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DECOMPOSED ANALYSIS OF CARBON PRODUCTIVITY: THE CASE OF ROMANIA

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Abstract
This paper presents the carbon productivity (CP) analysis for Romania for the period 2008-2021. The decomposition analysis, i.e. the Log Mean Divisia Index method, multiplicative form, was used. Carbon productivity was decomposed at the level of three influencing factors: carbon intensity, energy intensity and sectoral structure of gross value added. Calculations were performed considering current and constant prices of GVA. The decomposition results showed a general increase in CP over the period as well as positive and negative influences of the three drivers. The improvement in carbon productivity was realized as a result of decreasing total carbon dioxide emissions and increasing gross value added per economy. Carbon emissions decreased significantly in 2021 compared to 2008, in contrast to final energy consumption. The real growth in CP in 2021 was about twice that in 2008. The largest increase in CP, however, was achieved in 2009. Throughout the studied period, there were years in which all influencing factors simultaneously had positive influences.

Keywords: *carbon productivity, Logarithmic Mean Divisia Index (LMDI), carbon intensity, energy intensity, economic structure*

JEL Classification: *F64, Q49, Q5*

INTRODUCTION

Global warming has become one of the most pressing and major problems for mankind (Yang & Chen, 2011). It has been generated by the substantial increase in CO_2 and other gases as an effect of human activities (IPCC, 2007). Energy production from fossil fuels, including oil, gas, and coal, together with deforestation, has been and remains the leading source of carbon emissions. According to the European Commission, the rate of increase in global warming is 0.2°C every ten years. Experts in the field warn that a 2°C increase in temperature since before the industrial revolution will have serious consequences not only for nature but also for human health and living standards. Keeping global warming below this threshold is an extremely important target to reduce the risk of dangerous and catastrophic climate change. In order to better understand the importance of reducing greenhouse effects, the European Commission briefly describes the main consequences of climate change, namely: natural, social, economic and territorial (European Commission, 2015)). In this context, it is imperative that the whole world focuses its efforts towards reducing carbon emissions (Lu et al., 2018). According to the Emissions Gap Report 2024, without a significant reduction in emissions by 2030, achieving the climate goals of the Paris Agreement (limiting global warming to 1.5°C or even 2°C) will become impossible or extremely difficult (United Nations Environment Programme, 2024).

In order to track the evolution of these effects, many specialists have recently turned their attention to analyzing energy consumption and carbon emissions. The literature is replete with papers that often focus on industry as the major contributor. In order to identify the factors with the greatest impact, a breakdown of energy consumption and carbon emissions by influencing factors is often used.

One of the methods often used in data decomposition analysis is the so-called Index Decomposition Analysis (IDA). It was introduced in the literature in the 1970s, the term being attributed to Ang and Zhang (2000) and Ang (2015). The method measures the effect of influencing factors on changes in an indicator by comparing two periods / years, thus allowing the identification of the factors that contributed most to the change in that indicator.

The method has been and is often used in determining the impact of technological and economic changes on energy consumption in general, and of changes in industrial production structure on electricity consumption in particular. From this point of view, IDA is a useful tool in energy analysis and decision making (Ang, 2015), as well as in CO_2 emissions analysis (Ang, 2004). While the method initially had applicability in retrospective analysis, it has subsequently been used in prospective analysis (Ang, 2015).

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For a long time, the decomposition analysis was based on the Laspeyres index. After 1990, however, on the Divisia index. The latter method was proposed by Boyd et al. (1988), and was called the arithmetic mean of the Divisia index (AMDI) method. Since 2000, however, the most common approach for ADI is the specific approach of the logarithmic mean of the Divisia index - LMDI - method (Ang et al., 1998), which is now considered the most popular decomposition algorithm (Meng & Niu, 2012). LDMI knows two forms: additive and multiplicative. The former provides the determination of the change of an indicator and factor influences in absolute magnitudes and the latter in relative magnitudes. The advantage of LMDI lies in the fact that factor influences are determined without obtaining residuals (Ang & Choi, 1997; Ang & Liu, 2001; Ang, 2005; González et al., 2014; Bianco et al., 2024).

In foreign literature, however, there is also a plethora of work analyzing another important indicator, namely carbon productivity (CP). This reflects the amount of GDP that returns per unit of CO2 emissions (Kaya & Yokobori, 1999).

Bălănică-Dragomir et al. (2024) carried out a decomposed analysis of carbon emissions in Romania for the period 2008-2021 using the LMDI method. González et al. (2014) did the same at the EU Member State level for the period 2001-2010. The latter chose a different CO_2 decomposition model and included Romania in their study.

The present paper focuses, however, on the analysis of the evolution of CP at Romanian level. For its realization, the LMDI decomposition method was used in order to establish the contributions of the influencing factors on the analyzed indicator. For this purpose, aggregate statistical data were used at the level of four sectors of economic activity as well as at the national level. Although we had hoped to extend the analysis period as close to the present as possible, the lack of available statistical data limited us to 2021.

I. LITERATURE REVIEW CARBON PRODUCTIVITY

CP is an indicator of assessing economic efficiency in relation to environmental impact. It allows tracking economic and environmental efficiency over time being appreciated by specialists as an important indicator of sustainable economic growth and development (Qi et al., 2022). From this point of view, CP is considered as an effective combination of environmental protection index and economic development (Lu et al., 2018), thus highlighting the link between the level of economic development and the level of environmental protection (Hu & Liu, 2016)

Other authors, such as Long et al. (2016), consider CP to be a concept of CO_2 emission efficiency in a given period of economic growth. In fact, by its level, CP shows the stage of development of a country (Jiankun & Mingshan, 2011), and is also considered by specialists as an important indicator in measuring a country's performance in reducing global warming (Jiankun & Mingshan, 2011; Liu & Oka, 2024). Some experts believe that, through its variation, carbon productivity can highlight a country's contributions to addressing climate change (He et al., 2010; Meng & Niu, 2012; Lu et al., 2015) and reducing carbon emissions (Chen et al., 2020).

According to Chen et al. (2018), CP can be compared with labor and capital productivity because it highlights the output that returns per unit of carbon resources consumed by an economy. The carbon emissions considered in the calculation of CP are considered inputs of energy and material production from the perspective of the economy. Therefore, CP follows the principle of maximizing output with minimum inputs of carbon resources. The same authors state that increasing CP is the main way to promote low-carbon economic development.

The study of CP is particularly necessary in the current context of climate change. Improving energy efficiency and controlling CO_2 emissions are major objectives of energy policies (González et al., 2014). CP is also taken into account by rating agencies in their evaluations of companies. Some studies (Jung et al., 2023) show that there is a link between CP and the financial market, with equities and investment opportunities being negatively influenced by unfavorable firm-level carbon emissions developments. As such, CP is a relevant indicator to measure a firm's efficiency and is used as a criterion for investment choices.

The decomposition of CP by influencing factors allows decision makers to determine appropriate measures (Liu & Oka, 2024; Lu et al., 2018) to increase this indicator (to reduce carbon intensity, increase energy efficiency, and sectoral adjustment in favor of low-carbon-intensive and energy-efficient economic activities). CP improvement can thus be the result of the introduction of technological innovation and / or economic / sectoral adjustment (Meng & Niu, 2012; Hu & Liu, 2016).

II. METHODOLOGY

The indicators used in the analysis were: CO_2 emissions (E), final energy consumption (C) and, instead of GDP, gross value added (GVA). Statistical data were taken from the website of the National Institute of Statistics (NIS) and grouped by the four economic sectors mentioned below. CO_2 emissions intensity and energy intensity,

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both at national level and by sector, and the shares of each sector in total GVA were also calculated in advance. Total final energy consumption has excluded household energy consumption.

The calculation was carried out in two variants of GVA: 1) in current prices; 2) in constant prices (year 2008). The GDP deflator taken from the World Bank Group website was used to express GVA in constant prices.

The LMDI method in the multiplicative form was used to decompose CP. The analyzed indicator was decomposed according to the model used by Liang et al. (2017), which was adapted at the sectoral level in relation: agriculture (including forestry and fish farming) - A; industry (including construction) - I; transport and storage - T; other activities - O (see relations 1 and 2).

$$\mathrm{CP} = \frac{\mathrm{GVA}}{\mathrm{E}} = \frac{1}{\frac{\mathrm{E}}{\mathrm{GVA}}} = \frac{1}{\sum_{i=1}^{4}\frac{\mathrm{E_i}}{\mathrm{GVA}}} \quad (1) \text{ and } \sum_{i=1}^{4}\frac{\mathrm{E_i}}{\mathrm{GVA}} = \sum_{i=1}^{4}\frac{\mathrm{E_i}}{\mathrm{C_i}}\cdot\frac{\mathrm{C_i}}{\mathrm{GVA_i}}\cdot\frac{\mathrm{GVA_i}}{\mathrm{GVA}} = \sum_{i=1}^{4}\mathrm{EC_i}\cdot\mathrm{IE_i}\cdot\mathrm{s_i} \quad (2)$$

where: E, $\mathrm{E_i}$ = total CO_2 emissions of sector "i"; GVA, $\mathrm{GVA_i}$ = total gross value added respectively of sector 'i';; $\mathrm{C_i}$ = final energy consumption of sector "i"; $\mathrm{EC_i} = \frac{\mathrm{E_i}}{\mathrm{C_i}}$ = CO_2 intensity of sector "i"; $\mathrm{IE_i} = \frac{\mathrm{C_i}\cdot}{\mathrm{GVA_i}}$ = energy intensity of sector "i"; $\mathrm{s_i} = \frac{\mathrm{GVA_i}}{\mathrm{GVA}}$ = structure of GVA by "i" sectors.

The steps in the analysis were as follows:

1. Determining the change in CP of one year from the previous year;

2. Determining the change in CP due to the contribution of: a) carbon intensity by sectors of activity; b) energy intensity by sectors of activity; c) sectoral to the realization of total GVA.

All CP values are greater than 1. The increase in CP is given by its increasing trend. According to relation (2), CP will increase if: 1) CO_2 intensity and energy intensity decrease; 2) the sectoral adjustment is in favor of the sectors with the lowest levels of CO_2 intensity and energy intensity (services/other economic activities).

The relationships for determining the change in CP and the contributions of the three influencing factors on CP are summarized below (see Table 1).

Table 1. Relations used in CP decomposition analysis - LDMI, multiplicative form

Formula	**Explanations**
1. CP Modification (DCP)	
$\mathrm{DCP} = \frac{\mathrm{CP_1}}{\mathrm{CP_0}}$ (3) iar $\mathrm{DCP} = \mathrm{D(EC_i)}\cdot\mathrm{D(IE_i)}\cdot\mathrm{D(s_i)}$ (4)	$\mathrm{DCP} = \begin{cases} >1, & \Rightarrow\nearrow \mathrm{CP} \\ =1, & \Rightarrow \mathrm{CP=constant} \\ <1, & \Rightarrow\searrow \mathrm{CP}\end{cases}$ $\mathrm{CP_1}, \mathrm{CP_0}$ = carbon productivity in the current, previous year
2. Modification of the CP as a result of the contribution:	
a. emission intensity of CO2 - $D(EC_i)$	
$\mathrm{D(EC_i)} = 1/\left[\exp(\sum_{i=1}^{4}\bar{w}_i\cdot\ln\left(\frac{\mathrm{EC_{i1}}}{\mathrm{EC_{i0}}}\right))\right]$ (5) and $\bar{w}_i = \frac{(E_{i1}-E_{i0})/(\ln E_{i1}-\ln E_{i0})}{\sum_{i=1}^{4}[(E_{i1}-E_{i0})/(\ln E_{i1}-\ln E_{i0})]}$ (6)	$\mathrm{EC_{i1}}, \mathrm{EC_{i0}}$ = current intensity of CO_2 emissions prior of sector "i", where $i = 4$; $\bar{w}_i$ = logarithmic mean; exp = exponential function; E_{i1}, E_{i0} = current CO_2 emissions, prior to sector "i"
b. energy intensity - $D(IE_i)$	
$\mathrm{D(IE_i)} = 1/\left[\exp(\sum_{i=1}^{4}\bar{w}_i\cdot\ln\left(\frac{\mathrm{IE_{i1}}}{\mathrm{IE_{i0}}}\right))\right]$ (7)	$\mathrm{IE_{i1}}, \mathrm{IE_{i0}}$ = current energy intensity, prior to sector "i"
c. sectoral - $D(s_i)$	
$\mathrm{D(s_i)} = 1/\left[\exp(\sum_{i=1}^{4}\bar{w}_i\cdot\ln\left(\frac{\mathrm{s_{i1}}}{\mathrm{s_{i0}}}\right))\right]$ (8)	$\mathrm{s_{i1}}, \mathrm{s_{i0}}$ = current GVA structure, prior to sector "i"

III. PRELIMINARY ANALYSIS

1) Carbon intensity (absolute size) and economic structure (%)

From a sectoral point of view, all drivers fluctuated over the period. Fig. 1 and 2 show the evolution of CO_2 intensity and GVA structure for both CP scenarios (current and constant prices). The values of carbon intensity and GVA structure were the same for the two variants, hence the graphical representations were also identical.

According to Fig. 1, the intensity of CO_2 emissions recorded the highest level in industry. Its values ranged between a minimum of 6.855 (year 2021) and a maximum of 9.817 (year 2011). At the opposite pole were transports, with values ranging between 0.798 - 1.087, these being the best positioned. The CO_2 intensity in industry was 12.15 times higher than that in transports in 2012 (maximum ratio reached). According to Fig. 1, in 2021 compared to 2008, there is: an obvious trend of decreasing CO_2 intensity in the case of industry (from 9.163

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to 6.855); a less obvious one in the case of transport and agriculture (from 1.087 to 0.823 in transport and from 3.562 to 3.545 in agriculture); and one of maintaining the level in the case of other economic activities.

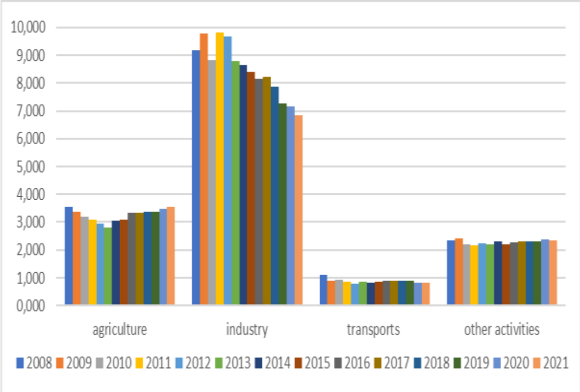

Figure 1. CO_2 emission intensity by sector, GVA current and constant prices (2008-2021)
Source: own calculations based on NIS data

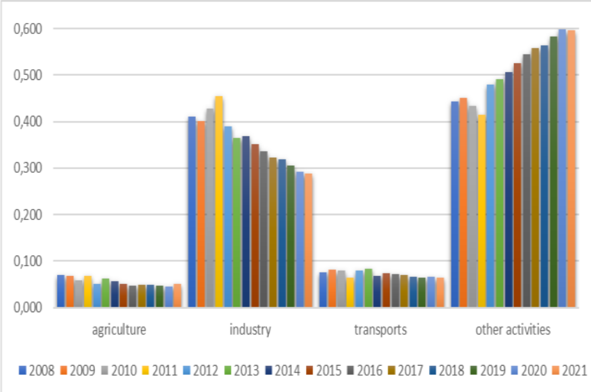

Figure 2. Structure of GVA by sector, GVA current and constant prices (2008-2021) - %
Source: own calculations based on NIS data

Regarding the structure of GVA (Fig. 2 and Table 5), the largest share was held by other economic activities (between 44.32% and 59.57%), followed by industry, transport and agriculture. The cumulative values of the sectors located in the first two positions were between 85.2% (in 2009) and 89% (in 2020). It should be noted, however, that other activities recorded the lowest energy intensity and the second lowest CO_2 intensity, while industry had the highest CO_2 intensity and the second highest energy intensity.

2) *Energy intensity (absolute size)*

In Fig. 3 and 4, the evolution of energy intensity is presented according to GVA current and constant prices, the two being different (in constant prices being higher). The most energy-efficient sector was that of other activities (services) followed, in order, by agriculture, industry and transport. As can be seen, the difference between transport and other activities is significant. In 2020, the highest ratio between the energy intensities of the two sectors was recorded, over 29 times. Comparing Fig. 3 and 4, we find completely different developments in transport and agriculture. Thus, if in 2021 compared to 2008 the energy intensity decreased in the GVA current prices variant, in the other, it increased. Similarly, in the case of the agricultural sector. As was natural, at the sectoral level, the energy intensities - GVA in constant prices exceed those in current prices.

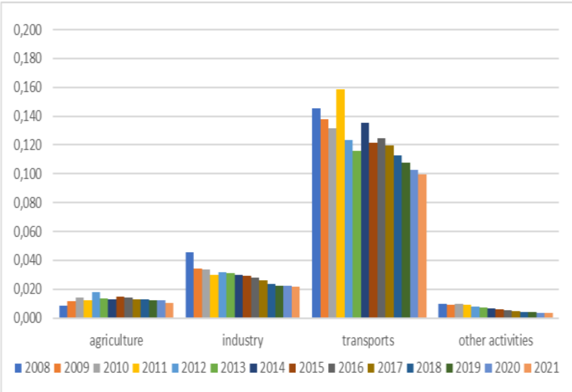

Figure 3. Energy intensity by sectors, by GVA current prices (2008-2021)
Source: own calculations based on NIS data

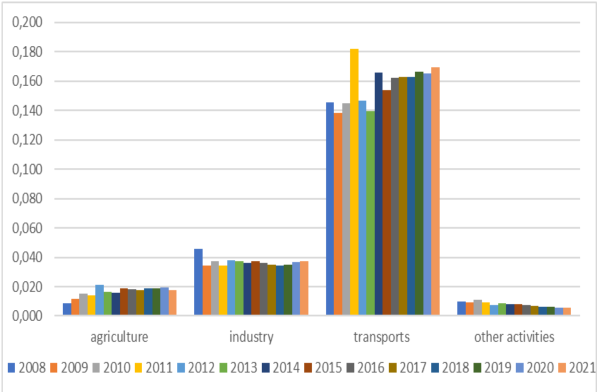

Figure 4. Energy intensity by sectors by GVA constant prices (2008-2021)
Source: own calculations based on NIS data

3) *Relative changes in influencing factors*

Table 2 presents the coefficients of the annual changes of the three influencing factors for the current price variant. Supra-unitary coefficients represent annual increases, while sub-unitary coefficients represent decreases. However, to improve CO_2 and energy intensity, the coefficients must be sub-unitary. In terms of CO_2 intensity, industry was the sector with the best evolution in this indicator. Energy efficiency improved, in general, by activity sectors. The sector with the best evolution was that of services, which only recorded an increase in energy intensity in 2010.

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Regarding GVA, an annual increase in the share of other activities is generally observed. Agriculture and transport also changed their contributions (by increasing them) over six years (see Table 2, supra-unitary coefficients).

Table 2. Influencing factors change – GVA current prices

Years	Carbon emissions intensity				Energy intensity change				Structure of the GVA			
	A	I	T	O	A	I	T	O	A	I	T	O
09/08	0.943	1.066	0.809	1.034	1.377	0.745	0.948	0.924	0.958	0.977	1.054	1.019
10/09	0.949	0.903	1.045	0.906	1.179	0.992	0.951	1.103	0.860	1.069	0.997	0.961
11/10	0.967	1.112	0.928	0.993	0.887	0.886	1.208	0.943	1.162	1.061	0.801	0.955
12/11	0.959	0.987	0.935	1.026	1.428	1.058	0.776	0.814	0.764	0.857	1.228	1.160
13/12	0.944	0.905	1.089	0.992	0.767	0.980	0.939	0.951	1.217	0.934	1.053	1.021
14/13	1.098	0.985	0.960	1.045	0.949	0.952	1.169	0.891	0.895	1.012	0.824	1.034
15/14	1.007	0.972	1.034	0.961	1.136	0.990	0.899	0.943	0.900	0.952	1.071	1.036
16/15	1.083	0.972	1.032	1.020	0.964	0.948	1.027	0.923	0.952	0.959	0.980	1.035
17/16	1.001	1.005	1.004	1.024	0.929	0.929	0.959	0.885	1.023	0.957	0.980	1.027
18/17	1.009	0.959	0.997	1.001	1.002	0.923	0.941	0.891	1.013	0.993	0.936	1.011
19/18	0.996	0.925	1.019	1.004	0.926	0.947	0.954	0.872	0.956	0.955	0.978	1.032
20/19	1.031	0.982	0.906	1.015	1.005	1.003	0.954	0.902	0.944	0.957	1.013	1.025
21/20	1.022	0.959	1.001	0.990	0.845	0.971	0.973	0.982	1.136	0.988	0.991	0.997

Source: own calculations based on NIS data

Table 3 differs from Table 2 only in terms of the values of changes in energy intensity. As was natural, unlike those in Table 2, these are higher because the amount of energy consumption was reported to lower values of GVA, obtained through deflation.

Table 3. Influencing factors change – GVA constant prices (year 2008=100)

Years	Carbon emissions intensity				Energy intensity change				Structure of the GAV			
	A	I	T	O	A	I	T	O	A	I	T	O
09/08	0.943	1.066	0.809	1.034	1.377	0.745	0.948	0.924	0.958	0.977	1.054	1.019
10/09	0.949	0.903	1.045	0.906	1.300	1.093	1.049	1.216	0.860	1.069	0.997	0.961
11/10	0.967	1.112	0.928	0.993	0.922	0.921	1.256	0.855	1.162	1.061	0.801	0.955
12/11	0.959	0.987	0.935	1.026	1.482	1.098	0.805	0.814	0.764	0.857	1.228	1.160
13/12	0.944	0.905	1.089	0.992	0.777	0.993	0.952	1.148	1.217	0.934	1.053	1.021
14/13	1.098	0.985	0.960	1.045	0.965	0.968	1.189	0.906	0.895	1.012	0.824	1.034
15/14	1.007	0.972	1.034	0.961	1.173	1.022	0.928	0.974	0.900	0.952	1.071	1.036
16/15	1.083	0.972	1.032	1.020	0.989	0.973	1.054	0.947	0.952	0.959	0.980	1.035
17/16	1.001	1.005	1.004	1.024	0.972	0.972	1.004	0.926	1.023	0.957	0.980	1.027
18/17	1.009	0.959	0.997	1.001	1.064	0.980	1.000	0.946	1.013	0.993	0.936	1.011
19/18	0.996	0.925	1.019	1.004	0.990	1.013	1.021	0.933	0.956	0.955	0.978	1.032
20/19	1.031	0.982	0.906	1.015	1.047	1.045	0.993	0.939	0.944	0.957	1.013	1.025
21/20	1.022	0.959	1.001	0.990	0.893	1.026	1.027	1.037	1.136	0.988	0.991	0.997

Source: own calculations based on NIS data

According to the data in Table 3, compared to the other sectors, the services sector recorded a more favorable trend in terms of energy intensity, with the annual change coefficients remaining below 1 for most of the analyzed period. The highest increases in energy intensity were recorded in the agriculture sector, where the coefficients reached significantly higher values compared to the other sectors, peaking at 1.482 in 2012 compared to 2011. In contrast, the industrial sector experienced years in which energy intensity decreased, as well as years in which it was slightly above the level recorded in the previous year.

IV. RESULTS AND DISCUSSION

Table 4 shows the annual changes in the CP as well as the contributions of the influencing factors on the CP as a result of applying the LMDI method in the two calculation variants. The supra-unitary values show the total increases in the CP, respectively the increases in the CP as a result of the contributions of the three influencing factors: carbon intensity, energy intensity and economic structure. On the contrary, the sub-unitary values highlight decreases in the CP as a whole and in the CP as a result of the influence of the factors.

As can be seen, for the GVA current prices variant, in the analyzed period there was only one year in which the CP decreased (2011). For all other years, the coefficients of the change in the CP were supra-unitary,

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highlighting favorable developments in the CP. The largest increases in CP were achieved in 2009 (1.26 times). 2013 (1.174 times) and 2019 (1.172 times) and the smallest in 2010 (1.042 times).

The contributions of the influencing factors on the CP were as follows (see Table 4):

1. CO_2 intensity had a negative influence on CP only in 2009, 2011 and 2017. This meant a decrease in CP as a result of changes in CO_2 intensities at sectoral level;
2. Energy intensity caused the decrease in CP only in 2012, thus showing a negative influence, while in the rest of the years its influence was positive;
3. Except for 2010 and 2011, changes in the GVA structure had a positive influence on CP.

We also note two distinct periods in which the three influencing factors of the CP had simultaneous positive contributions, namely 2013-2016 and 2018-2021 (see also Fig. 5).

By year, the three influencing factors had the greatest contributions to the growth of the CP as follows: CO_2 intensity in 2010; energy intensity in 2009; economic structure for 2012 (see Table 4 and Fig. 5).

Table 4. Results of Decomposition Analysis LMDI method (multiplicative form)

Years	GVA current prices					GVA constant prices				
	DCP (EC)	**DCP (IE)**	**DCP (si)**	**DCP**	**CP change**	**DCP (EC)**	**DCP (IE)**	**DCP (si)**	**DCP**	**CP change**
2009/2008	0.957	1.296	1.016	**1.261**	↗	0.957	1.245	1.016	**1.211**	↗
2010/2009	1.095	1.001	0.950	**1.042**	↗	1.095	0.945	0.950	**0.984**	↘
2011/2010	0.917	1.104	0.963	**0.975**	↘	0.917	1.064	0.963	**0.940**	↘
2012/2011	1.014	0.971	1.126	**1.109**	↗	1.014	0.938	1.126	**1.070**	↗
2013/2012	1.085	1.030	1.051	**1.174**	↗	1.085	1.016	1.051	**1.158**	↗
2014/2013	1.011	1.040	1.003	**1.055**	↗	1.011	1.023	1.003	**1.037**	↗
2015/2014	1.024	1.018	1.036	**1.081**	↗	1.024	0.986	1.036	**1.046**	↗
2016/2015	1.018	1.049	1.035	**1.106**	↗	1.018	1.023	1.035	**1.078**	↗
2017/2016	0.994	1.077	1.036	**1.109**	↗	0.994	1.029	1.036	**1.059**	↗
2018/2017	1.035	1.082	1.010	**1.131**	↗	1.035	1.019	1.010	**1.065**	↗
2019/2018	1.062	1.063	1.039	**1.172**	↗	1.062	0.994	1.039	**1.096**	↗
2020/2019	1.021	1.010	1.033	**1.066**	↗	1.021	0.970	1.033	**1.024**	↗
2021/2020	1.033	1.033	1.007	**1.075**	↗	1.033	0.978	1.007	**1.075**	↗

Source: own calculations based on NIS data

Comparing the influences of the factors established in the two variants (Table 4), we observe their different nature in the case of energy intensity in certain years. These are the years: 2010, 2015, 2019, 2020 and 2021. The influences are positive in the first case and negative in the second case. For the other two influencing factors (CO_2 intensity and GVA structure) the nature of the influences on CP is the same for each year (either positive or negative). Another difference is found in the case of the change in CP in 2010 (see Table 4). Here, we find that carbon productivity increased in the first situation, but decreased in the second. It should also be noted that, in terms of value, the changes in CP and the contributions of energy intensity are smaller in the case of GVA at constant prices. The largest increases in the CP were achieved in 2009 (1.211 times), 2013 (1.158 times) and 2019 (1.096 times) and the smallest in 2020 (1.024 times).

For a better visualization of the influence of factors on the CP, Fig. 5 and 6 are also shown below. In the constant prices version, the three influencing factors of the CP had simultaneous positive contributions in the following years: 2013, 2014, 2016 and 2018 (Fig. 6). The influencing factors contributed the most as follows: CO_2 intensity in 2010; energy intensity in 2009; economic structure in 2012 (see Table 4 and Fig. 6).

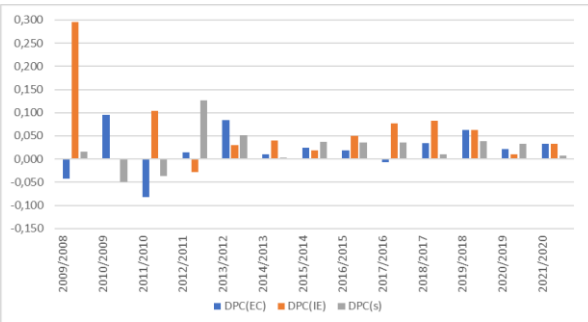

Figure 5. Influence of factors on CP– GVA current prices
Source: own calculations based on NIS data

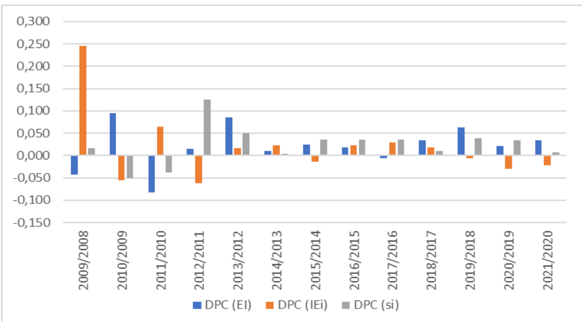

Figure 6. Influence of factors on CP– GVA constant prices
Source: own calculations based on NIS data

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Looking more closely at Fig. 5, we can say that energy intensity contributed most often significantly to the growth of GDP. In contrast, according to Fig. 6, CO_2 intensity and economic structure contributed most often.

According to our calculations, the trend of GDP was increasing, GDP calculated in current prices was higher than that in constant prices. The real increase in GDP, however, was approximately twice (from 5.079 in 2008 to 10.588). This was generated by the increase in GVA in the context of reducing CO_2 emissions. In 2021, CO_2 emissions represented 62.8% of those in 2008, which means a decrease of 37.2%. GVA in current prices was 2.23 times higher in 2021 than in 2008 and GVA in constant prices was 1.31.

According to data from the National Institute of Statistics (INS) and the calculations performed, the sectoral trends in energy consumption, CO_2 emissions, and gross value added (GVA) are presented in Table 5.

Table 5. Shares of energy consumption, CO_2 emissions, and GVA by sector (%)

Years	Energy consumption				CO_2 emissions				GVA			
	A	I	T	O	A	I	T	O	A	I	T	O
2008	1.73	53.89	31.92	12.45	1.09	87.60	6.16	5.15	7.03	41.00	7.66	44.32
2009	2.68	46.08	37.47	13.77	1.72	85.69	6.27	6.32	6.73	40.06	8.07	45.15
2010	2.68	48.03	34.94	14.35	1.72	85.48	6.47	6.32	5.79	42.81	8.04	43.37
2011	2.91	47.71	35.73	13.65	1.67	87.15	5.67	5.51	6.72	45.44	6.44	41.40
2012	3.40	46.32	36.47	13.80	1.94	86.53	5.61	5.93	5.14	38.94	7.91	48.01
2013	3.34	44.61	37.94	14.10	2.00	84.20	7.09	6.70	6.25	36.39	8.33	49.03
2014	2.97	45.07	38.32	13.63	1.97	84.30	6.92	6.81	5.60	36.83	6.86	50.71
2015	3.18	44.37	38.53	13.92	2.19	83.46	7.44	6.91	5.04	35.08	7.35	52.53
2016	3.06	42.35	40.65	13.94	2.41	81.60	8.54	7.44	4.79	33.64	7.20	54.36
2017	3.18	41.16	41.80	13.86	2.55	80.84	8.94	7.68	4.91	32.18	7.06	55.85
2018	3.57	41.80	40.81	13.82	2.95	80.35	8.88	7.83	4.97	31.96	6.61	56.46
2019	3.46	41.31	41.64	13.59	3.05	78.76	9.91	8.29	4.75	30.51	6.47	58.27
2020	3.42	41.43	42.01	13.13	3.18	79.27	9.25	8.30	4.48	29.21	6.55	59.75
2021	3.41	41.25	42.01	13.33	3.36	78.41	9.59	8.64	5.09	28.85	6.49	59.57

Source: own calculations based on NIS data

Therefore, the following statements can be made:

1. Industry was for a long time (between 2008-2016) the sector with the highest final energy consumption. In 2008, it recorded 53.89% of total consumption (9.115 thousand tons of oil equivalent) and in 2021 approx. 41% (6.849 thousand tons). This decrease is explained by the modernization and restructuring of the industry in recent years. Energy-intensive industries (metallurgical, thermo-energy or machine building) have gradually reduced / ceased their activities (Bălănică-Dragomir et al., 2024), being replaced by more energy-efficient and less polluting ones (less energy-intensive industries, information technology, services). Industry was second, between 2008-2016, to transport. However, the difference between industry and transport has decreased significantly. Services remained in third place until 2017, while agriculture almost doubled its energy consumption from 1.73% in 2008 to 3.41% in 2021.

2. In terms of CO_2 emissions (Table 5), although there was a decrease in absolute value, industry and construction led by far, starting from a share of 87.6% in 2008 and reaching 78.41% in the last year. The decrease was determined by the restructuring of the industry. Transport was far behind, with shares of 6.16% in 2008 and 9.59% in 2021, followed by other activities (5.15%-8.64%). Agriculture was the least polluting sector, with shares ranging between 1.09% (in 2008) and 3.36% (in 2021). It is also worth mentioning that the decreasing trend was specific only to the industrial sector (from 83,522.05 thousand tons to 46,951.75 thousand tons of CO_2), all the others registering annual increases.

3. In absolute terms, total and sectoral GVA fluctuated throughout the entire period analyzed. Changes in the economic structure were, however, evident (Table 5). With the exception of 2011, services held the largest share, followed by industry, transport and agriculture. Agriculture suffered a decrease from 7.03% in 2008 to 5.09% in 2021. However, the strongest decline was recorded by the industrial and construction sectors by over 10% (from 41% in 2008 to 28.85% in 2021), while the largest increase was recorded by the other activities sector (from 44.32% in 2008 to 59.57% in 2021). Transport generally experienced fluctuations. The latter produced 7.66% of total GVA in 2008 and 6.49% in 2021.

V. CONCLUSIONS

The analysis of the decomposition of the CP was based on three important influencing factors (carbon intensity, energy intensity and economic structure) and on four important economic sectors (agriculture; industry and construction; transport; services).

At the level of Romania, we witnessed an increase in the CP over the analyzed period. The calculations performed showed that in 2021 compared to 2008, the CP increased almost twice. This was determined by the

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increase in GVA, on the one hand, and the reduction in carbon emissions, on the other. In 2021 compared to 2008, total CO_2 emissions and total final energy consumption decreased by 37.2% (from 95,346.63 thousand tons to 59,881.570 thousand tons) and 1.82% respectively (from 16,913 thousand tons of oil equivalent to 16,605 thousand tons), while GVA in current prices increased by 122.57% (from 484,248.80 lei million to 1,077,778.3 lei million) and by 30.93% in constant prices (from 484,248.80 lei million to 634,050.96 lei million).

The decomposition results highlighted the following aspects:

- with minor exceptions, there was an annual improvement in the CP;
- the largest increases in CP (GVA current prices) were determined by the decrease in CO_2 and energy intensity but also by the change in the economic structure in favor of services;
- at the industry level (the largest final energy consumer and polluter) both CO_2 and energy intensity decreased as well as the share in the economy;
- in the current prices variant, the positive influences on the CP were dominated by those of energy intensity, and in the constant prices variant by those of the economic structure (increasing the share of services - with lower CO_2 and energy intensities - and decreasing the share of industry - with higher CO_2 and energy intensities);
- there was simultaneity of positive influences of the three influencing factors, for both calculation variants, in the years 2013, 2014, 2016 and 2018;
- there was simultaneity of positive influences of all factors during two periods, in the current prices variant (2013-2016, 2018-2021);
- lack of simultaneity of negative influences of influencing factors on the CP;
- the decrease in the CP in 2010 and 2011 occurred due to the decrease in energy efficiency and the negative adjustment of the economic structure.

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