

Are Driving Forces of CO₂ Emissions Different across Countries?

Insights from Identity and Econometric Analyses

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Abstract

This paper investigates factors behind the growth of carbon dioxide emissions over the 35 years between 1980 and 2015 in more than 100 countries, using an index decomposition technique (the Logarithmic Mean Divisia Index). The results are further confirmed using an econometric technique (the general method of moments). The study finds that economic growth, measured in per capita gross domestic product, and population growth are the main drivers of the growth of carbon dioxide emissions during 1980–2015. Although economic growth is mainly responsible for the growth of emissions in high-, upper-middle-, and lower-middle-income countries, population growth

that is primarily responsible for it in low-income countries. More than 70 percent of the global growth in carbon dioxide emissions over the past 35 years was contributed by upper-middle-income countries. Improved energy efficiency, reflected in the declining energy intensity of gross domestic product, has substantially contributed to limit global carbon dioxide emissions at the current level; otherwise, the world's current carbon dioxide emissions would have been 40 percent higher. Despite the recent rapid expansion of renewable energy, its contribution to slowing the growth of global carbon dioxide emissions is not noticeable yet, due to its small share in the global energy supply mix.

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Are Driving Forces of CO₂ Emissions Different across Countries? Insights from Identity and Econometric Analyses¹

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1. Introduction

Over the past several decades, CO₂ emissions have been increasing steadily in most countries around the world along with economic growth, population growth, industrialization and urbanization. At the global level (Fig. 1), the annual energy consumption and CO₂ emissions have been increasing by, respectively 2.0% and 1.7%, on average, over the 35 years during the 1980-2015 period. During the same period, the world economy has been growing at the rate of 2.9% and population is growing at the rate of 1.5%, on average, annually [1].

In this paper, we investigate the driving forces behind the rapid growth of CO₂ emissions in more than 100 countries for the 35 years during the 1980-2015 period. We also analyze how the roles of the driving factors change in different groups of countries differentiated by their income.

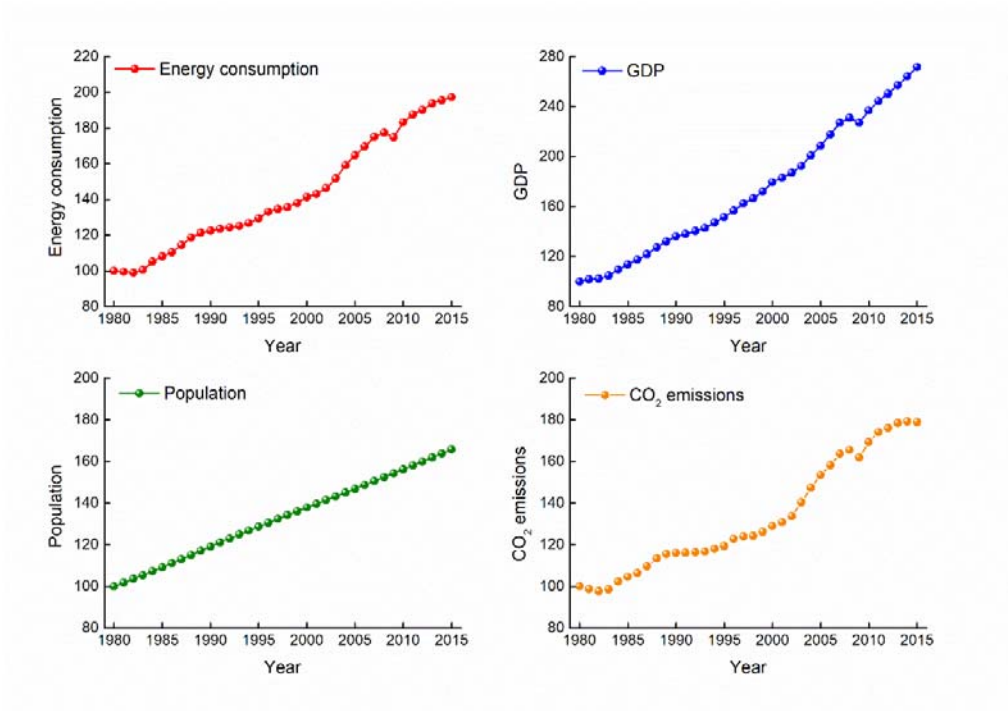


Fig. 1. Trends of global CO₂ emissions, energy consumption, GDP and population (1980-2015)

Data source: [1, 2]. **Note:** the value of each item in 1980 is equal to 100.

Two different approaches are found to be used in the literature to determine the causes of CO₂ growth. Broadly, these approaches can be classified into two groups: identity approach and econometric approach. The first decomposes the independent variables to calculate their relative roles in driving the emission growth; it is also called index decomposition analysis, pioneered by Professor B.W. Ang of Singapore National University [3]. The second uses the standard econometric approach to check the causality between the dependent and independent variables.

Within the decomposition or identity approach, there are several specific techniques, of which the Logarithmic Mean Divisia Index (LMDI) method introduced by Ang and Zhang in 2000 [4] has been widely used. The popularity of this technique has increased due to its ability to handle cases with zero values without leaving residuals, consistency in aggregation, and path independency [5-9]. Since the 2000s, a growing body of studies has employed the LMDI approach to identify the factors impacting CO₂ at the country and regional levels (see Table A1). For instance, at the regional level, González et al. [10] decompose CO₂ in the European Union (EU) from 2000 to 2010 into five factors. Other scholars investigated CO₂ at the country level (Hatzigeorgiou et al. [11] for Greece, Tunç et al. [12] for Turkey, Oh et al. [13] for the Republic of Korea, de Freitas and Kaneko [14] for Brazil, O'Mahony et al. [15] for Ireland, Zhang et al. [16] for China, Feng et al. [17] for the United States, and Mousavi et al. [18] for the Islamic Republic of Iran, among others).

On the econometric side, various methods are employed where the focus of these studies is usually the relation between CO₂ and income and carried out at the national, regional and global levels. At the national level, Bento and Moutinho [19] explore the linkage between renewables energy adoption and CO₂ emissions in Italy using Toda-Yamamoto causality tests. Similar studies have been conducted by Bélaïd and Youssef [20] for Algeria and Danish et al. [21] for Pakistan. At the regional level, Dong et al. [22, 23] use the VECM panel Granger causality method to estimate how expansion of renewable energy consumption would reduce CO₂ emissions in the BRICS countries

(i.e., Brazil, Russia Federation, India, China, and South Africa). Other similar regional studies include Dogan and Seker [24] and Jebli et al. [25].

The added value of this paper is to complement the analysis using the LMDI approach with the econometric approach -- the generalized method of moments so that results derived from the former technique can be validated or strengthened with the latter thereby enhancing the robustness of the findings. Unlike many existing studies that determine the drivers of CO₂ growth at the national or regional level, this study considers a global analysis using data from 100 plus countries.³ The data span (1980-2015) considered in this study is much longer as compared to other existing literature.

The remainder of this paper is structured as follows. Section 2 outlines the methodology and data used. Section 3 discusses the results from the decomposition analysis. Section 4 discusses the results from the econometric analysis. Section 5 conducts a comparison of the results between the two approaches: statistical vs. numerical. Section 6 offers policy discussion and concluding remarks.

2. Methodology and data

Let us define global CO₂ emissions from energy consumption in a country for a given year with the following identity:

$$C = \sum_i \sum_j C_{ij} = \sum_i \sum_j \frac{C_{ij}}{E_{ij}} \cdot \frac{E_{ij}}{E_i} \cdot \frac{E_i}{GDP_i} \cdot \frac{GDP_i}{P_i} \cdot P_i \quad (1)$$

where C denotes the global CO₂ emissions; C_{ij} represents the amount of CO₂ emissions of energy type j in country i ; E_{ij} stands for the energy consumption by energy type j consumed in country i ; E_i , GDP_i , and P_i refer to the total primary

³ Two other global studies include Wang et al. [26] and Bacon et al. [27]. However, their period of analysis is much shorter than the one used in this paper.

[26] Wang S, Li G, Fang C. Urbanization, economic growth, energy consumption, and CO₂ emissions: Empirical evidence from countries with different income levels. *Renew Sust Energy Rev.* 2017.

[27] Bacon RW, Bhattacharya S, Damania R, Kojima M, Lvovsky K. Growth and CO₂ emissions: how do different countries fare. *Environment Department Papers.* 2007;113.

energy consumption, GDP, and total population in country i , respectively.

Eq. (1) can then be written as follows:

$$C = \sum_i \sum_j EC_{ij} \times ECS_{ij} \times EI_i \times PCG_i \times P_i \quad (2)$$

where $EC_{ij} = C_{ij}/E_{ij}$ denotes the emission coefficient of fossil fuel j in country i ; $ECS_{ij} = E_{ij}/E_i$ denotes the energy mix of fossil fuel j in country i ; $EI_i = E_i/GDP_i$ is the energy intensity in country i ; and PCG_i and P_i are the per capita GDP and total population of country i , respectively.

Below we first present the identity approach -- LMDI methodology-- (Section 2.1) followed by the econometric approach - General Method of Moments (GMM) in Section 2.2. The fundamental difference between these techniques is that the LMDI approach assumes that relationship between the independent and dependent variables already exists, it only measures the relative importance of each independent variable to influence the change in the dependent variable. On the other hand, the econometric approach does not assume the relationship between the independent and dependent variables, instead it investigates if such relationship exists or it estimates the causal links between CO₂ emissions and their potential determinants. Since the LMDI is the outcome of a numerical analysis, it does not account for variability and uncertainty. LMDI does not account for all data points, as it only includes the start and ending points, which may result in biased estimates. If the data exhibit good accuracy, averaging across all countries should account for lack of precision in the estimates. However, if the data exhibit lack of precision, then the LMDI estimates yield biased results. And LMDI does not account for some factors due to its limitation in specification (e.g., LMDI cannot accommodate the quadratic term of GDP).

GMM is a statistical method that weighs observations using a measure of precision and controls country- and time-specific effects. Thus, it provides a more robust analysis of the causal links between CO₂ emissions and their determinants.

Another key difference between LMDI and GMM especially in the global analysis

is that LMDI counts the weight of an individual country in the global effects. Meaning that the global change in CO₂ is largely influenced by big countries such as China and

the United States (see the $L(C_{ij}^t, C_{ij}^0) = \frac{C_{ij}^t - C_{ij}^0}{\ln(C_{ij}^t / C_{ij}^0)}$ component in Equations 4 to 8). This

causes the results to be biased towards larger countries and effects of driving factors from small countries do not show up. For example, if the energy intensity of GDP in many countries is improving significantly, but decreasing in the large countries, the improvements in many countries will be overshadowed by deteriorations in the aggregate or the global result. The GMM method, on the other hand, corrects this bias by putting an equal weight on each country for a given driver. The results under the GMM are more representative of all countries instead of large countries only. Therefore, complementing LMDI analysis with GMM brings additional insights in the analysis.

2.1. The LMDI decomposition method

Using the LMDI decomposition technique, the following relationship can be derived from Eq. (2):

$$\Delta C = C_t - C_0 = \Delta C_{EC} + \Delta C_{ECS} + \Delta C_{EI} + \Delta C_{PCG} + \Delta C_P \quad (3)$$

where superscripts t and 0 denote the final year and benchmark year; and ΔC_{EC} , ΔC_{ECS} , ΔC_{EI} , ΔC_{PCG} , and ΔC_P refer to emission coefficient effect, energy mix effect, energy intensity effect, income effect, and population growth effect, respectively. The five effects can be deduced as follows:

$$\Delta C_{EC} = \sum_i \sum_j L(C_{ij}^t, C_{ij}^0) \times \ln(EC_{ij}^t / EC_{ij}^0) \quad (4)$$

$$\Delta C_{ECS} = \sum_i \sum_j L(C_{ij}^t, C_{ij}^0) \times \ln(ECS_{ij}^t / ECS_{ij}^0) \quad (5)$$

$$\Delta C_{EI} = \sum_i \sum_j L(C_{ij}^t, C_{ij}^0) \times \ln(EI_i^t / EI_i^0) \quad (6)$$

$$\Delta C_{PCG} = \sum_i \sum_j L(C_{ij}^t, C_{ij}^0) \times \ln(PCG_i^t / PCG_i^0) \quad (7)$$

$$\Delta C_P = \sum_i \sum_j L(C_{ij}^t, C_{ij}^0) \times \ln(P_i^t / P_i^0) \quad (8)$$

where $L(C_{ij}^t, C_{ij}^0) = \frac{C_{ij}^t - C_{ij}^0}{\ln(C_{ij}^t / C_{ij}^0)}$, and subscripts i and j are energy and country types,

respectively.

2.2. Econometric methodology

For the GMM approach, we convert Eq. 2 to the relationship expressed in Eq. 9. In addition, we added one more factor, square of GDP per capita to investigate if the environmental Kuznets curve (EKC) ([28] & [29]) occurs. Note in Eq. 9 that we assumed a log-log relation between CO₂ emissions and the driving factors.

$$\ln CO_{2it} = \beta_0 + \beta_1 \ln EC_{it} + \beta_2 \ln ECS_{it} + \beta_3 \ln EI_{it} + \beta_4 \ln PCG_{it} + \beta_5 \ln PCG_{it}^2 + \beta_6 \ln P_{it} + \mu_{it} \quad (9)$$

where subscripts i and t denote country and year, respectively; β_1 - β_6 are the parameters to be estimated; CO_2 represents the amount of CO₂ emissions (measured in million tonnes, Mt); EC indicates the emission coefficient (measured in tonnes/toe); ECS denotes energy mix (measured in the share of dirty fossil fuels (i.e., coal and petroleum) in total final energy consumption, %); EI describes energy intensity (measured in tonnes/10,000 US\$); PCG (PCG^2) stands for per capita GDP (squared) (measured in 1,000 US\$); P is population size (measured in billions); β_0 is a constant term; and μ is a random error term.

The dynamic relationship between CO_2 and its determinants suggests one should use a dynamic panel model, where the first-order lagged term of CO_2 (i.e., CO_{2it-1}) is taken into account and introduced into our empirical model (into Eq. (9)):

$$\ln CO_{2it} = \beta_0 + \beta_1 \ln CO_{2it-1} + \beta_2 \ln EC_{it} + \beta_3 \ln ECS_{it} + \beta_4 \ln EI_{it} + \beta_5 \ln PCG_{it} + \beta_6 \ln PCG_{it}^2 + \beta_7 \ln P_{it} + \mu_{it} \quad (10)$$

An endogenous problem due to the correlation between the independent variable and error term results in biased estimates when conventional panel data estimation methods, such as pooled ordinary least squares (OLS), fixed effect, and random effect, are adopted. However, the GMM estimator proposed by Arellano and Bond [30] and developed by Arellano and Bover [31] and Blundell and Bond [32], provides a solution to the endogeneity and also controls individual- and time-specific effects.

Two different types of GMM estimators are usually used in the literature: (i) difference GMM (i.e., first-difference GMM and orthogonal-difference GMM) developed by Arellano and Bond [30]; and, (ii) system GMM (Arellano and Bover [31])

and Blundell and Bond [32]). The main difference between the two methods is in the choice of the endogenous variables and corresponding instrumental variables. As reported by Sung et al. [33], the system GMM estimator is theoretically more efficient than the difference GMM estimator because it allows for a richer set of instruments. The difference GMM estimator may also suffer from weak finite sample bias when the cross-section dimension (N) is large enough. In our sample, the cross-section dimension (N=110) and time dimension (T=8). In this paper we adopt the system GMM estimator.

The efficiency of the system GMM depends on the following two specification tests: (i) the difference-in-Hansen test for too many instruments; and (ii) the Arellano and Bond test for second-order autocorrelation (i.e., AR(2) test). When employing our data, the analysis suggests that there is no instruments proliferation or we do not have too many instruments.

2.3. Data

We use a balanced panel data set for 110 countries, with eight data points covering 1980-2015 corresponding to 1980, 1985, 1990, 1995, 2000, 2005, 2010, and 2015. Prior to the Kyoto Protocol adopted in 1997, CO₂ emissions were not much of a concern. However, mounting concerns to the environment and the need to limit CO₂ emissions ignited worldwide concerns, (e.g., the establishment of the UNFCCC and the 2015 Paris Climate Change Conference). To understand how changes in awareness of climate change impacts CO₂, the analysis not only investigates the whole period of analysis, but also looks at two subsamples: early (1980-1990) and late (2005-2015) periods.

The 110 countries are classified into four groups based on their per capita gross national income (GNI) calculated using the World Bank Atlas method 2016 [34]: low-income countries (LI countries, less than \$1,005), lower-middle-income countries (LMI countries, \$1,006-\$3,955), upper-middle-income countries (UMI countries, \$3,956-\$12,235), and high-income countries (HI countries, more than \$12,236). The low-income subpanel in this study consists of data for 10 countries, while the lower-middle-

income, upper-middle-income, and high-income subpanels comprise data for 28 countries, 28 countries, and 44 countries, respectively (see Table A2 in Appendix A).

The data on CO₂ emissions from fuel combustion are collected from the CO₂ Emissions from Fuel Combustion 2017 published by the International Energy Agency (IEA) [35], while IEA's World Energy Balances [36] provides the data on energy consumption across the globe. In this study, we use primary energy supplied defined as energy production plus energy imports plus increase in stocks (which is negative if the stock decreases), minus energy exports and international bunkers. In addition, the data on GDP and population are obtained from the World Development Indicators (WDI) published by the World Bank [2], in which the data on GDP are in 2010 constant prices.

3. Results from the Decomposition Analysis

3.1. Decomposition results of global CO₂ emissions changes

The decomposition results are depicted in Fig. 2a. The group with the highest contribution to global CO₂ growth during the 1980-2015 period is UMI countries, contributing 71.3%, followed by the LMI, HI, and LI countries, which contributed 21.7%, 9.8%, and 0.3%, respectively.

As shown in Figs. 2b and 2c, only the energy intensity effect (ΔC_{EI}) for the 1980-2015 period is negative, while the income effect (ΔC_{PCG}), population effect (ΔC_P), emission coefficient effect (ΔC_{EC}), and energy mix effect (ΔC_{ECS}) are positive. These results suggest that, while economic and population growth have been driving up CO₂ emissions over the 1980-2015 period, improving energy efficiency is slowing down that growth. CO₂ growth would have been even faster had there been no improvements of energy efficiency. Note that global CO₂ emissions increased by more than 80% over the last 35 years (1980-2015). Total CO₂ emissions added during that time are more than 14,000 million tons (Fig. 1c). If the average energy intensity of GDP remained at the 1980 level, global CO₂ emissions in 2015 would have been almost 14,000 million tons (or more than 40%) higher than the actual level in that year.

The income or economic growth effect is the primary factor driving CO₂ emissions

up in most countries, in all groups of countries considered and ultimately at the global level.

Although change in energy intensity slowed down global emissions by 98.9%, the change was overwhelmed by changes in income (148.9%) and population (48.5%) resulting in an increase in global emissions of 103.1% (see Fig. 2b) - see also Table A4.

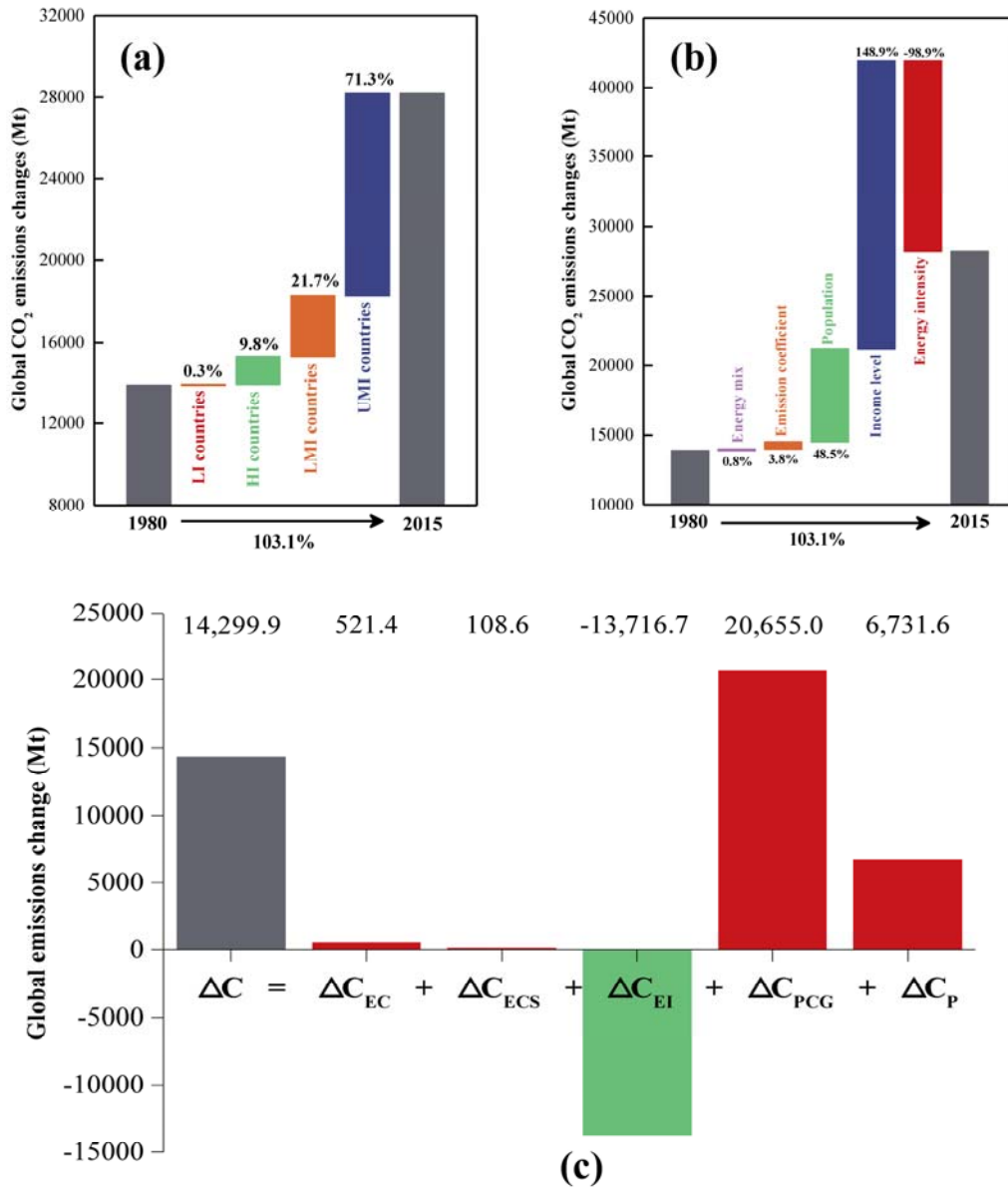


Fig. 2. Decomposition results of the global CO₂ emissions changes between 1980 and 2015. *Note:* (a) indicates the contributions of various subpanels to the global emissions changes, (b) indicates the contributions of various driving forces, and (c) indicates the detailed decomposition results. In Fig. 2(c) ΔC denotes the total emissions changes, while ΔC_{EC} , ΔC_{ECS} , ΔC_{EI} , ΔC_{PCG} , and ΔC_P refer to the effects of emission coefficient, energy mix, energy intensity, income, and population on the global

emissions changes, respectively; the grey bars indicate the total changes in the global emissions during the corresponding period, the green bars represent the effects decreasing emissions in the period, and the red bars stand for the effects increasing emissions in the period.

It would be interesting to see the relationship between CO₂ emission growth and driving factors at different periods. For this, we divide the entire period (1980-2015) into two periods: early period (1980-1990) and the late period (2005-2015) (see Section 2.3).⁴ Changes in the global emissions from the four income-based subpanels over the periods 1980-1990 and 2005-2015 are shown in Fig. 3. For both subperiods, countries with the highest increase in global emissions were mainly UMI countries, contributing 7.9% and 6.3% to the increase of global emissions, respectively.

The LMI countries contributed 3.3% and 2.7% over these two periods, respectively, to the increase in global emissions. On the other hand, between 1980 and 1990 HI countries contributed 2.4% to the increase in global emissions. Growth of CO₂ emissions in the HI countries is slowing down yet still positive since 2005 (see Fig. 3). In addition, the LI countries' contribution to CO₂ emissions is small; LI countries contributed 0.1% to the increase in global emissions over the two investigated periods. These results have strong policy or international negotiation implications regarding climate change mitigation. While high-income countries are historically responsible for the current level of CO₂ concentration in the earth's atmosphere, upper-middle income countries are more responsible in more recent years (over the last few decades). Therefore, CO₂ emission mitigation efforts should be focused on upper-middle income countries. This does not, however, mean other groups of countries do not pay attention to reduce their CO₂ emissions.

⁴ The analysis can be carried out for every year for all 110 countries.

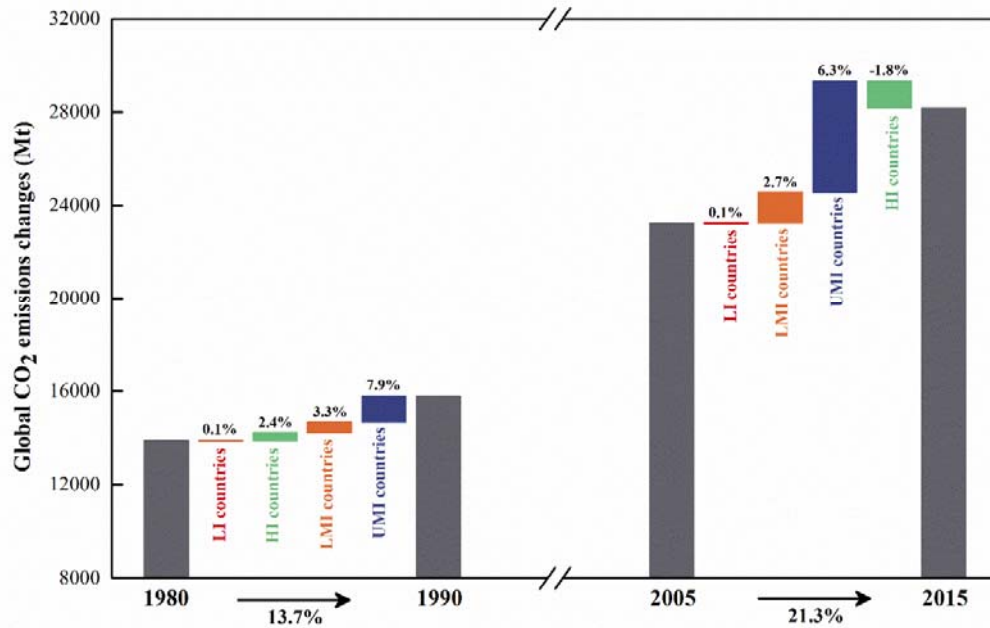


Fig. 3. Changes in the global emissions from the four income-based subpanels over the period 1980-1990 and 2005-2015.

Fig. 4 displays the decomposition results and the contributions of the various factors to global emissions over the early and late periods. Global CO₂ emissions increased during the investigated period and the signs of the various effects did not change over time. In both periods, the economic growth or income effect is the primary driver to increase global CO₂ emissions, especially in the 2005-2015 period. Population growth also made some contribution. Improved energy efficiency helped to slow the CO₂ growth in both periods, much more strongly in the 2005-2015 period than earlier (1980-1990). It is interesting to note that despite the rapid expansion of renewable energy more recently, its share in the global energy supply mix is still small and has not contributed much to limit global CO₂ emissions.

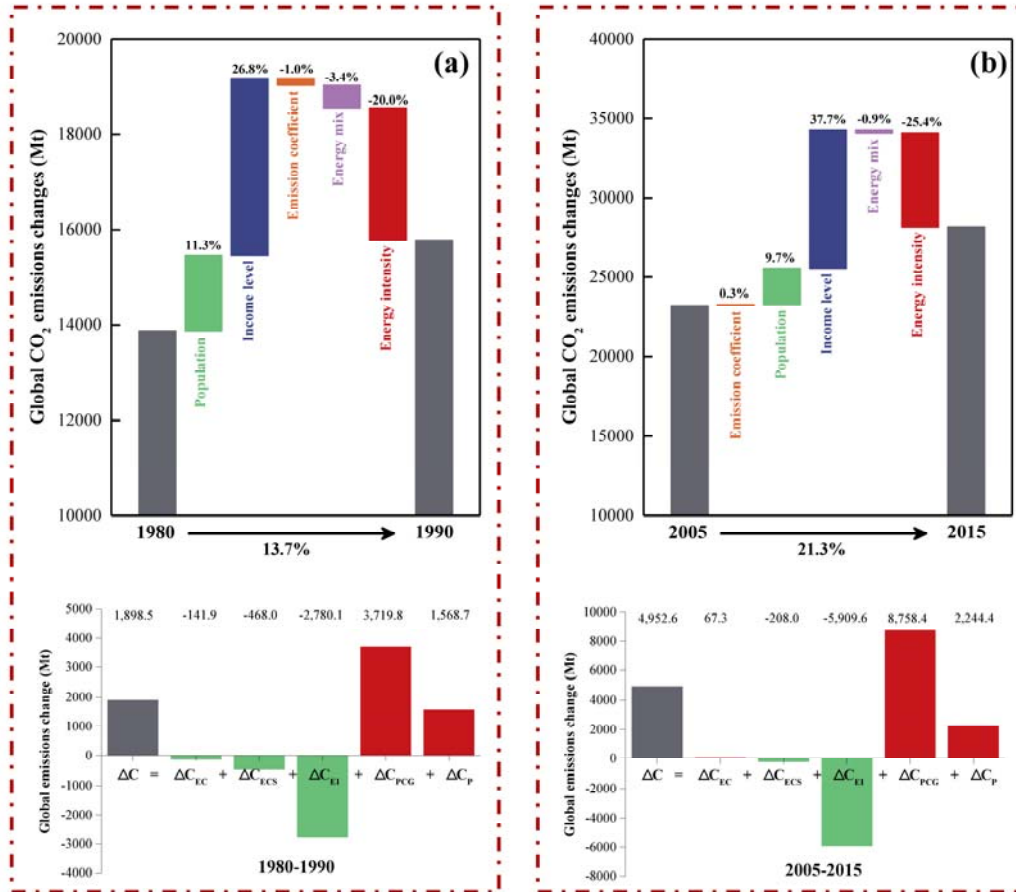


Fig. 4. Decomposition results and the contributions of various driving forces to the global emissions changes over the early and late periods. *Note:* (a) the upper part denotes the early period (i.e., 1980-1990), and (b) the lower part denotes the late period (i.e., 2005-2015).

3.2. Decomposition results in countries with different income levels

What role would different drivers play across different groups of countries to influence CO₂ emission growth? Figure 5 plots the impacts of various factors on CO₂ growth in different groups of countries. Change in the income level was the primary factor of increasing emissions in the countries with high income levels, such as the HI, UMI, and LMI countries; while change in population size was the main effect behind the increase in emissions for the countries with low income levels, such as the LI countries. Improved energy efficiency helped to slow down emission growth in all groups of countries in both periods. Its effect is more prominent in the HI and UMI groups of countries. In addition, changes in energy mix were a significant factor in

reducing CO₂ emissions in HI countries.

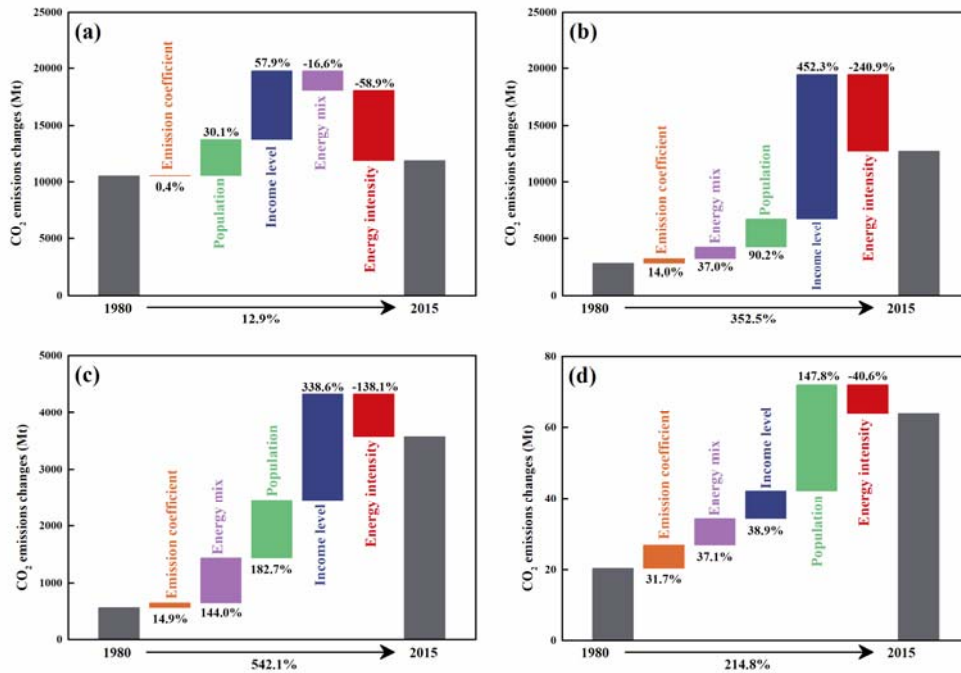


Fig. 5. Contributions of various driving forces to the emissions changes in countries with different income levels between 1980 and 2015. *Note:* (a) HI countries, (b) UMI countries, (c) LMI countries, and (d) LI countries.

Fig. 6 depicts the contributions of various driving forces to the emissions changes in countries with different income levels between 1980 and 1990, and between 2005 and 2015. It reveals some interesting facts. First, the income effect, which drives CO₂ growth, is much stronger in UMI and LMI group countries. This effect is stronger in the later period (2005-2015) as compared to the earlier period in all groups of countries except the HI group of countries where the reverse is the case. For the LI group of countries, the income effect is negative during the early period as the per capita GDP (i.e., economic growth) depicted a downward trend (see also Fig. B1 in Appendix B) due slower GDP growth as compared to population growth. The fuel mix effect has helped to slow down the CO₂ emission growth only in the HI group of countries. Although fuel mix contributed to increase CO₂ emissions, its effect weakened over time. The change of fuel mix effect in UMI is mainly dominated by China where natural gas

consumption increased by more than fourfold between 2005 and 2015 (in China it soared since 2005, from $482.0 \times 10^8 \text{ m}^3$ in 2005 to $1,973.0 \times 10^8 \text{ m}^3$ in 2015, with an average annual growth rate of 15.1% [37]). Detailed contributions of various factors to these four subpanels are also listed in Tables A5-A8.

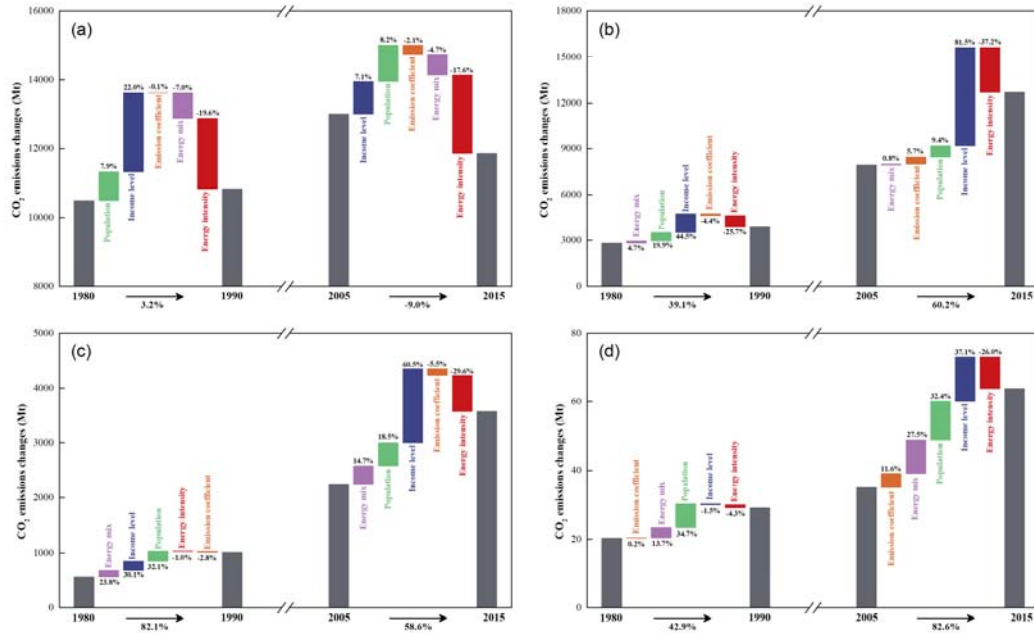


Fig. 6. Contributions of various driving forces to the emissions changes in countries with different income levels between 1980 and 1990, and between 2005 and 2015. *Note:* (a) HI countries, (b) UMI countries, (c) LMI countries, and (d) LI countries.

4. Results from the Econometric Analysis

4.1. The estimation results

The results of the analysis using the GMM technique are presented in Table 1. In the table, column 1 presents the empirical results for 110 countries, while columns 2-5 depict the empirical results for the HI, UMI, LMI, and LI groups of countries, respectively. As shown in the bottom of Table 1, the null hypotheses of the Hansen and AR (2) tests cannot be rejected, indicating that the instruments remain valid and that there is no evidence for second-order serial correlation.

The coefficient of the lag stock of CO₂ (i.e., $\ln CO_{2it-1}$) is positive and strongly significant. If countries emitted large amounts of CO₂ in the past, then they are likely

to continue emitting large amounts of CO₂ in the future in the absence of any policy intervention; this finding is consistent with Lee et al. [38].

Table 1. System GMM estimation results for **full sample (1980-2015)**.

Dependent variable: $\ln CO_2$					
Variable	(1)	(2)	(3)	(4)	(5)
	Global panel	HI countries	UMI countries	LMI countries	LI countries
$\ln CO_{2it-1}$	0.718*** (35.898)	0.445*** (15.847)	0.584*** (16.592)	0.640*** (16.156)	0.085** (2.246)
$\ln EC_{it}$	0.057*** (2.960)	0.594*** (16.444)	0.059** (2.275)	0.027*** (7.270)	0.050* (1.780)
$\ln ECS_{it}$	0.331*** (14.089)	0.052** (2.323)	0.475*** (11.507)	0.507*** (9.463)	0.976*** (11.504)
$\ln EI_{it}$	0.445*** (13.891)	0.619*** (17.098)	0.509*** (9.586)	0.471*** (7.369)	0.308*** (11.927)
$\ln PCG_{it}$	0.290*** (9.283)	1.504*** (18.572)	0.768*** (7.756)	0.334*** (6.267)	0.267*** (3.722)
$\ln PCG_{it}^2$	-0.045*** (-3.649)	-0.201*** (-14.844)	-0.148*** (-3.163)	0.049 (1.647)	-0.185** (-2.054)
$\ln P_{it}$	0.270*** (13.040)	0.534*** (18.528)	0.838*** (12.071)	0.886*** (9.131)	0.865*** (13.223)
Constant	2.605*** (9.292)	1.253*** (4.201)	1.186*** (3.570)	0.985*** (7.648)	0.844*** (3.311)
Hansen test	0.103	0.194	0.649	0.582	0.412
AR(2) test	0.229	0.152	0.172	0.202	0.188
Turning point	25,084	42,152	13,391	-	-

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively; the values in parentheses represent t-statistics; the values of Hansen and AR(2) tests represent p-values; and the unit of turning point is 2010 US\$.

4.1.1 Results from the 110-country panel

The estimated coefficients of $\ln GDP$ and $(\ln GDP)^2$ are positive and negative, respectively, suggesting the presence of the EKC curve. Note that the EKC is a phenomenon of the long run [39, 40], further suggesting that the countries with different income levels should follow a long-term strategy that achieves the targeted balance between reduced CO₂ emissions and high economic growth.

The results further indicate that, for the whole sample of 110 countries, the estimated coefficients of $\ln EC$, $\ln ECS$, $\ln EI$, $\ln PCG$, and $\ln P$ are positive and significant at a 1% significance level. Similar to the decomposition analysis presented in Section 3 above (see also Figs. B1 & B2 in Appendix B), the econometric analysis suggests that the change in emission increased with per capita GDP (i.e., economic growth) and population growth. These two factors are the primary drivers of the increase of CO₂ between 1980 and 2015, while changes in fuel mix (i.e., increasing share of clean fuels in total primary energy supply) and improving energy efficiency (i.e., decreasing energy intensity of GDP) slowed this increase in growth of CO₂ during the same period.

4.1.2 Differences in impacts across income levels

The theoretical EKC is an inverted U-curve, with the coefficients of $\ln GDP$ and $(\ln GDP)^2$ positive and negative, respectively. However, in the results in columns 2-5, only for HI and UMI countries the estimated coefficients of $\ln GDP$ and $(\ln GDP)^2$ are positive, and negative respectively. For HI and UMI countries, the estimated turning points are \$42,152 and \$13,391, respectively. In contrast, we cannot identify the turning point of the EKC hypothesis for LMI and LI countries. The large gap between the current economic level in LMI and LI countries (\$2,030 and \$599 in 2015, respectively; see Fig. 7) and the turning point of EKC may result in the data failing to identify the peak in CO₂ emissions.

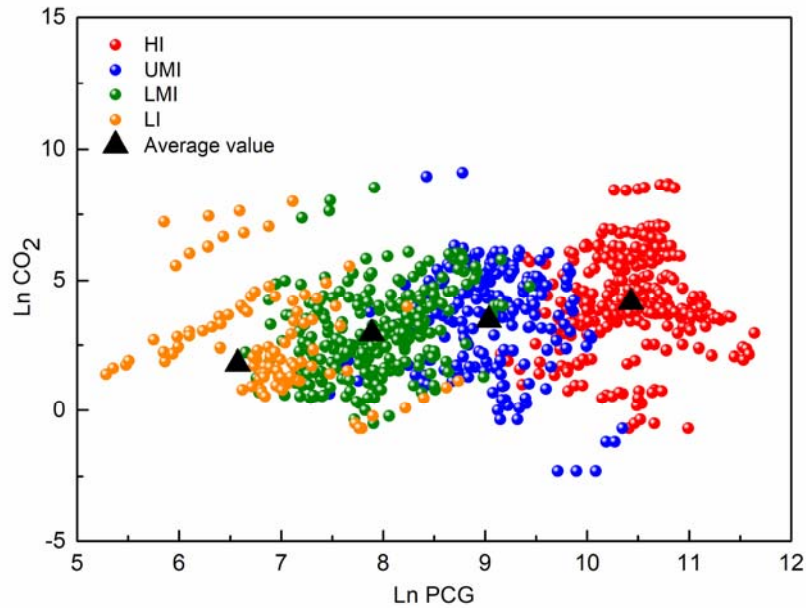


Fig. 7. The distribution of global CO₂ emissions and per capita GDP in countries with different income levels. *Data sources:* IEA [35] and World Bank [2].

With regard to the estimated coefficients of $\ln EC$, $\ln ECS$, $\ln EI$, $\ln PCG$, and $\ln P$, the four subpanels (i.e., HI, UMI, LMI, and LI countries) provide similar results to those of the LMDI estimates above, that is, they are both positive and significant. However, as seen in Figs. B1 & B2 in Appendix B, between 1980 and 2015, the trends of the five factors vary across time, with energy intensity displaying a downward trend while per capita GDP and population display upward trends.

The effects of the five factors on emissions vary (see Fig. 8). The common factors are the effects of energy intensity, income growth, and population growth, the former mitigating CO₂, whereas the latter two increasing CO₂.

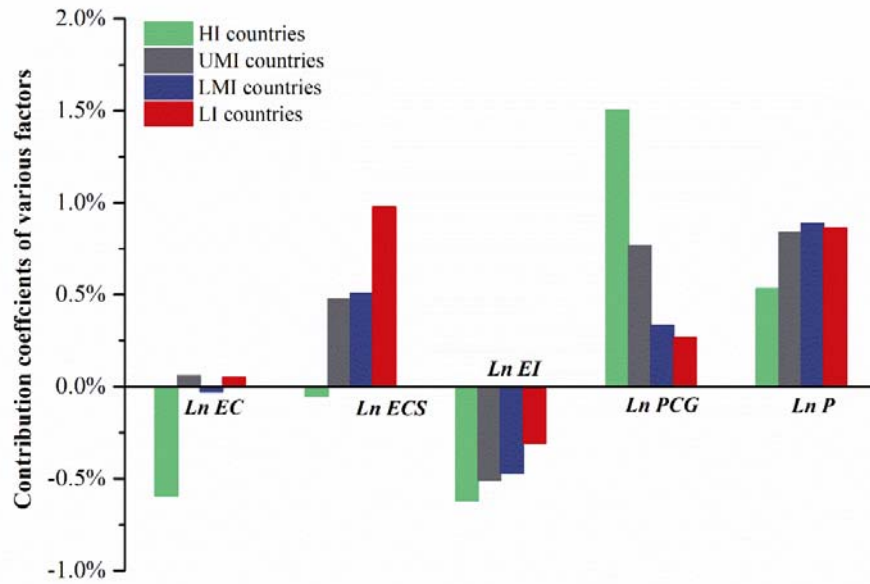


Fig. 8. Contribution coefficient of each factor for each panel between 1980 and 2015.

4.2. Time and the importance of the various factors

We utilize the system GMM technique to further estimate Eq. (10) for the early period (1980-1990) and late period (2005-2015), respectively; the results are listed in Tables 2 and 3. According to the bottom of Tables 2 and 3, for each income group, both tests (i.e., Hansen test and AR (2) test) fail to reject the null hypothesis. Furthermore, for each income group in Tables 2 and 3, the estimated coefficients of $\ln CO_{2it-1}$ are significantly positive, suggesting that there are persistent CO₂ emissions from one year to the next.

Table 2. System GMM estimation results for early period (1980-1990).

Dependent variable: $\ln CO_2$					
Variable	(1)	(2)	(3)	(4)	(5)
	Global panel	HI countries	UMI countries	LMI countries	LI countries
$\ln CO_{2it-1}$	0.643*** (15.801)	0.418*** (7.018)	0.520*** (6.612)	0.601*** (7.507)	0.067** (2.558)
$\ln EC_{it}$	0.057*** (3.643)	0.575*** (6.797)	0.079*** (2.885)	0.014*** (3.257)	0.003** (2.025)

$\ln ECS_{it}$	0.425*** (9.124)	0.103* (1.724)	0.595*** (6.452)	0.563*** (5.367)	0.941*** (6.564)
$\ln EI_{it}$	0.476*** (7.541)	0.621*** (7.067)	0.566*** (4.850)	0.481*** (4.895)	0.169*** (8.787)
$\ln PCG_{it}$	0.341*** (5.735)	2.012*** (9.042)	0.687*** (4.366)	0.379*** (4.612)	0.158** (2.393)
$\ln PCG_{it}^2$	0.014* (1.733)	0.226*** (6.861)	-0.065 (-1.670)	0.052 (1.250)	0.012 (0.049)
$\ln P_{it}$	0.344*** (8.454)	0.560*** (9.200)	0.804*** (6.429)	0.839*** (5.479)	0.789*** (9.364)
Constant	0.812*** (5.830)	2.026*** (3.955)	1.186*** (3.570)	0.648*** (2.986)	1.168** (2.076)
Hansen test	0.121	0.390	0.493	0.603	0.115
AR(2) test	0.224	0.192	0.178	0.149	0.191
Turning point	-	-	-	-	-

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively; the values in parentheses represent t-statistics; the values of Hansen and AR(2) tests represent p-values; and the unit of turning point is 2010 US\$.

4.2.1 The 110-country panel

According to the first column in Table 2, for the 110-country panel, the estimated coefficients of $\ln EC$, $\ln ECS$, $\ln EI$, $\ln PCG$, and $\ln P$ between 1980 and 1990 are positive and significant at a 1% significance level. GDP per capita and population were the primary drivers leading to an increase in CO₂ emissions between 1980 and 1990, while the factors that slowed the increase of the emissions over the same period were emission coefficient, energy mix, and energy intensity.

The first column in Table 3 indicates that the estimated coefficients of the variables between 2005 and 2015 are positive and significant. Furthermore, Figs. B1 & B2 in Appendix B suggest that emission coefficient, per capita GDP, and population were the primary driving forces of increasing CO₂ emissions between 2005 and 2015, while the factors that slowed the increase of the emissions over the same period were energy mix

and energy intensity (these latter variables depict a downward trend over time).

Table 3. System GMM estimation results for late period (2005-2015).

Dependent variable: $\ln CO_2$					
Variable	Global panel	HI countries	UMI countries	LMI countries	LI countries
$\ln CO_{2it-1}$	0.815*** (23.035)	0.248*** (4.804)	0.456*** (5.915)	0.572*** (7.350)	0.104*** (3.804)
$\ln EC_{it}$	0.017** (2.482)	0.793*** (15.251)	0.353*** (4.111)	0.033** (2.401)	0.293*** (3.044)
$\ln ECS_{it}$	0.210*** (5.038)	0.017*** (3.606)	0.151*** (2.376)	0.523*** (4.938)	1.073*** (6.783)
$\ln EI_{it}$	0.401*** (7.028)	0.814*** (15.376)	0.541*** (5.998)	0.773*** (4.804)	0.170*** (5.149)
$\ln PCG_{it}$	0.213*** (3.686)	2.611*** (14.150)	2.789*** (7.060)	0.232** (2.041)	0.229* (1.955)
$\ln PCG_{it}^2$	-0.001 (-0.080)	0.258*** (12.143)	0.567*** (6.562)	0.219 (1.186)	-0.175 (-0.577)
$\ln P_{it}$	0.181*** (4.941)	0.738*** (14.232)	0.857*** (7.214)	0.941*** (5.404)	0.870*** (6.607)
Constant	0.943*** (7.091)	0.963** (2.053)	0.746** (2.458)	1.193*** (4.420)	1.283*** (5.189)
Hansen test	0.163	0.158	0.178	0.156	0.606
AR(2) test	0.220	0.106	0.110	0.237	0.122
Turning point	-	-	-	-	-

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively; the values in parentheses represent t-statistics; the values of Hansen and AR(2) tests represent p-values; and the unit of turning point is 2010 US\$.

4.2.2 Varying income levels across countries

Fig. 9 details the impact of each of the factors. In general, the main factors affecting the emissions for the four income groups did not change much over time. However, it is noteworthy that over time, the impact of changes in energy mix and

economic growth, i.e., $\ln ECS$ and $\ln PCG$, would become more significant in developing countries, especially in the UMI countries.

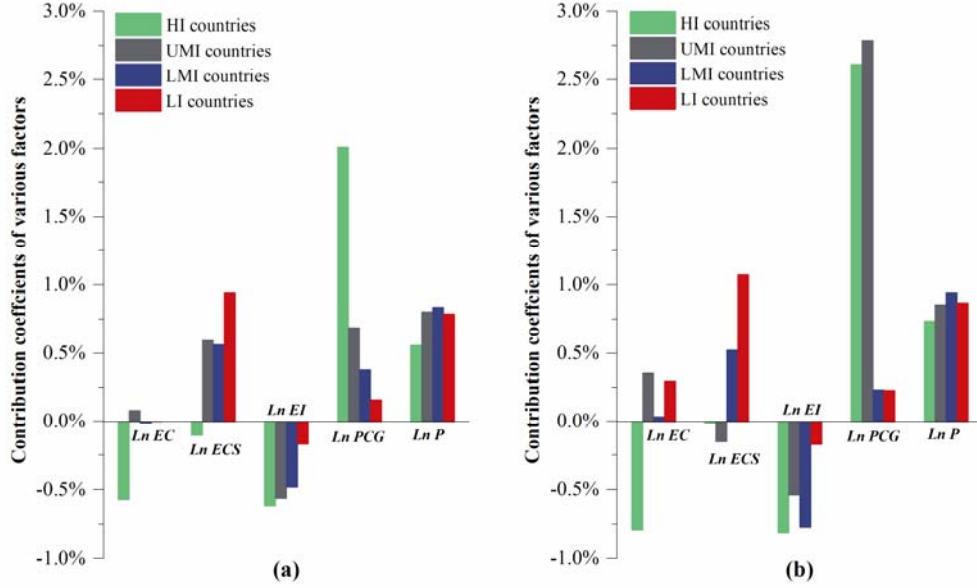


Fig. 9. Contribution coefficient of each factor for each panel over the a) early period (1980-1990) and b) late period (2005-2015).

5. Comparing the two approaches: LMDI versus system GMM

To further compare the two methods, we calculated the marginal impacts of various factors on CO_2 growth using Eq. (11); the detailed results are listed in Table A8.

$$E_f = \frac{\Delta(CO_2)_f / (CO_2)_f}{\Delta f / f} \quad (11)$$

where E_f denotes the marginal impact of the factor f on CO_2 growth; f indicates various factors affecting CO_2 emissions (i.e., EC , ECS , EI , PCG , and P); CO_2 denotes the amount of total CO_2 emissions; and $\Delta(CO_2)_f$ represents the amount of CO_2 emissions changes affected by the factor f (i.e., ΔC_{EC} , ΔC_{ECS} , ΔC_{EI} , ΔC_{PCG} , and ΔC_P).

We compare the results estimated using the LMDI and the system GMM methods through the comparison of the marginal impacts of various factors on CO_2 growth. The

same marginal impact is calculated once under the LMDI method and once under the GMM method. We do this for the whole sample but also for the different income groups (Table 4). From this table, we can see that the level of the marginal impacts of various factors on CO₂ growth obtained by the LMDI method are significantly bigger than that of the GMM. This may be because, as addressed previously (i.e., section 2), the system GMM estimator takes into account each country's characteristics when calculating the marginal impact whereas the LMDI method ignores the individual characteristics. The difference in the results between LMDI and GMM are important to understand how CO₂ growth responds to change in a given driver. Since the LMDI results are biased towards the country size (i.e., they are skewed due to China and the United States, the larger countries' results), the response indicators (or marginal impact here) based on LMDI may be biased. The response indicators estimated based on GMM analysis are more credible.

Table 4. A comparison in the marginal impacts of various factors on CO₂ growth between system GMM technique and LMDI method for the period 1980-2015.

Panel	<i>EC</i>	<i>ECS</i>	<i>EI</i>	<i>PCG</i>	<i>PCG</i> ²	<i>P</i>
GMM method						
Global	0.057	0.331	0.445	0.290	-0.045	0.270
HI	0.594	0.052	0.619	1.504	-0.201	0.534
UMI	0.059	0.475	0.509	0.768	-0.148	0.838
LMI	0.027	0.507	0.471	0.334	0.049	0.886
LI	0.050	0.976	0.308	0.267	-0.158	0.865
LMDI method						
Global	1.654	0.080	4.042	2.325	NA	0.724
HI	0.024	0.646	1.464	0.760	NA	1.086
UMI	0.661	3.978	8.904	2.087	NA	1.724
LMI	0.362	2.877	4.089	1.983	NA	1.846
LI	2.573	4.413	0.658	1.638	NA	0.911

Note: EC indicates emission coefficient; ECS denotes energy mix; EI describes energy intensity; PCG^2 (PCG^2) stands for per capita GDP (squared); and P is population size.

6. Conclusions

In this study, we measured the role of various factors that have driven CO₂ emissions over the past 35 years at the global level and different groups of countries by their current income level (i.e., high income, upper-middle income, lower-middle income, and low income). We employ data from 110 countries in two different techniques: Index decomposition technique (identity analysis) and an econometric technique. We also examined if a factor has influenced CO₂ growth differently during different time intervals: early period of the study horizon (1980-2015) and late interval of the study horizon (2005-2015).

The results from our identity and econometric analysis reveal that income (measured in terms of per capita GDP) growth and population growth are the major drivers for the increased CO₂ emissions during the period. Improved energy efficiency (i.e., decreasing energy intensity of GDP) has slowed down the growth; otherwise, CO₂ emissions would have increased even further.

Improvement of energy efficiency has contributed in all groups of countries to slow down their CO₂ emission growth. This factor is more prominent in the high-income and upper-middle-income groups of countries. The fuel mix factor or the increasing share of low carbon (e.g., natural gas) or no carbon (e.g., renewable) fuels in the total primary energy supply mix contributed to slow down CO₂ growth in the high-income group of countries. It is income growth that is responsible for CO₂ growth in the upper-income and middle-income countries. Population growth is more responsible for CO₂ emission growth in low-income countries, although they have a very small role in the growth of global CO₂ emissions.

The analysis provides some important policy insights. Although one could argue that upper-middle-income countries' per-capita emissions are lower than that of high-income countries and therefore pressure should still be on high-income countries, our

analysis shows that since the upper-middle-income group of countries is mostly responsible for the recent global CO₂ growth, more efforts should be paid to reduce their CO₂ emissions. This study does not mean that these countries have to take on most of the financial burden to reduce their CO₂ emissions. How to share the global burden of CO₂ reduction is a different question and it is beyond the scope of this study. Improving energy efficiency has contributed historically to slow down the CO₂ growth and this effect is basically driven through various policies (e.g., incentives for energy efficiency improvements) and technological innovation. Although the world has witnessed a rapid expansion of renewable energy more recently, the expansion is still too small to make a noticeable impact in limiting the growth of global CO₂ emissions. Further expansion of clean and renewable energy would be needed for a noticeable impact on slowing down the global CO₂ growth.

Acknowledgments

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Appendix A

Table A1. Selected prior studies on decomposition of CO₂ emissions using the LMDI approach (2008-2018). *Source:* Compiled by the authors.

Author [ref.]	Study area	Study period	Driving force
Hatzigeorgiou et al. [11]	Greece	1990-2002	1, 2, 3
Tunç et al. [12]	Turkey	1970-2006	2, 4, 5, 6
Oh et al. [13]	Korea, Rep.	1990-2005	1, 2, 4, 5
Pani and Mukhopadhyay [41]	114 countries	1992-2004	1, 3, 5, 6
Vinuya et al. [42]	United States	1990-2004	1, 2, 3, 5, 6
de Freitas and Kaneko [14]	Brazil	1970-2009	2, 3, 4, 5, 6, 7
Zhang et al. [43]	China	1995-2009	2, 4, 5, 6, 8
O'Mahony et al. [15]	Ireland	1990-2010	2, 4, 5, 6, 8
O'Mahony [44]	Ireland	1990-2010	1, 2, 3, 5, 6
Zhang et al. [16]	China	1991-2009	6, 7, 9, 10, 11, 12
González et al. [10]	European Union	2001-2010	1, 2, 3, 5, 6

Feng et al. [17]	United States	1997-2013	2, 3, 5, 13, 14
Xie et al. [45]	China	1995-2013	2, 5, 6, 15, 16
Mousavi et al. [18]	Iran, Islamic Rep.	2003-2014	2, 3, 4, 5, 6
Henriques and Borowiecki [46]	Europe, North America and Japan	1980-2011	1, 2, 3, 5, 6
Shahiduzzaman and Layton [47]	United States	1973-2014	1, 2, 3, 5, 6
Chen et al. [48]	Macao	2000-2011	2, 4, 5, 8

Notes: **a)** 1. Income effect, 2. Energy mix effect, 3. Population effect, 4. Economic structure effect, 5. Energy intensity effect, 6. Emission coefficient effect, 7. Economic activity effect, 8. GDP, 9. Electricity generation efficiency effect, 10. Thermal power structure effect, 11. Electricity structure effect, 12. Electricity intensity effect, 13. Consumption pattern effect, 14. Production structure effect, 15. Industrial activity effect, and 16. Industrial scale effect; and **b)** EU denotes European Union and US denotes United States.

Table A2. List of countries based on income level.

Subpanel	Countries
Low-income countries (10 countries)	Benin, Democratic Republic of Congo, Ethiopia, Haiti, Mozambique, Nepal, Senegal, Tanzania, Togo, and Zimbabwe
Lower-middle-income countries (28 countries)	Angola, Bangladesh, Bolivia, Cameroon, Republic of Congo, Côte d'Ivoire, Arab Republic of Egypt, El Salvador, Ghana, Guatemala, Honduras, India, Indonesia, Jordan, Kenya, Morocco, Myanmar, Nicaragua, Nigeria, Pakistan, Philippines, Sri Lanka, Sudan, Syrian Arab Republic, Tunisia, Vietnam, Republic of Yemen, and Zambia
Upper-middle-income countries (28 countries)	Albania, Algeria, Argentina, Brazil, Bulgaria, China, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Gabon, Islamic Republic of Iran, Iraq, Jamaica, Lebanon, Libya, Malaysia, Mauritius, Mexico, Panama, Paraguay, Peru, Romania, South Africa, Thailand, Turkey, and Venezuela, RB
High-income countries (44 countries)	Australia, Austria, Bahrain, Belgium, Brunei, Darussalam, Canada, Chile, Curacao, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Gibraltar, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, the Republic of Korea, Kuwait, Luxembourg, Malta, New Zealand, Netherlands, Norway, Qatar, Oman, Poland, Portugal, Saudi Arabia, Singapore, Slovak Republic, Spain, Sweden, Switzerland, Trinidad and Tobago, United Arab Emirates, United Kingdom, United States, and Uruguay

Table A3. Eight possible cases with zero values.

Case	X_{ij}^0	X_{ij}^t	C_{ij}^0	C_{ij}^t	$\Delta C_{X_{ij}} = \frac{C_{ij}^t - C_{ij}^0}{\ln(C_{ij}^t / C_{ij}^0)} * \ln\left(\frac{X_{ij}^t}{X_{ij}^0}\right)$
1	0	+	0	+	$\Delta C_{X_{ij}} = C_{ij}^t$
2	+	0	+	0	$\Delta C_{X_{ij}} = -C_{ij}^0$
3	0	0	0	0	0
4	+	+	0	+	0
5	+	+	+	0	0
6	+	+	0	0	0
7	+	0	0	0	0
8	0	+	+	+	0

Table A4. Decomposition results of the emissions changes and contributions of various driving forces **across the globe** over the early period (1980-1990), late period (2005-2015), and entire period (1980-2015).

Period	1980-1990	2005-2015	1980-2015
Emissions change (Mt)			
Overall change	1,898.5	4,952.6	14,299.9
<i>EC</i>	-141.9	67.3	521.4
<i>ECS</i>	-468.0	-208.0	108.6
<i>EI</i>	-2, 780.1	-5,909.6	-13,716.7
<i>PCG</i>	3,719.8	8,758.4	20,655.0
<i>P</i>	1,568.7	2,244.4	6,731.6
Contribution (%)			
Growth rate	13.7	21.3	103.1
<i>EC</i>	-1.0	0.3	3.8
<i>ECS</i>	-3.4	-0.9	0.8
<i>EI</i>	-20.0	-25.4	-98.9
<i>PCG</i>	26.8	37.7	148.9
<i>P</i>	11.3	9.7	48.5

Note: *EC*, *ECS*, *EI*, *PCG*, and *P* refer to emission coefficient, energy mix, energy intensity, income, and population, respectively.

Table A5. Decomposition results of the emissions changes and contributions of various driving forces in the **HI countries** over the early period (1980-1990), late period (2005-2015), and entire period (1980-2015).

Period	1980-1990	2005-2015	1980-2015
Emissions change (Mt)			
Overall change	338.0	-1,165.1	1,357.6
<i>EC</i>	-3.5	-267.2	40.5
<i>ECS</i>	-733.9	-610.3	-1,737.7
<i>EI</i>	-2,053.6	-2,285.2	-6,184.4
<i>PCG</i>	2,304.7	928.2	6,081.7
<i>P</i>	824.2	1,069.4	3,157.5
Contribution (%)			
Growth rate	3.2	-9.0	12.9
<i>EC</i>	-0.1	-2.1	0.4
<i>ECS</i>	-7.0	-4.7	-16.6
<i>EI</i>	-19.6	-17.6	-58.9
<i>PCG</i>	22.0	7.1	57.9
<i>P</i>	7.9	8.2	30.1

Note: *EC*, *ECS*, *EI*, *PCG*, and *P* refer to emission coefficient, energy mix, energy intensity, income, and population, respectively.

Table A6. Decomposition results of the global emissions changes and contributions of various driving forces in the **UMI countries** over the early period (1980-1990), late period (2005-2015), and entire period (1980-2015).

Period	1980-1990	2005-2015	1980-2015
Emissions change (Mt)			
Overall change	1,095.4	4,770.7	9,886.4
<i>EC</i>	-122.8	453.7	391.7
<i>ECS</i>	131.0	61.9	1,038.6
<i>EI</i>	-719.9	-2,948.2	-6,756.7
<i>PCG</i>	1,247.9	6,457.0	12,683.9
<i>P</i>	559.3	746.4	2,528.9
Contribution (%)			
Growth rate	39.1	60.2	352.5
<i>EC</i>	-4.4	5.7	14.0
<i>ECS</i>	4.7	0.8	37.0
<i>EI</i>	-25.7	-37.2	-240.9
<i>PCG</i>	44.5	81.5	452.3
<i>P</i>	19.9	9.4	90.2

Note: *EC*, *ECS*, *EI*, *PCG*, and *P* refer to emission coefficient, energy mix, energy intensity, income, and population, respectively.

Table A7. Decomposition results of the global emissions changes and contributions of various driving forces in the **LMI countries** over the early period (1980-1990), late period (2005-2015), and entire period (1980-2015).

Period	1980-1990	2005-2015	1980-2015
Emissions change (Mt)			
Overall change	456.4	1,318.1	3,012.3
<i>EC</i>	-15.6	-123.2	82.8
<i>ECS</i>	132.1	330.7	800.2
<i>EI</i>	-5.7	-667.0	-767.3
<i>PCG</i>	167.4	1,360.3	1,881.5
<i>P</i>	178.2	417.3	1,015.2
Contribution (%)			
Growth rate	82.1	58.6	542.1
<i>EC</i>	-2.8	-5.5	14.9
<i>ECS</i>	23.8	14.7	144.0
<i>EI</i>	-1.0	-29.6	-138.1
<i>PCG</i>	30.1	60.5	338.6
<i>P</i>	32.1	18.5	182.7

Note: *EC*, *ECS*, *EI*, *PCG*, and *P* refer to emission coefficient, energy mix, energy intensity, income, and population, respectively.

Table A8. Decomposition results of the global emissions changes and contributions of various driving forces in the **LI countries** over the early period (1980-1990), late period (2005-2015), and entire period (1980-2015).

Period	1980-1990	2005-2015	1980-2015
Emissions change (Mt)			
Overall change	8.7	28.9	43.6
<i>EC</i>	0.1	4.1	6.4
<i>ECS</i>	2.8	9.6	7.5
<i>EI</i>	-0.9	-9.1	-8.2
<i>PCG</i>	-0.3	13.0	7.9
<i>P</i>	7.0	11.3	30.0
Contribution (%)			
Growth rate	42.9	82.6	214.8
<i>EC</i>	0.2	11.6	31.7
<i>ECS</i>	13.7	27.5	37.1
<i>EI</i>	-4.3	-26.0	-40.6
<i>PCG</i>	-1.5	37.1	38.9
<i>P</i>	34.7	32.4	147.8

Note: *EC*, *ECS*, *EI*, *PCG*, and *P* refer to emission coefficient, energy mix, energy intensity, income, and population, respectively.

Table A8. The marginal impacts of various factors on CO₂ growth based on the LMDI

decomposition results.

Factor	Global panel	HI countries	UMI countries	LMI countries	LI countries
1980-2015					
<i>EC</i>	1.654	0.024	0.661	0.362	2.573
<i>ECS</i>	0.080	0.646	3.978	2.877	4.413
<i>EI</i>	4.042	1.464	8.904	4.089	0.658
<i>PCG</i>	2.325	0.760	2.087	1.983	1.638
<i>P</i>	0.724	1.086	1.724	1.846	0.911
1980-1990					
<i>EC</i>	0.178	0.005	4.407	0.339	0.042
<i>ECS</i>	0.532	0.742	1.895	1.496	1.361
<i>EI</i>	1.859	1.108	5.686	0.260	2.985
<i>PCG</i>	2.055	0.851	3.697	1.999	0.318
<i>P</i>	0.578	1.072	1.070	1.181	1.088
2005-2015					
<i>EC</i>	0.357	0.303	0.857	0.277	0.438
<i>ECS</i>	0.359	0.425	1.348	1.113	1.311
<i>EI</i>	3.430	1.181	2.421	1.475	0.227
<i>PCG</i>	2.450	1.000	1.275	1.089	0.925
<i>P</i>	0.764	1.161	1.143	1.086	1.048

Note: *EC* indicates emission coefficient; *ECS* denotes energy mix; *EI* describes energy intensity; *PCG* stands for per capita GDP; and *P* is population size.

Appendix B

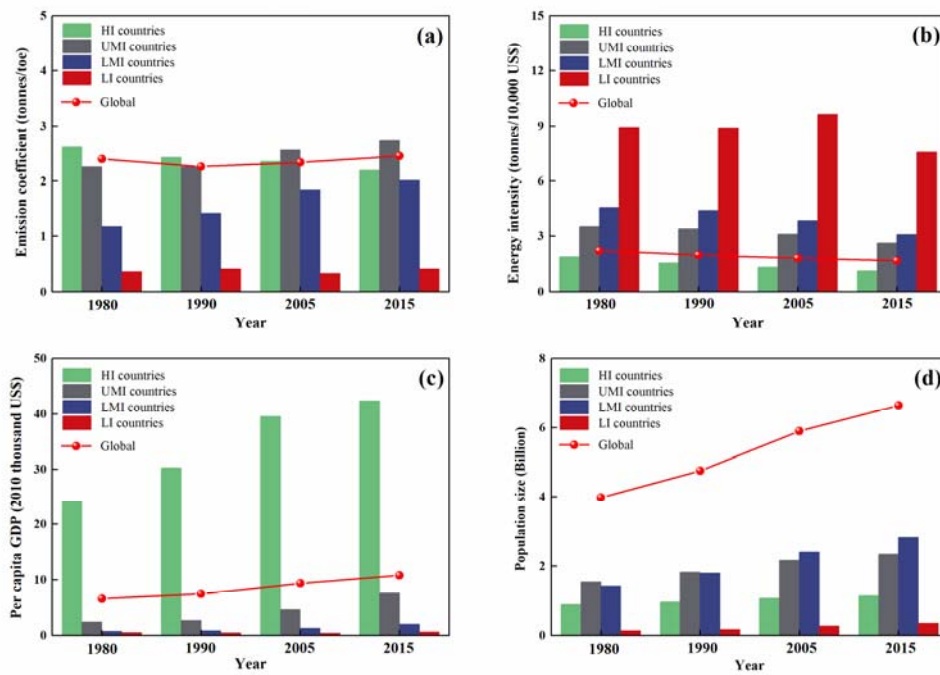


Fig. B1. Emission coefficient (EC), energy intensity (EI), per capita GDP (PCG), and population size (P) in different subpanels from 1980 to 2015. *Data sources:* IEA's World Energy Balances 2017 [36] and World Bank's WDI [2].

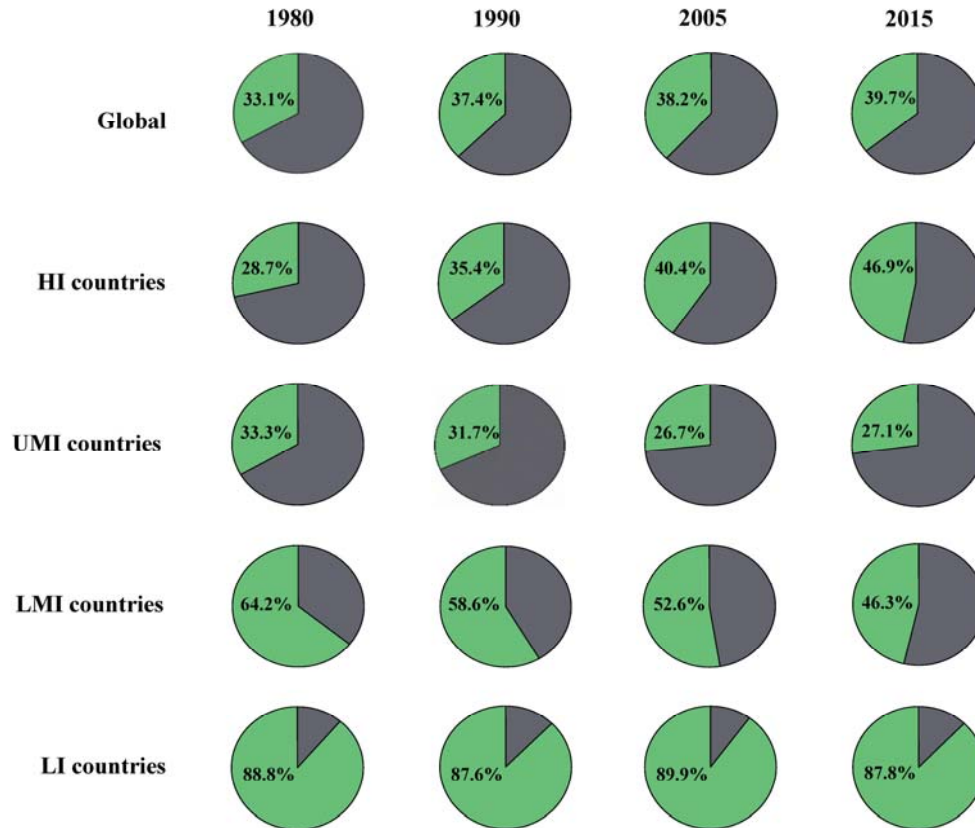


Fig. B2. Energy mix in different subpanels from 1980 to 2015. *Note:* Grey denotes the share of coal and oil, which represents the energy mix in this study, while green indicates the share of natural gas, renewable energy, and others (see the numbers). *Data source:* IEA’s World Energy Balances 2017 [36].