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A decomposition and decoupling analysis for carbon dioxide emissions: evidence from OECD countries

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Abstract

Despite the huge difference in their climatic regimes, the OECD countries are among the world's largest energy consumers and emitters of greenhouse gases, particularly carbon dioxide. Nonetheless, no studies have been conducted to decompose and decouple the long-term influential primary factors of carbon emissions for these countries. In this research, the Log Mean Divisia Method I is used to inspect the contribution of several influencing factors to fill this knowledge gap. Moreover, Tapio (Transp Policy 12(2):137–151, 2005) decomposition analysis (DA) is performed to investigate the driving forces of CO_2 emissions over the 1990–2019 years. The study provides an in-depth analysis of how to reduce CO_2 emissions and the factors that contribute to their variation, which is crucial for both global and regional climate change policies. DA shows that, up to 2004, the activity effect and the population effect drove the emissions to increase; while, in more recent years, the activity effect was able to curb the emissions. Decoupling analysis show the prevalence of the expansive negative decoupling regime for the 1990–2004 and 2015–2019 periods, while several countries were in the strong decoupling phase over the central period (2005–2009). According to the results, further efforts to increase energy efficiency, political support for digitalization and decentralized energy systems, and setting up a unique emission trading system are recommended for air pollution reduction.

Keywords CO_2 emissions · Decomposition analysis · Decoupling analysis · LMDI · OECD

Abbreviations

BRICS	Brazil, Russia, India, China, South Africa
CH_4	Methane

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CO_2	Carbon dioxide
COVID-19	Corona Virus Disease
DA	Decomposition Analysis
DI	Decoupling Index
EU	European Union
FDIs	Foreign Direct Investments
GDIM	Generalized Divisia Index Method
GDP	Gross Domestic Product
GHG	Greenhouse Gas
IDA	Index Decomposition Analysis
LCU	Local Currency Unit
LMDI-I	Log Mean Divisia Method I
Mt	Megaton
N_2O	Nitrous oxide
OECD	Organization for Economic Co-operation and Development
TWh	Terawatt hour
SDA	Structural Decomposition Analysis
UK	United Kingdom
USA	United States of America
WB	World Bank

1 Introduction and literature review

Greenhouse Gas (GHG) emissions into the air might provoke climate change, which has been identified as the world's greatest environmental problem. GHG emissions such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) are mainly produced by using a high amount of fossil fuels. Among these pollutants, CO_2 emissions account for more than 76% of total GHG emissions, so that global CO_2 emissions increased from 20.64 billion tons in 1990 to 37.5 billion tons in 2022. Therefore, CO_2 emissions are the biggest share of the world's GHG emissions as well as the main source of global warming. The impacts of CO_2 emissions on human lives and different sectors of society are considerable. Recently, CO_2 emissions have been a potential hazard and threat to public health, particularly respiratory disease, and have reduced life expectancy. It is understandable that CO_2 emissions have not only significantly damaged the environment, but also may have a detrimental role on public health, social welfare, and economic development. Hence, the need for alleviating climate change has prompted the world to pay considerable attention to CO_2 emissions reduction (Magazzino, 2016b, 2019; Mallongi et al., 2021, 2023; Mele et al., 2021; Padilla et al., 2021; Rauf et al., 2021; Song et al., 2018).

Emissions continue to increase in many countries although progress has been registered in decoupling GHG emissions from economic activity. Historically, the Organization for Economic Cooperation and Development (OECD) countries have emitted most of the global GHG; however, there was also a sharp increase in emissions due to Brazil, Russia, India, China, South Africa (BRICS) countries. OECD members were responsible for more than 67% of global CO_2 emissions in 1971, 50% in 1990, and 35% today. Figure 1 shows the historical trend of CO_2 emissions and total energy consumption of OECD members from 1960 up to 2019. According to the projections, CO_2 emissions increased from 5168 Mt in 1960 to 11,335.12 Mt in 1990, then reached their peak in

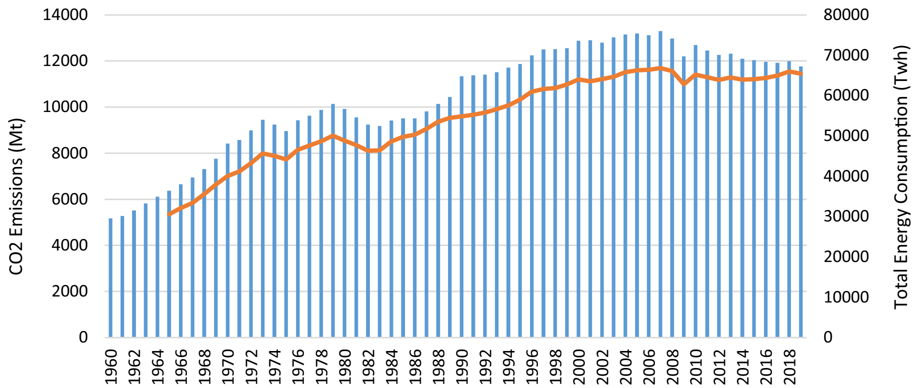

Fig. 1 CO_2 emissions and total energy consumption of OECD countries (1960–2019). Source: authors' elaborations on World Bank data

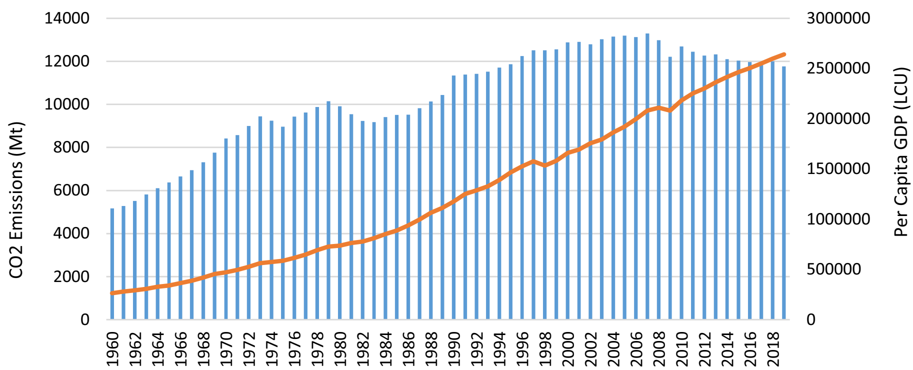

Fig. 2 CO_2 emissions and per capita GDP of OECD countries (1960–2019). *Source*: authors' elaborations on World Bank data

2007, around 13,294.7 Mt, and since then, international agreements for sustainable development, the Kyoto Protocol (1997), and the Paris Agreement (2015) gradually changed the energy mix among OECD members and have reduced the CO_2 emissions; however, these agreements progress is insufficient and could not stabilize emissions.

During the same period, a similar trend for the total energy consumption of OECD members is registered. Total energy consumption doubled, and reached its top, with a value of 66,795.83 TWh in 2007; then suddenly fell to 62,830.5 TWh in 2009 due to the global financial crisis, and since then it has remained almost constant. As shown in Fig. 2, per capita Gross Domestic Product (GDP) exhibits an increasing trend over time, with exception of 1998 and 2009 years. It increased ten times from 263,256.7 LCU in 1960 to 2,639,692.3 LCU in 2019. Recently, emissions have fallen in almost all OECD countries, partly as a result of the reduction in GDP growth rates due first to the sub-prime mortgage and sovereign debt crises, then to the Corona Virus Disease (COVID-19) pandemic, and finally to the conflict between Russia and Ukraine, but also to more daring environmental policies launched especially by the European Union (EU) and the change in energy consumption models, also imposed by the ongoing conflict (IEA, 2015; Song et al., 2018; OECD, 2020; Bersalli et al., 2022; Magazzino & Mele, 2022).

CO_2 emissions of OECD countries have been reduced in recent years, but the absolute amount of emissions is still high and unstable. To reduce CO_2 emissions avoiding climate change risks, international cooperation and regional policy-making are needed. CO_2 emissions are significantly dependent on economic activities and energy consumption, such that both variables move along with negative externality problems at a global and local scale. Emissions change over time due to variations in energy demand, economic structure, efficiency improvements, population density, investment in infrastructure, etc. In this regard, OECD members should reconsider their strategy for emissions abatement. To reach the goal, these countries should understand how to reduce emissions and which factors contribute to their dynamics. In addition, it is also important to evaluate the intensity of the relationship between economic growth and CO_2 emissions. Hence, this study aims to identify the driving factors behind CO_2 emissions, as well as which of them has been more significant on CO_2 emissions in the framework of decomposition; besides, decoupling analysis as a supplement emission assessment is used to analyze the conditions registered in each country (Alves & Moutinho, 2014; Tajudeen et al., 2018; Song et al., 2018; Yang et al., 2018; Wang et al., 2018; Wu et al., 2021). A useful way to realize the contribution of each effective factor to change in CO_2 emissions is the Decomposition Analysis (DA). DA provides a reliable measure of emissions changes and gives clarity regarding which factor has been more significant in driving the reduction/enhancement in CO_2 emissions. DA is one of the useful tools in order to investigate the driving factors in CO_2 emissions. DA method has been widely used within the field of energy policy to survey the decarbonization status among economic growth, energy consumption, and CO_2 emissions, measuring the impact of effective factors on CO_2 emissions. Moreover, this technique has been employed to inspect the key factors between carbon emissions and energy consumption (Chong et al., 2017; Pan et al., 2021), between energy and water (Li et al., 2019a), and in the industry sector (Kopidou & Diakoulaki, 2017; Yu et al., 2019). The Structural Decomposition Analysis (SDA), Index Decomposition Analysis (IDA), and Log Mean Divisia Method (LMDI) I and II are the main subgroups of the DA methods. LMDI-I method was proposed by Ang and Liu (2001) to conquer the aggregation and residual terms problems in both SDA and IDA methods. Hence, LMDI methods became the most appropriate and flexible within DA, and a considerable number of studies in energy economics used these methodologies: Zhang et al. (2011), Gonzalez et al. (2014), Cansino et al. (2015), Shahiduzzaman et al. (2015), Torrie et al. (2016), Dong et al. (2020), Lin and Long (2016), Mousavi et al. (2017), Zhao et al. (2017), Li et al. (2018), Wang and Zhou (2018), Cai and Ma (2018), Boqiang and Liu (2017), Song et al. (2018), Li et al. (2019b), Ran et al. (2019), Zhang et al. (2019a), Parker and Bhatti (2020), Ari et al. (2020), Cai et al. (2020), Hasan and Chongbo (2020), Jiang et al. (2020), Nieto et al. (2020), Eskander and Nitschke (2021), Karmellos et al. (2021), Padilla et al. (2021), Tenaw (2021), Zhang et al. (2021), Golas (2022), Gonzalez et al. (2022), Ozawa et al. (2002), Ruiz et al. (2022), Xu et al. (2022), and Wen et al. (2022). As a supplement to CO_2 emissions analysis, decoupling analysis helps regional policymakers to realize the level of green growth and adopt more focused interventions toward sustainable development. On the other hand, few studies have focused on the decoupling between CO_2 emissions and economic growth: Song et al. (2018) and Tenew et al. (2021). Hence, decomposition and decoupling analyses are applied to diverse fields and can reveal interesting outcomes.

In summary, the study aims to conduct DA to explore the driving factors of CO_2 emissions in OECD countries. Then, particular attention to decoupling analysis is paid, to understand the decoupling relationship between CO_2 emissions and economic growth during the years 1990–2019. In addition, an LMDI-I method based on the Kaya factor is developed to decompose and analyze the contributions of the main influencing factors. In seeking to fulfill the decoupling aim, Tapio's (2005) DA is implemented to map the status and degree of relationship between CO_2 emissions and economic growth over six different sub-periods.

Many research (see Table 4 in the "Appendix") have been conducted on the DA to explore the driving factors behind CO_2 emissions. Some studies analyzed decompositions of both CO_2 emissions and energy intensity, trying to investigate the driving factors of the changes in these variables. As an example, Zhang et al. (2011) analyzed CO_2 emissions in the Chinese transportation sector from 1985 to 2009 using LMDI method. The results proved that per capita economic activity was the key contributor to CO_2 emissions growth. Gonzalez et al. (2014) assessed the contributors behind the change in energy consumption across European countries during the period 2001–2008. The findings highlighted that economic activity is the main driving factor of energy consumption. Cansino et al. (2015) tried to analyze the contribution of CO_2 emissions to Spain's economy from 1995 to 2009. DA analysis indicated that renewable energy sources are the driving factors of CO_2 emissions. Taking an example from the chemical industry, Lin and Long (2016) stated that output per worker, industrial economic scale, energy intensity, and energy structure were the key driving forces in CO_2 in the Chinese chemical industry. Then, Boqiang and Liu (2017) studied China's CO_2 emissions from heavy industry for 1991–2015 years. Labour productivity, energy intensity, and industry scale are the contributors to the increase in emissions. Zhao et al. (2017) explored the leading factors of changes in both national and regional CO_2 emissions within China's provinces from 2000 to 2014. Decomposition results indicated that, at both national and regional scales, the economic activity factor is the main contributor to the increase in CO_2 emissions, and the energy intensity factor is the main key to emissions' reduction. At the same time, Mousavi et al. (2017) used three variations of LMDI method to identify the driving forces of CO_2 emissions from 2003 to 2014, claiming that the intensity of electricity generation and fossil fuel combustion are two major responsible factors for CO_2 emissions. Li et al. (2017) applied DA method to explore the leading factors of the variations in both national and regional CO_2 emissions, showing that the economic scale factor represents the driving force.

Later, Song et al. (2018) under the framework of Kaya identity, used LMDI decomposition method to understand the effects of CO_2 determinants in OECD countries from 2001 to 2015. Results implied that energy intensity and per capita GDP are the main driving factors of CO_2 emissions. Besides, the decoupling state between the CO_2 emissions, population, energy consumption, and GDP is recessive decoupling. Wang and Zhou (2018) investigated global per capita consumption-based emissions inequality by using the Theil index and IDA analysis from 1995 to 2009, providing that production outsourcing is more responsible than consumption regarding emissions inequality. Wang and Feng (2018) applied LMDI technique to decompose the variation in Chinese industrial CO_2 emissions. They explained that industrial activity is the most significant factor in emissions. Also, when looking at the sectoral subject, Cai and Ma (2018) performed a study to mitigate CO_2 emissions in Chinese commercial buildings from 2001 to 2015. The results indicated that GDP per capita and industry intensity reduce emissions, while the energy intensity effect is the main factor of the increase in CO_2. Ran et al. (2019) applied LMDI method to evaluate CO_2 emissions from the electric power sector in China during 1998–2017. Economic growth is the major factor in emissions increase. Zhang et al. (2019b) studied Chinese provincial-level driving mechanism of CO_2 emissions for the power sector during 2004–2014.

The results suggested that the change in CO_2 emissions of the power sector could be mainly attributed to the economic scale, industrial intensity, and also energy intensity within provinces. Li et al., (2019a, 2019b) investigated the leading factors of changes in emissions for the transportation sector within megacities during 1960–2001. Decomposition results introduce rapid urbanization and motorization factors as major driving factors of emissions.

Also, Hasan and Chongbo (2020) investigated the historical CO_2 emissions of the electricity industry in Bangladesh over the period 1979–2018, highlighting that government action, population intensity, and substitution exert a positive impact, while carbon and power intensity exhibit a negative role in the emissions. Jiang et al. (2020) applied LMDI technique across the Chinese non-residential power sector over the period 2007–2016. Empirical results showed that economic growth is the main influencing factor; on the contrary, population growth has an insignificant role in the growth of non-residential power consumption. Parker and Bhatti (2020) documented Asian CO_2 emissions across fourteen countries from 1971 to 2017. They claimed that the per capita indicator is the most important parameter, while carbonization and energy intensity are the least significant in determining the dynamics and fluctuation of emissions. Ari et al. (2020) studied the main contributors to Turkey's CO_2 emissions for the transportation sector in the 2000–2017 years. LMDI method findings revealed that economic growth is the leading factor of the emissions in the transportation sector; however, population and emissions intensity factors have a positive effect. At the same time, Cai et al. (2020) studied China's CO_2 emissions by decomposing and analyzing the driving factors. For this aim, LMDI method was applied to data from 1996 to 2016. Findings indicated that economic activity plays a key role in emissions. Nieto et al. (2020) studied the Indian energy transition to a lower-carbon economy using LMDI approach to analyze the contributors behind the CO_2 emissions from 1990 to 2016. The results of the study indicated that the economic growth of India is the leader in CO_2 emissions.

Recently, a few studies have addressed the review of decomposition and decoupling analysis. Tenaw (2021) provided a DA on energy intensity in Ethiopia for the period 1990–2017, revealing that efficiency is the main driving factor; besides, industrialization and Foreign Direct Investments (FDIs) stock exert a positive effect on energy intensity; while, economic growth, renewable energy, and industrial quality show a negative impact on energy intensity factor. For the EU, Karmellos et al. (2021) investigated seven driving factors of CO_2 emissions from electricity generation over the years 2000–2018. The analyzed factors were economic activity, population, electricity intensity, electricity trade, energy intensity, generation structure, and emissions factors. Eskander and Nitschke (2021) examined energy use and CO_2 emissions in UK universities. They noted that the emissions coefficient, intensity, and affluence are the major contributors to total emissions. At the same time, Padilla et al. (2021) found the key leaders of CO_2 emissions and energy intensity by applying LMDI method based on Kaya identity from 1971 to 2017 for Colombia. Population effect is discovered as the main driving force. Zhang et al. (2021) analyzed the influencing factors of CO_2 emissions for the industry sector in China during 2000–2019. The Generalized Divisia Index Method (GDIM) is used for DA. According to the results, the added value of the industry sector is the key contributor to the increase in emissions.

More recently, Wen et al. (2022) studied a GDIM model across the Chinese industrial sub-sector from 2000 to 2017 and claimed that the investment scale is the main driving force for the CO_2 emissions whilst carbon intensity of investment, energy intensity, and investment efficiency assisted in reducing emissions. Ruiz et al. (2022) analyzed and compared the driving factors of the CO_2 emissions for the six largest emitters (China, USA, EU, India, Russia, and Japan). The Kaya-LMDI analysis method and Granger causality technique were used to disentangle the relationship among variables over the period 1990–2018. Results proved that economic growth is the main driving factor. Also, energy intensity is a leading factor in reducing CO_2 emissions. Gonzalez et al. (2022), by using the LMDI method, tried to track the change in Spanish GHG emissions over the period 2008–2018. The results of the DA indicated that energy intensity played a crucial role. Xu et al. (2022) analyzed the decomposition of residential electricity-related CO_2 emissions in China's provinces over the period 1997–2019. LMDI findings showed that income growth is the main factor behind CO_2 emissions in most provinces.

The current research decomposes the CO_2 emissions into main factors by using LMDI-I method to explore the driving factors of the emissions. Besides, Tapio's (2005) decoupling analysis is applied to uncover the decoupling degree between CO_2 and economic growth. Compared with previous literature, to the best of our knowledge, no further research—except Song et al. (2018)—performed decomposition and decoupling analysis for OECD countries. In addition, the gap in the literature studies is in different ways; firstly, this study presents a long-term (1990–2019) analysis of decomposition and decoupling. Secondly, the LMDI-I method is improved in the study for OECD members. Thirdly, this study investigates decoupling status to investigate the relationship between economic growth and carbon emissions for OECD members for 6 sub-periods, a topic never addressed in previous research. Therefore, the study is the first in-depth research in the field of decomposition and decoupling analysis for all OECD countries.

The structure of the study is as follows. After the introduction and literature review provided in this Sect. 1, in the next Sect. 2 the data and methodology of decomposition and decoupling analysis are described. In the following Sect. 3, the empirical findings along with a discussion of the results are given. Finally, Sect. 4 contains the main conclusions together with policy implications.

2 Materials and methods

The empirical approach followed in this study uses LMDI-I decomposition method to disentangle the change in CO_2 emissions into a set of possible driving factors and add quantitative analysis to perceive the changes in predefined macroeconomics and energy-related factors. The index illustrates the effects of human activities on the environment, according to the Kaya identity, which was introduced by Kaya (1989), and then re-formalized by Zhang and Ang (2001). It is the most widely used and important analytical technique to detect the driving forces of CO_2 emissions from fossil fuels because of its simple structure and conceptualization. For this purpose, this paper uses LMDI method to identify the factors influencing CO_2 emissions due to its benefits in precisely describing outcomes. Population, GDP, energy intensity, fuel mix, and emission coefficients are the factors to consider. The impact of these variables on emissions has been extensively studied for various countries through different methodologies. As a result, the issue is not whether the factors impact the emissions or not, but rather how much influence they have. After assessing the impact of these factors on CO_2 emissions, the extent of emission intensity and the decoupling of OECD economies from CO_2 emissions are considered to examine future trends. Several studies (Boqiang & Liu, 2017; Cai & Ma, 2018; Cai et al., 2020; Jiang et al., 2020; Hasan & Chongbo, 2020; Nieto et al., 2020; Eskander & Nitschke, 2021; Karmellos et al., 2021) and the Fourth Assessment Report of the

IPCC used Kaya based LMDI decomposition method to identify the possible driving factors of CO_2 emissions. Therefore, we applied accordingly LMDI-I method to confirm the contribution of several influencing factors and detect the key factors of CO_2 emissions for OECD countries. The study also aims to provide information for policymakers to point the energy policies in the right direction.

2.1 Decomposition analysis

In this study DA is developed on the Kaya identity, in which CO_2 emissions can be decomposed into a set of possible influencing factors as follows:

$$CO_{2_{i,t}} = \frac{CO_{2_{i,t}}}{FE_{i,t}} \times \frac{FE_{i,t}}{TE_{i,t}} \times \frac{TE_{i,t}}{GDP_{i,t}} \times \frac{GDP_{i,t}}{POP_{i,t}} \times POP_{i,t} \tag{1}$$

where CO_2 denotes carbon emissions, *FE* denotes fossil energy consumption, *TE* denotes total energy consumption, *GDP* denotes Gross Domestic Product, *POP* denotes population, i represents the specific individual (country), and t is the time identifier. Equation (1) can be re-written as Eq. (2) (Cai & Ma, 2018; Hasan & Chongbo, 2020):

$$C_{it} = CI_{i,t} \times ES_{i,t} \times EI_{i,t} \times AE_{i,t} \times P_{i,t} \tag{2}$$

where C_{it} is carbon emissions, CI_{it} is carbon intensity (CO_2/FE), which implies the amount of emissions emitted per unit of fossil energy consumption; ES_{it} is energy structure (FE/TE), which means the substitutions of fossil energy consumption; EI_{it} is energy intensity (TE/GDP), which shows the total energy consumption per unit of GDP; AE_{it} is the activity effect (GDP/POP), which represents Gross Domestic Product per capita, and P_{it} is the population (Boqiang & Liu, 2017; Karmellos et al., 2021).

Without residual factors through LMDI method, the arithmetic and cumulative change in carbon emissions for a specific time period can be distributed into the five possible influencing factors as in the following equations:

$$\Delta C = C_{t_2} - C_{t_1} \tag{3}$$

$$\Delta C = \Delta CI + \Delta ES + \Delta EI + \Delta AE + \Delta P \tag{4}$$

ΔC is the change in CO_2 emissions, C_{t_1} refers to CO_2 emissions at time t_1, and C_{t_2} represents CO_2 emissions at time t_2. ΔCI, ΔES, ΔEI, ΔAE, and ΔP are changes in carbon intensity, energy structure, energy intensity, activity effect, and population, respectively.

The individual effect of each component of Eq. (4) can be calculated as Eqs. (5)–(9).

$$\Delta CI = L(C_{t_2} - C_{t_1}) \times Ln\left(\frac{CI_{t_2}}{CI_{t_1}}\right) \Rightarrow \left(\frac{C_{t_2} - C_{t_1}}{Ln\left(\frac{C_{t_2}}{C_{t_1}}\right)}\right) \times Ln\left(\frac{CI_{t_2}}{CI_{t_1}}\right) \tag{5}$$

Table 1 States of decoupling model analysis

	State		$\frac{\Delta C}{C_0}$	$\frac{\Delta GDP}{GDP_0}$	DI
1	Strong Decoupling	GDP increasing, CO_2 emissions decreasing	−	+	< 0
2	Weak Decoupling	GDP and CO_2 emissions are increasing	+	+	[0, 0.8)
3	Expansive Coupling	GDP and CO_2 emissions are increasing	+	+	[0.8, 1.2)
4	Expansive Negative Decoupling	GDP and CO_2 emissions are increasing	+	+	> 1.2
5	Strong Negative Decoupling	GDP decreasing, CO_2 emissions increasing	+	−	< 0
6	Weak Negative Decoupling	GDP and CO_2 emissions are decreasing	−	−	[0, 0.8)
7	Recessive Coupling	GDP and CO_2 emissions are decreasing	−	−	[0.8, 1.2)
8	Recessive Decoupling	GDP and CO_2 emissions are decreasing	−	−	> 1.2

Sources: Tapio (2005) and Karmellos et al. (2021)

$$\Delta ES = L(C_{t_2} - C_{t_1}) \times Ln\left(\frac{ES_{t_2}}{ES_{t_1}}\right) \Rightarrow \left(\frac{C_{t_2} - C_{t_1}}{Ln\left(\frac{C_{t_2}}{C_{t_1}}\right)}\right) \times Ln\left(\frac{ES_{t_2}}{ES_{t_1}}\right) \tag{6}$$

$$\Delta EI = L(C_{t_2} - C_{t_1}) \times Ln\left(\frac{EI_{t_2}}{EI_{t_1}}\right) \Rightarrow \left(\frac{C_{t_2} - C_{t_1}}{Ln\left(\frac{C_{t_2}}{C_{t_1}}\right)}\right) \times Ln\left(\frac{EI_{t_2}}{EI_{t_1}}\right) \tag{7}$$

$$\Delta AE = L(C_{t_2} - C_{t_1}) \times Ln\left(\frac{AE_{t_2}}{AE_{t_1}}\right) \Rightarrow \left(\frac{C_{t_2} - C_{t_1}}{Ln\left(\frac{C_{t_2}}{C_{t_1}}\right)}\right) \times Ln\left(\frac{AE_{t_2}}{AE_{t_1}}\right) \tag{8}$$

$$\Delta P = L(C_{t_2} - C_{t_1}) \times Ln\left(\frac{P_{t_2}}{P_{t_1}}\right) \Rightarrow \left(\frac{C_{t_2} - C_{t_1}}{Ln\left(\frac{C_{t_2}}{C_{t_1}}\right)}\right) \times Ln\left(\frac{P_{t_2}}{P_{t_1}}\right) \tag{9}$$

where the term $L(C_{t_2}\text{-}C_{t_1})$ is the logarithmic weight average (Boqiang & Liu, 2017; Hasan & Chongbo, 2020; Karmellos et al., 2021).

2.2 Decoupling analysis

Tapio (2005) proposed the decoupling model to evaluate the state of transition toward a low-carbon economy. According to the model, there are eight states, which show a process of decoupling between economic growth and carbon emissions (Table 1). The ideal state is

Table 2 Description of the study variables

Variables	Unit	Source	Mean	Std. Dev	Skewness	Kurtosis
CO_2 emissions	Mtoe	World Bank	324.63	854.02	5.22	30.73
Fossil energy consumption	Mtoe	Our World in Data	117.53	305.02	117.53	305.08
Total energy consumption	Mtoe	World Bank	142.09	353.35	142.09	353.35
GDP (constant)	BLCU	World Bank	6.64×10^4	2.28×10^5	4.70	28.20
Population	M	World Bank	32.64	52.85	3.40	16.68

Source: authors' elaborations

to achieve negative carbon emissions along with economic growth. The Decoupling Index (DI) can be presented as in Eqs. (10) and (11).

$$DI_t = \left(\frac{\frac{\Delta C}{C_0}}{\frac{\Delta GDP}{GDP_0}} \right) \Rightarrow (\frac{\left(\frac{\Delta CI}{CI_0}\right) + \left(\frac{\Delta ES}{ES_0}\right) + \left(\frac{\Delta EI}{EI_0}\right) + \left(\frac{\Delta AE}{AE_0}\right) + \left(\frac{\Delta P}{AP_0}\right)}{\left(\frac{\Delta GDP}{GDP_0}\right)} \tag{10}$$

$$DI_t = DI_{CI} + DI_{ES} + DI_{EI} + DI_{AE} + DI_P \tag{11}$$

where DI_t represents the efforts to improve the environment in time t, DI_{CI} the efforts to optimize fossil energy consumption, DI_{ES} the efforts to change energy structure, DI_{EI} the efforts to optimize energy intensity, DI_{AE} the efforts to improve output per capita, and DI_P the efforts to optimize population scale (Boqiang & Liu, 2017; Karmellos et al., 2021; Tapio, 2005).

2.3 Data

In this study, time-series data over the period 1990–2019 for the OECD countries have been collected. CO_2 emissions, fossil energy consumption, total energy consumption, GDP, and population were used in the empirical analysis. All data are derived from World Bank (WB) and Our World in Data databases.[1] It is worth noting that the GDP data are on constant price. The basic descriptive statistics on these series are given in Table 2.

3 Results and discussion

3.1 Results of the decomposition analysis

Following the LMDI-I approach from Eqs. (3–11), the findings of the decomposition analysis for OECD countries are presented in Figs. 1, 2, 3, 4, 5, 6, 7, 8 and 9 for the period 1990–1994, 1995–1199, 2000–2004, 2005–2009, 2010–2014, 2015–2019, and 1990–2019. In the following figures, the contribution of each possible driving factor is shown for all

[1] https://ourworldindata.org/.

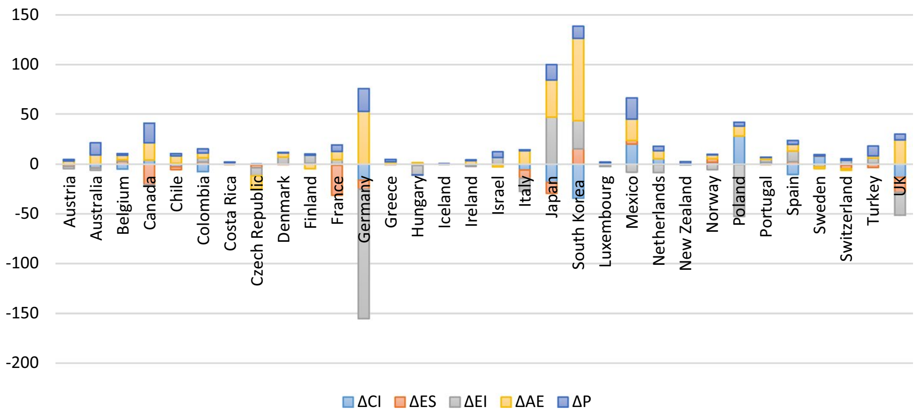

Fig. 3 Decomposition of CO_2 emissions for OECD countries (1990–1994). *Source*: authors' elaborations on World Bank data

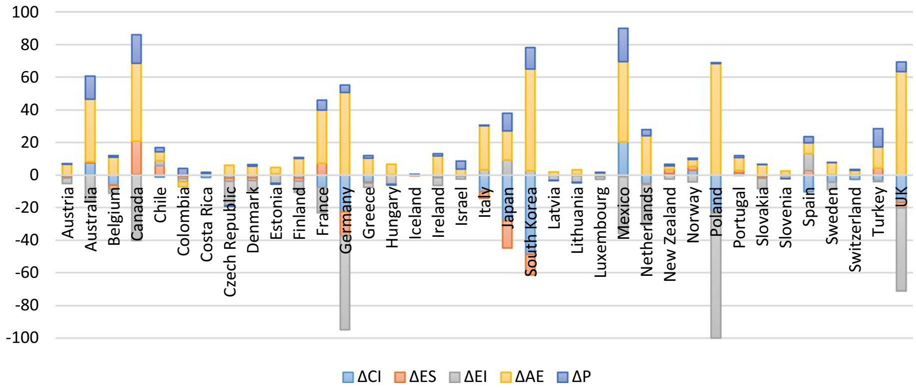

Fig. 4 Decomposition of CO_2 emissions for OECD countries (1995–1999). *Source*: authors' elaborations on World Bank data

sub-periods. It is worth noting that the USA is excluded from the figures because of its high variations in the results and depicted in an individual figure.

Following the decomposition results in the OECD countries for the period 1990–1994 in Fig. 3, it is evident that Germany (with a total effect of − 79.50 Mt), Czech Republic (− 25.49), and the UK (− 21.30) were the pioneer countries of CO_2 reduction. On the contrary, South Korea (103.98), Japan (70.38), and Mexico (58.28) were responsible for the greater increase in CO_2 emissions. The leading factors that conduct CO_2 emissions to increase were the activity effect (especially in South Korea and Germany), the energy intensity effect (for Germany and Japan), and the population effect (for Germany and Mexico). It seems that the energy intensity effect (*ΔEI*), had a significant negative impact in most countries (total effect: − 236.01 Mt). Due to the impact of aged technology on production, the activity effect registered high positive scores in South Korea (82.65) and Japan (37.28). Notwithstanding, the energy intensity effect and energy structure had a remarkable contribution to CO_2 reductions in the majority of the countries. Using less energy to

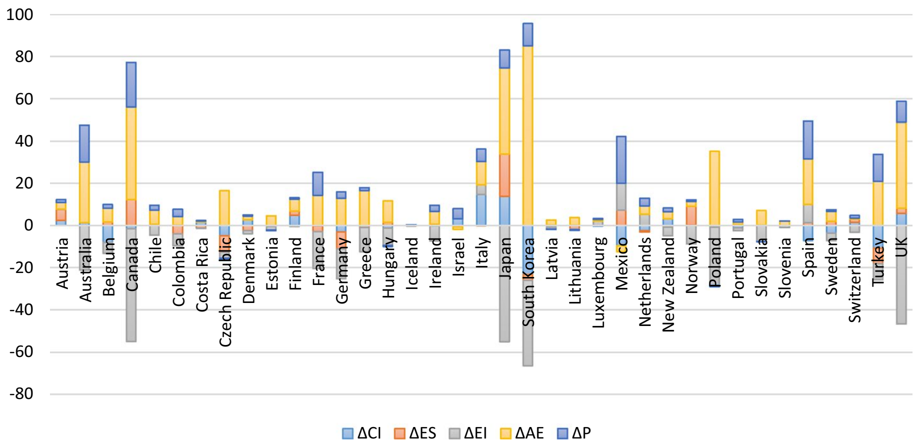

Fig. 5 Decomposition of CO_2 emissions for OECD countries (2000–2004). *Source*: authors' elaborations on World Bank data

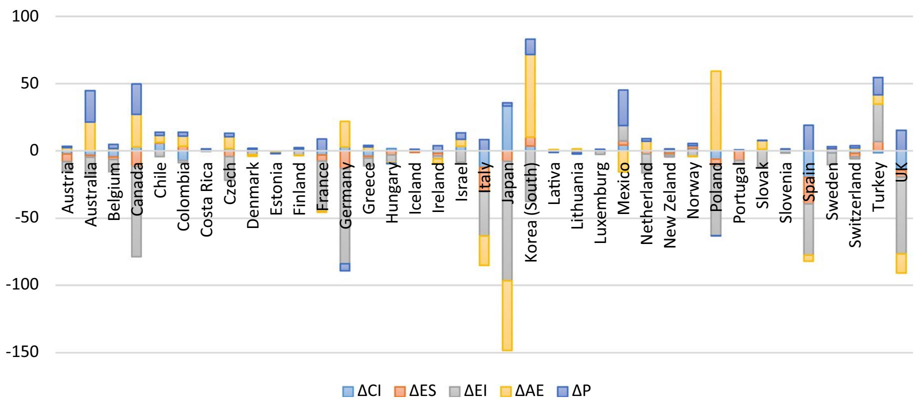

Fig. 6 Decomposition of CO_2 emissions for OECD countries (2005–2009). *Source*: authors' elaborations on World Bank data

produce, CO_2 emissions declined in Germany, Poland, the UK, Italy, and France. Sustainable energy substitution policies in Canada, France, the UK, Japan, and Italy diminished CO_2 emissions. Our findings were mainly in line with Parker and Bhatti (2020), Gonzalez et al. (2014), and Hasan and Chongbo (2020) analysis. According to Parker and Bhatti (2020), the economic activity and in the next step, energy intensity, were the most drivers in explaining of CO_2 emissions in both South Korea and Japan. Gonzalez et al. (2014) found that the activity effect in large economics as Germany was the main factor of CO_2 emissions. Also, Hasan and Chongbo (2020) believed that the population effect was one of the main leaders of CO_2 emissions around the world.

In Fig. 4, the results of the DA and the driving forces are presented for the period 1995–1999. It can be observed that Mexico, Canada, Australia, and Turkey increased their CO_2 emissions by 53.95, 45.69, 44.03, and 24.16 Mt, respectively. The most significant reduction in emissions can be seen in Germany, while the rest of the

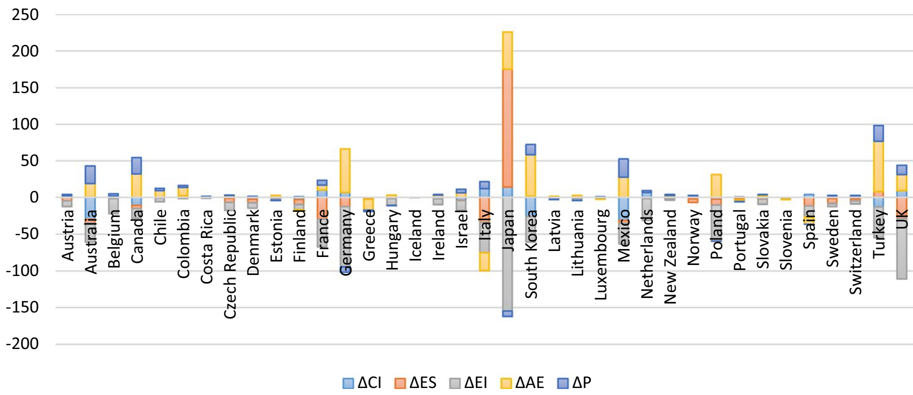

Fig. 7 Decomposition of CO2 emissions for OECD countries (2010–2014). *Source*: authors' elaborations on World Bank data

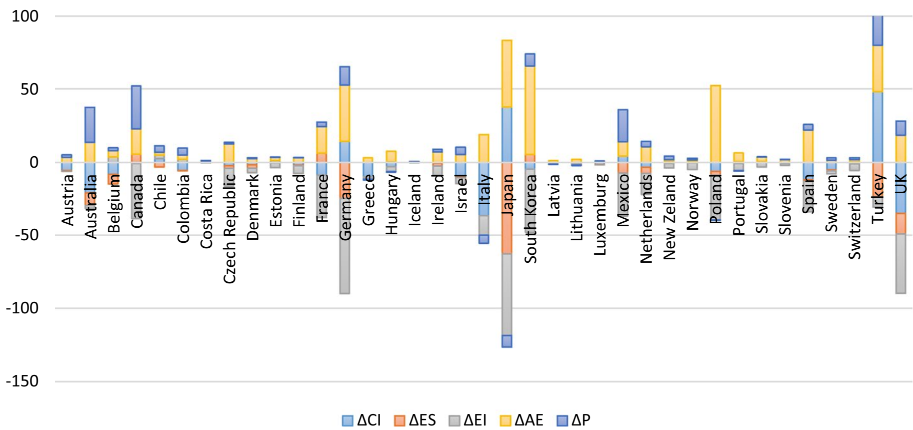

Fig. 8 Decomposition of CO_2 emissions for OECD countries (2015–2019). *Source*: authors' elaborations on World Bank data

countries—with some exceptions—raised their emissions. The main driving factor relating to the CO_2 emissions was the activity effect (total effect: 619.60 Mt). In this respect, all the countries in the sample registered an increase in emissions, with some remarkable cases (Poland, the UK, and South Korea). Also, the energy intensity had the most pronounced impact in Poland (− 76.70 Mt). The second driving force of the CO_2 emissions increase was the population: Mexico, Canada, Australia, and South Korea registered an increase in population. It is evident that the carbon intensity effect drove CO_2 emissions down in most of the countries, especially South Korea (− 48.60) and Poland (− 22.92). In addition, the energy structure effect had a slightly negative contribution in several countries. In comparison with Fig. 1, the activity effect was more pronounced for the period 1994–1999, while the energy intensity effect was smoothed through technological improvement in Colombia, Denmark, Finland, France, Israel, and Portugal. Regarding the carbon intensity effect, most of the countries had a significant

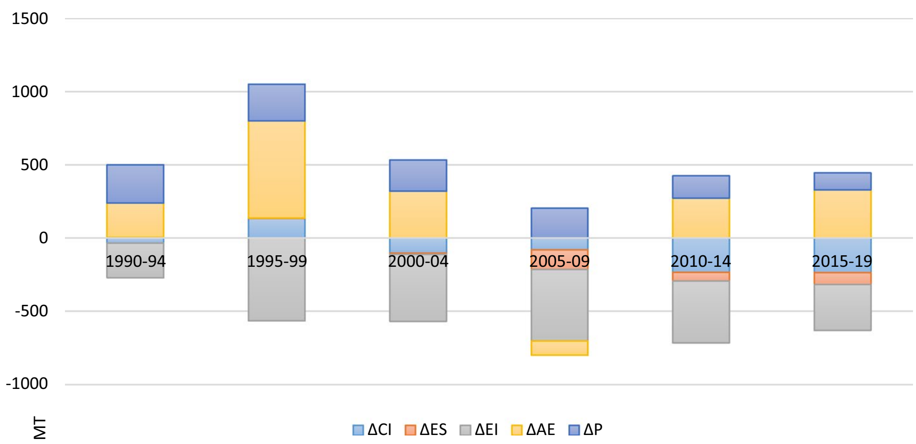

Fig. 9 Decomposition of CO_2 emissions for the USA. *Source*: authors' elaborations on World Bank data

contribution to emissions reduction, especially South Korea. The effects of activity and energy intensity factors on CO_2 emissions are in line with the results of Gonzalez et al. (2014) for Germany, Torrie et al. (2016) for Canada, Parker and Bhatti (2020) for South Korea, Eskandader and Nitschke (2021) and Karmellos et al. (2021) for the UK, Golas (2022) for Poland, and Ozawa (2002) for Mexico.

Regarding the decomposition and driving forces results for the period 2000–2004, it can be seen that most countries further enhanced their emissions: above all, Spain, Italy, Mexico, South Korea, Japan, Australia, and Canada registered a significant contribution. In addition, in several countries the economic activity effect and the population effect had a notable contribution to emissions. The biggest enhancement in CO_2 emissions due to the activity effect was in South Korea (with 85.03 Mt), while for the rest of the sample this effect was limited between 0.24 (Iceland) and 43.83 Mt (Canada). On the other hand, the population raised almost everywhere, notably in Mexico (22.04 Mt). In relation to the energy structure (total effect: 25.93 Mt), it exerted a relatively small contribution, with the biggest negative value in Germany (− 7.95), Czech Republic (− 7.76), and Turkey (− 7.22 Mt) due to substitution policies. Two main factors, energy intensity and carbon intensity, had been driving CO_2 emissions to decrease. The energy intensity effect had a significant negative impact in most countries (especially in Japan, Canada, the UK, and South Korea) due to technological development, and the biggest positive value in Mexico (12.82 Mt). Regarding the carbon intensity effect, it is easily evident that it had a small negative contribution (total effect: − 22.10 Mt), and CO_2 emissions relatively decreased along with fuel consumption. Moreover, it is worth noticing that CO_2 emissions increased due to development in activity structure and an increase in population more than in the previous periods; while, reduction factors showed a relatively small impact than before. Several previous studies—i.e., Shahiduzzaman et al. (2015), Torrie et al. (2016), Parker and Bhatti (2020), Eskandader and Nitschke (2021), Karmellos et al. (2021), Golas (2022), and Gonzalez et al. (2022)—stated that the energy intensity, activity effect, and population factor were the most driving factors of CO_2 emissions in different countries (South Korea, Japan, Poland, Canada, Australia, and the UK), which are consistent with our results. However, we found a different driving factor for emissions in Spain, which is in contrast with the analysis of Gonzalez et al. (2022).

The results of DA and the contribution of driving forces for the period 2005–2009 are shown in Fig. 6. It is clear that most countries, due to a global financial crisis (although with some exceptions), reduced their CO_2 emissions, so that the whole effect was equal to − 386.99 Mt. Considerable contractions in CO_2 emissions were registered for Japan (− 112.61), the UK (− 75.48), Italy (− 76.77), Germany (− 67.51), and Spain (− 63.01 Mt). In most countries, the main driving factor contributing to the enhancement of CO_2 emissions was the population effect, with a total effect of 177.99 Mt. The remarkable increases in CO_2 emissions due to the demographic factor can be found in Mexico, Australia, and Canada. On the other hand, the energy intensity effect (with a total effect of − 572.59 Mt) sensibly drove emissions' reductions, especially in Japan (− 88.78), Germany (− 70.50), Canada (− 67.09), the UK (− 57.03), and Poland (− 51.41 Mt). Also, the economic structure effect exerted a negative impact on CO_2 emissions. In South Korea, Turkey, Colombia, and Mexico the economic structure effect had a contribution to the rise of CO_2 emissions. Several factors had been forcing CO_2 emissions to decrease. In all countries—with the exception of Turkey, Mexico, and Iceland—the energy intensity effect led CO_2 emissions to decrease, and the biggest decrease in CO_2 emissions for Japan. On the other hand, the carbon intensity effect (total effect: − 23.31 Mt) provoked a decrease in CO_2 emissions in several countries, especially in Spain (− 19.88), the UK (− 14.65), and Italy (− 12.39 Mt). The results for this sub-period, and particularly the impacts of activity effect, energy intensity, and population effects on CO_2 emissions, are largely comparable with those from the analysis in Gonzalez et al. (2014), Torrie et al. (2016), Hasan and Chongbo (2020), Parker and Bhatti (2020), Eskandader and Nitschke (2021), Karmellos et al. (2021), Golas (2022), and Gonzalez et al. (2022). Notwithstanding, a different driving factor—namely, the energy intensity—has been isolated here, in contrast with Ari et al. (2020) and Karmellos et al. (2021) findings for the case of Turkey and Italy, respectively.

The DA and relative contribution of the driving factors in CO_2 emissions from 2010 to 2014 for OECD countries are given in Fig. 7. According to the results, almost all the countries reduced their CO_2 emissions. A significant reduction in CO_2 emissions is found for Italy (− 77.78) and the UK (− 66.94 Mt), with the rest of the countries' reduction was limited between − 43.41 (France) and − 1.06 Mt (Estonia). The highlighted factor in most countries which led CO_2 emissions to increase was the economic activity effect (total effect: 380.82 Mt), remarkably in Turkey (69.10), Germany (59.39), South Korea (57.33), and Japan (50.98 Mt). The second leading factor of CO_2 emissions was the population effect, which was positive in different countries, notably Mexico (24.77), Australia (24.03), Canada (22.63), and Turkey (20.88 Mt). On the other hand, several driving factors led CO_2 emissions to decrease, in which the energy intensity effect (total effect: − 751.70 Mt) was the most effective one in lots of countries, with the exceptions of Portugal (0.95), Greece (0.37), and Norway (0.29 Mt). Over these years, a remarkable reduction in emissions due to this specific effect was found in Japan with a value of − 154.94 Mt. Moreover, in Mexico, Australia, and South Korea, the carbon intensity effect had a significant negative contribution of − 30.58, − 29.66, and − 25.66 Mt, respectively. The energy structure effect exerted a marginally negative impact almost everywhere, except for Japan (160.69 Mt). In comparison with previous literature on this topic, the results by Gonzalez et al. (2014) for Germany, Ari et al. (2020) for Turkey, and Parker and Bhatti (2020) for South Korea are in the line with those presented in this paper. However, we established a different driving factor (the energy intensity), which is different with respect of Parker and Bhatti (2020) and Karmellos et al. (2021) for Japan and the UK, respectively.

In Fig. 8, we report the results of DA and contributions of each driving factor in CO_2 emissions in OECD countries for the period 2015–2019. The results reveal that the emissions decreased in the sample. However, some countries registered an increase, like Turkey (72.82) and South Korea (26.27 Mt). The emissions were essentially driven by the energy intensity and the economic activity effects. The main driving factor contributing to the reduction of emissions in several countries was the energy intensity (total effect: − 446.69 Mt), with a considerable negative impact in Germany (− 65.25) and Japan (− 55.71 Mt). On the other hand, the activity effect drove the CO_2 emissions to rise, especially in South Korea (60.40) and Poland (52.33 Mt). Regarding the impact of the energy structure effect (total effect: -150.43 Mt), it was evident that due to successful substitution and shift in the fuel mix, it had a negative contribution with significant values in Japan (− 62.62), Germany (− 24.73), and Turkey (− 23.88 Mt). The carbon intensity had, generally speaking, a smaller negative effect, with a positive peak in Turkey (48.05) and a negative one in Italy (− 36.46 Mt). These results, above all the impact of the activity effect and energy intensity on CO_2 emissions, are close to ones provided by Torrie et al. (2016), Ari et al. (2020), Parker and Bhatti (2020), Karmellos et al. (2021), and Golas (2022).

The DA and the relative contribution of the driving factors in CO_2 emissions in all the sub-periods for the USA are depicted in Fig. 9. According to the decomposition results, it is clearly evident that the USA increased its CO_2 emissions for the periods 1990–1994 and 1995–1999. Then, due to the global financial crises, the emissions sharply decreased by approximately -596.53 Mt. For the rest of the period, a relatively small reduction can be seen. Moreover, several driving factors drove emissions to change. The population effect with a value of 261.20 Mt was the main driving force that increases emissions in the USA for the period 1990–94 when the energy intensity effect led emissions to decrease by approximately − 236 Mt. The main driving factor contributing to the enhancement of emissions in the period 1995–1999 was the economic activity effect; however, the energy intensity effect drove emissions to decrease. For the period 2000–2004, it is obvious that the economic activity and population effect had a positive effect on emissions. In addition, most of the contributing factors excluding the population effect led to an emissions decrease for the period 2005–2009. The energy intensity and energy structure effects had a considerable impact. The economic activity along with population growth showed a significant contribution with positive values of 272.64 and 151.44 Mt for the period 2010–2014. At the same time, energy intensity and energy structure effect due to green energy policies and gradually shift to renewable fuel mix had a remarkable contribution to emissions reduction, by approximately − 419.5 and − 60.34 Mt. These findings are in the line with Dong et al. (2020) results for the decomposition of the US CO_2 emissions from 1997 to 2017. Regarding the last period, it is clear that the impacts of the economic activity and energy intensity effects found significant. The energy intensity effect, unlike the economic activity effect, drove emissions to decrease with a value of − 313.7 Mt. The carbon intensity and energy structure effects led emissions to reduce by approximately − 236.7 and − 81.32 Mt, respectively.

Finally, the results of the DA and the contribution of each driving factor in emissions for OECD countries for the period 1990–2019 are presented in Fig. 10. Based on the results, it is evident that the emissions increased over this time period (with a global effect of 529.58 Mt). The most significant increase was in South Korea with a value of 383.53 Mt, while Germany (− 237.78), the UK (− 217.88), and Italy (− 103.79 Mt) led emissions to decrease. The economic activity effect played a great role in the increase of emissions in all countries (total effect: 3160.10 Mt), with peaks in South Korea (501.60), Poland (350.11), and Germany (319.77 Mt). The population effect was the other contributor factor that ran emissions to increase, with the highest contribution in Mexico (150.70) and Canada (150.35 Mt). On the contrary, the energy intensity effect reduced the emissions, especially

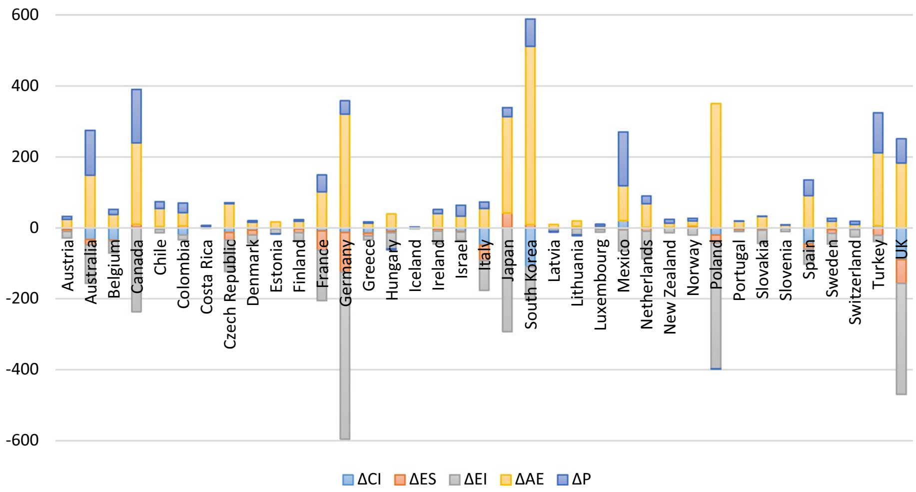

Fig. 10 Decomposition of CO_2 emissions for OECD countries (1990–2019). *Source*: authors' elaborations on World Bank data

Fig. 11 Decomposition of CO_2 emissions for USA (1990–2019). *Source*: authors' elaborations on World Bank data

in Germany (− 469.80), Poland (− 354.85), the UK (− 312.03), and Japan (− 292.29 Mt). The energy structure effect played a negative impact in most countries, with a few exceptions. The carbon intensity effect revealed a relatively small negative impact in most countries.

Furthermore, the results of the DA and the contribution of each driving force in emissions in the USA for the period 1990–2019 are presented in Fig. 11. It is evident that emissions decreased for the period, and the most reduction factor was the energy intensity effect with the value of − 2678.97 Mt, followed by carbon intensity and energy, respectively. Moreover, it seems that the economic activity and population effects had a significant positive contribution. The main driving factor contributing to the growth in emissions was the economic activity effect of 2108.92 Mt, and the population effect drove the emissions to increase by approximately 1321.07 Mt.

Overall, the DA helps us to depict some general conclusions on how CO_2 emissions are affected. According to the results, the economic activity effect was the significant influencing force in emissions. The effect was most considerable in the USA and South Korea during the years of the analysis. The production structure of all countries revealed significant changes in energy consumption, notably a decrease in fossil energy consumption in the USA, Germany, Poland, the UK, and Canada. Using more efficient generation technologies for the improvement of energy intensity was clear in all countries, specifically in the 2005–2009 period due to the global financial crisis. The ineffectiveness of energy policies for a sustainable fuel mix and CO_2 mitigation were evident, specifically in European countries. The growth of population increased energy demand in countries where a significant population effect was registered, specifically in the USA, Canada, Mexico, and Australia, although there were some exceptions with negative growth rates, such as Estonia and Poland. As expected, the CO_2 intensity effect had a negligible impact in most countries; however, it was an important factor in the USA.

3.2 Decoupling analysis

We calculated the trend of the decoupling index based on Eqs. (10) and (11). Table 3 presents the results of the decoupling analysis, the decoupling degree of each country for CO_2 emissions and economic growth during various time periods.

According to the results, it is evident that most countries were in an expansive negative decoupling situation during the period 1990–1994 when they increased their CO_2 emissions at a higher rate than the growth of the economy. Specifically, Germany, Hungary, Italy, and Poland were in a state of strong decoupling, which means that they decreased CO_2 emissions along with an increase in economic growth. Czech Republic was the only country in a state of recessive decoupling, where both CO_2 emissions and economic growth decreased, which is called “green de-growth”. At the same time, the UK experienced a weak decoupling situation, when economic growth increased and CO_2 emissions increased at a rate between 0 and 0.8. It seems that both Finland and Sweden experienced the worst possible condition as they were in strong negative decoupling states; indeed, both of them increased their CO_2 emissions while economic growth went down.

For the period 1995–1999, most countries were in a state of expansive negative decoupling. Colombia, Czech Republic, Estonia, Latvia, and Lithuania were in a state of strong decoupling, meaning that they were successful in fulfilling green policies in that period. Denmark, Germany, Poland, and Slovakia were in a weak decoupling state. For Hungary and Luxembourg, it is evident that both CO_2 emissions and economic growth increased approximately at the same rate, which resembled an expansive coupling state.

The results of the decoupling analysis for the period 2000–2004 suggest that the majority of the countries were driven to an expansive negative decoupling state. However, Germany and Slovakia were in a state of weak decoupling during that period.

Based on the results of the decoupling analysis for the period 2005–2009, it is clear that the global financial crisis shifted the majority of countries to a strong decoupling situation. It means that economic growth increased, but CO_2 emissions decreased, which might be considered a case of “green policies”. Australia, Chile, Colombia, Costa Rica, Iceland, Israel, Japan, South Korea, Mexico, Switzerland, and Turkey were in a state of expansive negative decoupling, which means that economic growth increased and CO_2 emissions increased at different rates of more than 1.2. Denmark, Estonia, Hungary, and Italy were in a state of recessive decoupling or green de-growth situation. On the other hand, Slovenia

Table 3 The decoupling state of each country for all study periods

Period	State	Countries
1990–1994	Expansive Negative Decoupling	25: Austria, Australia, Belgium, Canada, Chile, Colombia, Costa Rica, Denmark, France, Greece, Iceland, Ireland, Israel, Japan, South Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Portugal, Spain, Switzerland, Turkey, USA
	Recessive Decoupling	1: Czech Republic
	Strong Decoupling	4: Germany, Hungary, Italy, Poland
	Strong Negative Decoupling	2: Finland, Sweden
	Weak Decoupling	1: UK
1995–2009	Expansive Negative Decoupling	27: Austria, Australia, Belgium, Canada, Chile, Costa Rica, Finland, France, Greece, Iceland, Ireland, Israel, Italy, Japan, South Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, Slovenia, Spain, Sweden, Switzerland, Turkey, UK, USA
	Strong Decoupling	5: Colombia, Czech Republic, Estonia, Latvia, Lithuania
	Weak Decoupling	5: Denmark, Germany, Poland, Slovakia
	Expansive Coupling	2: Hungary, Luxembourg
2000–2004	Expansive Negative Decoupling	34: Austria, Australia, Belgium, Canada, Chile, Colombia, Costa Rica, Czech Republic, Estonia, Denmark, Finland, France, Greece, Hungary, Iceland, Ireland, Italy, Japan, South Korea, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland, Turkey, UK, USA
	Weak Decoupling	2: Germany, Slovakia
2005–2009	Expansive Negative Decoupling	11: Australia, Chile, Colombia, Costa Rica, Iceland, Israel, Japan, South Korea, Mexico, Switzerland, Turkey
	Strong Decoupling	20: Austria, Belgium, Canada, Czech Republic, Finland, France, Germany, Greece, Ireland, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Portugal, Slovakia, Spain, Sweden, UK, USA
	Recessive Decoupling	4: Denmark, Estonia, Hungary, Italy
	Weak Decoupling	2: Slovenia, Norway
	Expansive Coupling	1: Poland

Table 3 (continued)

Period	State	Countries
2010–2014	Expansive Negative Decoupling	13: Australia, Canada, Chile, Colombia, Costa Rica, Iceland, South Korea, Mexico, New Zealand, Portugal, Slovenia, Spain, Turkey
	Strong Decoupling	16: Austria, Belgium, Czech Republic, Denmark, France, Germany, Hungary, Ireland, Latvia, Lithuania, Luxembourg, Netherlands, Slovakia, Sweden, Switzerland, UK
	Expansive Coupling	4: Israel, Japan, Poland, Estonia
	Recessive Decoupling	3: Finland, Greece, Italy
	Weak Decoupling	1: USA
2015–2019	Expansive Negative Decoupling	22: Austria, Australia, Belgium, Canada, Chile, Colombia, Costa Rica, Hungary, Iceland, Ireland, Israel, South Korea, Latvia, Lithuania, Luxembourg, Mexico, New Zealand, Poland, Slovakia, Slovenia Turkey, USA
	Expansive Coupling	3: Czech Republic, Portugal, Spain
	Strong Decoupling	9: Denmark, Finland, Germany, Greece, Italy, Japan, Norway, Switzerland, UK
	Weak Decoupling	4: Estonia, France, Netherlands, Sweden
1990–2019	Expansive Negative Decoupling	21: Austria, Australia, Belgium, Canada, Chile, Colombia, Costa Rica, Iceland, Ireland, Israel, Japan, South Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Portugal, Spain, Turkey, USA
	Weak Decoupling	10: Czech Republic, Finland, France, Greece, Hungary, Latvia, Lithuania, Slovakia, Sweden, UK
	Strong Decoupling	3: Denmark, Germany, Italy
	Expansive Coupling	4: Estonia, Poland, Slovenia, Switzerland

Source: authors' elaborations

and Denmark were driven to a state of weak decoupling during the global financial crisis period. Poland was the only country in a state of expansive coupling.

After the years of the global financial crisis, specifically for the period 2010–2014, it is clear that Australia, Canada, Chile, Colombia, Costa Rica, Iceland, South Korea, Mexico, New Zealand, Portugal, Slovenia, Spain, and Turkey were in a state of expansive negative decoupling. Most of the countries (16) were led to a case of green policies, meaning that they managed to fulfill green energy policies in that period. Israel, Japan, Poland, and Estonia were in a state of expansive coupling. It seems that Finland, Greece, and Italy were in a green de-growth situation due to the consequences of the global financial crisis. In addition, the USA was the only country that experienced a state of weak decoupling.

For the last period, between 2015 and 2019, the results of the decoupling analysis present a significant shift towards expansive negative decoupling for the majority of countries. They increased their CO_2 emissions at a higher rate than the growth of the economy. Meanwhile, Denmark, Finland, Germany, Greece, Italy, Japan, Norway, Switzerland, and the UK were led to a state of strong decoupling or green policies. The Czech Republic, Portugal, and Spain were the countries in a state of expansive coupling. At the same time, Estonia, France, the Netherlands, and Sweden registered a weak decoupling.

Finally, the results of the decoupling analysis for the period 1990–2019 show that most countries (21) were in a state of expansive negative decoupling. At the same time, Denmark, Germany, and Italy were in a state of strong decoupling. The countries in a state of weak decoupling were including the Czech Republic, Finland, France, Greece, Hungary, Latvia, Lithuania, Slovakia, Sweden, and the UK. While Estonia, Poland, Slovenia, and Switzerland increased both economic growth and CO_2 emissions at the same rate.

Overall, the considerable point was that the implementation of green energy policies has shifted most of the European countries towards a significant change in the state of decoupling between CO_2 emissions and economic growth. Meanwhile, South Korea, Australia, Chile, Costa Rica, Iceland, Mexico, and Turkey were always in a state of expansive negative decoupling, which is the worst scenario for decoupling. Besides, Austria, Belgium, Canada, Ireland, New Zealand, Slovenia, Luxembourg, the USA, Colombia, Israel, Portugal, Spain, and Switzerland were mostly observed in a state of expansive negative decoupling, with the exceptions of the global financial crisis and the following years. Finally, Estonia, Hungary, and Poland were countries with unstable states of decoupling.

4 Conclusions and policy implications

The study aims to analyze the main leading factors affecting CO_2 emissions for OECD member countries over the period 1990–2019. Through a DA and a decoupling analysis the whole period as well as six sub-periods (1990–1994, 1995–1999, 2000–2004, 2005–2009, 2010–2014, 2015–2019) have been investigated. Various driving factors—energy structure, energy intensity, activity effect, and population effect—have been taken into account. The study presents a comprehensive analysis of CO_2 emissions in the OECD area. To identify factors influencing CO_2 emissions in the sample, the LMDI approach was used. Then, the decoupling state of economic growth and CO_2 emissions was assessed.

The results of the DA show that, in the first part of the time span (the sub-periods 1990–1994, 1995–1999, and 2000–2004), the activity effect and the population effect represent the main driving factors leading to a rise in CO_2 emissions, more than counterbalancing the remaining three effects. A sensible change is observed since the 2005–2009 years, when the total emissions started to decline thanks to a massive impact of the energy intensity effect, which—together with energy structure and carbon intensity effects—were able to more than compensate for the activity and the population effects.

Our empirical findings are not directly comparable with the existing literature, as the effects that decompose the CO_2 emissions are distinct. Nevertheless, similar findings can be detected in several previous papers like: Zhang et al. (2011), Mousavi et al. (2017), Zhao et al. (2017), Li et al. (2018), Song et al. (2018), Parker and Bhatti (2020), Ran et al. (2019), Ari et al. (2020), Cai et al. (2020), Jiang et al. (2020), Nieto et al. (2020), Kamellos et al. (2021), Zhang et al. (2021), Ruiz et al. (2022), and Xu et al. (2022), who stated that economic activity has a considerable strong effect on CO_2 emissions.

Regarding the decoupling analysis, according to our estimates, a great majority of the countries experienced an expansive negative decoupling phase over the 1990–2004 period; afterward, several countries shifted to a strong decoupling regime for the following ten years. Finally, as a result of the economic-financial crisis, the expansive negative decoupling returned to prevailing. In the same line, Song et al. (2018) affirmed that most of the OECD members were in a recessive decoupling state from 2001 to 2015.

DA and decoupling analyses suggest relevant policy recommendations. In fact, the relevance of the effect of the main driving factors capable of lowering CO_2 emissions emerges (as a consequence of the energy intensity effect and the population effect). This is especially urgent in countries that are lagging behind in the decarbonization process to obtain energy and in improving energy efficiency. To the decoupling of CO_2 emissions from economic activity, the energy efficiency effect might represent a significant and beneficial factor; therefore, it is useful to continue efforts to increase energy efficiency in all OECD countries. Moreover, further political support for digitalization and decentralized energy systems, as well as for the creation of energy communities capable of increasing local electricity supply, would be relevant; indeed, these systems and institutions allow various advantages such as the more efficient use of renewable energies, thus managing to favor decarbonization. Along with these recommendations, a unique carbon trading system in a form of carbon pricing can be an effective approach to limit climate change (Magazzino, 2016a).

Although this study tried to present a comprehensive study of CO_2 emissions in the OECD countries, further investigations are necessary to understand the sample's emissions in a detailed way. The limitations of the study are related to the set of variables used, since a wider selection of series on socio-economic and environmental characteristics may allow more in-depth analyses. Future research may address alternative socio-economic indexes, such as urbanization rate, industrial development, education level, and population structure; evaluate different pollutant agents, such as CH_4 and N_2O; expand the investigation to sub-sectors, i.e. agriculture, industry, service, and transportation sectors.

Appendix

See Table 4.

Table 4 Summary of the studies on decomposition and decoupling analysis

Author(s)	Aim(s)	Sample	Decomposition method	Driving factor(s)
Zhang et al. (2011)	Investigate the potential factors influencing CO_2 emissions	China (1985–2009)	LMDI	Per capita economic activity
Gonzalez et al. (2014)	Analyze the factor behind the energy consumption	EU-27 (2001–2008)	LMDI	Energy efficiency
Cansino et al. (2015)	Analyze the contribution of drivers of CO_2 emissions	Spain (1995–2009)	LMDI	Renewable energy sources
Lin and Long (2016)	Explore the driving factors of CO_2 emissions changes	China, chemical industry (2005–2011)	LMDI	Output per worker and industry structure
Mousavi et al. (2017)	Quantify driving forces of CO_2 emissions	Iran (2003–2014)	LMDI	Economic activity
Zhao et al. (2017)	Explore the driving factors of the changes in CO_2 emissions	China (2000–2014)	SDA and LMDI	Economic activity
Boqiang and Liu (2018)	Explore the influencing factors of CO_2 emissions from heavy industry	China (1991–2015)	LMDI	Labor productivity, energy intensity, and industry scale
Li et al. (2018)	Analyze the contributions of influencing factors of CO_2 emissions	China (2004–2014)	LMDI	Per capita GDP
Wang and Zhou (2018)	Analyze global emission inequality	Global scale (1995–2009)	Theil index and IDA	Per capita energy consumption
Cai and Ma (2018)	Decompose the CO_2 emissions of Chinese commercial building	China (2001–2015)	LMDI	Energy intensity
Wang and Feng (2018)	Decompose the changes in industrial CO_2 emissions	China (2000–2015)	LMDI	Industrial activity
Song et al. (2018)	Decomposition and decoupling analysis of CO_2 emissions	OECD (2001–2015)	LMDI	Energy Intensity and GDP
Li et al., (2019a, 2019b)	Investigate the driving forces of CO_2 emissions from the transportation sector	Global megacities (1960–2001)	LMDI	Urbanization effect for 1960–1970, per capita trip distance for 1970–1980, energy intensity for 1980–1990, and motorization effect for 1990–2000

Table 4 (continued)

Author(s)	Aim(s)	Sample	Decomposition method	Driving factor(s)
Zhang et al. (2019b)	Understanding provincial-level driving factors of CO_2 emissions in the power sector	China (2004–2014)	LMDI	Economic scale, industrial intensity, and energy intensity
Ran et al. (2019)	Evaluate CO_2 emissions from the electric power sector	China (1998–2017)	LMDI	Economic growth
Parker and Bhatti (2020)	Explore the driving forces of CO_2 emissions	14 countries (1971–2017)	LMDI	Per capita income
Ari et al. (2020)	Analyze the main contributions to CO_2 emissions	Turkey (2000–2017)	LMDI	Economic growth
Hasan and Chongbo (2020)	Examining the drivers of CO_2 emissions from the electricity sector	Bangladesh (1979–2018)	LMDI	Activity effects, population, and energy structure
Cai et al. (2020)	Decomposition and analyze the important factors of CO_2 emissions	China (1996–2016)	LMDI	Economic activity
Nieto et al. (2020)	Analyze the main driving forces of CO_2 emissions	India (1990–2016)	LMDI	GDP
Jiang et al. (2020)	Factors influencing residential energy consumption	China (2007–2016)	LMDI	Economic growth
Karmellos et al. (2021)	Investigate the driving factors of CO_2 emissions from electricity generation	EU-27 and UK (2000–2018)	LMDI	Economic activity
Eskander and Nitschke (2021)	Evaluate the progress of the UK universities in greening the energy sources	UK, (2012–2013 and 2018–2019)	LMDI	Emission intensity and affluence effects
Tenaw (2021)	Investigate the main driving forces of energy intensity	Ethiopia (1990–2017)	LMDI	Efficiency factor
Padilla et al. (2021)	Analyze the driving forces of CO_2 emissions and energy intensity	Colombia (1971–2017)	LMDI	Sectoral energy intensity and efficiency improvements
Zhang et al. (2021)	Analyze the key factors that influence CO_2 emissions	China (2000–2019)	GDIM	GDP of the industry

Table 4 (continued)

Author(s)	Aim(s)	Sample	Decomposition method	Driving factor(s)
Wen et al. (2022)	Analyze the major driving forces of CO_2 emissions	China (2000–2017)	GDIM	Investment scale
Ruiz et al. (2022)	CO_2 emissions and causal relationships	China, USA, EU, India, Russia, and Japan (1990–2018)	LMDI	Economic growth
Gonzalez et al. (2022)	Tracking the change in Spanish greenhouse gas emissions	Spain (2008–2018)	LMDI	Energy intensity
Xu et al., (2022)	Decomposition of residential electricity-related CO_2 emissions	China (1997–2019)	LMDI	Income improvement

Source: authors' elaborations

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References

Alves, M. R., & Moutinho, V. (2014). Decomposition of energy-related GHG emissions in agriculture over 1995–2008 for European countries. *Applied Energy, 114*, 949–957.

Ari, I., Isik, M., & Sarica, K. (2020). Driving forces of Turkey's transportation sector CO_2 emissions: An LMDI approach. *Transport Policy, 97*, 210–219.

Bersalli, G., Trondle, T., Lilliestam, J. (2022). The effects of economic crisis on carbon emission peaks and structural change in OECD and G20 countries. In *43rd IAEE international conference*, Tokyo, Japan.

Boqiang, L., & Liu, K. (2017). Using LMDI to analyze the decoupling of Carbon dioxide emissions from China's heavy industry. *Sustainability, 9*(1198), 1–16.

Cai, W., & Ma, M. (2018). What drives the carbon mitigation in Chinese commercial building sector? Evidence from decomposition an extended Kaya identity. *Science of the Total Environment, 634*, 884–899.

Cai, W., Yang, J., Ma, M., Li, L., Liu, C., Ma, X., Li, L., & Chen, X. (2020). Driving forces of China's CO_2 emissions from energy consumption based on Kaya-LMDI methods. *Science of the Total Environment, 711*(134569), 1–15.

Cansino, J. M., Braza, A. S., & Arevalo, M. L. R. (2015). Driving forces of Spain's CO_2 emissions: A LMDI decomposition approach. *Renewable and Sustainable Energy Review, 48*, 749–759.

Chong, C. H., Liu, P., Ma, L., Li, Z., Ni, W., Li, X., & Song, S. (2017). LMDI decomposition of energy consumption in Guangdong Province, China, based on an energy allocation diagram. *Energy, 133*, 525–544.

Dong, K., Wang, Zh., Jiang, Q., Mubarik, MSh., & Dong, X. (2020). Decomposition of the US CO_2 emissions and its mitigation potential: An aggregate and sectoral analysis. *Energy Policy, 147*(111925), 1–10.

Eskandar, S. M. S. U., & Nitschke, J. (2021). Energy use and CO_2 emissions in the UK universities: An extended Kaya identity analysis. *Journal of Cleaner Production, 309*(127199), 1–11.

Golas, Z. (2022). Changes in energy-related carbon dioxide emissions of the agricultural sector in Poland from 2000 to 2019. *Energies, 15*, 1–18.

Gonzalez, P. F., Landajo, M., & Presno, M. J. (2014). Multilevel LMDI decomposition of changes in aggregate energy consumption: A cross country analysis in the EU-27. *Energy Policy, 68*, 576–584.

González, P. F., Presno, M. J., & Landajo, M. (2022). Tracking the change in Spanish greenhouse gas emissions through an LMDI decomposition model: A global and sectoral approach. *Journal of Environmental Science*, *139*, 114–122.

Hasan, M. M., & Chongbo, W. (2020). Estimating energy-related CO_2 emission growth in Bangladesh: The LMDI decomposition method approach. *Energy Strategy Review, 32*(100565), 1–14.

International Energy Agency (IEA). (2015). *CO_2 emissions from fuel combustion*. IEA.

Jiang, S., Zhu, Y., He, G., Wang, Q., & Lu, Y. (2020). Factors influencing China's non-residential power consumption: Estimation using the Kaya-LMDI methods. *Energy, 201*(117719), 1–10.

Karmellos, M., Kosmadakis, V., Dimas, P., Tsakanikas, A., Flyaktos, N., Taliotis, C., & Zachariadis, T. (2021). A decomposition and decoupling analysis of carbon dioxide emissions from electricity generation: Evidence from the EU-27 and the UK. *Energy, 231*(20861), 1–12.

Kopidou, D., & Diakoulaki, D. (2017). Decomposing industrial CO_2 emissions of Southern European countries into production- and consumption-based driving factors. *Journal of Cleaner Production, 167*, 1325–1334.

Li, H., Lin, J., Zhao, Y., & Kang, J. N. (2019a). Identifying the driving factors of energy-water nexus in Beijing from both economy- and sector-wide perspectives. *Journal of Cleaner Production, 235*, 1450–1464.

Li, W., Ma, L., Chong, Ch., Zhang, X., Liu, P., Li, Zh., & Ni, W. (2018). LMDI decomposition of energy-related CO_2 emissions based on energy and CO_2 allocation Sankey diagrams: The method and an application to China. *Sustainability, 10*(344), 1–37.

Li, X., Su, S., Zhang, Z., & Kong, X. (2017). An integrated environmental and health performance quantification model for pre-occupancy phase of buildings in China. *Environmental Impact Assessment Review, 63*, 1–11.

Li, Y., Tu, M., Bao, L., Wei, Y., Orfila, O., Li, W., & Gruyer, D. (2019b). Logarithmic mean Divisia index decomposition of CO_2 emissions from urban passenger transport: An empirical study of global cities from 1960–2001. *Sustainability, 11*(4310), 1–16.

Lin, B., & Long, H. (2016). Emissions reduction in China's chemical industry-Based on LMDI. *Renewable and Sustainable Energy Reviews, 53*, 1348–1355.

Magazzino, C. (2016a). Economic growth, CO_2 emissions and energy use in the South Caucasus and Turkey: A PVAR analyses. *International Energy Journal, 16*(4), 153–162.

Magazzino, C. (2016b). The relationship among real GDP, CO_2 emissions, and energy use in South Caucasus and Turkey. *International Journal of Energy Economics and Policy, 6*(4), 672–683.

Magazzino, C. (2019). Testing the stationarity and convergence of CO_2 emissions series in MENA countries. *International Journal of Energy Sector Management, 13*(4), 977–990.

Magazzino, C., & Mele, M. (2022). A new machine learning algorithm to explore the CO_2 emissions-energy use-economic growth trilemma. *Annals of Operations Research*. https://doi.org/10.1007/s10479-022-04787-0

Mallongi, A., Stang, S., Astuti, R. D. P., Rauf, A. U., & Natsir, M. F. (2023). Risk assessment of fine particulate matter exposure attributed to the presence of the cement industry. *Global Journal of Environmental Science and Management, 9*(1), 43–58.

Mallongi, A., Rauf, A. U., Lee, K., Daud, A., Hatta, M., Madhoun, W. A., & Astuti, R. D. P. (2021). Potentially toxic element levels in atmospheric particulates and health risk estimation around industrial areas of Maros. *Indonesia. Toxics, 9*(328), 1–14.

Mele, M., Gurrieri, A. R., Morelli, G., & Magazzino, C. (2021). Nature and climate change effects on economic growth: An LSTM experiment on renewable energy resources. *Environmental Science and Pollution Research, 28*, 41127–41134.

Mousavi, B., Lopez, N. S. A., Biona, J. B. M., Chiu, A. S. F., & Blesl, M. (2017). Driving forces of Iran's CO_2 emissions from energy consumption: An LMDI decomposition approach. *Applied Energy, 206*, 804–814.

Nieto, A. M., Ruiz, G. O., & Ramos, J. E. G. (2020). Is India on the right pathway to reduce CO_2 emissions? Decomposition and enlarged Kaya identity using the LMDI method for the period 1990–2016. *Science of the Total Environment, 737*(139638), 1–12.

Organization for Economic Co-operation and Development (OECD). (2020). *Environment at a glance indicator, climate change*. OECD.

Ozawa, L., Sheinbaum, C., Martin, N., Worrell, E., & Price, L. (2002). Energy use and CO_2 emissions in Mexico's iron and steel industry. *Energy, 27*(3), 225–239.

Pan, L., Zhang, T., Li, W., Li, Z., & Zhou, C. (2021). Sector-level evaluation of China's CO_2 emissions: Trend evolution and index ranking. *Journal of Cleaner Production, 286*, 125453.

Padilla, E., Patino, L. I., & Alcantara, V. (2021). Driving forces of CO_2 emissions and energy intensity in Colombia. *Energy Policy, 151*, 112130.

Parker, S., & Bhatti, M. I. (2020). Dynamics and drivers of per capita CO_2 emissions in Asia. *Energy Economics, 89*, 104798.
Ran, Q., Mai, L., & Wu, H. (2019). A LMDI decomposition analysis of carbon dioxide emissions from the electric power sector in Northwest China. *Natural Resources Modelling, 33*, 1–23.
Rauf, A. U., Mallongi, A., Hatta, M., Madhoun, W. A., Amiruddin, R., Rahman, S. A., Wahyu, A., & Astuti, R. D. P. (2021). Community health risk assessment of total suspended particulates near a cement plant in Maros Regency. *Indonesia. Journal of Health & Pollution, 11*(30), 1–13.
Ruiz, G. O., Nieto, A. M., Glope, A. A., & Ramos, J. E. G. (2022). CO_2 emissions and causal relationship in the six largest world emitters. *Renewable and Sustainable Energy Reviews, 162*, 112435.
Song, M., Chen, J., Wang, P., Cui, L., & Huang, S. (2018). Decomposition and decoupling of CO_2 emissions in OECD. *Applied Energy, 231*, 937–950.
Shahiduzzaman, M., Layton, A., & Alam, K. (2015). Decomposition of energy-related CO_2 emissions in Australia: Challenges and Policy Implications. *Economic Analysis and Policy, 45*, 100–111.
Tapio, P. (2005). Towards a theory of decoupling: Degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. *Transport Policy, 12*(2), 137–151.
Tajudeen, I. A., Wossink, A., & Banerhee, P. (2018). How significant is energy efficiency to mitigate CO_2 emissions? Evidence from OECD countries. *Energy Economics, 72*, 200–221.
Tenaw, D. (2021). Decomposition and macroeconomic drivers of energy intensity: The case of Ethiopia. *Energy Strategy Reviews, 35*, 100641.
Torrie, R. D., Stone, Ch., & Layzell, D. B. (2016). Understanding energy systems change in Canada: Decomposition of total energy intensity. *Energy Economics, 56*, 101–106.
Wang, H., & Zhou, P. (2018). Assessing global CO_2 emission inequality from consumption perspective: An index decomposition analysis. *Ecological Economics, 154*, 257–271.
Wang, M., & Feng, C. (2018). Using an extended logarithmic mean Divisia index approach to assess the role of economic factors on industrial CO_2 emissions of China. *Energy Economics, 76*, 101–114.
Wang, Q., Zhao, M., Li, R., & Su, M. (2018). Decomposition and decoupling analysis of carbon emissions from economic growth: A comparative study of China and the United States. *Journal of Cleaner Production*, *197*(1), 178–184. https://doi.org/10.1016/j.jclepro.2018.05.285
Wen, H. X., Chen, Z., Yang, Q., Liu, J. Y., & Nie, P. Y. (2022). Driving forces and mitigating strategies of CO_2 emissions in China: A decomposition analysis based on 38 industrial sub-sectors. *Energy, 245*, 123262.
Wu, T. H., Huang, S. W., & Chung, Y. F. (2021). Analyzing the relationship between energy security performance and decoupling of economic growth from CO_2 emissions for OECD countries. *Renewable and Sustainable Energy Reviews, 152*, 111633.
Xu, L., Chen, L., Xia, L., Eang, Y., & Yang, Z. (2022). Decomposition of residential electricity-related CO_2 emissions in China, a spatial–temporal study. *Journal of Environmental Management, 320*, 115754.
Yu, M., Zhao, X., & Gao, Y. (2019). Factor decomposition of China's industrial electricity consumption using structural decomposition analysis. *Structural Change and Economic Dynamics, 51*, 67–76.
Yang, L., Yang, Y., Zhang, X., & Tang, K. (2018). Whether China's industrial sectors make efforts to reduce CO_2 emissions from production? A decomposed decoupling analysis. *Energy, 160*(1), 796–809.
Zhao, Y., Li, H., Qiao, X., Liu, Y., Li, Y., Wang, S., Zhang, Z., Zhang, Y., & Weng, J. (2017). Identifying the driving forces of national and regional CO_2 emissions in China: Based on temporal and spatial decomposition analysis models. *Energy Economics, 68*, 522–538.
Zhang, C., Su, B., Zhou, K., & Yang, S. (2019a). Analysis of electricity consumption in China (1990–2016) using index decomposition and decoupling approach. *Journal of Cleaner Production, 209*, 224–235.
Zhang, M., Wang, W. W., & Zhou, M. (2011). Using LMDI method to analyze transport sector CO_2 emissions in China. *Energy, 36*, 5909–5915.
Zhang, Y., Liao, Ch., Wang, S., Fang, J., Zheng, H., & Liu, J. (2019b). Driving forces of provincial-level CO_2 emissions in China's power sector based on LMDI method. *Energy Procedia, 158*, 3859–3864.
Zhang, C., Zhang, W., Luo, W., Gao, X., & Zhang, B. (2021). Analysis of influencing factors of carbon emissions in China's Logistics industry: A GDIM-based indicator decomposition. *Energies, 14*(5742), 1–23.