DOES THE ENVIRONMENTAL KUZNETS CURVE HOLD ACROSS SECTORS? EVIDENCE FROM DEVELOPING AND EMERGING ECONOMIES

Documents de travail GREDEG
GREDEG Working Papers Series

Supratim Das Gupta
Marco Baudino
Saikat Sarkar

GREDEG WP No. 2024-17

https://ideas.repec.org/s/gre/wpaper.html

Does the environmental Kuznets curve hold across sectors? Evidence from developing and emerging economies

Supratim Das Gupta*[1], Marco Baudino †[2], and Saikat Sarkar‡[1,3]

[1]Amrut Mody School of Management, Ahmedabad University, Ahmedabad, India
[2]Université Côte d'Azur, CNRS, GREDEG, France
[3]Department of Economics & Politics ,Visva Bharati University, Santiniketan, India

May, 2024

Abstract

This paper explores the growth-energy-pollution nexus of the environmental Kuznets curve (EKC) considering the joint contribution to CO2 emissions of the different sectors of the economy for a set of 43 emerging and developing countries. Since energy consumption and contribution to GDP growth can vary remarkably among sectors, the latter are likely to be characterized by heterogeneous responses to pollution from macroeconomic factors. We adopt an index decomposition approach disentangling the effect of energy consumption from intra-sectoral shifts in economic activities, which allows to evaluate improvements in energy efficiency across sectors. For the empirical analysis, we employ System and Difference GMM estimations using longitudinal observations from 1998 to 2019. Our econometric results reveal substantial heterogeneity of responses to carbon dioxide reduction across sectors. Particularly, we validate the existence of the EKC in energy-related measures for the sole manufacturing sector, and in GDP growth for the commercial and public sector. On the other hand, while emissions increase proportionately with growth in the transportation sector, energy efficiency measures seem to be ineffective in curtailing emissions in both the transportation and commercial and public sectors. Our results bear recommendations for the achievement of effective carbon neutrality policies.

*Corresponding author. E-mail: supratim.dasgupta@ahduni.edu.in;
Assistant Professor, Amrut Mody School of Management, Ahmedabad University. Address: Amrut Mody School of Management, Ahmedabad University, Head Facilities and Services, Central Campus, Navrangpura, Ahmedabad, Gujarat 380009, India. Phone: +91 079619111344

†E-mail: marco.baudino@univ-cotedazur.fr

‡E-mail: saikat.sarkar@ahduni.edu.in

Highlights

- We explore the presence of sector-level EKCs for a set of 43 emerging and developing economies.
- The energy intensity index is decomposed into improvements in energy efficiency and shifts in sectoral economic activities.
- In relation to economic growth, the EKC is only validated for the commercial and public sector.
- In relation to energy-related measures, the EKC is validated for the sole manufacturing and construction sector.

Keywords: Environmental Kuznets Curve; Energy Intensity Decomposition; CO2 Emissions.

JEL Classification: Q01; Q53; O13.

Word Count: 6659

List of Abbreviations

- CO2 Emissions: Carbon Dioxide Emissions (million tonnes of CO2)
- EKC: Environmental Kuznets Curve
- FDI: Foreign Direct Investment
- GDP: Gross Domestic Product (constant 2015 US$)
- GVA: Gross Value Added (constant 2015 US$)
- GHG: Greenhouse gases
- GMM: Generalized Method of Moments
- GNI: Gross National Income (referred to but not used as data)
- MENA: Middle East and North Africa
- MSW: Municipal Solid Waste
- OECD: Organization for Economic Cooperation and Development
- UNSDG: United Nations Sustainable Development Goals
- E_t = total energy consumption (terajoules)
- Y_t = GDP
- en_t = aggregate energy intensity
- en_0 = aggregate energy intensity in base year
- I_t = aggregate energy intensity index
- L_t^{EFF} = Laspeyres Efficiency Index
- L_t^{ACT} = Laspeyres Activity Index
- P_t^{EFF} = Paasche Efficiency Index
- P_t^{ACT} = Paasche Activity Index
- F_t^{EFF} = Fisher Efficiency Index
- F_t^{ACT} = Fisher Activity Index

1 Introduction

In light of recent contributions demonstrating the sector-specific nature of pollutant sources (Guo et al., 2022[20]; Huo et al., 2022[22]; Halkos et al., 2021[21]; Ru et al., 2018[49]), sector-specific solutions need to be adopted for achieving carbon neutral policies. Growth led with higher emissions in certain sectors such as manufacturing, commercial or transportation, for example, can be considered to be in conflict with the UN Sustainable Development Goals (UNSDGs) of responsible consumption and production, the building of sustainable infrastructures and cities, and access to clean energy (UNSDG, 2023[57]). For any country, the contribution to total output from the various sectors of the economy can have varied impacts on total energy consumption and emissions. Tajudeen et al. (2018)[51] define the aggregate energy intensity of a country as the product of economic activity and energy intensity summed across all the sectors of the economy. Thus, each sector becoming more or less energy intensive (improvements or declines in energy efficiency) along with its relative share in total economic output is what determines a nation's aggregate energy intensity. Although not considered explicitly by the authors, improvements in energy efficiency, even if similar across sectors, would still have heterogeneous impacts on aggregate carbon emissions for a country. In fact, different sectors may primarily use different fuels with different carbon/emission intensity; for instance, improvements in energy efficiency in the transportation and manufacturing sectors may exert a large impact on emissions if they are heavily dependent on carbon-emitting fossil fuels.

In this work, we aim at offering a comprehensive examination of the interdependency between emissions, GDP growth, and energy intensity at a sectoral level. To address our question of the nexus between emissions, GDP and energy consumption, we consider the sectors which are common across all the variables: that is, manufacturing and construction, transportation, commercial and public and agriculture, forestry and fishing. Specifically, the objective of this study is to detect evidence of the Environmental Kuznets Curve (EKC) at the sector level for a large set of emerging and developing countries. To the best of our knowledge, prior contributions have focused on selecting specific sectors for individual countries (see, e.g., recent contributions by Feng and Wang (2018)[17], Chen et al. (2022)[14], and Ma and Cai (2019)[34][1]), or have considered total emissions at the economy-level for different sets of countries (see, e.g., Muhammad (2019)[36], Khan and Ozturk (2021)[31], and Wang (2023)[59]). Our study possibly provides the first attempt to investigate the EKC considering more than one sector and multiple countries at the same time. In addition, following the index decomposition approach adopted in recent studies (see, e.g., Jain, 2023[25]; Patiño et al., 2021[44]; Ma and Cai, 2019[34]; Tajudeen et al., 2018[51]), we attempt to effectively decouple the contribution of sectoral activity and energy-related measures to emissions. Following the theoretical framework of recent contributions (Bennedsen et al., 2023[8]; Jiang et al., 2021[27]; Pata, 2018[43]), this work considers total CO2 emissions from fuel combustion and the value added share in GDP from each sector of the economy. While covering the four sectors of manufacturing and construction, transportation, commercial and public, and agriculture and forestry, we make an additional contribution to the literature by decomposing the energy intensity index into the efficiency and activity

[1]These studies focus, respectively, on the transportation sector, the residential, and the commercial and building sectors for China.

indexes for each of these sectors as in Tajudeen et al. (2018)[51][2].

All in all, we believe that this paper contributes to the EKC literature by advancing our current understanding on the sectoral emission-growth-energy nexus in developing and emerging countries, thereby suggesting potential energy-related improvements for multiple sectors of the economy. The remainder of the paper is organized as follows: Section 2 provides a brief literature review, Section 3 explains the data sources and methodology, Section 4 focuses on the empirical findings and Section 5 concludes.

2 Literature review

The literature on the EKC is extensive, covering a wide range of environmental outcomes, sectors of the economy, countries, and structural determinants[3].

For the transportation sector, studies such as by Guo et al. (2022)[20] for China show an inverted U- shaped relationship between GDP *per capita* and the sector's carbon emissions which is consistent with the existence of the EKC. A negative effect on the transportation sector's emissions is exerted by a higher transportation consumption price index which includes the cost of the vehicle, fuel and other costs. The paper further segregates the 30 Chinese provinces into four groups accounting for differences in GDP and emissions, with results remaining substantially invariant. For the agriculture and forestry sector, Chandio et al. (2020)[13] examine the dynamic relationship between crop production, livestock production power consumption, power consumption in agriculture, forest and CO2 emissions in China. Their findings pinpoint the prevalence of a long-run relationship between these variables and CO2 emissions, calling for the Chinese government to revisit its policies in connection with crop production and livestock to conduct policies directly bearing on CO2 emissions. Jeong and Kim (2013)[26], in the context of Korea, study greenhouse gas (GHG) emissions from the manufacturing sector and find that sectors which are more coal- and oil-intensive are responsible for higher shares in total GHG emissions. Results show that GHG emission reductions are mostly due to change in the structure of the manufacturing sector and reduced energy intensity across sectors varies according to the share of energy consumption amongst

[2]Specifically, we employ the Fisher index decomposition, which is is the geometric mean of the Laspeyres and Paasche indexes. As it will be explained in a following section, the calculations for the efficiency and activity indexes for each of the Laspeyres and Paasche indexes come out to be equal for each of the sectors. In addition, although the two indexes imply different decompositions, the associated residuals may equally explain significant variability in the underlying index of energy intensity. Generally speaking, contributions performing energy index decomposition in the literature remain limited. Torvanger (1991)[54] decomposes the manufacturing sector's energy intensity for 9 OECD countries and finds small differences in computations between the Laspeyres index and the Divisia index. In a more recent study, Jain(2023)[25] uses index decomposition analysis to demonstrate how in India the increase in energy consumption in the manufacturing sector during the period 2011-2019 has been partially contained by improvements in both structural changes and energy efficiency. Similarly, Zakari et al. (2021)[63] employ Fisher Ideal index decomposition analysis to show how structural reforms negatively impacted energy consumption in the Nigerian manufacturing sector during the 1991-2014 period.

[3]In its seminal definition, the EKC hypothesis refers to an inverse U-shaped relationship between economic activity and gas emissions (Müller-Fürstenberger and Wagner, 2007[37]); namely, growth increases are coupled with environmental degradation until a certain point, after which economic expansion leads conversely to environmental improvement. This reverse trend generally occurs thanks three macro-drivers affecting the economy as a whole: the scale, composition, and technique effects (see Brock et al., 2005[12]).

the latter. In other words, structural changes in the manufacturing sector imply a change in the proportion of energy-intensive industries in that sector. Boubellouta and Kusch-Brandt (2020)[11] analyze the presence of the EKC for e-waste in Europe (EU28 + 2) for the period 2000-2016, arguing that e-waste generation is connected with change in *per capita* GDP. While earlier studies focusing on a waste Kuznets curve have used Municipal Solid Waste (MSW), plastic waste and medical waste, the paper includes electrical and electronic waste and information and technology goods. Their results confirm the presence of an inverted U-shaped relationship between *per capita* GDP and e-waste, thus confirming the validity of the EKC. More recent contributions such as Khan and Ozturk (2021)[31] examine the EKC hypothesis under the moderating factor of financial sector development for a set of 88 developing economies over the period 2000-2014. Controlling for average years of schooling and population size, the paper reveals how financial sector development is associated with greater trade flows and foreign direct investment (FDI) flows. Employing generalized method of moments (GMM) estimation techniques to tackle issues of endogeneity and serial correlation for dynamic panels, the authors find the existence of the EKC between income and *per capita* emissions. The strong dependence of current emissions on past emission levels detected in the study further reflects the fact that the structure of economies evolve slowly through time. The authors also find a positive relationship between population size and *per capita* emissions, showing how increases in population exert a greater dependence on society due to greater production and consumption of goods, thereby increasing total emissions[4]. At the same time, the authors also validate the pollution haven hypothesis (PHH), since their findings reveal how for developing economies, trade flows and FDI flows are associated to greater emissions. Therefore, opening up the financial sector and financial sector development can come with more emission-intensive products, production processes and capital shifted to developing economies from other nations taking advantage of lax environmental laws. Results in the paper also show that financial sector development alone with greater credit access for environment-friendly technologies such as solar rooftops, for example, can help in reducing emissions. Muhammad (2019)[36] detects similar results when analyzing 68 developed and emerging countries in the Middle Eastern and North African (MENA) region for 2001 - 2017. Specifically, the empirical results validate a relationship between increased energy consumption and economic growth translating into higher emissions; at the same time, certain developing economies managed nevertheless to adopt technological solutions which allowed them to obtain gains in energy efficiency. Wang et al. (2023)[59], using a large dataset of 208 countries for the period 1990-2018, investigate the nexus between emissions, GDP, human capital, trade openness, renewable energy consumption and natural resource rents. The study confirms the presence of an inverted U-shaped relation between *per capita* income and emissions at a global level with a turning point in income of approximately 19,200 US$. The authors further show that increases in human capital and trade openness increase carbon emissions before the turning point, but lead to a reduction after the turning point. At the same time, renewable energy decreases emission intensity at a different pace before and after the turning point. Specifically, renewable energy consumption decreases emissions in a more sustained fashion before the turning

[4] Papers by Guo et al., 2022 [20], Patiño et al., 2021[44] and Ma and Cai, 2019[34] using population, affluence and technology models, for example, find the effect of population to exert a positive effect on emissions.

point than after it. When considering human capital, the relationship with emissions is positive before reaching the turning point but negative thereafter. This is explained by the fact that human capital accumulation leads to greater economic activity causing greater emissions; however, as an economy progresses, there are increases in productivity, innovations in energy-efficient and low-carbon technologies due to human capital accumulation which causes a decline in emissions. For reasons explained above, trade openness enables countries to move pollution-intensive industries to other countries, affecting environmental quality. But after the EKC turning point, trade openness may indirectly contribute to emission reduction through economic exchanges. Finally, investing natural resource rents in modern technologies can promote economic development and reduce emissions after the EKC turning point; however, in countries with weak institutions, dependence on natural resource rents can cause further exploitation and consumption of natural resources at the cost of negative environmental externalities.

3 Data and methodology

3.1 Data

In this study, we consider 43 emerging and developing economies (according to the International Monetary Fund (2023)[24] classification) focusing on carbon dioxide (CO2) emissions from fuel combustion, energy consumption and real GDP for the years 1998-2019. We consider the IMF's Fiscal Monitor Database as it takes a country's monetary and fiscal position into account towards prescribing consistent macroeconomic policies leading to overall financial and price stability. This is especially important in our opinion as it would truly reflect the development path of a country in recent times. On the other hand, World Bank's classification divides countries according to GNI per capita using the World Bank Atlas Method (The World Bank (2023)[53]). To maintain commonality across sectors for which data is available for all variables, we use sector-level data for the following four sectors of the economy: manufacturing and construction, transportation, commercial and public, and agriculture, forestry and fishing[5]. In detailing through sectors for the group of countries as a whole, we find the GDP shares of manufacturing and commercial and public sectors to be the largest; for carbon dioxide emissions, the shares are the greatest for the manufacturing and transportation sectors followed by those of the residential sector. On the other hand, for energy consumption, the shares are found to be highest for transportation, manufacturing and the residential sectors[6]. The four sectors register substantial heterogeneity in terms of contribution to GDP, energy consumption and carbon dioxide emissions. All in all, the results from

[5]Since the fishing component for this sector is zero (or negligible for a large number of countries), from now onwards we refer to this sector as *agriculture and forestry*.

[6]We have data for six sectors on CO2 emissions from fuel combustion in millions of tonnes of CO2: Electricity and Heat, Manufacturing and Construction, Transportation, Residential, Commercial and Public, Agriculture and Forestry (OECD, 2023[39]); five sectors for sectoral Gross Value Added in constant 2015 US$: Mining/Quarry and Utilities, Commercial and Public, Manufacturing and Construction, Transportation, Agriculture, Forestry and Fishing (UN Data, 2023[58]; UNSTATS, 2023[56]); five sectors for energy consumption in Terajoules: Manufacturing and Construction, Transportation, Residential, Commercial and Public, Agriculture and Forestry (UNSTATS, 2023[56]).

Figs. 1-3 are self explanatory[7,8]; while the commercial and public sector denotes a quite large contribution to GDP, the emission and energy shares are relatively low[9]; on the other hand, the manufacturing and construction sector shows a significant contribution for all the three variables, while the transportation sector exhibits high energy consumption and emissions[10]. Finally, it is noteworthy noticing how the share of the agriculture and forestry sector remains negligible in all cases.

For sectoral GDP, we use the gross value added (GVA) contribution for each sector. The corresponding real GDP (in constant 2015 US $) data is obtained from UNSTATS (2023)[56]. In terms of national accounting, household consumption is part of final consumption expenditure which represents a further component of GDP. On the other hand, as the GVAs for the other four sectors add to total value added in an economy, it is not meaningful to have/add the GVAs for the manufacturing and construction, transport, commercial and public and agriculture and forestry and the residential sector's share (household consumption expenditure) together. This distinction is even more important since our analysis is based at a sectoral level.[11] Emission data is obtained from the World Bank (2023)[52], while energy consumption data from UN Energy Balance (2023)[55].

Descriptive statistics for our data are reported in Tab. 1. The list of the countries considered can be found in the Appendix.

[TAB. 1 HERE]

In Tab. 2 we additionally report for each sector the average percentage annual change in carbon and energy intensities over time. The latter are expressed, respectively, as the ratio of CO2 emissions and energy consumption over GDP. It is noteworthy noticing how all sectors registered a decrease in carbon intensity in the last considered time period (2012-2019), with the commercial and public sector displaying the highest drop in magnitude. At the same time, in the same time period, energy intensity increased for all sectors with the exception of the commercial and public sectors.

[TAB. 2 HERE]

[7]From now onwards, for the sake of simplicity, we will refer to the manufacturing and construction sector simply as *manufacturing* sector.

[8]As mentioned in the Introduction section, in Figs. 2 and 3 we do not account for the residential sector, which is the main contributor to energy consumption and carbon dioxide emissions. The contribution of Electricity and Heat is also not included in the carbon emissions.

[9]In broad terms, this can be explained by the fact that in the last two decades, developing and emerging economies have witnessed a sustained increased of the tertiary sector share to total GDP (UN Data, 2023[58]). Consequently, this has also opened up jobs in IT, telecommunications and related industries which use relatively energy-efficient technologies (Khan and Ozturk, 2021[31]).

[10]More people in developing countries have increased spending on private modes of transportation and witnessed an increasing expansion in the manufacturing sector, leading to increases in energy usage (Guo et al. (2022)[20]; Jeong and Kim (2013)[26]).

[11]Tajudeen et al. (2018)[51], employing the four sectors of our analysis and the residential sector (share as per household consumption expenditure) do aggregate energy intensity decomposition at a country level combining all the sectors together. Private personal consumption expenditure is taken as the share of the residential sector in Jain (2023)[25].

When disaggregating emissions by country (Fig. 4), it is not surprising to notice how China and India remain among the major polluting economies. Cross-country heterogeneity also emerges in relation to energy consumption (Fig. 5) and real GDP (Fig. 6). When taking into account the share of various sectors in the total value added[12], we find that the overall share for Brazil in total world GDP is around 2% over the years 1998 - 2019. For India and China, this share has doubled and tripled, respectively, from around 1.5% to 3% and from around 6% to 18% from 1998 to 2019 (UNdata, 2023[58]; UNSTATS, 2023[56]). On the other hand, the overall shares of other large emerging economies such as Mexico and Russia have grown to be around 1.5% in recent years, while for Chile, Egypt, Indonesia, Malaysia, Saudi Arabia and South Africa they have remained relatively stable (between 0.2% to 0.8% over the years).

[FIG. 1 HERE]

[FIG. 2 HERE]

[FIG. 3 HERE]

[FIG. 4 HERE]

[FIG. 5 HERE]

[FIG. 6 HERE]

3.2 Methodology

3.2.1 Energy Intensity Index

We employ index decomposition analysis to decompose energy intensity into an efficiency index and an activity index. Specifically, we use the Fisher index decomposition (Fisher, 1921[19]) for its desirable properties of providing perfect decomposition without unexplained residuals, among others, as explained earlier (Tajudeen et al., 2018[51], Ang, 2004[3]). Following Tajudeen et al. (2018)[51], aggregate energy intensity en_t for a country is given by:

$$en_t = \frac{E_t}{Y_t} = \sum_j \left(\frac{E_{jt}}{Y_{jt}}\right)\left(\frac{Y_{jt}}{Y_t}\right) = \sum_j en_{jt} s_{jt} \tag{1}$$

[12]Sectoral economic activity is defined as the share of a sector in the gross value added for an economy in constant 2015 US$.

where, given sector j, en_{jt} represents sectoral energy intensity and s_{jt} denotes the sectoral share of real GDP (sectoral GVA contribution to real GDP). E_t and Y_t are total energy consumption and total output or GDP; E_{jt} and Y_{jt} denote energy consumption and GVA contribution for sector j at time t respectively. Eq. (1) shows that the aggregate energy intensity is the product of sectoral energy intensity and the sectoral contribution to GDP. This implies that for a country as a whole, sector j's improvements/reductions in energy intensity and its contribution to total GDP (this aggregated over all sectors of an economy) would determine how a country would be doing in terms of its aggregate energy intensity. As an example, for developing economies such as India and China, with a growing manufacturing and commercial and public sector and the service sector, aggregate energy intensity may improve due to both sectors becoming energy efficient and change in sectoral economic activities. However, since our analysis is at a sectoral level, we only consider sectoral energy intensity and sectoral share in GDP for the four sectors of the economy (manufacturing and construction, transport, commercial and public and agriculture and forestry).

To arrive at an aggregate energy intensity index I_t, we divide the energy intensity in year t, en_t, by the energy intensity in some base year, en_0, to get:

$$I_t = \frac{en_t}{en_0} = \frac{\sum_j en_{jt}s_{jt}}{\sum_j en_{j0}s_{j0}} \tag{2}$$

The following equations define the Laspeyres, Paasche and Fisher indexes:

$$\begin{aligned} Laspeyres: L_t^{EFF} &= \frac{\sum_j en_{jt}s_{j0}}{\sum_j en_{j0}s_{j0}}; \\ L_t^{ACT} &= \frac{\sum_j en_{j0}s_{jt}}{\sum_j en_{j0}s_{j0}} \end{aligned} \tag{3}$$

$$\begin{aligned} Paasche: P_t^{EFF} &= \frac{\sum_j en_{jt}s_{jt}}{\sum_j en_{j0}s_{jt}}; \\ P_t^{ACT} &= \frac{\sum_j en_{jt}s_{jt}}{\sum_j en_{jt}s_{j0}} \end{aligned} \tag{4}$$

$$\begin{aligned} Fisher: F_t^{EFF} &= (L_t^{EFF} \mathrm{x} P_t^{EFF})^{\frac{1}{2}}; \\ F_t^{ACT} &= (L_t^{ACT} \mathrm{x} P_t^{ACT})^{\frac{1}{2}}; \end{aligned} \tag{5}$$

where EFF and ACT stand for the efficiency and activity indexes respectively. The aggregate energy intensity index I_t, which is the ratio of aggregate energy intensity in year t to that in year 0, can thus be decomposed into an efficiency index and an activity index. The efficiency index holds the sectoral GDP contributions constant so that changes in energy intensity are only related to changes in energy efficiency. Conversely, the activity index denotes changes in energy intensity which are due to changes in sectoral economic activity.

From equation Eq. (2) and using Eqs. (3) to (5), the aggregate energy intensity index can be written as the product of efficiency and activity indexes:

$$I_t = \frac{en_t}{en_0} = F_t^{EFF} \mathrm{x} F_t^{ACT} \tag{6}$$

For this paper, the analysis at a sectoral level is carried out by first following the two components of Eq. (1). Multiplying en_{jt} with s_{jt} for each sector and then dividing by the same product for the base year gives us the energy intensity index for each sector j. Similarly, for the Laspeyres and Paasche indexes given in Eqs. (3) and (4) above, we can derive the component for each sector; hence, the Fisher index can also be obtained as in Eq. (5). It is straightforward to see that, for any given sector j (thus ignoring the summation over all sectors), L_t^{EFF} and P_t^{EFF} would both equal the ratio $\frac{en_{jt}}{en_{j0}}$. Similarly, L_t^{ACT} and P_t^{ACT} would both equal the ratio $\frac{s_{jt}}{s_{j0}}$ which is the relative sectoral economic activity in year t compared to that in the base year. It follows that each of the Laspeyres and Paasche indexes would equal the Fisher index according to Eq. (5). It can be seen that for each sector j, Eq. (2) holds as $I_{jt} = F_t^{EFF_j} \text{x} F_t^{ACT_j}$. This proves that perfect decomposition exists. So, for sector j, a rise in sectoral energy intensity relative to GVA share to the same ratio for the base year would imply the sector becoming more energy intensive. This would entail decreases in the efficiency index. Similarly, a rise in the sectoral economic activity share relative to the energy intensity over the base year for sector j would entail an increase in the activity index for the sector. A rise or fall in the efficiency index or in the activity index can be associated with changes in emissions. Namely, decreasing activity (or efficiency) indexes entail declining emissions, and therefore environmental amelioration. On the contrary, increasing indexes entail increased emissions and therefore increased environmental deterioration. In broad terms, changes in total emissions for a country depend on the number of industries within each sector of the economy and, given changes in the efficiency or activity indexes for the sectors, their relative fuel mix of relatively dirty or clean fuel sources[13].

In Tab. 3, we provide summary results for the energy intensity, efficiency, and activity indexes at a sectoral level across 43 countries which is the subject of our analysis. For this, we split the time period into three intervals: 1998-2004; 2005-2011; 2012-2019 with the base year as 2015. According to Tajudeen et al. (2018)[51], our period considered, 1998 - 2019 has been equally divided into three periods. The vertical axis in Fig. 8 represents the coefficient of variation in decimal numbers. At a sectoral level as in Fig. 8, Fig. 7 shows the average annual change as well as the average annual change (cumulative) as a percentage.

From the graph of sectoral energy intensity decomposition (Fig. 7) and as depicted in Tab. 3, we observe that the agriculture and forestry sector had greater fluctuations among all three indexes: intensity, efficiency, and activity. For both the indexes of intensity and efficiency, the average annual change for agriculture and forestry sector is negative. The most negative values are seen for the period 2005-2011 for the intensity and efficiency indexes. Similar results are again seen for the period 2005-2011 across these two indexes for the agriculture and forestry sector for the coefficient of variation (Fig. 8). It is interesting to see that the coefficient of variation for all other sectors, manufacturing and construction, transportation and commercial and public for all three indexes of intensity, efficiency and activity decrease consistently over the three periods. For the agriculture and forestry sector, only a steep decline is observed between 2005-2011 to 2012-2019. Comparing the three indexes across sectors and the index decomposition, it seems some countries may have been able to decrease their energy intensity by improvement in energy efficiency while others may not have been able to achieve this. Thus, further analysis at a country level is needed. It must also be remembered that emerging economies, in their phase of economic growth, may have

[13]As stressed, for this study, we consider the total CO2 emissions from fuel combustion, whereas we do not investigate the source of emissions for each sector or industry.

drastic changes in economic structure leading to changes in patterns of demand for energy and resulting emissions. As for the case of Colombia analyzed by Patiño et al. (2021)[44], changes in the economy brought about by structural changes across the transport, agriculture and services sector has effects on energy intensity and energy efficiency.

[TAB. 3 HERE]

[FIG. 7 HERE]

[FIG. 8 HERE]

3.2.2 Model Specification

As mentioned above, our objective is to explore the dynamic relationship between emissions, GDP and energy trends in developing and emerging economies relying upon the Kuznets curve hypothesis as a core framework. Following Tajudeen et al. (2018)[51], Boubellouta and Kusch-Brandt (2021)[10], and Puertas and Marti (2021)[46] we estimate the following model specification:

$$e_{j,i,t} = \beta_{j,1}\, e_{j,i,t-1} + \beta_{j,2}\, gdp_{j,i,t} + \beta_{j,3}\, {gdp_{j,i,t}}^2 + \beta_{j,4}\, act_{j,i,t} + \beta_{j,5}\, {act_{j,i,t}}^2 + \beta_{j,6}\, eff_{j,i,t} + \beta_{j,7}\, {eff_{j,i,t}}^2 + \eta_{j,i} + \epsilon_{j,i,t} \tag{7}$$

$$u_{j,i,t} = \eta_{j,i} + \epsilon_{j,i,t} \tag{8}$$

$$\eta_{j,i} \sim IID(0, {\sigma_\eta}^2),\ \epsilon_{j,i,t} \sim IID(0, {\sigma_\epsilon}^2),\ and\ E[\eta_{j,i}\epsilon_{j,i,t}] = 0 \tag{9}$$

where j indicates sector, i indicates country and t stands for time $[j = 1, 2, 3, 4; i = 1, 2, ..., 43; t = 1, 2, ..., 22]$. $e_{j,i,t}$ represents sectoral $CO2$ emissions, gdp is sectoral real GDP, and $act_{j,i,t}$ and $eff_{j,i,t}$ are the two indexes for activity and efficiency, respectively. All variables are in natural logarithms. Finally, $\eta_{j,i}$ captures country specific effects for each sector potentially correlated with the lag of the dependent variable, and $\epsilon_{j,i,t}$ is the error term.

Given the presence of a lagged dependent variable in our model specification, the use of ordinary pooled OLS (POLS) estimation may lead to biased coefficient estimates. In broad terms, three alternative estimation methods are generally employed to estimate the dynamic panel model specification of Eq. (7): Fixed Effects (FE); Difference GMM; and System GMM. In dynamic contexts, GMM methods are generally preferred over FE, since they address more effectively issues related to heteroskedasticity, endogeneity and serial correlation, which are common phenomena encountered in panel data analysis (Roodman, 2009a[48]). Besides, if some explanatory variables do not tend to vary significantly over time, GMM estimators can deal with this issue more effectively, since they use both between and within variation for the determination of the coefficients rather than just the within variation as the FE does. Finally, as highlighted by Nickell (1981)[38], besides dynamic panel bias, FE estimators can suffer of small-sample bias when the number of time periods is reduced and the lagged dependent variable denotes high degrees of persistence (Alonso-Borrego and Arellano, 1999[2]). Generally, employing GMM methods is particularly useful when the cross-section is larger than the time period (Arellano and Bond, 1991[4]). Since our panel data consist of 43 cross-sectional units (43 individual countries) and a relatively smaller time period of 22 years (from 1998 to 2019), the GMM estimator represents a suitable technique to estimate our model specification. To eliminate the unobserved effects, a first difference transformation of Eq. (7) can be performed so that:

$$\begin{aligned}\Delta e_{j,i,t} = \beta_{j,1}\ \Delta e_{j,i,t-1} + \beta_{j,2}\ \Delta gdp_{j,i,t} + \beta_{j,3}\ \Delta gdp_{j,i,t}{}^2 + \beta_{j,4}\ \Delta act_{j,i,t} + \beta_{j,5} \\ \Delta act_{j,i,t}{}^2 + \beta_{j,6}\ \Delta eff_{j,i,t} + \beta_{j,7}\ \Delta eff_{j,i,t}{}^2 + \Delta\epsilon_{j,i,t}\end{aligned} \tag{10}$$

where Δ is the first difference operator. Taking first difference in Eq. (8) yields:

$$\Delta u_{j,i,t} = \Delta\eta_{j,i} + \Delta\epsilon_{j,i,t} \Rightarrow u_{j,i,t} - u_{j,i,t-1} = (\eta_{j,i} - \eta_{j,i}) + (\epsilon_{j,i,t} - \epsilon_{j,i,t-1}) \Rightarrow \Delta u_{j,i,t} = \epsilon_{j,i,t} - \epsilon_{j,i,t-1} \tag{11}$$

Difference GMM estimation can be implemented after the first differentiation of the data has eliminated the fixed effects components (Roodman, 2009b[47]). However, the first differencing might produce a source of bias since the differenced error term could be correlated with the lagged emissions variable. To overcome this issue, Arellano and Bover (1995)[5] and Blundell and Bond (1998)[9] proposed a System GMM estimation. The latter employs two equations: one first-differenced (where the explanatory variables are instrumented by their lagged levels) and one in levels (where variables are instrumented by their lagged first difference). Specifically, variables in differences are instrumented using the lags of their own levels, whereas variables in levels are instrumented using the lags of their own difference. As highlighted by Blundell and Bond (1998)[9], the first differenced moment conditions in Difference GMM are augmented by level moment conditions in System GMM for more efficiency in estimation[14]. For this analysis, we use both two-step Difference and System GMM estimators, which result to be more robust against misspecification and endogeneity in the presence of pseudo time-invariant explanatory variables[15]. To ensure the validity of the econometric estimates, we conduct a series of additional robustness checks. First, we address potential endogeneity issues of our independent variables by instrumenting them with a two-lag instrumental matrix used as an instrument for the first-differenced model. Secondly, we additionally run a one-step System and Difference GMM for all of our model specifications.

[14] At the same time, System GMM requires the additional orthogonality condition for which the differences used as instruments are uncorrelated with the error term.

[15] The two-step procedure, by using the heteroscedastic weight matrix and the instruments in levels, reduces the loss of information, but it also introduces the risk of overidentification; in order to avoid instrument proliferation we follow Roodman (2009a[48], 2009b[47]) by only using two lags in the estimation procedure. The bias in the two-step standard errors is corrected with the Windmeijer (2005)[62] finite sample correction procedure.

4 Empirical findings

4.1 Unit Root and Panel Cointegration tests

Previous to performing our econometric estimates, we run different panel unit root tests to validate the hypothesis of stationarity within the data. In the literature, both first- and second-generation unit root tests are generally employed to address stationarity concerns. Among first-generation tests, the Harris Tzavalis (HT) test has been largely utilized since it provides a good fit for the data in case of balanced panels (Baltagi, 2008[7]). On the other hand, a main weakness of first-generation tests stems from the fact that the latter do not consider cross-sectional dependence among error terms, which if present might lead to biased and inconsistent test statistics. To cope with such issue, we employ augmented Dickey Fuller (CADF) and cross-sectionally Im Pesaran Shin (CIPS) second-generation unit root tests, that are robust to cross-sectional dependence among disturbances and cross-sectional units (Pesaran, 2007[45]; Im et al., 2003[23]). To check preemptively for the presence of cross-sectional dependence, we run both Pesaran and Friedman cross-sectional dependence tests. The corresponding test statistics are, respectively, 12.346 ($p < 0.01$) and 27.746 ($p < 0.05$), thus indicating the presence of cross-sectional dependence in our data. In Tab. 4 we report CADF and CIPS test statistics, together with HT results. When considering CADF and CIPS test statistics, the null hypothesis of non-stationarity is not rejected for several variables in our dataset. However, all variables become stationary after taking the first difference.

[TAB. 4 HERE]

Since not all our variables are stationary in levels, a long-term significant relationship among GDP, energy, and emissions exists in the presence of cointegration among the latter. To test for variables' cointegration, we employ three cointegration tests: the Kao's residual, the Pedroni, and the Westerlund cointegration tests[16]. The test statistics for the cointegration tests are displayed in Tab. 5.

[TAB. 5 HERE]

From Tab. 5, the null hypothesis of no cointegration is rejected by all the tests statistics, indicating the statistical meaningfulness of coefficient estimates for emissions, growth and energy measures.

4.2 Econometric estimates

Tabs. 6-9 report the econometric estimates for each sector. From the tables, the lagged levels of carbon dioxide emissions denote a positive impact on the current levels of

[16]The Kao's residual test is generated by a Monte-Carlo process and is particularly indicated for reduced time dimensions. The null hypothesis of absence of cointegration among the data is evaluated using both Dickey Fuller (DF) and Augmented Dickey Fuller (ADF) type tests (Kao, 1999[29]).

emissions. These findings mirror the results of recent contributions studying emission behaviors in developing countries, revealing how past emissions do affect current emission levels across different sectors of the economy (Wang et al., 2023[60]; Wenbo and Yan, 2018[61]; Ayesu, 2023[6]; Oryani et al., 2021[42]; Oliveira et al., 2022[40]). This result from our analysis emerging across all sectors might indicate that unsuccessful policy efforts in emerging economies aiming at curtailing emissions can translate into negative spillovers effects in terms of increase in current CO2 emissions. When considering GDP growth, this exerts a linear positive effect on emissions in the manufacturing and transportation sectors[17]. Conversely, an inverted U-shaped relationship emerges when considering the commercial and public sector, as seen in Tab. 8 and Tab. 12, with a turning point of 316367 (1,000 real US$). Finally, a non significant impact is detected for the agriculture and forestry sector. Our findings corroborate those from Ru et al. (2018)[49] who find a linear relationship between *per capita* CO2 emissions and *per capita* income for a large group of 199 countries (high, middle and low income countries) for the industry and transportation sectors for the years 1980-2014. However, future projections about total emissions and income relationship by the authors using integrated assessment models (IAMs) show a gradual decline in emissions for the transportation sector. This may be due to the presence of developed economies showing stronger environmental preferences and better access to cleaner modes of transportation. From Tab. 7, we find a mild positive and convex relationship reflecting the need to greater transportation in developing economies with growing incomes. Lin et al., 2014[32] analyzing sectoral value additions, energy consumption and carbon emissions for the manufacturing sector in China, find that a long-run relationship between the variables does exist. Specifically, carbon emissions adjust to a long-run equilibrium as caused by changes in shares of the manufacturing sector and energy consumption. However, the dearth of a causal relation running from energy consumption and emissions to growth in the manufacturing sector suggests that there remains reduction potential for energy consumption in the manufacturing sector, which would also lead to less emissions. The positive relationship we find between emissions and manufacturing and construction value added is further reiterated by Adjei-Mantey and Adams (2023)[1] who also find a long-run positive relationship between industrial growth and increased emissions. An inverted U-shape (EKC) relation is also found between GDP growth and the share of manufacturing value added for a large group of industrialized and developing and emerging industrial economies by Halkos et al. (2021)[21]. In the current literature, studies analyzing the decoupling of economic development from carbon emissions generated from commercial and public buildings remain scant. Our empirical results support the findings of recent contributions adopting index decomposition analysis to investigate the nexus between development and emissions generation in the tertiary sector. Particularly, Chen et al. (2022)[14] and Ma and Cai (2019)[34] find out how sustained development in commercial and public buildings in China has been followed by an effective low carbon development roadmap, thus confirming the existence of an inverted U-shaped relationship (EKC). Wenbo and Yan (2018)[61] further argue how the implementation of environmental regulations has helped China to reach its peak of carbon emission intensity (measured as the ratio of emissions to GDP) and better regulations would help the country reach its goal of peaking total carbon emissions by

[17]The robustness checks in Tab. 11 validate the linear impact of GDP growth on emissions for the transportation sector.

2030. The effect of regulations have been stronger in the more developed eastern region of China, possibly again showing the inverse relation between emissions and growth after a certain income level with greater access to energy-efficient technologies.

When considering the efficiency and activity indexes, interesting results emerge. The manufacturing sector registers an inverted U-shaped relationship for both the two indexes, suggesting how both improvements in energy efficiency and the reconfiguration of intra-sectoral economic activities played a role in generating energy savings after some threshold values. Conversely, the transportation sector registers adverse structural shifts in environmental outcomes captured by a U-shaped relationship between the activity index and emissions. As seen in Tab. 7 and Tab. 11, we also find an inverted U-shape relationship in certain cases. When energy intensity can be expressed as a decomposition between activity and efficiency indexes at a sectoral level, our results follow Patiño et al. (2021)[44]; specifically, the authors, examining the Colombian case for the period 1975-2016, show how decreases in aggregate energy intensity in the transportation sector are driven mostly by sectoral energy intensity effects. The authors also find sectoral shares (activity index) for transportation and industry to be increasing (and decreasing, respectively) over the years and having a large impact on the aggregate energy intensity levels. This can be explained by a greater percentage of the population having access to private transportation needs and the development of public/mass transit systems for developing and emerging economies as a whole. While this can lead to less polluting and energy efficient systems for countries after incomes crossing a certain threshold, our results for a large group show carbon emissions to decrease and then increase. Patiño et al. (2021)[44] show carbon dioxide emissions to fall largely due to declines in energy intensity and as shown by Jain (2023)[25], energy intensity improvements and energy savings have been observed in India during 2011-2019 for the industrial sector as a whole. However, the activity shares for this sector has also increased over the years. Finally, a U-shaped relationship also emerges between the efficiency index and emissions for the commercial and public sector. This result is in line with Patiño et al. (2021)[44] who also show sectoral energy intensity to increase in recent years for the service sector in Colombia. Studies such as by Ferrada et al. (2022)[18], using index decomposition analysis, suggest how in the commercial and public sector, the emergence of more efficient, cleaner and cost-effective end-use technologies still lags behind compared to developed countries. Nevertheless, this gap is expected to shrink in the next two decades leading to emissions curtails in the tertiary sector (Jain, 2023[25]; Patiño et al., 2022[44]). For the agriculture and forestry sector, no significant relationships emerge for emissions and the two energy indexes. Conversely, energy efficiency gains in the transportation sector have been registered in different countries thanks to a deeper penetration of renewable technologies such as biofuels, hybrid vehicles, and lithium-ion batteries (Junior et al., 2022[28]; Dharmala et al., 2022[16]; Feng and Wang., 2018[17][18]). Robustness checks in Tabs. 10-13 validate our empirical findings.

[TAB. 6 HERE]

[18]Feng and Wang, 2018[17], in analyzing the transportation sector, find evidence of a decrease in energy efficiency gains followed by a subsequent increase, thus providing evidence for the existence of a U-shaped curve in technological amelioration.

[TAB. 7 HERE]

[TAB. 8 HERE]

[TAB. 9 HERE]

[TAB. 10 HERE]

[TAB. 11 HERE]

[TAB. 12 HERE]

[TAB. 13 HERE]

5 Conclusion

Given the sector-specific nature of pollutant sources, exploring EKC patterns at the sectoral level becomes relevant for the formulation of effective carbon-neutral strategies. In this paper, we investigate the joint impact of sectoral economic growth and energy-related measures on carbon dioxide emissions in order to understand such patterns. For the analysis, we consider a sample of 43 emerging and developing economies from 1998 to 2019. We employ index decomposition analysis to decompose the energy intensity index into an efficiency index and activity index using the Fisher index decomposition. The Fisher index lends itself to certain desirable properties such as giving perfect decomposition without unexplained residuals. Our empirical findings reveal how energy efficiency, switches in economic activities, and contribution of GDP growth vary substantially among sectors, which translates into heterogeneous responses to CO2 emissions. Compared to previous sectoral studies in the literature, we find a linear positive impact of growth on carbon dioxide emissions for all sectors with the exception of the commercial and public sector (and a non-significant effect for the agriculture and forestry sector). Since the contribution to GDP of the tertiary industry is expanding at an increasing rate in developing and emerging economies, maintaining carbon neutrality remains an essential task for global emission abatement targets (UNSDG, 2023[57]). In the light of this, policies should be formulated considering the presence of reduced energy efficiency gains in the tertiary industry. In this regard, effective policy strategies might focus on green building development; e.g., encouraging the usage of green building materials and equipment (Chen et al., 2015[15]; Zuo and Zhao, 2014[65]) or the application of renewable energy sources such as solar panels (Liu et al., 2017[33]). At the same time, considering the green supply chain of civil and commercial constructions (Ma and Cai, 2019[34]), measures such as corporate credit ratings and building product ratings might prove to be effective in promoting building energy efficiency. On the other hand, being the manufacturing and transportation sectors large contributors to emissions from fuel combustion for countries considered in our study, policies should be undertaken to optimize energy efficiency in such sectors. Studies for a large group of industrialized and developing economies (Halkos et al., 2021[21]) and China (Lin et al., 2014[32]) analyzing the manufacturing sector demonstrate how emission reduction measures can be undertaken without affecting long term growth. Since energy consumption is associated with greater emissions, this study suggests how reducing energy intensity and adopting energy efficiency measures would reduce emissions while not affecting long-run growth in the manufacturing sector. In this context, the general reduction in manufacturing energy intensity, reasonably driven by economic growth and increased energy prices, has been providing incentives to invest in new technology and industrial processes (Sadath and Acharya, 2015[50]). In line with Ma and Cai (2019)[34], we argue that encouraging income tax reductions and exemptions for green energy companies might serve as a valuable policy tool in order to promote long-run carbon neutrality in the industrial sector.

On the other hand, the reconfiguration of economic activities within the transportation sector appears to have negatively contributed to emission abatement. In line with Feng and Wang (2018)[17] and Guo et al. (2022)[20], while the contribution of the transportation sector to GDP might be large in emerging economies such as China, measures to reduce emissions in the transportation sector might be more effective in regions with higher levels of development. At the same time, the implementation of such measures might be difficult in view of managerial and other institutional failures. Related increase in emissions in the transportation sector associated with GDP growth might also be fostered by a high correlation between fuel consumption and income in emerging economies across income levels (Ru et al., 2018[49]). Hence, an increase in fuel prices (causing an increase in the transportation sector's price index), if not associated with large increases in *per capita* income levels, may reduce carbon emissions from this sector (Guo et al., 2022[20]). Technological solutions often advocated to cope with increased emissions in the transportation sector generally include vehicle electrifications and usage of biofuels, although both face challenges in developing economies (Moreira et al., 2022[35]). In this regard, if the imposition of eco-standards for new vehicle emissions and fuels can be seen as a more cumbersome option for developing countries, retrofitting and replacement of high-emission older vehicles might represent a more viable solution (Kaygusuz et al., 2012[30]; Ong et al., 2012[41]; Zhou et al., 2010[64]).

All in all, the findings from our study suggest how improving energy efficiency and strategically shifting economic activities among sectors might have the potential to reduce CO2 emissions. As such, it becomes imperative for policymakers in developing countries to prioritize enhancing energy efficiency and consider transitioning high-energy intensity sectors to a lower level. Although of interest, our study has some limitations; *in primis*, it lacks a proper comprehensive approach required in order to suggest effective decarbonization policies. For instance, in our analysis we considered output growth as the only economic factor outside the energy matrix; nonetheless, due to lack of data availability, we could not take into account important determinants such as the costs of distribution of energy resources or the utility of agents. Indeed, our simple framework does not address the issue, for example, that firms operating in the commercial and public sector might not be willing to invest in more expensive but efficient technologies (e.g., heat pumps). In this regard, to achieve successful adoption outcomes, either subsidies or financing mechanisms should be adopted by policy makers. We leave these issues for future research.

6 Appendix

6.1 Countries considered in our study

Argentina, Azerbaijan, Bahrain, Bolivia, Botswana, Brazil, Bulgaria, Chile, China (incl. Hong Kong), Colombia, Costa Rica, Croatia, Egypt, Hungary, India, Indonesia, Iran, Iraq, Jamaica, Kazakhstan, Kuwait, Libya, Malaysia, Mexico, Morocco, Pakistan, Philippines, Poland, Qatar, Romania, Russia, Saudi Arabia, South Africa, Sri Lanka, Turkey, Thailand, Trinidad and Tobago, Tunisia, Turkmenistan, Ukraine, United Arab Emirates, Uruguay, Vietnam.

7 Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

8 Acknowledgements

We would like to thank colleagues at our respective institutions for their valuable guidance, inputs and suggestions.

9 Declaration of Interest

'Declarations of Interest: none'

10 Author Contributions

Supratim Das Gupta: Conceptualization; Investigation; Data curation; Roles/Writing - original draft; Writing - review & editing; Project administration; Supervision
Marco Baudino: Formal analysis; Methodology; Resources; Software; Roles/Writing - original draft; Writing - review & editing.
Saikat Sarkar: Data Curation; Methodology; Roles/Writing - original draft; Formal Analysis; Validation.

References

[1] Kwame Adjei-Mantey and Samuel Adams. "Renewable energy, foreign direct investment and carbon dioxide emissions: Do sectoral value additions and policy uncertainty matter?" In: *Energy Nexus* 10 (2023), p. 100193.

[2] Cesar Alonso-Borrego and Manuel Arellano. "Symmetrically normalized instrumental-variable estimation using panel data". In: *Journal of Business & Economic Statistics* 17.1 (1999), pp. 36–49.

[3] Beng Wah Ang. "Decomposition analysis for policymaking in energy:: which is the preferred method?" In: *Energy policy* 32.9 (2004), pp. 1131–1139.

[4] Manuel Arellano and Stephen Bond. "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations". In: *The review of economic studies* 58.2 (1991), pp. 277–297.

[5] Manuel Arellano and Olympia Bover. "Another look at the instrumental variable estimation of error-components models". In: *Journal of econometrics* 68.1 (1995), pp. 29–51.

[6] Enock Kojo Ayesu. "Does shipping cause environmental emissions? Evidence from African countries". In: *Transportation Research Interdisciplinary Perspectives* 21 (2023), p. 100873.

[7] Badi Hani Baltagi and Badi H Baltagi. *Econometric analysis of panel data*. Vol. 4. Springer, 2008.

[8] Mikkel Bennedsen, Eric Hillebrand, and Sebastian Jensen. "A neural network approach to the environmental Kuznets curve". In: *Energy Economics* (2023), p. 106985.

[9] Richard Blundell and Stephen Bond. "Initial conditions and moment restrictions in dynamic panel data models". In: *Journal of econometrics* 87.1 (1998), pp. 115–143.

[10] Bilal Boubellouta and Sigrid Kusch-Brandt. "Relationship between economic growth and mismanaged e-waste: Panel data evidence from 27 EU countries analyzed under the Kuznets curve hypothesis". In: *Waste Management* 120 (2021), pp. 85–97.

[11] Bilal Boubellouta and Sigrid Kusch-Brandt. "Testing the environmental Kuznets Curve hypothesis for E-waste in the EU28+ 2 countries". In: *Journal of Cleaner Production* 277 (2020), p. 123371.

[12] William A Brock et al. "Handbook of economic growth". In: (2005).

[13] Abbas Ali Chandio et al. "Dynamic relationship among agriculture-energy-forestry and carbon dioxide (CO 2) emissions: empirical evidence from China". In: *Environmental Science and Pollution Research* 27 (2020), pp. 34078–34089.

[14] Minxia Chen et al. "Carbon Kuznets curve in China's building operations: Retrospective and prospective trajectories". In: *Science of the Total Environment* 803 (2022), p. 150104.

[15] Xi Chen, Hongxing Yang, and Lin Lu. "A comprehensive review on passive design approaches in green building rating tools". In: *Renewable and Sustainable Energy Reviews* 50 (2015), pp. 1425–1436.

[16] Nikhilesh Dharmala et al. "Win-win transportation strategies for India: Linking air pollution and climate mitigation". In: *Energy and Climate Change* 3 (2022), p. 100072.

[17] Chao Feng and Miao Wang. "Analysis of energy efficiency in China's transportation sector". In: *Renewable and Sustainable Energy Reviews* 94 (2018), pp. 565–575.

[18] Francisco Ferrada et al. "Energy planning policies for residential and commercial sectors under ambitious global and local emissions objectives: A Chilean case study". In: *Journal of Cleaner Production* 350 (2022), p. 131299.

[19] Irving Fisher. "The best form of index number". In: *Quarterly Publications of the American Statistical Association* 17.133 (1921), pp. 533–551.

[20] Mingyuan Guo et al. "Environment Kuznets curve in transport sector's carbon emission: evidence from China". In: *Journal of Cleaner Production* 371 (2022), p. 133504.

[21] George Halkos, Jaime Moll de Alba, and Valentin Todorov. "Analyzing manufacturing sector and selected development challenges: A panel data analysis". In: *Energy* 235 (2021), p. 121253.

[22] Tengfei Huo et al. "China's commercial building carbon emissions toward 2060: An integrated dynamic emission assessment model". In: *Applied Energy* 325 (2022), p. 119828.

[23] Kyung So Im, M Hashem Pesaran, and Yongcheol Shin. "Testing for unit roots in heterogeneous panels". In: *Journal of econometrics* 115.1 (2003), pp. 53–74.

[24] International Monetary Fund. "On the Path to Policy Normalization". In: *Fiscal Monitor* (Apr. 2023). Accessed: 21 June 2023. URL: `https://www.imf.org/en/Publications/FM/Issues/2023/04/03/fiscal-monitor-april-2023`.

[25] Manisha Jain. "Estimates of energy savings from energy efficiency improvements in India using Index Decomposition Analysis". In: *Energy for Sustainable Development* 74 (2023), pp. 285–296.

[26] Kyonghwa Jeong and Suyi Kim. "LMDI decomposition analysis of greenhouse gas emissions in the Korean manufacturing sector". In: *Energy Policy* 62 (2013), pp. 1245–1253.

[27] Qingquan Jiang, Shoukat Iqbal Khattak, and Zia Ur Rahman. "Measuring the simultaneous effects of electricity consumption and production on carbon dioxide emissions (CO2e) in China: new evidence from an EKC-based assessment". In: *Energy* 229 (2021), p. 120616.

[28] Antonio Djalma Nunes Ferraz Júnior et al. "Liquefied biomethane from sugarcane vinasse and municipal solid waste: Sustainable fuel for a green-gas heavy duty road freight transport corridor in Sao Paulo state". In: *Journal of Cleaner Production* 335 (2022), p. 130281.

[29] Chihwa Kao. "Spurious regression and residual-based tests for cointegration in panel data". In: *Journal of econometrics* 90.1 (1999), pp. 1–44.

[30] Kamil Kaygusuz. "Energy for sustainable development: A case of developing countries". In: *Renewable and sustainable energy reviews* 16.2 (2012), pp. 1116–1126.

[31] Muhammad Khan and Ilhan Ozturk. "Examining the direct and indirect effects of financial development on CO2 emissions for 88 developing countries". In: *Journal of environmental management* 293 (2021), p. 112812.

[32] Boqiang Lin, Mohamed Moubarak, and Xiaoling Ouyang. "Carbon dioxide emissions and growth of the manufacturing sector: Evidence for China". In: *Energy* 76 (2014), pp. 830–837.

[33] Zhijian Liu et al. "Design of high-performance water-in-glass evacuated tube solar water heaters by a high-throughput screening based on machine learning: A combined modeling and experimental study". In: *Solar Energy* 142 (2017), pp. 61–67.

[34] Minda Ma and Weiguang Cai. "Do commercial building sector-derived carbon emissions decouple from the economic growth in Tertiary Industry? A case study of four municipalities in China". In: *Science of the Total Environment* 650 (2019), pp. 822–834.

[35] Jose R Moreira, Sergio A Pacca, and Jose Goldemberg. "The reduction of CO2e emissions in the transportation sector: Plug-in electric vehicles and biofuels". In: *Renewable and Sustainable Energy Transition* 2 (2022), p. 100032.

[36] Bashir Muhammad. "Energy consumption, CO2 emissions and economic growth in developed, emerging and Middle East and North Africa countries". In: *Energy* 179 (2019), pp. 232–245.

[37] Georg Müller-Fürstenberger and Martin Wagner. "Exploring the environmental Kuznets hypothesis: Theoretical and econometric problems". In: *Ecological Economics* 62.3-4 (2007), pp. 648–660.

[38] Stephen Nickell. "Biases in dynamic models with fixed effects". In: *Econometrica: Journal of the econometric society* (1981), pp. 1417–1426.

[39] OECD. "GHG Emissions from fuel combustion (summary)". In: *IEA CO2 Emissions from Fuel Combustion Statistics: Greenhouse Gas Emissions from Energy* (2023). Accessed: 21 June 2023. DOI: `https://doi.org/https://doi.org/10.1787/445ec5dd-en`. URL: `https://www.oecd-ilibrary.org/content/data/445ec5dd-en`.

[40] Henrique Viana Espinosa de Oliveira and Vitor Moutinho. "Do renewable, non-renewable energy, carbon emission and KOF globalization influencing economic growth? Evidence from BRICS'countries". In: *Energy Reports* 8 (2022), pp. 48–53.

[41] HC Ong, TMI Mahlia, and HH Masjuki. "A review on energy pattern and policy for transportation sector in Malaysia". In: *Renewable and Sustainable Energy Reviews* 16.1 (2012), pp. 532–542.

[42] Bahareh Oryani et al. "The role of electricity mix and transportation sector in designing a green-growth strategy in Iran". In: *Energy* 233 (2021), p. 121178.

[43] Ugur Korkut Pata. "Renewable energy consumption, urbanization, financial development, income and CO2 emissions in Turkey: testing EKC hypothesis with structural breaks". In: *Journal of cleaner production* 187 (2018), pp. 770–779.

[44] Lourdes Isabel Patiño, Vicent Alcántara, and Emilio Padilla. "Driving forces of CO2 emissions and energy intensity in Colombia". In: *Energy Policy* 151 (2021), p. 112130.

[45] M Hashem Pesaran. "A simple panel unit root test in the presence of cross-section dependence". In: *Journal of applied econometrics* 22.2 (2007), pp. 265–312.

[46] Rosa Puertas and Luisa Marti. "Eco-innovation and determinants of GHG emissions in OECD countries". In: *Journal of Cleaner Production* 319 (2021), p. 128739.

[47] David Roodman. "A note on the theme of too many instruments". In: *Oxford Bulletin of Economics and statistics* 71.1 (2009), pp. 135–158.

[48] David Roodman. "How to do xtabond2: An introduction to difference and system GMM in Stata". In: *The stata journal* 9.1 (2009), pp. 86–136.

[49] Muye Ru et al. "The long-term relationship between emissions and economic growth for SO2, CO2, and BC". In: *Environmental Research Letters* 13.12 (2018), p. 124021.

[50] Anver C Sadath and Rajesh H Acharya. "Effects of energy price rise on investment: Firm level evidence from Indian manufacturing sector". In: *Energy Economics* 49 (2015), pp. 516–522.

[51] Ibrahim A Tajudeen, Ada Wossink, and Prasenjit Banerjee. "How significant is energy efficiency to mitigate CO2 emissions? Evidence from OECD countries". In: *Energy Economics* 72 (2018), pp. 200–221.

[52] The World Bank. *CO2 emissions from residential buildings and commercial and public services (% of total fuel combustion)*. Accessed: 21 June, 2023. 2023. URL: https://data.worldbank.org/indicator/EN.CO2.BLDG.ZS?view=chart.

[53] The World Bank. "World Bank Country and Lending Groups Country Classification". In: *Data* (2023). Accessed: 21 June 2023. URL: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

[54] Asbjørn Torvanger. "Manufacturing sector carbon dioxide emissions in nine OECD countries, 1973–87: A Divisia index decomposition to changes in fuel mix, emission coefficients, industry structure, energy intensities and international structure". In: *Energy economics* 13.3 (1991), pp. 168–186.

[55] United Nations. "Energy Balance Visualization". In: *United Nations Statistics Division* (2023). Accessed: 21 June 2023. URL: https://unstats.un.org/unsd/energystats/dataPortal/.

[56] United Nations. "National Accounts". In: *United Nations Statistics Division* (2023). Accessed: 21 June 2023. URL: https://unstats.un.org/unsd/snaama/Downloads.

[57] United Nations. *The 17 Goals*. Department of Economic and Social Affairs Sustainable Development. Accessed: 21 June, 2023. 2022. URL: https://sdgs.un.org/goals.

[58] United Nations. "UNdata A world of information". In: *United Nations Statistics Division* (2023). Accessed: 21 June 2023. URL: https://data.un.org.

[59] Qiang Wang, Fuyu Zhang, and Rongrong Li. "Revisiting the environmental kuznets curve hypothesis in 208 counties: The roles of trade openness, human capital, renewable energy and natural resource rent". In: *Environmental Research* 216 (2023), p. 114637.

[60] Zongrun Wang, Haiqin Fu, and Xiaohang Ren. "Political connections and corporate carbon emission: New evidence from Chinese industrial firms". In: *Technological Forecasting and Social Change* 188 (2023), p. 122326.

[61] Guo Wenbo and Chen Yan. "Assessing the efficiency of China's environmental regulation on carbon emissions based on Tapio decoupling models and GMM models". In: *Energy Reports* 4 (2018), pp. 713–723.

[62] Frank Windmeijer. "A finite sample correction for the variance of linear efficient two-step GMM estimators". In: *Journal of econometrics* 126.1 (2005), pp. 25–51.

[63] Abdulrasheed Zakari et al. "Impact of Nigeria's industrial sector on level of inefficiency for energy consumption: Fisher Ideal index decomposition analysis". In: *Heliyon* 7.5 (2021).

[64] Nan Zhou, Mark D Levine, and Lynn Price. "Overview of current energy-efficiency policies in China". In: *Energy policy* 38.11 (2010), pp. 6439–6452.

[65] Jian Zuo and Zhen-Yu Zhao. "Green building research–current status and future agenda: A review". In: *Renewable and sustainable energy reviews* 30 (2014), pp. 271–281.

Tables and figures

Table 1: Descriptive statistics.

Sector	Variable	Mean	S.D.	Min	Max
Manufacturing	Co2 emissions (million tonnes)	89098.038	341079.234	200	3096508
and construction	Real gdp (1,000 real US$)	112264.546	422434.334	751.338	4952458
	Energy consumption (terajoules)	1746409	5048468	7559	4.05e+07
Transportation	Co2 emissions (million tonnes)	51312.733	99534.165	960	955595
	Real gdp (1,000 real US$)	35355.973	104330.443	270.263	1311277
	Energy consumption (terajoules)	1305344	3951683	13740	2.71e+07
Commercial	Co2 emissions (million tonnes)	5798.152	17608.986	0	150923.745
and public	Real gdp (1,000 real US$)	157939.105	485685.065	1922.241	14874564
	Energy consumption (terajoules)	368768	1374299	0	9112583
Agriculture	Co2 emissions (million tonnes)	7084.137	18924.966	0	167696.265
and forestry	Real gdp (1,000 real US$)	40485.965	124232.442	71.660	1107907
	Energy consumption (terajoules)	138774.254	290777.923	0	1935521

Note: S.D.= Standard deviation, Min = Minimum value, Max = Maximum value.

Table 2: Carbon and energy intensity trends by sector.

Sector	Years	Carbon intensity (average annual change)	Energy intensity (average annual change)
Manufacturing	(1998-2004)	-30.70 %	-6.80 %
and construction	(2005-2011)	-35.09 %	-24.14 %
	(2012-2019)	-18.53 %	15.23 %
Transportation	(1998-2004)	-3.12 %	-16.49 %
	(2005-2011)	-14.17 %	-40.05 %
	(2012-2019)	-10.30 %	6.56 %
Commercial	(1998-2004)	-23.55 %	-12.75 %
and Public	(2005-2011)	166.02 %	-17.12 %
	(2012-2019)	-48.53 %	-16.15 %
Agriculture	(1998-2004)	8.90 %	38.63 %
and Forestry	(2005-2011)	-56.63 %	20.11 %
	(2012-2019)	-12.13 %	7.30 %

Note: Carbon intensity is expressed in million tonnes of CO2 per unit of GDP.
Energy intensity is expressed in terajoules per unit of GDP.

Table 3: Summary statistics of energy indexes.

Index	Sector	Years	Mean	S.D.	Min	Max	Coefficient of variation	Average annual change	Average annual change (cumulative)
Intensity									
	Manufacturing and construction	(1998-2004)	1.57	0.81	0.38	5.56	0.51	-3.97%	-3.97%
		(2005-2011)	2.79	0.38	0.41	2.61	0.14	-3.87%	-3.92%
		(2012-2019)	0.99	0.15	0.52	1.85	0.15	-1.66%	-3.17%
	Transportation	(1998-2004)	1.16	0.33	0.49	2.78	0.28	-0.47%	-0.47%
		(2005-2011)	1.06	0.22	0.31	2.42	0.21	-1.06%	-0.77%
		(2012-2019)	1.00	0.13	0.32	1.70	0.13	-0.37%	-0.77%
	Commercial and Public	(1998-2004)	0.67	0.46	0.00	1.91	0.69	0.61%	-2.94%
		(2005-2011)	1.05	0.66	0.02	5.29	0.63	8.71%	0.61%
		(2012-2019)	1.02	0.22	0.59	3.17	0.22	-0.81%	4.66%
	Agriculture and Forestry	(1998-2004)	4.67	11.80	0.05	79.31	2.53	-0.24%	2.84%
		(2005-2011)	2.93	7.58	0.17	57.81	2.59	-36.25%	-0.24%
		(2012-2019)	1.26	1.76	0.07	21.02	1.40	-8.36%	-0.24%
Efficiency									
	Manufacturing and construction	(1998-2004)	1.69	1.45	0.30	10.47	0.86	-7.06%	-7.06%
		(2005-2011)	1.17	0.39	0.29	2.54	0.33	-3.95%	-5.51%
		(2012-2019)	0.99	0.14	0.50	1.60	0.14	-0.72%	-3.91%
	Transportation	(1998-2004)	1.53	0.70	0.53	4.30	0.46	-3.11%	-3.11%
		(2005-2011)	1.19	0.41	0.34	3.96	0.34	-3.26%	-3.18%
		(2012-2019)	1.00	0.17	0.34	2.27	0.17	-1.17%	-2.51
	Commercial and Public	(1998-2004)	0.71	0.56	0.00	3.95	0.78	0.17%	0.17%
		(2005-2011)	1.09	0.77	0.02	6.32	0.70	8.70%	4.43%
		(2012-2019)	1.02	0.23	0.59	3.05	0.22	-1.12%	2.58%
	Agriculture and Forestry	(1998-2004)	3.72	9.61	0.05	58.52	2.58	7.96%	7.96%
		(2005-2011)	2.71	7.39	0.13	65.02	2.73	-35.89%	-13.96%
		(2012-2019)	1.27	1.74	0.08	20.80	1.37	-7.38%	-11.77%
Activity									
	Manufacturing and construction	(1998-2004)	1.08	0.50	0.18	4.63	0.46	-0.09%	-0.09%
		(2005-2011)	1.08	0.20	0.51	2.05	0.18	-0.25%	-0.17%
		(2012-2019)	1.00	0.09	0.76	1.67	0.08	-0.91%	-0.42%
	Transportation	(1998-2004)	0.85	0.34	0.25	3.17	0.40	1.10%	1.10%
		(2005-2011)	0.93	0.17	0.29	1.49	0.18	0.79%	0.94%
		(2012-2019)	1.01	0.08	0.55	1.43	0.08	0.87%	0.92%
	Commercial and Public	(1998-2004)	0.98	0.10	0.41	1.23	0.10	-0.03%	-0.03%
		(2005-2011)	0.97	0.07	0.63	1.33	0.07	4.68%	2.33%
		(2012-2019)	1.00	0.04	0.65	1.30	0.04	0.25%	1.63%
	Agriculture and Forestry	(1998-2004)	1.41	0.37	0.79	2.79	0.26	-1.75%	-1.75%
		(2005-2011)	1.17	0.25	0.61	2.71	0.21	-2.59%	-2.17%
		(2012-2019)	1.00	0.11	0.60	1.69	0.11	-0.85%	-1.73%

Note: S.D.= Standard deviation, Min = Minimum value, Max = Maximum value.

Table 4: Panel unit root test results.

Sector	Variable	CADF		CIPS		HT	
		Levels	First difference	Levels	First difference	Levels	First difference
Manufacturing	CO2 emissions	-2.508*		-2.740	-4.377***	0.8867	0.305***
and construction	Real gdp	-1.820**		-1.686	-3.527***	0.432	0.506***
	Energy consumption	-2.061	-3.079***	-2.585	-4.721***	0.868	0.416***
	Energy Efficiency	-2.681**		-2.898	-4.722***	0.710	-0.091***
	Energy activity	-2.244	-3.183***	-2.314	-3.891***	0.795	0.323***
Transportation	CO2 emissions	-2.203	-3.046***	-2.703	-4.351***	0.643	0.237***
	Real gdp	-1.770	-2.535**	-1.765	-3.260***	1.281	0.973***
	Energy consumption	-2.219	-2.907***	-2.215	-4.039***	0.653	0.097***
	Energy Efficiency	-2.667*		-2.531	-4.247***	0.721	0.107***
	Energy activity	-1.983	-2.858***	-1.876	-3.741***	0.735	-0.037***
Commercial	CO2 emissions	-2.342	-3.254***	-2.528	-3.915***	0.505	-0.106***
and public	Real gdp	-1.785	-2.454**	-1.512	-3.117***	-0.166	-0.500***
	Energy consumption	-2.310	-3.417***	-2.899*		0.539*	
	Energy Efficiency	-3.578**		-3.757**		0.712	-0.093***
	Energy activity	-3.030**		-3.357**		0.629*	
Agriculture	CO2 emission	-1.522	-2.361**	-1.788	-3.431***	0.461	-0.164***
and forestry	Real gdp	-2.080	-3.236***	-2.644	-4.741***	0.782	0.815***
	Energy consumption	-2.056	-3.347***	-2.248	-4.287***	0.419	-0.206***
	Energy Efficiency	-2.055	-3.409***	-2.301	-4.184***	0.255*	
	Energy activity	-1.768	-2.902***	-2.257	-4.106***	0.637	-0.060***

Note: CO2 emissions, real gdp and energy consumption are log-transformed.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Panel cointegration test results.

Method	Test statistic	Manufacturing and construction	Transportation	Commercial and public	Agriculture and forestry
Kao	ADF-t	-7.537***	-8.718***	-7.748***	-7.170***
	DF-t	-5.754***	-6.802***	-7.513***	-6.274***
Pedroni	Phillips-Perron t	-7.079***	-7.958***	-8.297***	-4.784***
	ADF-t	-9.955***	-5.763***	-6.338***	-4.737***
Westerlund	Variance ratio	-3.141**	-3.529**	15.871***	-3.141**

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Manufacturing and construction sector.

	(1) Sys-GMM	(2) Diff-GMM2	(3) FE	(4) POLS
l.e	0.557***	0.465***	0.610***	0.947***
	(0.013)	(0.011)	(0.027)	(0.011)
gdp	0.505*	0.397**	0.125	0.036
	(0.277)	(0.195)	(0.167)	(0.063)
gdp^2	-0.006	-0.007	0.005	0.001
	(0.013)	(0.009)	(0.008)	(0.003)
eff	0.419***	0.297***	0.273***	0.076**
	(0.029)	(0.016)	(0.047)	(0.033)
eff^2	-0.033***	-0.024***	-0.020***	-0.007*
	(0.005)	(0.004)	(0.005)	(0.004)
act	0.459***	0.480***	0.350***	-0.034
	(0.122)	(0.053)	(0.124)	(0.105)
act^2	-0.068***	-0.096***	-0.054**	0.013
	(0.022)	(0.007)	(0.026)	(0.024)
Hansen test	40.990	36.802		
AR(1)	-1.595	-1.561		
AR(2)	0.557	0.355		
N. of instruments	237	216		
Observations	886	843	886	886

Note: Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Transportation sector.

	(1) Sys-GMM	(2) Diff-GMM2	(3) FE	(4) POLS
l.e	0.281***	0.549***	0.615***	0.909***
	(0.017)	(0.122)	(0.025)	(0.013)
gdp	0.394***	0.717**	0.443***	0.042
	(0.061)	(0.280)	(0.102)	(0.039)
gdp^2	0.017***	-0.010	-0.002	0.002
	(0.003)	(0.015)	(0.005)	(0.002)
eff	0.291***	0.380***	0.318***	0.123**
	(0.026)	(0.142)	(0.066)	(0.050)
eff^2	-0.020***	-0.039	-0.036***	-0.021*
	(0.005)	(0.026)	(0.013)	(0.012)
act	-0.669***	-0.528**	-0.327**	-0.047
	(0.050)	(0.215)	(0.152)	(0.115)
act^2	0.139***	0.120*	0.089**	0.013
	(0.010)	(0.061)	(0.044)	(0.037)
Hansen test	36.386	42.252		
AR(1)	-1.371	-1.357		
AR(2)	1.269	1.162		
N. of instruments	237	236		
Observations	897	854	897	897

Note: Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Commercial and public sector.

	(1) Sys-GMM	(2) Diff-GMM2	(3) FE	(4) POLS
l.e	0.390***	0.055	0.551***	0.920***
	(0.062)	(0.038)	(0.032)	(0.015)
gdp	1.225***	0.795***	0.120	0.183***
	(0.133)	(0.113)	(0.150)	(0.046)
gdp^2	-0.028***	-0.018***	-0.003	-0.004***
	(0.003)	(0.003)	(0.003)	(0.001)
eff	-1.723***	-0.195*	0.044	-0.246*
	(0.321)	(0.110)	(0.161)	(0.141)
eff^2	0.896***	0.222***	0.135	0.184**
	(0.149)	(0.041)	(0.085)	(0.077)
act	14.247**	-9.314	8.420	-6.114
	(6.118)	(6.053)	(5.241)	(4.435)
act^2	-8.466***	3.114	-4.006	3.094
	(3.186)	(2.876)	(2.627)	(2.230)
Hansen test	23.400	24.088		
AR(1)	-2.763	-1.867		
AR(2)	-0.499	-1.417		
N. of instruments	237	216		
Observations	610	565	610	610

Note: Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Agriculture and forestry sector.

	(1) Sys-GMM	(2) Diff-GMM2	(3) FE	(4) POLS
l.e	0.668***	0.472***	0.702***	0.956***
	(0.047)	(0.035)	(0.027)	(0.014)
gdp	-0.640	-0.069	-1.195*	0.062
	(1.138)	(1.912)	(0.716)	(0.115)
gdp^2	0.023	-0.021	0.050	-0.001
	(0.061)	(0.100)	(0.037)	(0.006)
eff	0.003	0.097***	0.057***	-0.005
	(0.009)	(0.016)	(0.012)	(0.009)
eff^2	0.000	-0.001***	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
act	1.287**	0.747	0.169	-0.114
	(0.571)	(0.707)	(0.452)	(0.417)
act^2	-0.329	-0.218	-0.042	0.041
	(0.225)	(0.238)	(0.153)	(0.146)
Hansen test	24.481	30.794		
AR(1)	-2.756	-3.121		
AR(2)	0.654	0.582		
N. of instruments	237	216		
Observations	665	624	665	665

Note: Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Manufacturing and construction sector.

	(1) Sys-GMM (*gdp* endog.)	(2) Sys-GMM (*eff* endog.)	(3) Sys-GMM (*act* endog.)	(4) Sys-GMM (one-step)	(5) Diff-GMM2 (one-step)
l.e	0.673***	0.650***	0.664***	0.553***	0.467***
	(0.008)	(0.015)	(0.017)	(0.027)	(0.033)
gdp	0.075	0.268*	0.406***	0.573**	0.480
	(0.125)	(0.174)	(0.140)	(0.276)	(0.350)
gdp^2	0.010*	0.004	-0.005	-0.010	-0.013
	(0.006)	(0.008)	(0.007)	(0.013)	(0.016)
eff	0.335***	0.349***	0.350***	0.421***	0.310***
	(0.048)	(0.024)	(0.016)	(0.057)	(0.067)
eff^2	-0.024***	-0.023***	-0.025***	-0.035***	-0.031***
	(0.004)	(0.003)	(0.002)	(0.008)	(0.008)
act	0.388***	0.399***	0.343***	0.402**	0.491***
	(0.083)	(0.079)	(0.099)	(0.191)	(0.189)
act^2	-0.049***	-0.056***	-0.043	-0.058	-0.095**
	(0.018)	(0.016)	(0.028)	(0.042)	(0.041)
Hansen test	42.287	40.630	40.748	555.142	380.329
AR(1)	-1.601	-1.601	-1.609	-2.069	-13.408
AR(2)	0.552	0.566	0.565	0.661	0.430
N. of instruments	470	470	470	237	216
Observations	886	886	886	886	843

Note: Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Transportation sector.

	(1) Sys-GMM (*gdp* endog.)	(2) Sys-GMM (*eff* endog.)	(3) Sys-GMM (*act* endog.)	(4) Sys-GMM (one-step)	(5) Diff-GMM2 (one-step)
l.e	0.518***	0.583***	0.560***	0.259***	0.567***
	(0.022)	(0.037)	(0.006)	(0.030)	(0.124)
gdp	0.443**	0.591***	0.579***	0.427***	0.700**
	(0.176)	(0.145)	(0.113)	(0.150)	(0.292)
gdp^2	0.001	-0.011	-0.008	0.016**	-0.011
	(0.008)	(0.008)	(0.005)	(0.008)	(0.015)
eff	0.221***	0.106*	0.245***	0.275***	0.374**
	(0.059)	(0.083)	(0.024)	(0.082)	(0.154)
eff^2	-0.008	0.014	-0.018***	-0.017	-0.038
	(0.015)	(0.019)	(0.005)	(0.021)	(0.028)
act	-0.350***	-0.328***	-0.325***	-0.715***	-0.496***
	(0.133)	(0.116)	(0.089)	(0.185)	(0.175)
act^2	0.058*	0.073***	0.082***	0.144**	0.112**
	(0.042)	(0.027)	(0.023)	(0.063)	(0.053)
Hansen test	36.024	33.307	36.560	339.718	109.461
AR(1)	-1.364	-1.395	-1.372	-2.001	-1.442
AR(2)	1.193	1.220	1.194	2.200	1.249
N. of instruments	470	470	470	237	236
Observations	897	897	897	897	854

Note: Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Commercial and public sector.

	(1) Sys-GMM (gdp endog.)	(2) Sys-GMM (eff endog.)	(3) Sys-GMM (act endog.)	(4) Sys-GMM (one-step)	(5) Diff-GMM2 (one-step)
l.e	0.595***	0.567***	0.674***	0.415***	0.126***
	(0.044)	(0.030)	(0.043)	(0.038)	(0.048)
gdp	1.010***	0.816***	0.514***	1.144***	0.487***
	(0.181)	(0.119)	(0.100)	(0.105)	(0.157)
gdp^2	-0.023***	-0.018***	-0.012***	-0.026***	-0.011***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)
eff	-1.193***	-0.511*	-0.497*	-0.723***	-0.202
	(0.431)	(0.354)	(0.327)	(0.175)	(0.181)
eff^2	0.662***	0.402**	0.395***	0.422***	0.205**
	(0.194)	(0.158)	(0.130)	(0.093)	(0.091)
act	8.172	-9.665	-9.494	-1.164	2.640
	(6.672)	(7.764)	(8.670)	(5.374)	(4.731)
act^2	-4.504	4.741	4.432	-0.021	-1.665
	(3.328)	(3.899)	(4.312)	(2.705)	(2.372)
Hansen test	32.754	35.711	35.313	366.047	298.272
AR(1)	-3.293	-3.241	-3.337	-3.676	-7.195
AR(2)	-0.452	-0.496	-0.431	-0.672	-1.393
N. of instruments	461	462	462	237	216
Observations	610	610	610	610	565

Note: Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Agriculture and forestry sector.

	(1) Sys-GMM (gdp endog.)	(2) Sys-GMM (eff endog.)	(3) Sys-GMM (act endog.)	(4) Sys-GMM (one-step)	(5) Diff-GMM2 (one-step)
l.e	0.805***	0.817***	0.850***	0.768***	0.458***
	(0.071)	(0.036)	(0.030)	(0.029)	(0.039)
gdp	-0.873	-1.978	-2.332*	-2.127***	-0.011
	(2.245)	(1.767)	(1.355)	(0.594)	(1.451)
gdp^2	0.046	0.107	0.121*	0.106***	-0.031
	(0.117)	(0.089)	(0.067)	(0.031)	(0.075)
eff	-0.001	-0.013*	-0.002	-0.011	0.081***
	(0.005)	(0.007)	(0.005)	(0.017)	(0.019)
eff^2	0.000**	0.000***	0.000	0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
act	-0.056	0.288	-0.576	0.650	0.907
	(0.640)	(0.729)	(0.757)	(0.809)	(0.711)
act^2	0.121	0.030	0.356	-0.051	-0.280
	(0.224)	(0.265)	(0.318)	(0.299)	(0.259)
Hansen test	30.426	29.575	26.737	411.493	344.345
AR(1)	-3.009	-3.135	-3.233	-3.104	-10.500
AR(2)	0.680	0.668	0.693	0.671	0.970
N. of instruments	451	451	451	237	216
Observations	665	665	665	665	624

Note: Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

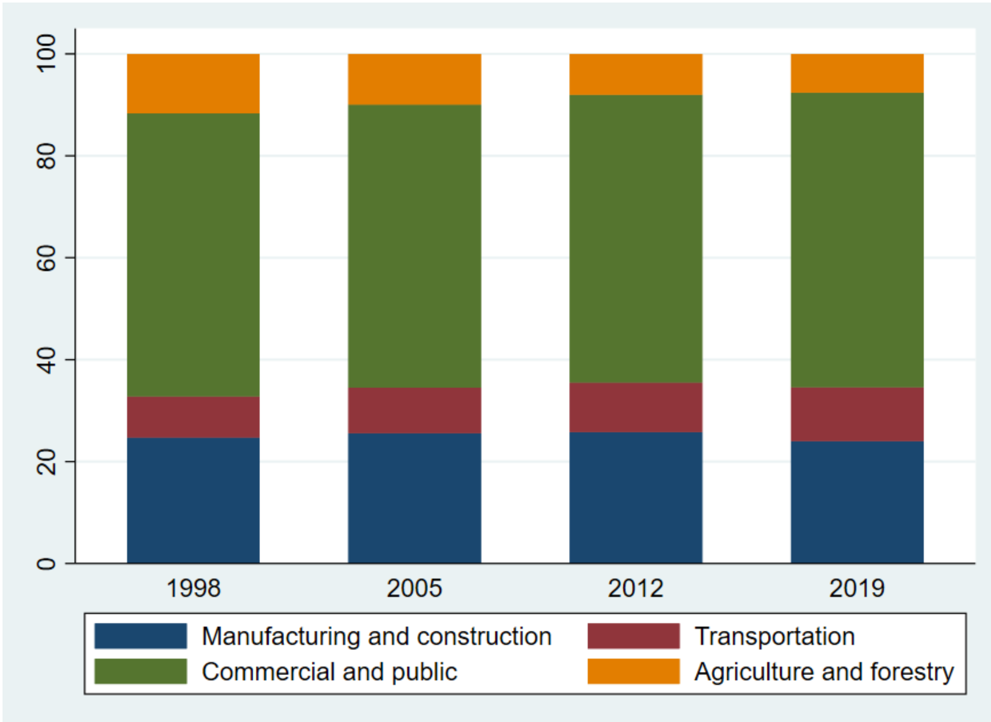


Figure 1: [COLOR FIGURE] Contribution to GDP by sector (%).

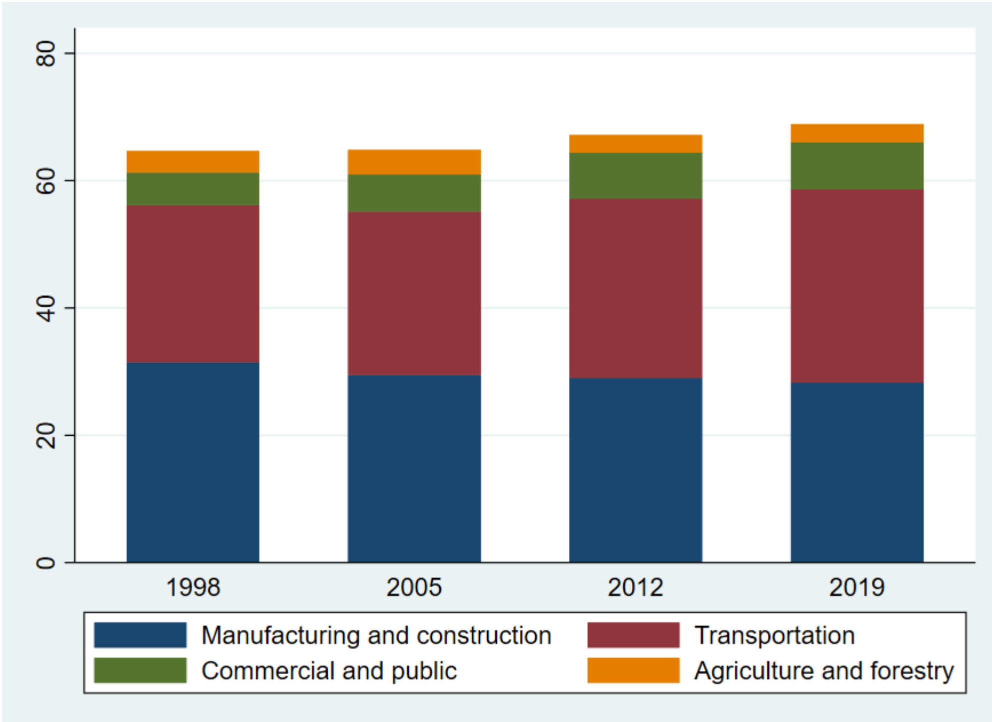


Figure 2: [COLOR FIGURE] Total energy consumption by sector (%).

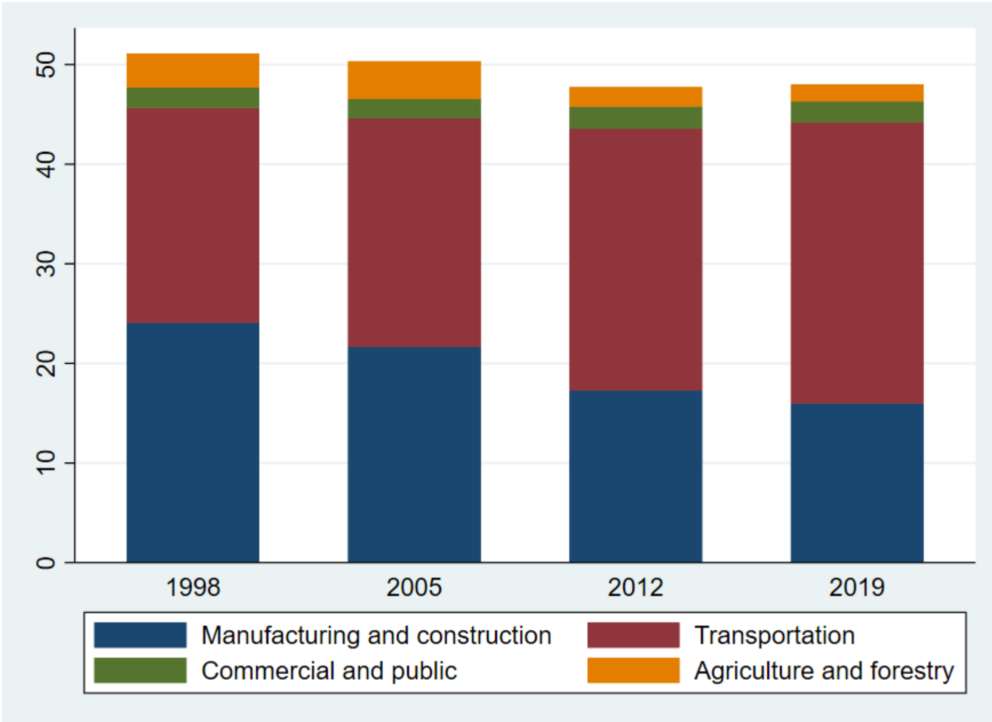
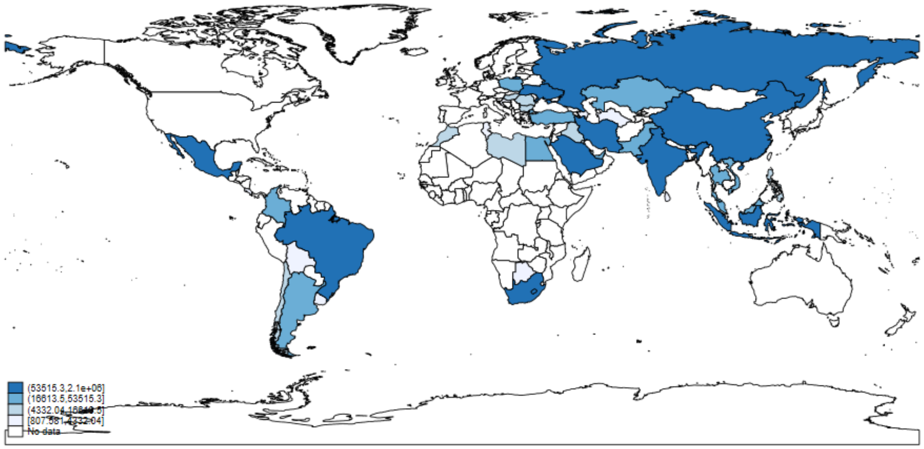
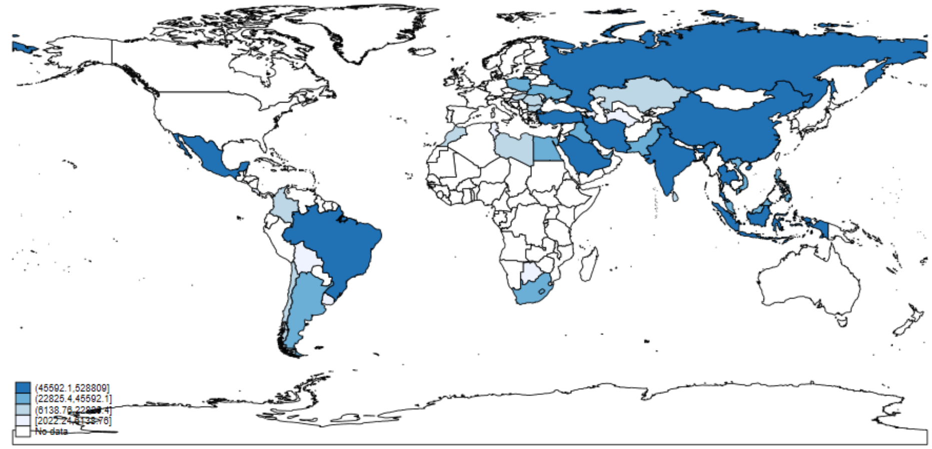


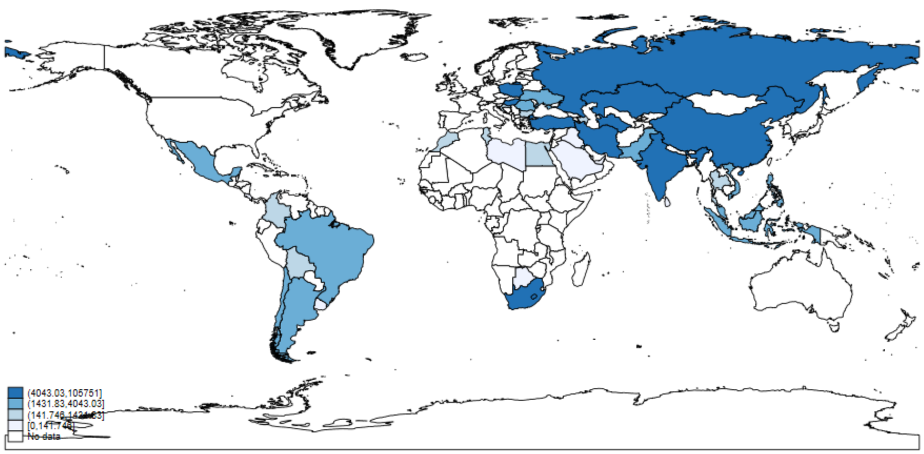
Figure 3: [COLOR FIGURE] Total CO2 emissions by sector (%).



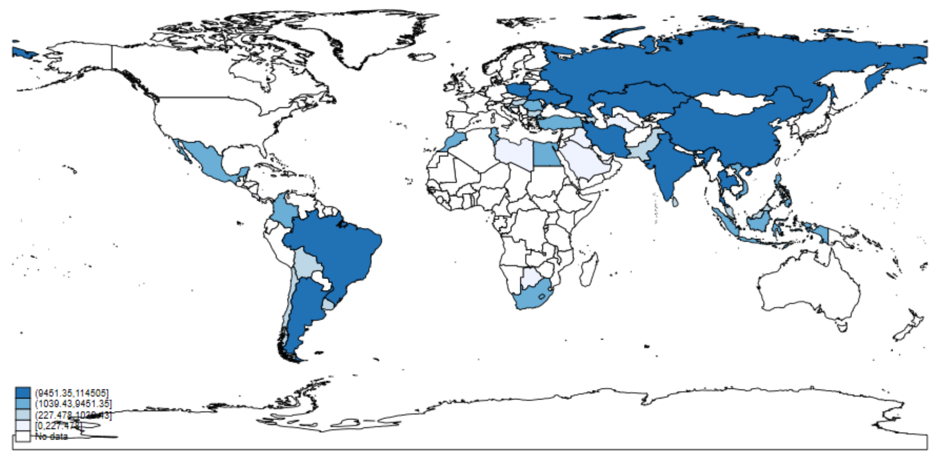
(a) Manufacturing and construction sector.



(b) Transportation sector.

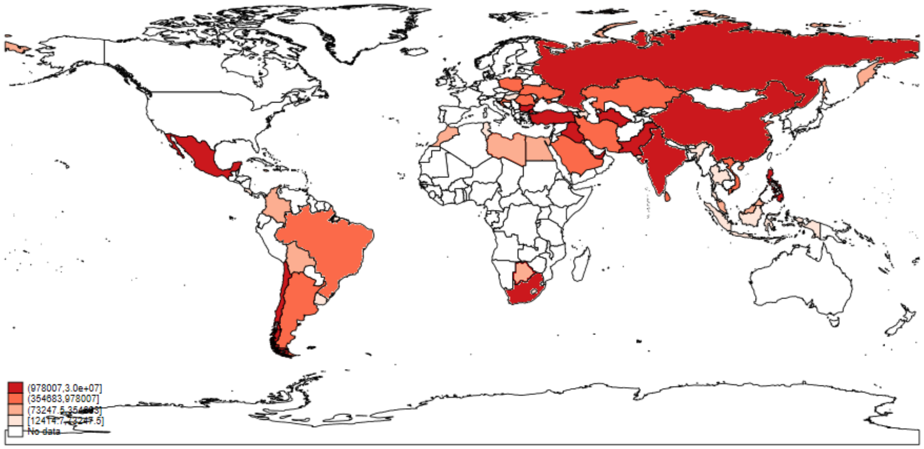


(c) Commercial and public sector.

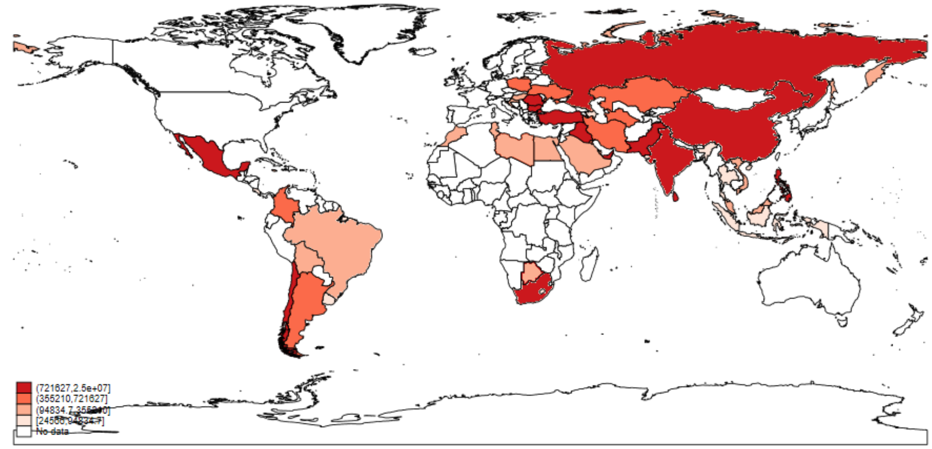


(d) Agriculture and forestry sector.

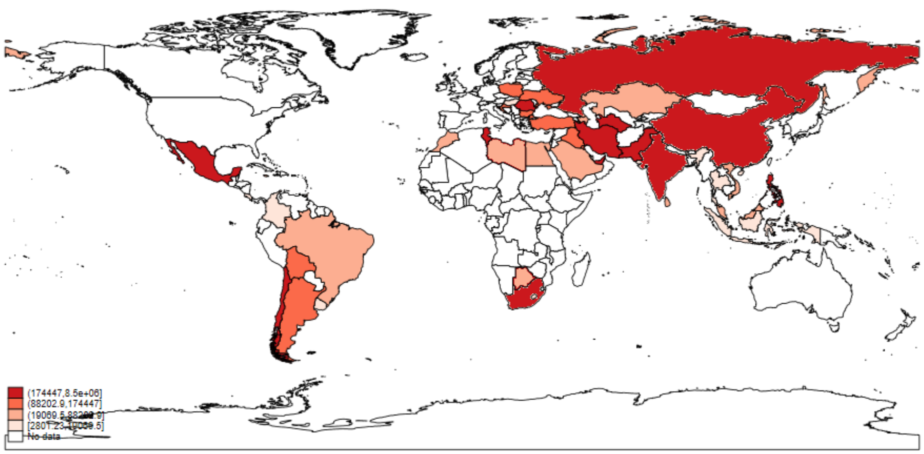
Figure 4: [COLOR FIGURE] Total CO2 emissions at sector level in million tonnes of CO2 (1998-2019).



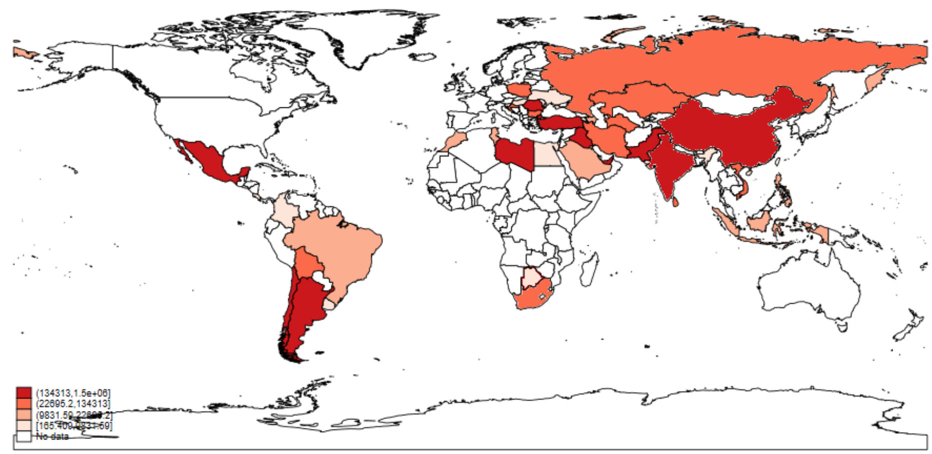
(a) Manufacturing and construction sector.



(b) Transportation sector.

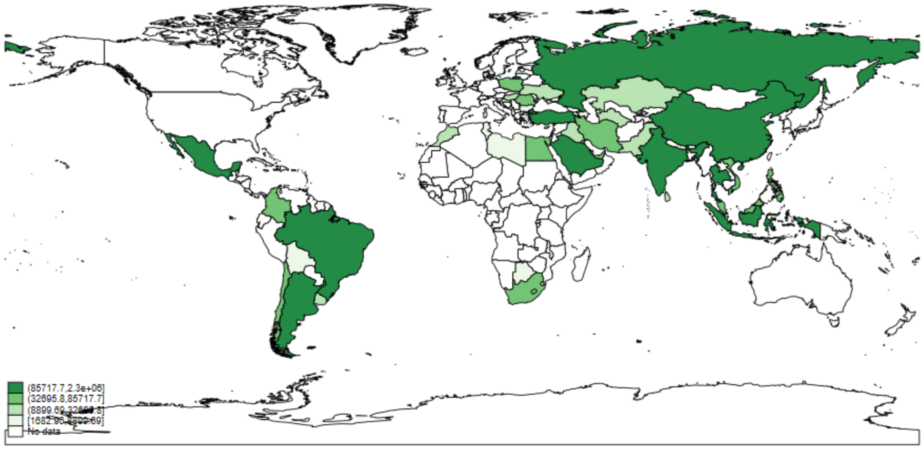


(c) Commercial and public sector.

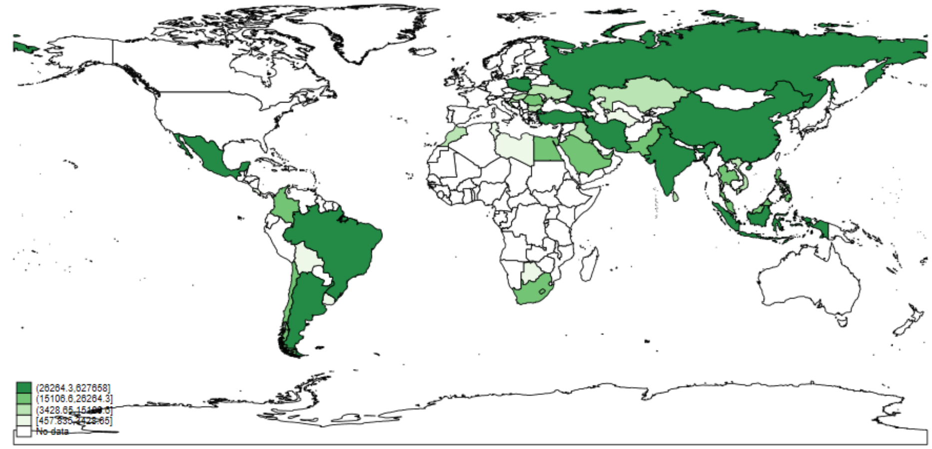


(d) Agriculture and forestry sector.

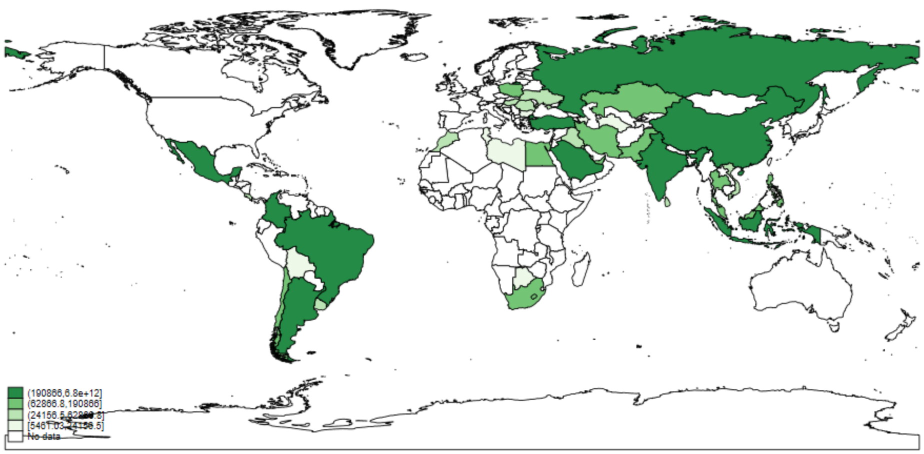
Figure 5: [COLOR FIGURE] Total energy consumption at sector level in Terajoules (1998-2019).



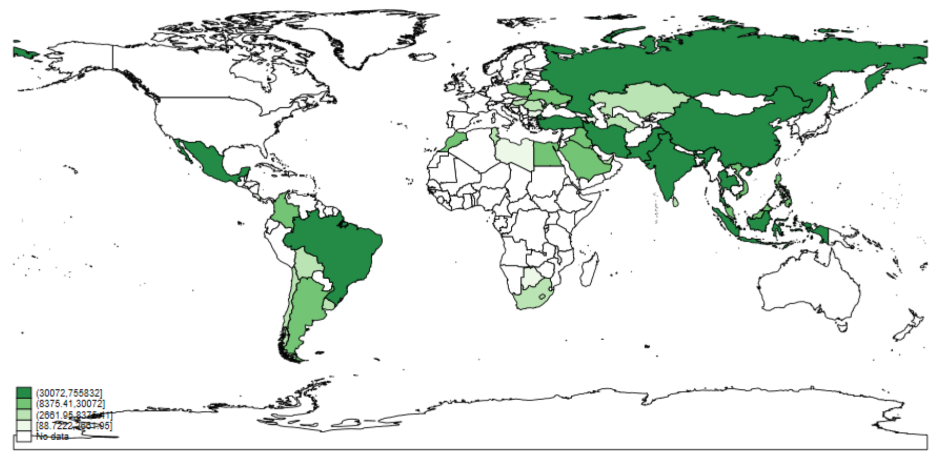
(a) Manufacturing and construction sector.



(b) Transportation sector.



(c) Commercial and public sector.



(d) Agriculture and forestry sector.

Figure 6: [COLOR FIGURE] Real sectoral GDP in 2015 constant US$ (1998-2019).

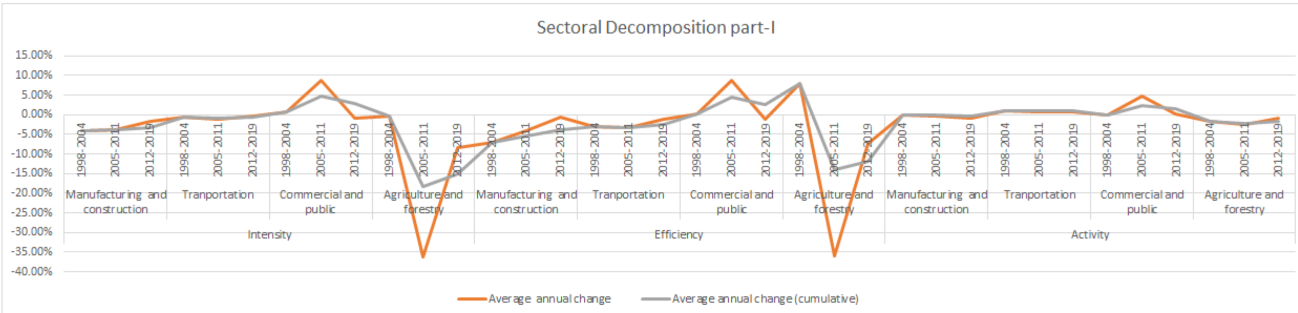


Figure 7: [COLOR FIGURE] Energy intensity and its decomposition by sector- part I.

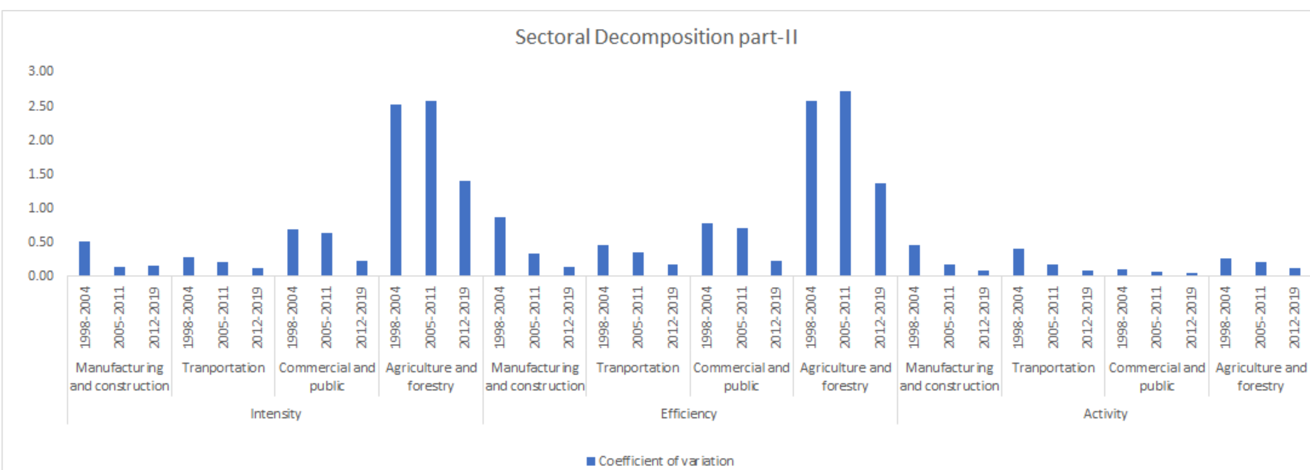


Figure 8: [COLOR FIGURE] Energy intensity and its decomposition by sector - part II.

DOCUMENTS DE TRAVAIL GREDEG PARUS EN 2024
GREDEG Working Papers Released in 2024

2024-01 Davide Antonioli, Alberto Marzucchi, Francesco Rentocchini & Simone Vannuccini
Robot Adoption and Product Innovation

2024-02 Frédéric Marty
Valorisation des droits audiovisuels du football et équilibre économique des clubs professionnels : impacts d'une concurrence croissante inter-sports et intra-sport pour la Ligue 1 de football

2024-03 Mathieu Chevrier, Brice Corgnet, Eric Guerci & Julie Rosaz
Algorithm Credulity: Human and Algorithmic Advice in Prediction Experiments

2024-04 Mathieu Chevrier & Vincent Teixeira
Algorithm Control and Responsibility: Shifting Blame to the User?

2024-05 Maxime Menuet
Natural Resources, Civil Conflicts, and Economic Growth

2024-06 Harald Hagemann
Hayek's Austrian Theory of the Business Cycle

2024-07 Rami Kacem, Abir Khribich & Damien Bazin
Investigating the Nonlinear Relationship between Social Development and Renewable Energy Consumption: A Nonlinear Autoregressive Distributed Lag (ARDL) Based Method

2024-08 Abir Khribich, Rami Kacem & Damien Bazin
The Determinants of Renewable Energy Consumption: Which Factors are Most Important?

2024-09 Abir Khribich, Rami Kacem & Damien Bazin
Assessing Technical Efficiency in Renewable Energy Consumption: A Stochastic Frontier Analysis with Scenario-Based Simulations

2024-10 Gianluca Pallante, Mattia Guerini, Mauro Napoletano & Andrea Roventini
Robust-less-fragile: Tackling Systemic Risk and Financial Contagion in a Macro Agent-Based Model

2024-11 Sandye Gloria
Exploring the Foundations of Complexity Economics: Unveiling the Interplay of Ontological, Epistemological, Methodological, and Conceptual Aspects

2024-12 Frédéric Marty
L'Intelligence Artificielle générative et actifs concurrentiels critiques : discussion de l'essentialité des données

2024-13 Leonardo Ciambezi
Left for Dead? The Wage Phillips Curve and the Composition of Unemployment

2024-14 Sophie Pommet, Sylvie Rochhia & Dominique Torre
Short-Term Rental Platforms Contrasted Effects on Neighborhoods: The Case of French Riviera Urban Destinations

2024-15 Katia Caldari & Muriel Dal Pont Legrand
Economic Expertise at War. A Brief History of the Institutionalization of French Economic Expertise (1936-1946)

2024-16 Michela Chessa & Benjamin Prissé
The Evaluation of Creativity

2024-17 SUPRATIM DAS GUPTA, MARCO BAUDINO & SAIKAT SARKAR
Does the Environmental Kuznets Curve Hold across Sectors? Evidence from Developing and Emerging Economies