<td>1.16E+10</td>
<td>2.34E+09</td>
<td>6.71E+09</td>
<td>4.02E+09</td>
</tr>
<tr>
<td>2009</td>
<td>6.69E+10</td>
<td>2.37E+09</td>
<td>1.17E+10</td>
<td>2.59E+09</td>
<td>7.14E+09</td>
<td>4.78E+09</td>
</tr>
<tr>
<td>2010</td>
<td>8.41E+10</td>
<td>3.09E+09</td>
<td>1.2E+10</td>
<td>3.21E+09</td>
<td>9.28E+09</td>
<td>5.26E+09</td>
</tr>
<tr>
<td>2011</td>
<td>1.01E+11</td>
<td>3.78E+09</td>
<td>1.4E+10</td>
<td>3.66E+09</td>
<td>1.11E+10</td>
<td>6.78E+09</td>
</tr>
<tr>
<td>2012</td>
<td>1.04E+11</td>
<td>3.52E+09</td>
<td>1.29E+10</td>
<td>4.12E+09</td>
<td>1.28E+10</td>
<td>5.66E+09</td>
</tr>
<tr>
<td>Year</td>
<td>Philippines</td>
<td>TOTAL</td>
<td>Iron&amp;Steel</td>
<td>Chemical&amp;Petrochemical</td>
<td>Nonmetallic minerals</td>
<td>Machinery</td>
</tr>
<tr>
<td>------</td>
<td>-------------</td>
<td>-------</td>
<td>------------</td>
<td>------------------------</td>
<td>---------------------</td>
<td>-----------</td>
</tr>
<tr>
<td>1980</td>
<td>1.15E+10</td>
<td>3.15E+08</td>
<td>2.41E+09</td>
<td>3.26E+08</td>
<td>1.15E+09</td>
<td>1.47E+09</td>
</tr>
<tr>
<td>1981</td>
<td>1.05E+10</td>
<td>2.41E+08</td>
<td>2.18E+09</td>
<td>2.97E+08</td>
<td>8.79E+08</td>
<td>1.52E+09</td>
</tr>
<tr>
<td>1982</td>
<td>7.71E+09</td>
<td>1.87E+08</td>
<td>1.74E+09</td>
<td>2E+08</td>
<td>9.08E+08</td>
<td>8.08E+08</td>
</tr>
<tr>
<td>1983</td>
<td>8.82E+09</td>
<td>7.93E+08</td>
<td>2.07E+09</td>
<td>2.87E+08</td>
<td>7.92E+08</td>
<td>8.02E+08</td>
</tr>
<tr>
<td>1984</td>
<td>6.93E+09</td>
<td>6.06E+08</td>
<td>1.24E+09</td>
<td>2.66E+08</td>
<td>7.66E+08</td>
<td>6.96E+08</td>
</tr>
<tr>
<td>1985</td>
<td>6.26E+09</td>
<td>3.48E+08</td>
<td>1.86E+09</td>
<td>1.75E+08</td>
<td>4.27E+08</td>
<td>4.11E+08</td>
</tr>
<tr>
<td>1986</td>
<td>6.95E+09</td>
<td>1.83E+08</td>
<td>1.98E+09</td>
<td>1.37E+08</td>
<td>4.71E+08</td>
<td>4.76E+08</td>
</tr>
<tr>
<td>1987</td>
<td>7.02E+09</td>
<td>2.75E+08</td>
<td>1.56E+09</td>
<td>2.27E+08</td>
<td>5.64E+08</td>
<td>5.63E+08</td>
</tr>
<tr>
<td>1988</td>
<td>9.4E+09</td>
<td>5.79E+08</td>
<td>1.76E+09</td>
<td>3.62E+08</td>
<td>7.17E+08</td>
<td>1.01E+09</td>
</tr>
<tr>
<td>1989</td>
<td>1.05E+10</td>
<td>3.82E+08</td>
<td>1.75E+09</td>
<td>4.73E+08</td>
<td>9.87E+08</td>
<td>1.47E+09</td>
</tr>
<tr>
<td>1990</td>
<td>1.32E+10</td>
<td>5.27E+08</td>
<td>2.3E+09</td>
<td>5.31E+08</td>
<td>1.52E+09</td>
<td>1.41E+09</td>
</tr>
<tr>
<td>1991</td>
<td>1.31E+10</td>
<td>4.76E+08</td>
<td>2.76E+09</td>
<td>5.39E+08</td>
<td>1.82E+09</td>
<td>1.43E+09</td>
</tr>
<tr>
<td>1992</td>
<td>1.47E+10</td>
<td>6.4E+08</td>
<td>3.32E+09</td>
<td>6.64E+08</td>
<td>1.81E+09</td>
<td>1.46E+09</td>
</tr>
<tr>
<td>1993</td>
<td>1.49E+10</td>
<td>8.25E+08</td>
<td>2.77E+09</td>
<td>6.15E+08</td>
<td>1.8E+09</td>
<td>1.52E+09</td>
</tr>
<tr>
<td>1994</td>
<td>1.62E+10</td>
<td>9.15E+08</td>
<td>3.43E+09</td>
<td>7.52E+08</td>
<td>2.1E+09</td>
<td>1.6E+09</td>
</tr>
<tr>
<td>1995</td>
<td>1.96E+10</td>
<td>1.03E+09</td>
<td>4.36E+09</td>
<td>9.03E+08</td>
<td>2.89E+09</td>
<td>1.64E+09</td>
</tr>
<tr>
<td>1996</td>
<td>2.37E+10</td>
<td>9.68E+08</td>
<td>5.82E+09</td>
<td>1.13E+09</td>
<td>3.89E+09</td>
<td>1.58E+09</td>
</tr>
<tr>
<td>1997</td>
<td>2.31E+10</td>
<td>9.14E+08</td>
<td>5.25E+09</td>
<td>1.05E+09</td>
<td>4.21E+09</td>
<td>1.59E+09</td>
</tr>
<tr>
<td>1998</td>
<td>1.96E+10</td>
<td>6.17E+08</td>
<td>3.46E+09</td>
<td>7.65E+08</td>
<td>4.27E+09</td>
<td>1.33E+09</td>
</tr>
<tr>
<td>1999</td>
<td>2.04E+10</td>
<td>7.54E+08</td>
<td>3.87E+09</td>
<td>8.48E+08</td>
<td>4.94E+09</td>
<td>1.39E+09</td>
</tr>
<tr>
<td>2000</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>------</td>
<td>-----------------</td>
<td>-----------------</td>
<td>-----------------</td>
<td>-----------------</td>
<td>-----------------</td>
<td>-----------------</td>
</tr>
<tr>
<td>2001</td>
<td>1.33E+10</td>
<td>4.1E+08</td>
<td>2.18E+09</td>
<td>4.07E+08</td>
<td>3.81E+09</td>
<td>9.92E+08</td>
</tr>
<tr>
<td>2002</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2003</td>
<td>1.13E+10</td>
<td>3.36E+08</td>
<td>2.51E+09</td>
<td>4.27E+08</td>
<td>2.91E+09</td>
<td>7.37E+08</td>
</tr>
<tr>
<td>2004</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2005</td>
<td>1.24E+10</td>
<td>3.97E+08</td>
<td>2.68E+09</td>
<td>4.9E+08</td>
<td>3.33E+09</td>
<td>7.68E+08</td>
</tr>
<tr>
<td>2006</td>
<td>1.27E+10</td>
<td>6.56E+08</td>
<td>2.04E+09</td>
<td>4.52E+08</td>
<td>4.45E+09</td>
<td>6.25E+08</td>
</tr>
<tr>
<td>2007</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2008</td>
<td>1.69E+10</td>
<td>6.78E+08</td>
<td>4.55E+09</td>
<td>6.4E+08</td>
<td>3.84E+09</td>
<td>5.32E+08</td>
</tr>
<tr>
<td>2009</td>
<td>1.9E+10</td>
<td>8.12E+08</td>
<td>4.09E+09</td>
<td>6.69E+08</td>
<td>6.41E+09</td>
<td>5E+08</td>
</tr>
<tr>
<td>2010</td>
<td>1.99E+10</td>
<td>8.64E+08</td>
<td>5.28E+09</td>
<td>7.84E+08</td>
<td>4.93E+09</td>
<td>5.02E+08</td>
</tr>
<tr>
<td>2011</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2012</td>
<td>2.28E+10</td>
<td>3.97E+08</td>
<td>1.67E+09</td>
<td>8.96E+08</td>
<td>1.03E+10</td>
<td>6.25E+08</td>
</tr>
</tbody>
</table>
### APPENDIX III

<table>
<thead>
<tr>
<th>Year</th>
<th>vs IEA (%)</th>
<th>vs EDGAR (%)</th>
<th>vs BP (%)</th>
<th>vs EIA (%)</th>
<th>vs CDIAC (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980</td>
<td>11.15%</td>
<td>-11.39%</td>
<td>-9.51%</td>
<td>0.73%</td>
<td>-7.23%</td>
</tr>
<tr>
<td>1981</td>
<td>13.60%</td>
<td>-10.02%</td>
<td>-8.24%</td>
<td>-2.39%</td>
<td>-3.04%</td>
</tr>
<tr>
<td>1982</td>
<td>13.39%</td>
<td>-10.54%</td>
<td>-3.61%</td>
<td>0.35%</td>
<td>-2.89%</td>
</tr>
<tr>
<td>1983</td>
<td>10.63%</td>
<td>-12.47%</td>
<td>-4.54%</td>
<td>-0.47%</td>
<td>-6.76%</td>
</tr>
<tr>
<td>1984</td>
<td>8.87%</td>
<td>-12.62%</td>
<td>-2.79%</td>
<td>-6.59%</td>
<td>-2.83%</td>
</tr>
<tr>
<td>1985</td>
<td>10.24%</td>
<td>-11.96%</td>
<td>-2.93%</td>
<td>-6.75%</td>
<td>-6.24%</td>
</tr>
<tr>
<td>1986</td>
<td>7.86%</td>
<td>-12.83%</td>
<td>-3.53%</td>
<td>-5.93%</td>
<td>-6.58%</td>
</tr>
<tr>
<td>1987</td>
<td>2.98%</td>
<td>-10.59%</td>
<td>-8.26%</td>
<td>-5.76%</td>
<td>-9.99%</td>
</tr>
<tr>
<td>1988</td>
<td>3.57%</td>
<td>-16.15%</td>
<td>-9.67%</td>
<td>-6.77%</td>
<td>-11.47%</td>
</tr>
<tr>
<td>1989</td>
<td>1.83%</td>
<td>-17.42%</td>
<td>-12.57%</td>
<td>-7.05%</td>
<td>-14.46%</td>
</tr>
<tr>
<td>1990</td>
<td>-1.63%</td>
<td>-20.32%</td>
<td>-9.63%</td>
<td>-9.21%</td>
<td>-16.14%</td>
</tr>
<tr>
<td>1991</td>
<td>-5.44%</td>
<td>-22.85%</td>
<td>-11.63%</td>
<td>-12.86%</td>
<td>-19.18%</td>
</tr>
<tr>
<td>1992</td>
<td>-7.10%</td>
<td>-24.29%</td>
<td>-14.36%</td>
<td>-15.53%</td>
<td>-21.60%</td>
</tr>
<tr>
<td>1993</td>
<td>-10.51%</td>
<td>-27.35%</td>
<td>-17.19%</td>
<td>-19.75%</td>
<td>-24.88%</td>
</tr>
<tr>
<td>1994</td>
<td>-10.98%</td>
<td>-27.40%</td>
<td>-16.17%</td>
<td>-20.73%</td>
<td>-25.17%</td>
</tr>
<tr>
<td>1995</td>
<td>-14.40%</td>
<td>-30.03%</td>
<td>-20.82%</td>
<td>-31.09%</td>
<td>-27.39%</td>
</tr>
<tr>
<td>1996</td>
<td>-15.18%</td>
<td>-30.94%</td>
<td>-23.37%</td>
<td>-22.43%</td>
<td>-30.52%</td>
</tr>
<tr>
<td>1997</td>
<td>-14.37%</td>
<td>-29.89%</td>
<td>-21.24%</td>
<td>-21.72%</td>
<td>-29.24%</td>
</tr>
<tr>
<td>1998</td>
<td>-15.94%</td>
<td>-30.29%</td>
<td>-22.89%</td>
<td>-24.52%</td>
<td>-30.65%</td>
</tr>
<tr>
<td>1999</td>
<td>-11.77%</td>
<td>-26.81%</td>
<td>-15.82%</td>
<td>-20.49%</td>
<td>-27.14%</td>
</tr>
<tr>
<td>2000</td>
<td>-6.78%</td>
<td>-21.49%</td>
<td>-12.72%</td>
<td>-16.09%</td>
<td>-22.76%</td>
</tr>
<tr>
<td>2001</td>
<td>-7.99%</td>
<td>-22.06%</td>
<td>-12.62%</td>
<td>-17.53%</td>
<td>-23.26%</td>
</tr>
<tr>
<td>2002</td>
<td>-6.53%</td>
<td>-21.48%</td>
<td>-12.74%</td>
<td>-12.77%</td>
<td>-21.03%</td>
</tr>
<tr>
<td>2003</td>
<td>-4.99%</td>
<td>-21.21%</td>
<td>-12.90%</td>
<td>-11.33%</td>
<td>-22.04%</td>
</tr>
<tr>
<td>2004</td>
<td>-7.47%</td>
<td>-22.88%</td>
<td>-14.31%</td>
<td>-14.68%</td>
<td>-21.81%</td>
</tr>
<tr>
<td>2005</td>
<td>-7.76%</td>
<td>-22.13%</td>
<td>-15.07%</td>
<td>-15.17%</td>
<td>-21.72%</td>
</tr>
<tr>
<td>2006</td>
<td>-5.07%</td>
<td>-20.43%</td>
<td>-11.88%</td>
<td>-14.23%</td>
<td>-19.52%</td>
</tr>
<tr>
<td>2007</td>
<td>-7.46%</td>
<td>-20.66%</td>
<td>-12.68%</td>
<td>-14.23%</td>
<td>-19.84%</td>
</tr>
<tr>
<td>2008</td>
<td>-5.93%</td>
<td>-19.17%</td>
<td>-12.60%</td>
<td>-12.88%</td>
<td>-22.40%</td>
</tr>
<tr>
<td>2009</td>
<td>-2.09%</td>
<td>-11.45%</td>
<td>-5.69%</td>
<td>-9.85%</td>
<td>-16.95%</td>
</tr>
<tr>
<td>2010</td>
<td>-1.11%</td>
<td>-10.39%</td>
<td>-3.72%</td>
<td>-7.92%</td>
<td>-10.78%</td>
</tr>
<tr>
<td>2011</td>
<td>0.73%</td>
<td>-7.59%</td>
<td>-1.89%</td>
<td>-4.60%</td>
<td>-11.15%</td>
</tr>
<tr>
<td>2012</td>
<td>1.90%</td>
<td>-8.06%</td>
<td>-2.21%</td>
<td>-0.92%</td>
<td></td>
</tr>
</tbody>
</table>

APPENDIX IEA vs Emission inventories (reference to Figure 3.41)
<table>
<thead>
<tr>
<th>Year</th>
<th>vs IEA (%)</th>
<th>vs EDGAR (%)</th>
<th>vs BP (%)</th>
<th>vs EIA (%)</th>
<th>vs CDIAC (%)</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980</td>
<td>21.95%</td>
<td>-2.77%</td>
<td>-0.71%</td>
<td>10.53%</td>
<td>1.79%</td>
<td>6.16%</td>
</tr>
<tr>
<td>1981</td>
<td>24.49%</td>
<td>-1.39%</td>
<td>0.56%</td>
<td>6.98%</td>
<td>6.27%</td>
<td>7.38%</td>
</tr>
<tr>
<td>1982</td>
<td>23.55%</td>
<td>-2.52%</td>
<td>5.03%</td>
<td>9.35%</td>
<td>5.81%</td>
<td>8.24%</td>
</tr>
<tr>
<td>1983</td>
<td>20.41%</td>
<td>-4.73%</td>
<td>3.90%</td>
<td>8.33%</td>
<td>1.48%</td>
<td>5.88%</td>
</tr>
<tr>
<td>1984</td>
<td>19.05%</td>
<td>-4.46%</td>
<td>6.30%</td>
<td>2.15%</td>
<td>6.25%</td>
<td>5.86%</td>
</tr>
<tr>
<td>1985</td>
<td>19.02%</td>
<td>-4.94%</td>
<td>4.80%</td>
<td>0.68%</td>
<td>1.23%</td>
<td>4.16%</td>
</tr>
<tr>
<td>1986</td>
<td>15.65%</td>
<td>-6.54%</td>
<td>3.44%</td>
<td>0.87%</td>
<td>0.17%</td>
<td>2.72%</td>
</tr>
<tr>
<td>1987</td>
<td>9.83%</td>
<td>-4.64%</td>
<td>-2.15%</td>
<td>0.51%</td>
<td>-4.00%</td>
<td>-0.09%</td>
</tr>
<tr>
<td>1988</td>
<td>10.76%</td>
<td>-10.33%</td>
<td>-3.40%</td>
<td>-0.30%</td>
<td>-5.33%</td>
<td>-1.72%</td>
</tr>
<tr>
<td>1989</td>
<td>8.31%</td>
<td>-12.17%</td>
<td>-7.01%</td>
<td>-1.14%</td>
<td>-9.02%</td>
<td>-4.20%</td>
</tr>
<tr>
<td>1990</td>
<td>5.14%</td>
<td>-14.83%</td>
<td>-3.41%</td>
<td>-2.96%</td>
<td>-10.37%</td>
<td>-5.29%</td>
</tr>
<tr>
<td>1991</td>
<td>1.27%</td>
<td>-17.37%</td>
<td>-5.35%</td>
<td>-6.67%</td>
<td>-13.43%</td>
<td>-8.31%</td>
</tr>
<tr>
<td>1992</td>
<td>-0.81%</td>
<td>-19.17%</td>
<td>-8.56%</td>
<td>-9.82%</td>
<td>-16.29%</td>
<td>-10.93%</td>
</tr>
<tr>
<td>1993</td>
<td>-4.92%</td>
<td>-22.81%</td>
<td>-12.02%</td>
<td>-14.73%</td>
<td>-20.19%</td>
<td>-14.93%</td>
</tr>
<tr>
<td>1994</td>
<td>-5.33%</td>
<td>-22.79%</td>
<td>-10.84%</td>
<td>-15.70%</td>
<td>-20.42%</td>
<td>-15.01%</td>
</tr>
<tr>
<td>1995</td>
<td>-9.49%</td>
<td>-26.01%</td>
<td>-16.28%</td>
<td>-27.14%</td>
<td>-23.22%</td>
<td>-20.43%</td>
</tr>
<tr>
<td>1996</td>
<td>-10.41%</td>
<td>-27.06%</td>
<td>-19.07%</td>
<td>-18.08%</td>
<td>-26.62%</td>
<td>-20.25%</td>
</tr>
<tr>
<td>1997</td>
<td>-9.51%</td>
<td>-25.91%</td>
<td>-16.77%</td>
<td>-17.27%</td>
<td>-25.22%</td>
<td>-18.94%</td>
</tr>
<tr>
<td>1998</td>
<td>-11.80%</td>
<td>-26.85%</td>
<td>-19.09%</td>
<td>-20.80%</td>
<td>-27.23%</td>
<td>-21.15%</td>
</tr>
<tr>
<td>1999</td>
<td>-7.82%</td>
<td>-23.53%</td>
<td>-12.04%</td>
<td>-16.93%</td>
<td>-23.88%</td>
<td>-16.84%</td>
</tr>
<tr>
<td>2000</td>
<td>-3.17%</td>
<td>-18.45%</td>
<td>-9.34%</td>
<td>-12.84%</td>
<td>-19.77%</td>
<td>-12.71%</td>
</tr>
<tr>
<td>2001</td>
<td>-4.36%</td>
<td>-18.98%</td>
<td>-9.17%</td>
<td>-14.27%</td>
<td>-20.22%</td>
<td>-13.40%</td>
</tr>
<tr>
<td>2002</td>
<td>-2.32%</td>
<td>-17.94%</td>
<td>-8.82%</td>
<td>-8.85%</td>
<td>-17.48%</td>
<td>-11.08%</td>
</tr>
<tr>
<td>2003</td>
<td>-0.86%</td>
<td>-17.78%</td>
<td>-9.11%</td>
<td>-7.47%</td>
<td>-18.65%</td>
<td>-10.77%</td>
</tr>
<tr>
<td>2004</td>
<td>-3.20%</td>
<td>-19.32%</td>
<td>-10.36%</td>
<td>-10.75%</td>
<td>-18.21%</td>
<td>-12.37%</td>
</tr>
<tr>
<td>2005</td>
<td>-3.11%</td>
<td>-18.20%</td>
<td>-10.79%</td>
<td>-10.89%</td>
<td>-17.77%</td>
<td>-12.15%</td>
</tr>
<tr>
<td>2006</td>
<td>-0.20%</td>
<td>-16.34%</td>
<td>-7.36%</td>
<td>-9.83%</td>
<td>-15.38%</td>
<td>-9.82%</td>
</tr>
<tr>
<td>2007</td>
<td>-2.93%</td>
<td>-16.77%</td>
<td>-8.41%</td>
<td>-10.03%</td>
<td>-15.92%</td>
<td>-10.81%</td>
</tr>
<tr>
<td>2008</td>
<td>-0.66%</td>
<td>-14.64%</td>
<td>-7.70%</td>
<td>-8.00%</td>
<td>-18.05%</td>
<td>-9.81%</td>
</tr>
<tr>
<td>2009</td>
<td>4.08%</td>
<td>-5.87%</td>
<td>0.25%</td>
<td>-4.17%</td>
<td>-11.72%</td>
<td>-3.49%</td>
</tr>
<tr>
<td>2010</td>
<td>4.96%</td>
<td>-4.89%</td>
<td>2.19%</td>
<td>-2.27%</td>
<td>-5.30%</td>
<td>-1.06%</td>
</tr>
<tr>
<td>2011</td>
<td>6.85%</td>
<td>-1.98%</td>
<td>4.07%</td>
<td>1.19%</td>
<td>-5.75%</td>
<td>0.88%</td>
</tr>
<tr>
<td>2012</td>
<td>7.92%</td>
<td>-2.64%</td>
<td>3.56%</td>
<td>4.92%</td>
<td>3.44%</td>
<td></td>
</tr>
</tbody>
</table>

APPENDIX IPCC vs Emission inventories (reference to Figure 3.42)
### APPENDIX IV

<table>
<thead>
<tr>
<th></th>
<th>BKB</th>
<th>diff (%)</th>
<th>Other Bituminous Coal</th>
<th>diff (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCVIPCCLOW_CO2LOW</td>
<td>662.8</td>
<td>0.116</td>
<td>NCV IEA_CO2LOW</td>
<td>261311. 2</td>
</tr>
<tr>
<td></td>
<td>585</td>
<td>838</td>
<td></td>
<td>0.056</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2NET</td>
<td>740.3</td>
<td>0.117</td>
<td>NCV IEA_CO2NET</td>
<td>276201. 6</td>
</tr>
<tr>
<td></td>
<td>058</td>
<td>949</td>
<td></td>
<td>0.019</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2HIGH</td>
<td>827.6</td>
<td>0.060</td>
<td>NCVIPCCLOW_CO2LOW</td>
<td>281634. 2</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>818</td>
<td></td>
<td>0.033</td>
</tr>
<tr>
<td>NCV IEA_CO2LOW</td>
<td>877.9</td>
<td>0.035</td>
<td>NCV IEA_CO2HIGH</td>
<td>291091. 9</td>
</tr>
<tr>
<td></td>
<td>582</td>
<td></td>
<td></td>
<td>0.022</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2LOW</td>
<td>908.6</td>
<td>0.079</td>
<td>NCVIPCCLOW_CO2NET</td>
<td>297682. 6</td>
</tr>
<tr>
<td></td>
<td>868</td>
<td>071</td>
<td></td>
<td>0.053</td>
</tr>
<tr>
<td>NCV IEA_CO2NET</td>
<td>980.5</td>
<td>0.035</td>
<td>NCVIPCCLOW_CO2HIGH</td>
<td>313731</td>
</tr>
<tr>
<td></td>
<td>375</td>
<td></td>
<td></td>
<td>0.163</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2NET</td>
<td>1014.</td>
<td>0.080</td>
<td>NCVIPCCNET_CO2LOW</td>
<td>365133. 7</td>
</tr>
<tr>
<td></td>
<td>856</td>
<td>144</td>
<td></td>
<td>0.056</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCV IEA_CO2HIGH</td>
<td>1096.</td>
<td>0.035</td>
<td>NCVIPCCNET_CO2NET</td>
<td>385940. 3</td>
</tr>
<tr>
<td></td>
<td>191</td>
<td></td>
<td></td>
<td>0.053</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2HIGH</td>
<td>1134.</td>
<td>0.238</td>
<td>NCVIPCCNET_CO2HIGH</td>
<td>406746. 8</td>
</tr>
<tr>
<td></td>
<td>557</td>
<td>133</td>
<td></td>
<td>0.061</td>
</tr>
<tr>
<td>NCVIPCCHIGH_CO2LOW</td>
<td>1404.</td>
<td>0.116</td>
<td>NCVIPCCHIGH_CO2LOW</td>
<td>431650. 4</td>
</tr>
<tr>
<td></td>
<td>733</td>
<td>838</td>
<td></td>
<td>0.056</td>
</tr>
<tr>
<td>NCVIPCCHIGH_CO2NET</td>
<td>1568.</td>
<td>0.117</td>
<td>NCVIPCCHIGH_CO2NET</td>
<td>456247. 2</td>
</tr>
<tr>
<td></td>
<td>86</td>
<td>949</td>
<td></td>
<td>0.053</td>
</tr>
<tr>
<td>NCVIPCCHIGH_CO2HIGH</td>
<td>1753.</td>
<td></td>
<td>NCVIPCCHIGH_CO2HIGH</td>
<td>480844</td>
</tr>
<tr>
<td></td>
<td>905</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coke Oven Coke</td>
<td>diff (%)</td>
<td></td>
<td>Sub-Bituminous Coal</td>
<td>diff (%)</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2LOW</td>
<td>10859.</td>
<td>0.118</td>
<td>NCVIPCCLOW_CO2LOW</td>
<td>85322.8 8</td>
</tr>
<tr>
<td></td>
<td>.13</td>
<td>077</td>
<td></td>
<td>0.035</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2NET</td>
<td>12141.</td>
<td>0.004</td>
<td>NCVIPCCLOW_CO2NET</td>
<td>88356.9 9</td>
</tr>
<tr>
<td></td>
<td>.35</td>
<td>855</td>
<td></td>
<td>0.040</td>
</tr>
<tr>
<td>NCV IEA CO2LOW</td>
<td>12200.</td>
<td>0</td>
<td>NCV IEA CO2LOW</td>
<td>91942.7 6</td>
</tr>
<tr>
<td></td>
<td>.3</td>
<td></td>
<td></td>
<td>0.525</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2LOW</td>
<td>12200.</td>
<td>0.070</td>
<td>NCVIPCCNET_CO2LOW</td>
<td>140226. 3</td>
</tr>
<tr>
<td></td>
<td>.3</td>
<td>922</td>
<td></td>
<td>0.035</td>
</tr>
<tr>
<td>NCVIPCCHIGH_CO2LOW</td>
<td>13065.</td>
<td>0.033</td>
<td>NCVIPCCHIGH_CO2LOW</td>
<td>140226. 3</td>
</tr>
<tr>
<td></td>
<td>.57</td>
<td>479</td>
<td></td>
<td>0.035</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2HIGH</td>
<td>13502.</td>
<td>0.010</td>
<td>NCV IEA_CO2NET</td>
<td>145212. 8</td>
</tr>
<tr>
<td></td>
<td>.99</td>
<td>211</td>
<td></td>
<td>0.040</td>
</tr>
<tr>
<td>NCV IEA CO2NET</td>
<td>13640.</td>
<td>0</td>
<td>NCVIPCCNET_CO2NET</td>
<td>145212. 8</td>
</tr>
<tr>
<td></td>
<td>.88</td>
<td></td>
<td></td>
<td>0.040</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2NET</td>
<td>13640.88</td>
<td>0.070</td>
<td>NCV IEA_CO2HIGH</td>
<td>151105.9</td>
</tr>
<tr>
<td>------------------</td>
<td>---------</td>
<td>-------</td>
<td>----------------</td>
<td>---------</td>
</tr>
<tr>
<td>NCVIPCCHIGH_CO2NET</td>
<td>14608.31</td>
<td>0.038</td>
<td>NCVIPCCNET_CO2HIGH</td>
<td>151105.9</td>
</tr>
<tr>
<td>NCV IEA_CO2HIGH</td>
<td>15170.69</td>
<td>0</td>
<td>NCVIPCCHIGH_CO2LOW</td>
<td>192903.9</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2HIGH</td>
<td>15170.69</td>
<td>0.070</td>
<td>NCVIPCCHIGH_CO2NET</td>
<td>199763.6</td>
</tr>
<tr>
<td>NCVIPCCHIGH_CO2HIGH</td>
<td>16246.63</td>
<td></td>
<td>NCVIPCCHIGH_CO2HIGH</td>
<td>207870.6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Coking Coal diff (%)</th>
<th>Biodiesels diff (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCVIPCCLOW_CO2LOW</td>
<td>17968.87</td>
</tr>
<tr>
<td>NCV IEA_CO2LOW</td>
<td>18180.75</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2NET</td>
<td>19471.42</td>
</tr>
<tr>
<td>NCV IEA_CO2NET</td>
<td>19701.02</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2HIGH</td>
<td>20788.72</td>
</tr>
<tr>
<td>NCV IEA_CO2HIGH</td>
<td>21033.86</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2LOW</td>
<td>21113.42</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2NET</td>
<td>22878.92</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2HIGH</td>
<td>23209.79</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2LOW</td>
<td>24426.75</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2NET</td>
<td>25150.58</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2HIGH</td>
<td>26852.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lignite diff (%)</th>
<th>Biogases diff (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCVIPCCLOW_CO2LOW</td>
<td>3388.073</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2NET</td>
<td>3764.525</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2HIGH</td>
<td>4286.341</td>
</tr>
<tr>
<td>NCV IEA_CO2LOW</td>
<td>5880.463</td>
</tr>
<tr>
<td>NCV IEA_CO2NET</td>
<td>6533.847</td>
</tr>
<tr>
<td>----------------</td>
<td>---------</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2LOW</td>
<td>7330.558</td>
</tr>
<tr>
<td>NCV IEA_CO2HIGH</td>
<td>7439.529</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2NET</td>
<td>8145.064</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2HIGH</td>
<td>9274.083</td>
</tr>
<tr>
<td>NCVIPCHIGH_CO2LOW</td>
<td>13305.89</td>
</tr>
<tr>
<td>NCVIPCHIGH_CO2NET</td>
<td>14784.32</td>
</tr>
<tr>
<td>NCVIPCHHIGH_CO2HIGH</td>
<td>16833.63</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Biogas Oil</th>
<th>diff (%)</th>
<th>Crude Oil</th>
<th>diff (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCVIPCCLOW_CO2LOW</td>
<td>311.68 92</td>
<td>0.183 946</td>
<td>NCVIPCCLOW_CO2LOW</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2NET</td>
<td>369.02 33</td>
<td>0.190 678</td>
<td>NCVIPCCLOW_CO2NET</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2HIGH</td>
<td>439.38 79</td>
<td>0.397 879</td>
<td>NCVIPCCLOW_CO2HIGH</td>
</tr>
<tr>
<td>NCV IEA_CO2LOW</td>
<td>614.21 11</td>
<td>0.007 463</td>
<td>NCV IEA_CO2LOW</td>
</tr>
<tr>
<td>NCVIEA_CO2NET</td>
<td>618.79 47</td>
<td>0.175 177</td>
<td>NCV IEA_CO2NET</td>
</tr>
<tr>
<td>NCV IEA_CO2HIGH</td>
<td>727.19 3</td>
<td>0.007 463</td>
<td>NCVIEA_CO2NET</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2LOW</td>
<td>732.61 98</td>
<td>0.181 858</td>
<td>NCV IEA_CO2NET</td>
</tr>
<tr>
<td>NCV IEA_CO2HIGH</td>
<td>865.85 27</td>
<td>0.007 463</td>
<td>NCVIEA_CO2NET</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2HIGH</td>
<td>872.31 43</td>
<td>0.418 743</td>
<td>NCVIPCCNET_CO2HIGH</td>
</tr>
<tr>
<td>NCVIPCHIGH_CO2LOW</td>
<td>1237.589</td>
<td>0.183 946</td>
<td>NCV IEA_CO2HIGH</td>
</tr>
<tr>
<td>NCVIPCHIGH_CO2NET</td>
<td>1465.24</td>
<td>0.190 678</td>
<td>NCVIPCHHIGH_CO2NET</td>
</tr>
<tr>
<td>NCVIPCHHIGH_CO2HIGH</td>
<td>1744.629</td>
<td></td>
<td>NCVIPCHHIGH_CO2HIGH</td>
</tr>
<tr>
<td>Blast Furnace Gas</td>
<td>Diff (%)</td>
<td>Gas Works</td>
<td>Diff (%)</td>
</tr>
<tr>
<td>------------------</td>
<td>----------</td>
<td>-----------</td>
<td>----------</td>
</tr>
<tr>
<td>NCV IEA CO2LOW</td>
<td>53208.29</td>
<td>0</td>
<td>34.49488</td>
</tr>
<tr>
<td>NCVIPCCNET C O2LOW</td>
<td>53208.29</td>
<td>0</td>
<td>34.49488</td>
</tr>
<tr>
<td>NCVIPCCLOW C O2LOW</td>
<td>53208.29</td>
<td>0</td>
<td>34.49488</td>
</tr>
<tr>
<td>NCVIPCHIGH C O2LOW</td>
<td>53208.29</td>
<td>0.187</td>
<td>34.49488</td>
</tr>
<tr>
<td>NCV IEA CO2NET</td>
<td>63169.66</td>
<td>0</td>
<td>41.06093</td>
</tr>
<tr>
<td>NCVIPCCNET C O2NET</td>
<td>63169.66</td>
<td>0</td>
<td>41.06093</td>
</tr>
<tr>
<td>NCVIPCCLOW C O2NET</td>
<td>63169.66</td>
<td>0.033</td>
<td>41.06093</td>
</tr>
<tr>
<td>NCVIPCHIGH C O2NET</td>
<td>63169.66</td>
<td>0.184</td>
<td>41.06093</td>
</tr>
<tr>
<td>NCV IEA CO2HIGH</td>
<td>74831.75</td>
<td>0</td>
<td>50.03144</td>
</tr>
<tr>
<td>Energy and Emissions Accounting: The case of Intra-Regional Industrial Shifts in SE Asia</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-----------------------------------------------</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| NCVIPCCNET_C O2HIGH | 74831.75 | 0 | NCVIPCCNET_C O2HIGH | 50.03144 | 19290.39 |
| NCVIPCCLOW_C O2HIGH | 74831.75 | 0 | NCVIPCCLOW_C O2HIGH | 50.03144 | 19976.36 |
| NCVIPCHIGH_ CO2HIGH | 74831.75 | 0 | NCVIPCHIGH_ CO2HIGH | 50.03144 | 19290.39 |

<table>
<thead>
<tr>
<th>Coke oven</th>
<th>Gas</th>
<th>diff (%)</th>
<th>Gas/diesel oil excl. biofuels</th>
<th>diff (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCV IEA CO2LOW</td>
<td>1868.686</td>
<td>0</td>
<td>NCVIPCCLOW_C O2LOW</td>
<td>19325.5</td>
</tr>
<tr>
<td>NCVIPCCNET_C O2LOW</td>
<td>1868.686</td>
<td>0</td>
<td>NCVIPCCLOW_C O2NET</td>
<td>193237.2</td>
</tr>
<tr>
<td>NCVIPCCLOW_C O2LOW</td>
<td>1868.686</td>
<td>0</td>
<td>NCVIPCCLOW_C O2HIGH</td>
<td>195062.6</td>
</tr>
<tr>
<td>NCVIPCHIGH_ CO2LOW</td>
<td>1868.686</td>
<td>0.190349</td>
<td>NCVIPCCNET_C O2LOW</td>
<td>196642.4</td>
</tr>
<tr>
<td>NCV IEA CO2NET</td>
<td>2224.388</td>
<td>0</td>
<td>NCV IEA CO2LOW</td>
<td>198014.3</td>
</tr>
<tr>
<td>NCVIPCCNET_C O2NET</td>
<td>2224.388</td>
<td>0</td>
<td>NCVIPCHIGH_ CO2LOW</td>
<td>198014.3</td>
</tr>
<tr>
<td>NCVIPCCLOW_C O2NET</td>
<td>2224.388</td>
<td>0</td>
<td>NCVIPCCLOW_C O2NET</td>
<td>200705.3</td>
</tr>
<tr>
<td>NCVIPCHIGH_ CO2NET</td>
<td>2224.388</td>
<td>0.218468</td>
<td>NCV IEA CO2NET</td>
<td>202105.5</td>
</tr>
<tr>
<td>NCV IEA CO2HIGH</td>
<td>2710.346</td>
<td>0</td>
<td>NCVIPCHIGH_ CO2NET</td>
<td>202105.5</td>
</tr>
<tr>
<td>NCVIPCCNET_C O2HIGH</td>
<td>2710.346</td>
<td>0</td>
<td>NCVIPCCNET_C O2HIGH</td>
<td>202601.3</td>
</tr>
<tr>
<td>NCVIPCCLOW_C O2HIGH</td>
<td>2710.346</td>
<td>0</td>
<td>NCV IEA CO2HIGH</td>
<td>204014.8</td>
</tr>
<tr>
<td>NCVIPCHIGH_ CO2HIGH</td>
<td>2710.346</td>
<td>0</td>
<td>NCVIPCHIGH_ CO2HIGH</td>
<td>204014.8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Kerosene</th>
<th>diff (%)</th>
<th>Municipal Waste (non-renewable)</th>
<th>diff (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCVIPCCLOW_C O2LOW</td>
<td>4625.095 0.0258 25</td>
<td>NCV IEA CO2LOW</td>
<td>941.08 92</td>
</tr>
<tr>
<td>NCVIPCCLOW_C O2NET</td>
<td>4744.538 0.0235 66</td>
<td>NCVIPCCNET_C O2LOW</td>
<td>941.08 92</td>
</tr>
<tr>
<td>NCVIPCCNET_C O2LOW</td>
<td>4856.349 0.0113 38</td>
<td>NCVIPCCLOW_C O2LOW</td>
<td>941.08 92</td>
</tr>
<tr>
<td>NCV IEA_CO2LOW</td>
<td>4911.41</td>
<td>0.0052</td>
<td>NCV IPCCHIGH_C O2LOW</td>
</tr>
<tr>
<td>NCVIPCCLOW_C O2HIGH</td>
<td>4936.973</td>
<td>0.0037</td>
<td>44</td>
</tr>
<tr>
<td>NCVIPCCHIGH_C O2LOW</td>
<td>4955.459</td>
<td>0.0053</td>
<td>08</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2NET</td>
<td>4981.764</td>
<td>0.0113</td>
<td>38</td>
</tr>
<tr>
<td>NCV IEA_CO2NET</td>
<td>5038.247</td>
<td>0.0089</td>
<td>69</td>
</tr>
<tr>
<td>NCVIPCCHIGH_C O2NET</td>
<td>5083.433</td>
<td>0.0197</td>
<td>48</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2HIGH</td>
<td>5183.822</td>
<td>0.0113</td>
<td>38</td>
</tr>
<tr>
<td>NCV IEA_CO2HIGH</td>
<td>5242.595</td>
<td>0.0089</td>
<td>69</td>
</tr>
<tr>
<td>NCVIPCCHIGH_C O2HIGH</td>
<td>5289.614</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCLOW_C O2LOW</td>
<td>4299.922</td>
<td>0.0243</td>
<td>51</td>
</tr>
<tr>
<td>NCVIPCCLOW_C O2NET</td>
<td>44046.927</td>
<td>0.0307</td>
<td>05</td>
</tr>
<tr>
<td>NCV IEA_CO2LOW</td>
<td>45398.72</td>
<td>0</td>
<td>NCVIPCCNET_CO2LOW</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2LOW</td>
<td>45398.72</td>
<td>0.0086</td>
<td>49</td>
</tr>
<tr>
<td>NCVIPCCLOW_C O2HIGH</td>
<td>45791.37</td>
<td>0.0155</td>
<td>67</td>
</tr>
<tr>
<td>NCV IEA_CO2NET</td>
<td>46504.21</td>
<td>0</td>
<td>NCVIPCCHIGH_C O2LOW</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2NET</td>
<td>46504.21</td>
<td>0.0396</td>
<td>2</td>
</tr>
<tr>
<td>NCV IEA_CO2HIGH</td>
<td>48346.69</td>
<td>0</td>
<td>NCV IEA_CO2NET</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2HIGH</td>
<td>48346.69</td>
<td>0.0363</td>
<td>02</td>
</tr>
<tr>
<td>NCVIPCCHIGH_C O2LOW</td>
<td>50101.76</td>
<td>0.0243</td>
<td>51</td>
</tr>
<tr>
<td>NCVIPCCHIGH_C O2NET</td>
<td>51321.77</td>
<td>0.0396</td>
<td>2</td>
</tr>
<tr>
<td>NCVIPCCHIGH_C O2HIGH</td>
<td>53355.13</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Lubricants | diff (%) | Natural Gas |
| NCVIPCCLOW_C O2LOW | 6465.798 | 85322.88 | 0.03556 | NCVIPCCLOW_C O2LOW | 66131 | 0 |
| NCVIPCCLOW_C O2NET | 6591.697 | 88356.99 | 0.040583 | NCVIPCCLOW_C O2NET | 66131 | 0 |
| NCV IEA_CO2LOW | 6762.559 | 91942.76 | 0.525148 | NCV IEA_CO2LOW | 66131 | 0 |
| NCVIPCCNET_CO 2LOW | 7758.957 | 140226.3 | 0 | NCVIPCCNET_CO 2LOW | 66131 | 0.033149 |
| NCVIPCCLOW_C O2HIGH | 7910.036 | 140226.3 | 0.03556 | NCVIPCCLOW_C O2HIGH | 68323.19 | 0 |
| NCV IEA_CO2NET | 8106.373 | 145212.8 | 0 | NCV IEA_CO2NET | 68323.19 | 0 |
| NCVIPCCNET_CO 2NET | 8115.071 | 145212.8 | 0.040583 | NCVIPCCNET_CO 2NET | 68323.19 | 0 |
| NCV IEA_CO2HIGH | 8164.276 | 151105.9 | 0 | NCV IEA_CO2HIGH | 68323.19 | 0.039216 |
| NCVIPCCNET_CO 2HIGH | 8264.217 | 151105.9 | 0.276614 | NCVIPCCNET_CO 2HIGH | 71002.53 | 0 |
| NCVIPCCHIGH_C O2LOW | 8323.247 | 192903.9 | 0.03556 | NCVIPCCHIGH_C O2LOW | 71002.53 | 0 |
| NCVIPCCHIGH_C O2NET | 8478.432 | 199763.6 | -1 | NCVIPCCHIGH_C O2NET | 71002.53 | 0 |
| NCVIPCCHIGH_C O2HIGH | 8538.993 | | | NCVIPCCHIGH_C O2HIGH | 71002.53 | |

<p>| Motor | Gasoline | diff (%) | Natural Gas | Liquids | diff (%) |
|-------|----------|----------|-------------|----------|
| NCVIPCCLOW_C O2LOW | 45135.11 | 0.026667 | NCVIPCCLOW_C O2LOW | 13524.08 | 0.051296 |
| NCVIPCCLOW_C O2NET | 46338.71 | 0.015279 | NCV IEA_CO2LOW | 14217.81 | 0.027955 |
| NCVIPCCNET_CO 2LOW | 47046.71 | 0.011287 | NCVIPCCNET_CO 2LOW | 14615.26 | 0.018984 |
| NCV IEA_CO2LOW | 47577.71 | 0 | NCVIPCCLOW_C O2NET | 14892.73 | 0.041317 |
| NCVIPCCHIGH_C O2LOW | 47577.71 | 0.015208 | NCVIPCCHIGH_C O2LOW | 15508.05 | 0.009583 |
| NCVIPCCNET_CO 2LOW | 48301.29 | 0.01059 | NCV IEA_CO2NET | 15656.66 | 0.027955 |
| NCVIPCCLOW_C O2HIGH | 48812.78 | 0.00069 | 0.012058 | NCVIPCCNET_CO 2NET | 16094.34 | 0.014702 |
| NCV IEA_CO2NET | 48846.45 | 0 | NCVIPCCLOW_C O2HIGH | 16330.96 | 0.045712 |
| NCVIPCCHIGH_C O2NET | 48846.45 | 0.041634 | NCVIPCCHIGH_C O2NET | 17077.48 | 0.00534 |
| NCVIPCCNET_CO 2HIGH | 50880.15 | 0.011287 | NCV IEA_CO2HIGH | 17168.67 | 0.027955 |</p>
<table>
<thead>
<tr>
<th>Source</th>
<th>Code</th>
<th>Unit</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCV IEA CO2HIGH</td>
<td>51454 .41</td>
<td>0</td>
<td>NCVIPCCNET_CO 2HIGH</td>
<td>17648.62</td>
<td>0.061 086</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCHIGH_C O2HIGH</td>
<td>51454 .41</td>
<td></td>
<td>NCVIPCCHIGH_C O2HIGH</td>
<td>18726.7</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source</th>
<th>Code</th>
<th>Unit</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCVIEA CO2LOW</td>
<td>191</td>
<td>24076.95</td>
<td>0</td>
<td>NCVIPCCNET CO 2LOW</td>
<td>79468 2.5</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>NCVIEA CO2NET</td>
<td>24076.95</td>
<td>0</td>
<td>NCVIPCCNET CO 2NET</td>
<td>79468 2.5</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCNET CO 2LOW</td>
<td>24076.95</td>
<td>0</td>
<td>NCVIPCCNET CO 2LOW</td>
<td>79468 2.5</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCNET CO 2HIGH</td>
<td>24466.4</td>
<td>0.008 718</td>
<td>NCVIPCCNET CO 2LOW</td>
<td>79468 2.5</td>
<td>0.17</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIEA CO2HIGH</td>
<td>24679.71</td>
<td>0</td>
<td>NCVIEA CO2HIGH</td>
<td>92977 8.5</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCNET CO 2HIGH</td>
<td>24679.71</td>
<td>0.006 759</td>
<td>NCVIPCCNET CO 2HIGH</td>
<td>92977 8.5</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCNET CO 2LOW</td>
<td>24846.53</td>
<td>0.025 035</td>
<td>NCVIPCCNET CO 2HIGH</td>
<td>92977 8.5</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCNET CO 2HIGH</td>
<td>25468.56</td>
<td></td>
<td>NCVIPCCNET CO 2HIGH</td>
<td>92977 8.5</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source</th>
<th>Code</th>
<th>Unit</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCVIEA CO2LOW</td>
<td>12681.16</td>
<td>0.015 235</td>
<td>NCVIPCCLOW CO 2LOW</td>
<td>43896 .31</td>
<td>0.012 632</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCLOW CO 2NET</td>
<td>12874.36</td>
<td>0.015 007</td>
<td>NCVIEA CO2LOW</td>
<td>44450 .79</td>
<td>0.029 106</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCLOW CO 2HIGH</td>
<td>13067.57</td>
<td>0.151 846</td>
<td>NCVIPCCNET CO 2LOW</td>
<td>45744 .57</td>
<td>0.022 222</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIEA CO2LOW</td>
<td>15051.82</td>
<td>0.005</td>
<td>NCVIPCHC_O2LOW</td>
<td>46761 .12</td>
<td>0.121 808</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCNET CO 2LOW</td>
<td>15127.08</td>
<td>0.010 185</td>
<td>NCVIPCCLOW CO 2NET</td>
<td>52457 0.012 632</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIEA CO2NET</td>
<td>15281.14</td>
<td>0.005</td>
<td>NCVIEA CO2NET</td>
<td>53119 .61</td>
<td>0.029 106</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Energy and Emissions Accounting: The case of Intra-Regional Industrial Shifts in SE Asia

<table>
<thead>
<tr>
<th>NCVIPCCNET_CO2NET</th>
<th>15357.55</th>
<th>0.009</th>
<th>NCVIPCCNET_CO2NET</th>
<th>54665.72</th>
<th>0.022</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCV IEA CO2HIGH</td>
<td>15510.46</td>
<td>0.005</td>
<td>NCVIPCCHIGH_CO2NET</td>
<td>55880.51</td>
<td>0.124</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2HIGH</td>
<td>15588.02</td>
<td>0.163</td>
<td>NCVIPCCLOW_CO2HIGH</td>
<td>62839.11</td>
<td>0.012</td>
</tr>
<tr>
<td>NCVIPCHIGH_CO2LOW</td>
<td>18137.44</td>
<td>0.015</td>
<td>NCV IEA CO2HIGH</td>
<td>63632.87</td>
<td>0.029</td>
</tr>
<tr>
<td>NCVIPCHIGH_CO2NET</td>
<td>18413.78</td>
<td>0.015</td>
<td>NCVIPCCNET_CO2HIGH</td>
<td>65484.97</td>
<td>0.022</td>
</tr>
<tr>
<td>NCVIPCHIGH_CO2HIGH</td>
<td>18690.11</td>
<td>0.163</td>
<td>NCVIPCHIGH_CO2HIGH</td>
<td>66940.19</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Paraffin Waxes</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NCVIPCCLOW_CO2LOW</td>
<td>746.8091</td>
<td>0.015</td>
<td>235</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2NET</td>
<td>758.1871</td>
<td>0.015</td>
<td>007</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2HIGH</td>
<td>769.5651</td>
<td>0.151</td>
<td>846</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCV IEA CO2LOW</td>
<td>886.4203</td>
<td>0.005</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCNET_CO2LOW</td>
<td>890.8524</td>
<td>0.010</td>
<td>185</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCV IEA CO2NET</td>
<td>899.9253</td>
<td>0.005</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCNET_CO2NET</td>
<td>904.425</td>
<td>0.009</td>
<td>957</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCV IEA CO2HIGH</td>
<td>913.4304</td>
<td>0.005</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCNET_CO2HIGH</td>
<td>917.9975</td>
<td>0.163</td>
<td>551</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCHIGH_CO2LOW</td>
<td>1068.136</td>
<td>0.015</td>
<td>235</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCHIGH_CO2NET</td>
<td>1084.41</td>
<td>0.015</td>
<td>007</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCHIGH_CO2HIGH</td>
<td>1100.684</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Petroleum Coke</th>
<th>diff (%)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NCVIPCCLOW_CO2LOW</td>
<td>25311</td>
<td>0.077</td>
<td>441</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCV IEA CO2LOW</td>
<td>27271.11</td>
<td>0.015</td>
<td>625</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCNET_CO2LOW</td>
<td>27697.22</td>
<td>0.074</td>
<td>789</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2NET</td>
<td>29768.67</td>
<td>0.077</td>
<td>441</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Dimitrios Pappas
<table>
<thead>
<tr>
<th>Description</th>
<th>Value 1</th>
<th>Value 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCV IEA_CO2NET</td>
<td>32073.98</td>
<td>0.015</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2NET</td>
<td>32575.14</td>
<td>0.077</td>
</tr>
<tr>
<td>NCVIPCCLOW_CO2HIGH</td>
<td>35111.76</td>
<td>0.016</td>
</tr>
<tr>
<td>NCVIPCCHIGH_CO2LOW</td>
<td>35708.11</td>
<td>0.059</td>
</tr>
<tr>
<td>NCV IEA_CO2HIGH</td>
<td>37830.85</td>
<td>0.015</td>
</tr>
<tr>
<td>NCVIPCCNET_CO2HIGH</td>
<td>38421.96</td>
<td>0.093</td>
</tr>
<tr>
<td>NCVIPCCHIGH_CO2NET</td>
<td>41996.87</td>
<td>0.179</td>
</tr>
<tr>
<td>NCVIPCCHIGH_CO2HIGH</td>
<td>49534.77</td>
<td></td>
</tr>
</tbody>
</table>