

Investigating the Relationship between Economic Activity and Energy Intensity of Low- to High-Income Countries using Spatial Decomposition

Meta Mouy, Neil Stephen Lopez*

Mechanical Engineering Department, De La Salle University, Manila, Philippines
 neil.lopez@dlsu.edu.ph

Drivers to CO₂ emissions are well-studied in literature. However, previous studies had focused mostly on individual countries or regions, and low to middle income countries are seldom investigated on. In this present work, the contributions of drivers to CO₂ emissions, particularly economic activity and energy intensity, of 195 countries grouped by income level are calculated and compared using the spatial logarithmic mean Divisia index (LMDI) method. As different countries belong to various income levels, they can be assumed to represent the future of other countries. Thus, the analysis can produce useful insights to guide the strategic planning of developing countries. Results show that countries generally tend to reduce their energy intensity as their economic activity increases, and this is evident across all income levels. Moreover, outliers such as China, Japan and the United States are seen from the data, and their unique characteristics are explored. Most interestingly, it is observed that the opportunity to decrease energy intensity decreases as the income levels rise, and this is most challenging for the lower-middle income countries. The results of this study suggest that the lower-middle income countries would mostly require international support to meet their climate change mitigation targets, and this would require further investigation and validation from other researchers.

1. Introduction

Global warming has been regarded as the most important challenge and core problem faced by humans to obtain sustainable development of the socioeconomic system (Zhu et al., 2019). In recent years, the world has experienced rapid economic and population growth with high energy consumption and emissions. In response to this concern, most of the countries have endeavored to advocate the international agreement on climate change by promoting energy conservation and carbon emissions reduction. There are several studies investigating carbon emission drivers across countries or regions using the logarithmic mean Divisia index (LMDI) decomposition analysis method. Earlier research directly decomposed the difference in carbon emissions between two regions or countries (Ang et al., 1999). Nevertheless, when the number of compared countries increased, it became computationally inefficient to decompose every single country. Afterwards, studies attempted to choose one region or country as a benchmark, where the differences in CO₂ emissions were calculated from (Ang et al., 2016).

One popular approach to examining drivers of global carbon emissions across countries and/or regions is the multi-regional (M-R) spatial decomposition model, proposed by Ang (2015). It can be used to identify factors which cause differences in CO₂ emissions among countries or among various regions within the same country. With this approach, a hypothetical benchmark country/region is created from the average of all countries/regions involved in the study. Most importantly, this model significantly decreases the decomposition cases, avoiding subjectivity in basic area options, achieving sophisticated circularity, and generating valuable information on emissions mitigation (Yuxiang et al., 2020).

The study of Li et al. (2017) utilized the M-R spatial decomposition model to compare the carbon emissions performance of China's 30 regions. The authors found that the gap in carbon emissions across China's 30 regions have been growing significantly, where economic activity was the primary contributing factor. Moreover, Cheng et al. (2021) adopted the spatial decomposition analysis methodology to understand the behaviour of

Chinese provinces which exceeded the average national emissions. On the other hand, Yuan et al. (2019) adopted spatial decomposition analysis to explore driving forces to household carbon emissions in China. The authors constructed a hypothetical province as the benchmark. The results showed that the energy intensity, income, and population growth were the major contributors to provincial differences in household carbon emissions. Furthermore, Lisaba and Lopez (2021) utilized spatial decomposition to benchmark carbon mitigating policies across Southeast Asian countries; Lopez et al. (2020) used the same methodology to decompose drivers to household energy use in Metro Manila, Philippines; while Nnadir et al. (2020) focused on emissions from the transport sector. In both, and as in most studies, economic activity and energy intensity were both identified as key contributing factors in emissions mitigation.

In this regard, while the M-R spatial decomposition technique has been able to show its effectiveness in benchmarking drivers across countries and regions, the novelty of this present paper is the comparison of drivers across different income levels. Particularly, this paper analyses the relationship between economic activity and energy intensity of various countries belonging to different income groups, as determined by the World Bank (2020). This study hypothesizes that since various countries belong to different income levels, they can represent the future development pathways of other countries. Thus, insights arising from this work can be used to plan and strategize the growth trajectory of developing economies, and to allow benchmarking between high-income countries. However, it has to be noted that analyses from this work are based on a macroeconomic perspective. More detailed microeconomic studies would be required to craft specific policy recommendations from this work.

2. Method and data

Income and population data of countries were extracted from the World Bank (2020), while energy-related data were extracted from the International Energy Agency. Particularly, this study utilized data from the year 2014, as it was deemed to be the most complete recent dataset available, considering that all 195 countries had to be included in the analysis.

The benchmark country for spatial decomposition was taken to be average of all countries within each income level (i.e. low, low-middle, high-middle and high). The spatial decomposition was performed per income level, and each country was compared to it corresponding benchmark. While several indices make up the identity function in Eq 1, only two factors will be analysed thoroughly in this paper, i.e. economic activity (Δact) and energy intensity (Δint). Their definitions are presented in Table 1.

Table 1: Summarizes the definitions of each variable used.

Variable	Definition
(Δact): Economic activity effect	Refers to the effect of gross domestic product (GDP) growth to emissions.
(Δint): Energy intensity effect	Refers to the effect of energy consumption per GDP (ktoe/USD) to emissions (tCO ₂).

To perform index decomposition analysis, the identity function below will be used.

$$C = population \times \frac{GDP}{population} \times \frac{energy}{GDP} \times \frac{energy_i}{energy} \times \frac{emission_i}{energy_i} = pop \times act \times int \times str \times emf \quad (1)$$

where C refers to carbon emissions (tCO₂); GDP refers to gross domestic product; energy_i refers to the energy consumption from fuel type i; and emission_i/energy_i refers to the carbon intensity of fuel type i. Furthermore, the equivalent effects for each term are shown on the righthand side of Eq. 1, where pop refers to the population effect; act refers to the economic activity effect; int refers to the energy intensity effect; str refers to the energy structure effect; and emf refers to the emission factor or carbon intensity effect.

Moreover, the following logarithmic functions (see Eqs 2 and 3) are utilized to calculate the individual effects. For brevity, only the functions for economic activity (Δact) and energy intensity (Δint) are shown, as they are the interest of this study. The logarithmic functions below offer complete decomposition, unlike other decomposition approaches which generate unexplained residuals.

$$\Delta act = \frac{C^R - C^\mu}{\ln C^R - \ln C^\mu} \ln \left(\frac{act^R}{act^\mu} \right) \quad (2)$$

$$\Delta int = \frac{C^R - C^\mu}{\ln C^R - \ln C^\mu} \ln \left(\frac{int^R}{int^\mu} \right) \quad (3)$$

The variable R refers to a specific country. As seen above, in spatial decomposition analysis, the comparison is between countries instead of between time periods. The variable μ refers to the hypothetical benchmark country, and is the average of all countries within each income group in this study.

3. Results and discussion

In spatial decomposition, the positive and negative values of different factors have different meanings than in traditional temporal decomposition. For instance, Δ_{act} is observed to be negative in some countries, e.g. Eritrea, Congo and Ethiopia, but it is positive in some, e.g. South Sudan and Yemen (see Figure 1). This indicates that South Sudan and Yemen have increased emissions due to economic activity as compared to the average. On the other hand, Eritrea, Congo and Ethiopia have less emissions due to economic activity than the average.

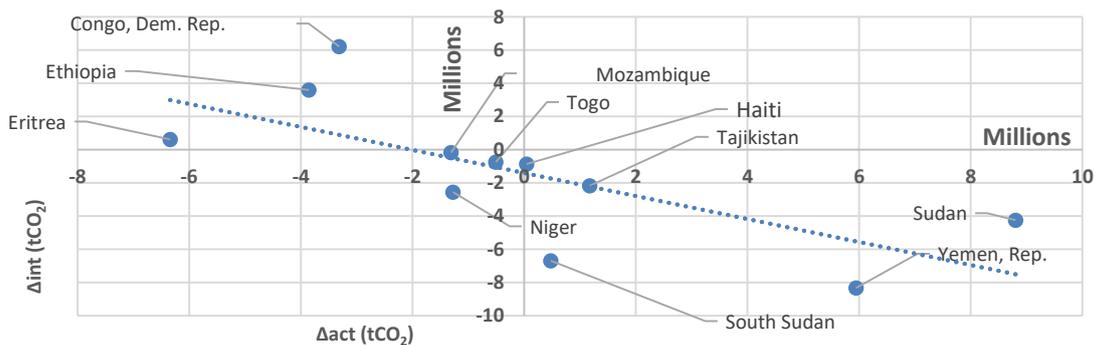


Figure 1: Economic Activity versus Energy Intensity in low-income countries.

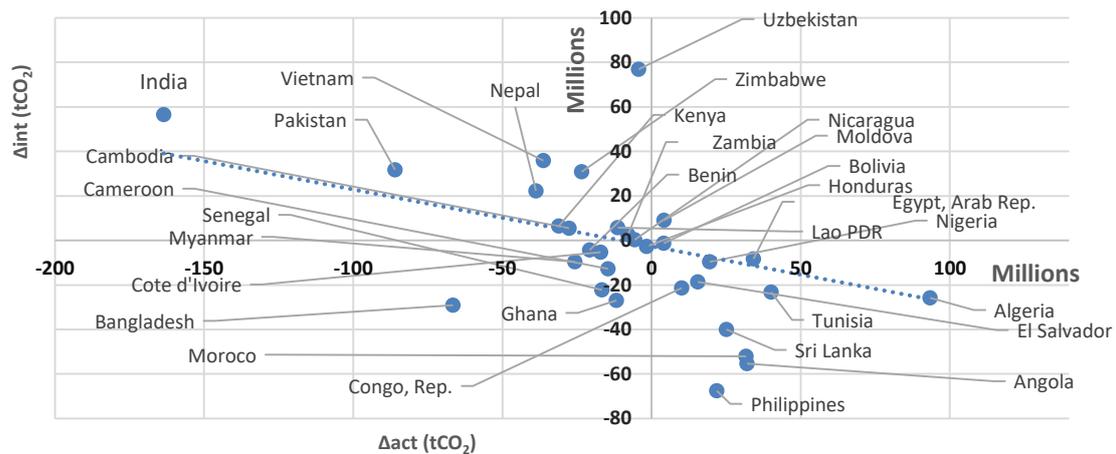


Figure 2: Economic Activity versus Energy Intensity in lower-middle income countries.

Decreasing energy intensity has been observed to be a major driving factor towards achieving a declining carbon economy (Metcalf, 2008). However, there are plenty of challenges to achieve this, especially for developing economies as these countries usually increase industrial production using fossil fuels to sustain a strong economic output. Generally, energy intensity is a measure of how efficiently the economy uses energy to produce GDP. As shown in Figures 1, 2, 3, and 4, the general trend is that energy intensity tends to decrease as the economic activity increases, and this is evident across all income groups. This suggests that countries tend to become more energy efficient as they develop. The study of Xue et al. (2012), focusing on developed countries, and Porzio et al. (2013), focusing on energy intensive industries, showed that many countries have attempted to decouple energy use from economic growth. Energy efficiency plays an important role in the reduction of energy intensity. In Europe, for instance, energy efficiency had effectively decreased primary and final energy consumption (European Commission, 2011). However, the replacement of fossil fuels by renewable energy sources cannot be captured by improvements in energy intensity, as implied in Carbajales et al. (2014) and in Kaygusuz et al. (2012) which focused on developing countries. Furthermore, Arroyo and Miguel (2020) indicated that energy intensity could be decreased to 54 % by 2030, as compared to year 2000 levels. The study by Cheng et al. (2019) indicated that energy intensity has decreased globally by a significant

amount over the last two decades. Similarly, Sharma et al. (2014) demonstrated that there has been a significant decrease in energy intensity across all countries, most notably in India, Indonesia, and Thailand.

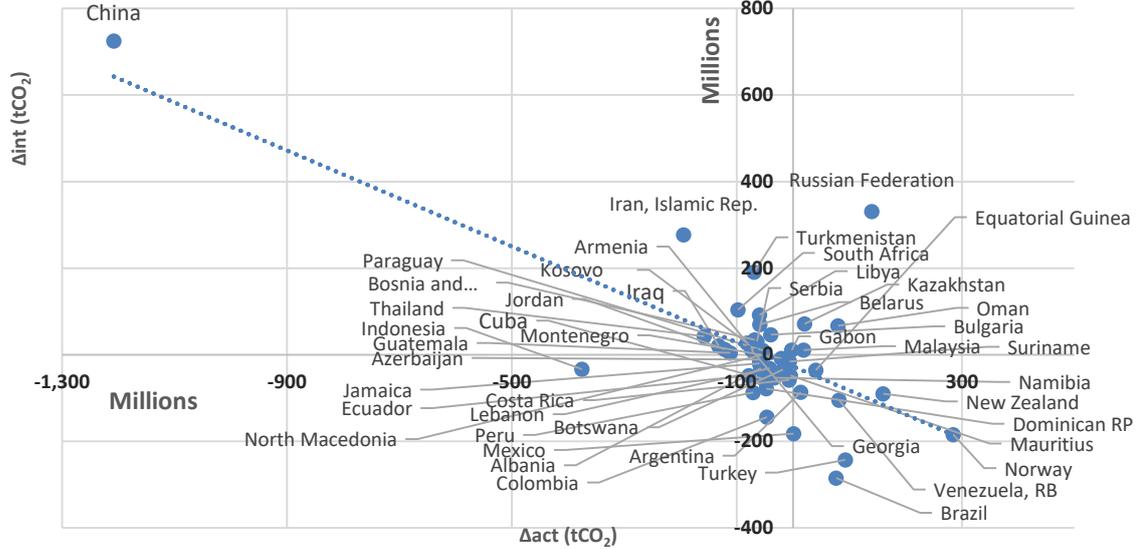


Figure 3: Economic Activity versus Energy Intensity in upper-middle income countries.

Notably, China is an outlier among upper-middle income countries (see Figure 3). This is primarily because of the country’s large population and being the world’s biggest energy consumer (Zhang et al., 2017). The United States is also an outlier among high-income countries (see Figure 4) due to its huge population and its high per capita energy consumption (US CET, 2008). The increase in energy consumption in the United States is closely related to its growth in GDP and other economic assumptions. The output of spatial analysis in Figure 4 illustrated that the energy intensity of the United States contributes to the reduction of its emissions, relative to other countries in the same income group. According to the U.S. Energy Information Administration, improvements in energy efficiency and other changes in the economy caused the country to decrease energy consumption per unit of economic output. This result mainly reflects the continued decline in the amount of coal consumption for electricity over the past decade as well as growth in renewable energy, mainly from wind and solar. Interestingly, coal use declined by nearly 15 %, and total clean energy consumption grew by 1 % compared with 2018 levels.

Similarly, Japan is also an outlier due to its large economy and energy use. Nevertheless, Japan’s energy intensity tends to notably decrease while economic activities grow as shown on Figure 4. In fact, Japan has the world’s highest energy efficiency according to Xie (2020), which compared China and Japan, and Otsuka (2018), which studied residential energy consumption in Japan.

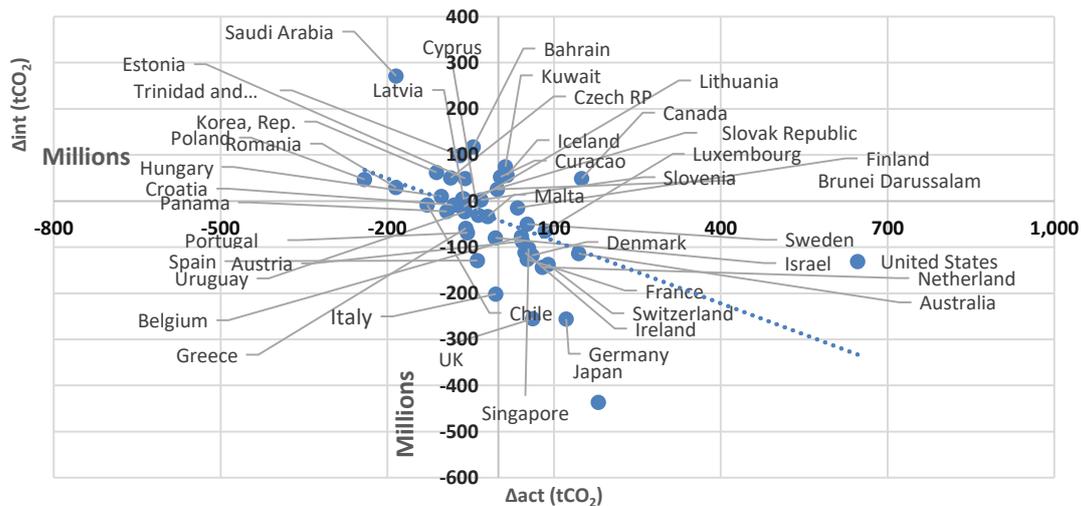


Figure 4: Economic Activity versus Energy Intensity of high-income countries.

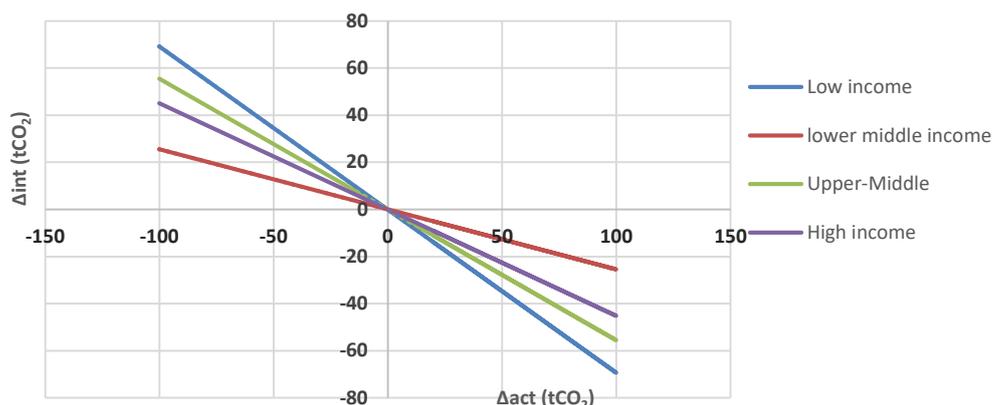


Figure 5: Plotting the slopes from various income levels with each other.

While on Figures 1 to 4, it might seem that the relationship between energy intensity and economic activity do not vary across income levels, plotting together the different trendlines in Figure 5 provides an interesting insight. The steepest slope belongs to the low-income countries, and this decreases as the income levels rise. This suggests that potential improvements in energy intensity decrease as income levels rise. As economies become more developed, there are less and less opportunities to improve energy efficiency on. However, it can be observed that the smallest slope comes from the lower-middle income countries, suggesting that this is the income level which is most constrained from a sustainable development context. These are usually the rapidly industrializing countries. Because of the nature of their economies, there are very-limited opportunities for them to reduce their energy intensity. Furthermore, with the pressures of climate change and international agreements, e.g. the Paris Agreement, it seems that these are the countries which will require more international support.

4. Conclusions

The objective of this paper is to look at how the spatial LMDI decomposition analysis method can investigate the relationship between economic activity and energy intensity of countries from various income levels. Using the M-R spatial LMDI methodology, the effects of economic activity and energy intensity are examined to reveal the changes and interregional discrepancy of global carbon emissions. Most interestingly, it is revealed that the lower-middle income countries are the ones which are mostly challenged to reduce their energy intensity and decouple energy use from economic growth. The results suggest that potentially, these are the countries which will require further international support to meet climate change-related commitments. This needs to be investigated further and validated by other researchers.

For the extending work, the study can investigate in more detail other drivers, such as population growth and energy structure, and relate them to economic activity and energy intensity as well. More in-depth regression-based analysis can also be performed on the data to analyse the evolution of countries as they evolve from one income level to another.

For future work, it would be interesting to perform statistical analysis on the data to quantitatively identify outliers in the data. It would also be interesting to perform sensitivity analysis on the data to study the significance of each effect to carbon emissions.

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