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Research article

Impact of asset intensity and other energy-associated CO_2 emissions drivers in the Nigerian manufacturing sector: A firm-level decomposition (LMDI) analysis

Fidelis I. Abam [a,*], Oliver I. Inah [b], Bethrand N. Nwankwojike [c]

[a] *Energy, Exergy, and Environment Research Group (EEERG), Department of Mechanical Engineering, University of Calabar, Nigeria*
[b] *Mechanical and Industrial Engineering Research Group (MIERG), Department of Mechanical Engineering, Cross River University of Technology, Calabar, Nigeria*
[c] *Department of Mechanical Engineering, Michael Okpara University of Agriculture Umudike, Nigeria*

A R T I C L E I N F O

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A B S T R A C T

The study considered the impacts of asset intensity and other energy-associated CO_2 emissions drivers in the Nigerian manufacturing sector from 2010 to 2020. The Logarithmic Mean Divisia Index (LMDI) was used to explore the driving factors of CO_2 emissions: asset intensity, economic output, economic structure, energy intensity, energy mix, and carbon emission coefficient. From the results, the CO_2 emissions decreased from 7.49 $MtCO_2$ in 2010 to 3.22 $MtCO_2$ in 2020. Furthermore, among the emissions drivers, the energy mix effect increased CO_2 emissions by 0.50 $MtCO_2$, followed by asset intensity (0.29 $MtCO_2$) and economic structure (0.11 $MtCO_2$). The energy intensity, economic output, and emission coefficient effects inhibited CO_2 emissions by −4.64 $MtCO_2$, −0.42 $MtCO_2$, and −0.01 $MtCO_2$ respectively. The contribution of the subsectors' emissions shows that the Other Manufacturing subsector emitted 14.62 $MtCO_2$, while Chemical and Pharmaceutical emitted 14.61 $MtCO_2$, Food, Beverages and Tobacco, 7.55 $MtCO_2$, Textile, Apparel, and Footwear, 6.63 $MtCO_2$, Basic Metal and Iron and Steel, 5.15 $MtCO_2$, Plastic and Rubber Products, 2.99 $MtCO_2$, Agro-Allied, 2.71 $MtCO_2$, Oil Refining, 2.01 $MtCO_2$, and Pulp and Paper Products, 1.76 $MtCO_2$. The results indicated that the effect of asset intensity on emission growth is significant and should not be overlooked. Likewise, the effects of CO_2 emission drivers were found to impact differently across the subsectors. The latter suggests that firm-specific indicators in the respective subsectors should be one of the primacies during policy development since the driving factors of CO_2 emissions fluctuate across the subsectors.

1. Introduction

Global warming and climate change in recent times are the most discussed subjects of the 21st century, as they endanger the sustainability of the ecosystem and livelihood. It centres on politics, business management, economics, and personal lifestyle preferences [1]. The CO_2 emissions constitute approximately 60 % of the overall greenhouse gasses (GHGs), which has continued to increase recently and remains a significant driver of climate change [2,3]. The rising CO_2 emissions are attributed to an increase in industrial and economic activities. In this regard, research on firms' carbon regimes has become progressively impending, prompting

* Corresponding author.
E-mail address: fidelisabam@unical.edu.ng (F.I. Abam).

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the need for corporate carbon decisions. However, obtaining firm-level carbon emissions data is one major challenge in quantifying the possibility of emission. This is customarily not divulged in firms' financial statements and is not mandated by most financial regulators [4]. In this respect, energy efficiency advocacy and its links between energy use, GHG emissions, and economic expansion have gained global attention [5–7].

Moreover, Nigeria's carbon emissions trajectory has increased simultaneously with the country's economic progression over the last two decades. Between 1990 and 2017, the country's emissions of GHGs grew by 11 %. All the sectors of the economy between these years witnessed growth in GHG emissions when compared [8]. About 25 % of Nigeria's energy is derived from fossil fuels, and about 48 % of the total electricity consumption is met by private generators [9]. Consequently, following the "Paris Agreement," Nigeria has recently committed in its Nationally Determined Contributions (NDC) to "the United Nations Framework Convention on Climate Change (UNFCCC) to reduce emissions" by 20 % by 2030 [10]. Hence, strict control of CO_2 emissions from Nigeria's manufacturing industries are critical to achieving Nigeria's 2030 and 2060 abatement targets.

However, in the light of the growing importance of sustainable business practices, many studies have examined the relationship between firm features and CO_2 emissions comprising firm size [11,12], firm location [13,14], capital-labour ratio [13], and ownership structure [15,16]. Similarly, "Cash-rich" firms, as measured by overall financial status, invest more in carbon reduction and utilize more renewable energy, resulting in low emissions of GHGs [17–20]. The latter claim is predicated on the idea that a firm with sufficient cash might finance aggressive capital expenditure policies for the environment. Following this disposition, it is thus apparent to ask if asset-intensive firms are more proactive in increasing their carbon emissions than their counterpart with limited asset investment. The argument on the relationship between firm asset intensity and CO_2 emissions has no data presented in the literature. Therefore, this exploratory study aims to close this gap by examining the effects of asset intensity and other energy-related determinants on firm carbon emissions in Nigeria's manufacturing sector.

Conversely, decomposition analysis has increasingly been applied in studying the nexus between the environment and the economy

Table 1
Reviewed studies on decomposition analysis based on LMD of the manufacturing sector and drivers of CO_2 emissions.

Author	Research topic	Drivers of CO_2 emissions	Method	Period	Research findings
[41]	Decomposition analysis of energy-related carbon emissions from UK manufacturing	Output, industrial structure, energy intensity, fuel mix, and electricity emission factor.	LMDI	1990–2007	The primary reason for the fall in emissions was a reduction in energy intensity.
[42]	Exploring the CO_2 emissions drivers in the Nigerian manufacturing sector through decomposition analysis and the potential of carbon tax (CAT) policy on CO_2 mitigation	Carbon intensity, firm energy intensity, cost structure, asset turnover, asset-to-equity, equity-funded production, and productive capacity utilization	LMDI	2010–2020	Energy intensity and equity-funded production were the leading drivers of increased emissions, while productive capacity utilization reduced emissions.
[43]	Decomposed the factors that affect the CO_2 emissions of China's manufacturing industry	Investment intensity, industrial scale, industrial activity, R&D efficiency, R&D intensity, energy intensity, and emission factor	LMDI	1995–2015	The industrial activity effect was the most crucial factor leading to increased CO_2 emissions in the manufacturing sector. On the other hand, energy intensity promoted the reduction of CO_2 emission.
[44]	Decomposition analysis of decoupling of manufacturing CO_2 emissions in Indonesia	Economic activity, industrial economic structure, industrial energy intensity, industrial energy mix, and emission coefficient factor.	LMDI	2012–2013	Growth in the manufacturing industry was the main driver of increasing CO_2 emissions, whereas reduction in energy intensity and energy consumption structure played an essential role in limiting these emissions.
[45]	Investigated the drivers of energy-related CO_2 emissions change of high-energy intensive industries in China.	Industrial scale, energy intensity, industrial structure, energy structure, carbon emission coefficient	LMDI	1986–2013	Energy intensity was the major contributor to the decline in CO_2 emissions. The effect was most significant in the chemical and non-metallic mineral products industry.
[46]	Empirical analysis of carbon emission accounting and influencing factors of energy consumption in China	GDP, investment, Intensity, R&D intensity, energy intensity, energy structure and R&D efficiency	LMDI	2004–2014	R&D and the energy intensity effects are the factors that inhibited the growth of carbon emissions. Conversely, GDP and investment intensity are the major factors that promoted the growth of carbon emissions.
[47]	Decomposition analysis of energy consumption in the Korean manufacturing sector	Activity effect, structure effect, and intensity effect.	LMDI	1991–2011	The activity effect increased energy consumption, whereas the structure and intensity effect reduced energy consumption and, thus, CO_2 emissions.
[48]	Decomposition and Decoupling Analysis of Energy-Related Carbon Emissions from China Manufacturing	production scale, infrastructure, energy intensity, fuel mix, and carbon emissions coefficient	LMDI	1996–2012	The production scale contributed the most to the increase in total carbon emissions, while the energy intensity was the most inhibiting factor. The effects of the infrastructure and fuel mix on the change in carbon emissions were relatively weak.

[21,22]. The research scopes of decomposition analysis are broad, including countries, regions, and industries [23–25] and in different sectors like energy, agriculture, industry, transportation, and construction [26–29]. The Logarithmic Mean Divisia Index (LMDI) approach is one of the index decomposition methods widely used for assessing changes in carbon emissions from different energy sources [30]. One advantage of the LMDI technique is its capacity to handle the factor-reversal test and the absence of unexplainable residuals in the outcomes [31]. The LMDI methods can be divided into multiplicative and additive decompositions. In the first method, the ratio of change relative to the reference period is employed [31], while the latter method decomposes the difference in the amount of change [32]. The LMDI approach has also been used to ascertain the critical drivers of CO_2 emissions in a given economic sector for different periods [33,34].

Many scholars have conducted decomposition studies across countries based on LMDI in different economic sectors using different indicators. Jaruwan et al. [35] evaluated the various sources of variations in carbon emissions in Thailand's manufacturing sector from 2000 to 2018 using LMDI. Five emissions drivers were considered: economic output effect, structural change effect, energy intensity effect, fuel-mix effect, and emission factor effect. The results indicated that the intensity effect increased. CO_2 emissions, while the structural change effect reduced CO_2 emissions. Similarly, Jaruwan et al. [36] performed the same studies in Thailand from 2005 to 2017 using the same emissions drivers [35]. The study concluded that the structural change effect helped reduce CO_2 emissions. Liu et al. [37] studies established that China's agricultural land use CO_2 emissions exhibited a non-equilibrium spatial distribution. Fertilizer, agricultural diesel, and agricultural (plastic) film were the primary sources of anthropogenic agricultural-land-use CO_2 emissions. Yang et al. [38] indicate that the energy intensity effect significantly promoted decoupling in urban Guangdong, followed by the family size effect. In contrast, the family size effect exerted the dominant influence on accelerating the decoupling in rural Guangdong. Furthermore, Xin et al. [39] and Song et al. [40] employed the LMDI technique to evaluate the driving factors of industrial carbon emissions (ICE) and the contributions of each province to China's ICE at different time intervals. Other studies based on the LMDI application are summarized in Table 1 [41–48].

1.1. *Knowledge gap and study contributions*

The studies presented in Table 1 have contributed substantially to enriching research in decomposition analysis. Though, from the reviewed energy-related drivers [41–48], the contributions of each driver are presented in Fig. 1. The energy intensity effect accounted for 24 % of the overall studied drivers, followed by the structural change, economic output effect, emission factor, and fuel mix, which contributed 16 %, 16 %, 11 %, and 7 % respectively. While others, for instance, energy structure, income effect, investment intensity, and substitution effect, were not greater than 2 %. However, apart from Inah et al. [42], none of the reviewed studies (Table 1) examined carbon emissions trajectory at the firm-level and asset intensity as a driver of emissions. Thus, to close this gap, the current research proposes including asset intensity as an emission driver and generating data that could assist in policy drive. The study objectives are thus: to evaluate the CO_2 emission trajectory of Nigeria's manufacturing sector at the firm level, identifying the key factors influencing emissions, and evaluating the impact of asset intensity on emission growth built on the LMDI technique.

2. Methodology and data analysis

2.1. *Estimation model of firm-level CO_2 emissions*

The total carbon emissions from firm F_T are expressed as Eq. (1);

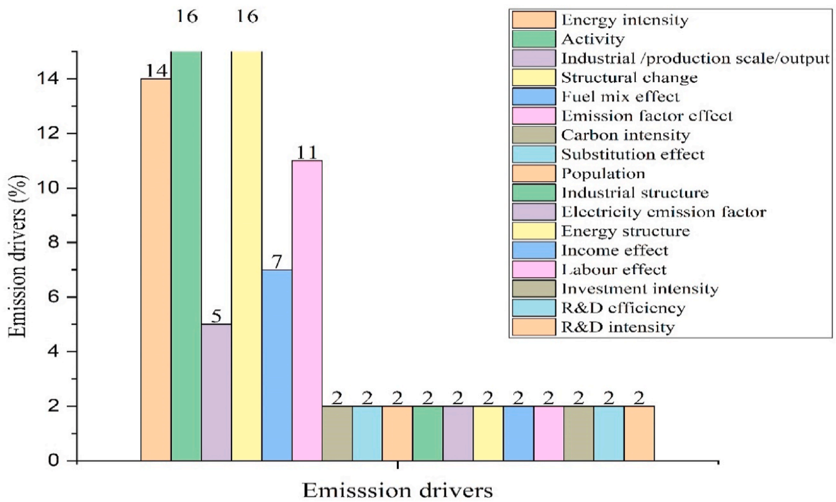

Fig. 1. Emission drivers applied to different reviewed studies.

$$F_T = DCO_2 + ICO_2 \quad (1)$$

where DCO_2 and ICO_2 indicate direct carbon emissions from fossil fuel consumption and indirect emissions from electricity generation. The equations describing the direct and indirect methods are based on the IPCC guidelines [49] and are expressed in Eqs. (2) and (3).

$$DCO_2 = \sum E_i \times NCV_i \times CEF_i \times COF_i \times \left(\frac{44}{12}\right) \quad (2)$$

$$ICO_2 = E_C \times EF_F \quad (3)$$

where E is the amount of energy source *i*, consumed, NCV is the average low calorific value, CEF is the carbon emission coefficient, COF is the carbon oxidation factor, $\frac{44}{12}$ denotes the conversion coefficient of carbon-to-carbon dioxide (Table 2). On the other hand, in Eq. (3), E_C is the amount of electricity consumed (kWh), and EF_F describes the electricity emission factor (7.88 $tCO_2/10^4$ kWh).

2.2. Decomposition of CO_2 emissions drivers

Furthermore, to investigate the main drivers of CO_2 emission changes, the Kaya identity, and the well-established LMDI methods were applied in Eq. (4) [50].

$$CO_2 = \frac{CO_2}{TOE} \times \frac{TOE}{GDP} \times \frac{GDP}{POP} \times POP \quad (4)$$

Eq. (4) establishes the relationship between the drivers of CO_2 emissions change, for example, CO_2 emissions per unit of total energy consumed (TOE), energy intensity $\left(\frac{TOE}{GDP}\right)$, and level of economic activity (GDP per capita and population, $\left(\frac{GDP}{POP}\right)$, respectively. Therefore, considering the peculiarity of CO_2 emissions at the firm level, the determining factors in Eq. (4) were transformed as presented in Eq. (5)

$$C^T = \sum_{ij} C_{ij}^T = \sum_{ij} \frac{C_{ij}}{E_{ij}} \times \frac{E_{ij}}{E_s} \times \frac{E_s}{Q_s} \times \frac{Q_s}{Q} \times \frac{Q}{A_s} \times A_s = \sum_{ij} A \times B \times C \times D \times E \times F \quad (5)$$

Eq. (5) links carbon emissions to A = asset intensity (A_s), B = manufacturing output/value added per asset utilized $\left(\frac{Q}{A_s}\right)$, C = economic structure $\left(\frac{Q_s}{Q}\right)$, D = energy intensity $\left(\frac{E_s}{Q_s}\right)$, E = energy mix $\left(\frac{E_{ij}}{E_s}\right)$, and F = carbon emission factor $\left(\frac{C_{ij}}{E_{ij}}\right)$.

Accordingly, the six determining factors on the right-hand side of Eq. (5) are aggregated at the subsector level at a reference time t_0 and later time T [51].

$$C^{t_0} = A^{t_0}.B^{t_0}.C^{t_0}.D^{t_0}.E^{t_0}.F^{t_0} \quad (6)$$

$$C^T = A^T.B^T.C^T.D^T.E^T.F^T \quad (7)$$

Therefore, the change in the value of energy-related CO_2 emissions can then be written as:

$$\Delta C = \sum \left|C^T - C^{t_0}\right| = A^T.B^T.C^T.D^T.E^T.F^T - A^{t_0}.B^{t_0}.C^{t_0}.D^{t_0}.E^{t_0}.F^{t_0} \quad (8)$$

The LMDI approach introduces an improved indexing method compared to previous factor-based methods. The coefficients Wij are defined as follows.

$$W_{IJ} = \frac{C_{ij}{}^T - C_{ij}{}^{t_0}}{\ln\left[C_{ij}{}^T\right] - \ln\left[C_{ij}{}^{t_0}\right]} \quad (9)$$

Therefore, the LMDI representation of total energy-related CO_2 emission is presented with the following relationship:

Table 2
Energy conversion factors and carbon emission coefficient.

Primary energy emission factors				
Energy	Average low calorific values (kJ/kg)	Carbon emission coefficient (kgC/GJ)	Rate of carbon oxidation fuel	CO_2 Emission factor (kg/kg. m^3)
Fuel oil (PMS)	41,816	21.1	0.985	3.1705
Diesel oil (AGO)	42,652	20.2	0.982	3.0959
Kerosene (HHK)	43,070	19.5	0.986	3.0179

$$\Delta C^T = W_{IJ} \times \ln\left[\frac{C_{ij}{}^T}{C_{ij}{}^{to}}\right] \tag{10}$$

By substituting terms of energy-related CO_2 emission and following the nomenclature of the current and reference years, the following expression is obtained:

$$\Delta C^T = W_{IJ} \times \ln\left[\frac{A^T.B^T.C^T.D^T.E^T.F^T}{A^{to}.B^{to}.C^{to}.D^{to}.E^{to}.F^{to}}\right] \tag{11}$$

Expanding the natural logarithm term in Eq. (11), the following expression is obtained:

$$\Delta C^T = W_{IJ} \times \left(\ln\left[\frac{A^T}{A^{to}}\right] + \ln\left[\frac{B_j{}^T}{B_j{}^{to}}\right] + \ln\left[\frac{C_{ij}{}^T}{C_{ij}{}^{to}}\right] + \ln\left[\frac{D_i{}^T}{D_i{}^{to}}\right] + \ln\left[\frac{E_i{}^T}{E_i{}^{to}}\right] + \ln\left[\frac{F_i{}^T}{F_i{}^{to}}\right]\right) \tag{12}$$

Also, expanding Eq. (12), the following form of expression is obtained:

$$\Delta C^T = W_{IJ} \times \ln\left[\frac{A^T}{A^{to}}\right] + W_{IJ} \times \ln\left[\frac{B_j{}^T}{B_j{}^{to}}\right] + W_{IJ} \times \ln\left[\frac{C_{ij}{}^T}{C_{ij}{}^{to}}\right] + W_{IJ} \times \ln\left[\frac{D_i{}^T}{D_i{}^{to}}\right] + W_{IJ} \times \ln\left[\frac{E_i{}^T}{E_i{}^{to}}\right] + W_{IJ} \times \ln\left[\frac{F_i{}^T}{F_i{}^{to}}\right] \tag{13}$$

Hence, simplifying Eq. (13):

$$\Delta C^T = C^T - C^{to} = \Delta C^T_{As} + \Delta C^T_{Act} + \Delta C^T_{Estr} + \Delta C^T_{Eint} + \Delta C^T_{Emix} + \Delta C^T_{Ems} \tag{14}$$

The variables on the right-hand of Eq. (14) can further be estimated as follows:

Asset intensity effect:

$$\Delta C^T_{As} = \sum_{ij} \frac{C^T_{ij} - C^{to}_{ij}}{InC^T_{ij} - InC^{to}_{ij}} \times In\left[\frac{As^T}{As^{to}}\right] \tag{15}$$

Economic output effect:

$$\Delta C^T_{ACT} = \sum_{ij} \frac{C^T_{ij} - C^{to}_{ij}}{InC^T_{ij} - InC^{to}_{ij}} \times In\left[\frac{B^T}{B^{to}}\right] \tag{16}$$

Economic structure effect

$$\Delta C^T_{Estr} = \sum_{ij} \frac{C^T_{ij} - C^{to}_{ij}}{InC^T_{ij} - InC^{to}_{ij}} \times In\left[\frac{C^T}{C^{to}}\right] \tag{17}$$

Energy intensity effect

$$\Delta C^T_{Eint} = \sum_{ij} \frac{C^T_{ij} - C^{to}_{ij}}{InC^T_{ij} - InC^{to}_{ij}} \times In\left[\frac{D^T}{D^{to}}\right] \tag{18}$$

Energy mix effect

$$\Delta C^T_{Emix} = \sum_{ij} \frac{C^T_{ij} - C^{to}_{ij}}{InC^T_{ij} - InC^{to}_{ij}} \times In\left[\frac{E^T}{E^{to}}\right] \tag{19}$$

Carbon emission effects

$$\Delta C^T_{Ems} = \sum_{ij} \frac{C^T_{ij} - C^{to}_{ij}}{InC^T_{ij} - InC^{to}_{ij}} \times In\left[\frac{F^T}{F^{to}}\right] \tag{20}$$

2.3. Data collection and analysis

The data collection comprises two major parts: (i) A literature review of relevant theories governing the drivers of industrial energy efficiency implementation and (ii) firms' performance indicators (e.g., sales, purchases, number of employees, stated capital/asset, and profit) as well as other essential characteristics including firms' ownership, geographical location, and firm age, etc. These indicators were all drawn from the firm's annual financial reports (between January 2010 and December 2020). After data treatment, 527 (2648 observations) firms were selected within Nigeria's south-south and southeast industrial regions [52]. They were further classified into nine (9) different subsectors based on their economic performance. Consequently, the LMDI technique was applied to estimate the underlying effects of CO_2 emission change. The flowchart for the procedure is shown in Fig. 2.

3. Results and discussion

3.1. Overall year-by-year CO_2 emissions and growth rate of Nigerian manufacturing sectors

Table 3 shows the changes in the level and structure of CO_2 emissions in Nigeria's manufacturing sector between 2010 and 2020. From the results, the total CO_2 emissions decreased from 7.49 $MtCO_2$ in 2010 to 3.22 $MtCO_2$ in 2020 (57 % reduction), with an average yearly decline of −6.31 %. The sector witnessed a critical structural change in asset expansion and economic output, leading to energy restructuring. Conversely, the trajectory of CO_2 emissions from electricity consumption in the sector decreased from 1.1 $MtCO_2$ in 2010 to 0.45 $MtCO_2$ in 2020. While the CO_2 emissions from fuel oil consumption decreased from 4.42 $MtCO_2$ in 2010 to 1.75 $MtCO_2$ in 2020, representing an annual decline of 60.41 %. However, the CO_2 emissions from diesel oil and kerosene consumption declined annually by 48.54 % and 70.15 %, respectively, with real-term emission difference of 1.16 $MtCO_2$ for diesel oil and 0.65 $MtCO_2$ kerosene consumption between 2010 and 2020.

Fig. 3 shows the firm-level structural change from 2010 to 2020. The firms' assets increased by 6 % between 2010 and 2011 and declined by 3 % in 2011 and 2012. From 2012 to 2013, the sector witnessed a growth rate of 6 %, while in the succeeding years, it showed a mixed tendency, alternating between positive and negative growth levels. However, there was a decrease in energy consumption, manufacturing value-added, and CO_2 emissions. The growth rates of these factors were negative in 2013 and 2014, ascribed to the economic downturn during these periods. Additionally, the CO_2 emissions increased by 7 % between 2010 and 2011 and decreased by 22 % between 2011 and 2012. The decrease in emissions was occasioned by the country's temporary economic setback triggered by the reduction in GDP from 7.8 % in 2010 to 6.7 % in 2011. Likewise, a decrease in the global economy and oil production shutdowns could be responsible for the decline in emissions [53]. The reduction in energy consumption pattern between 2015 and 2016 resulted in CO_2 emissions decrease by 39 %. Similarly, the decline in CO_2 emissions between 2019 and 2020 were also observed, attributed to changes in the energy consumption patterns brought about by the COVID-19 pandemic [54]. On the other hand, the country's economy expanded marginally in the first half of 2015, where real GDP growth stood at 3.14 % lower than the values obtained in 2014. Remarkably, the services and agriculture sectors were the primary growth drivers in the non-oil sector, with 5.9 % and 4.1 % growth rates, respectively [55].

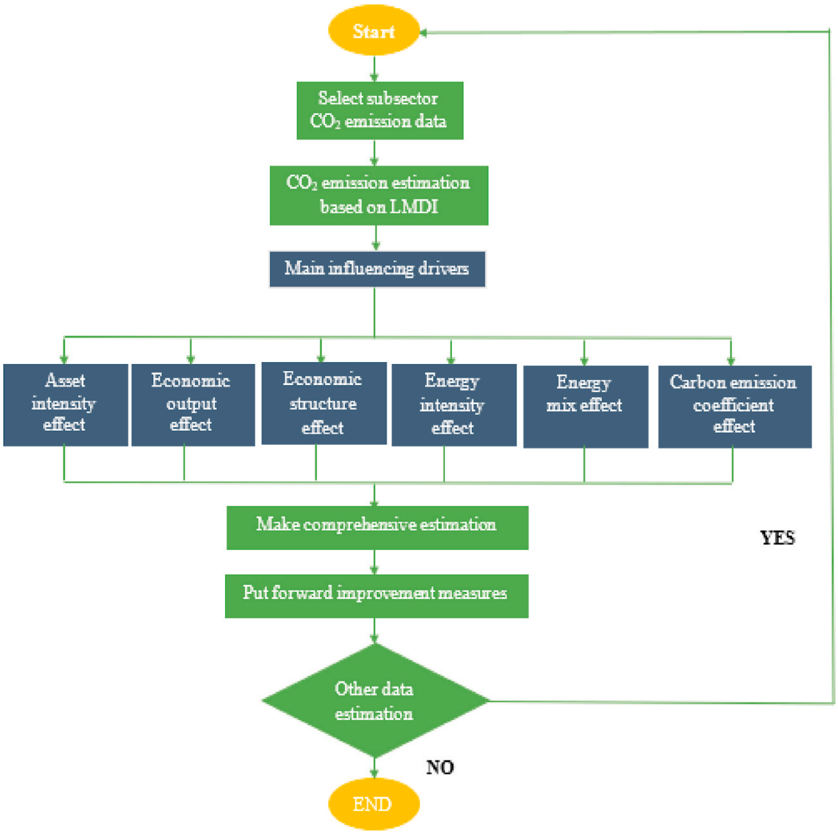

Fig. 2. CO_2 emission estimation procedure based on LMDI.

Table 3
Total Energy-related Carbon dioxide emission of Nigeria's manufacturing sector between 2010 and 2020 (Mt-CO_2).

Year	Electricity (CO_2)		Fuel oil (PMS)		Diesel oil (AGO)		Kerosene (HHK)		Total Carbon (CO_2) emissions	
	$MtCO_2$	Growth Rate (%)	$MtCO_2$	Growth Rate (%)	$MtCO_2$	Growth Rate (%)	$MtCO_2$	Growth Rate (%)	$MtCO_2$	Growth Rate (%)
2010	1.1	0	4.42	0	2.39	0	0.67	0	7.49	0
2011	1.1	0.00	4.47	1.13	2.42	1.26	1.12	67.16	8.01	6.94
2012	0.75	−31.82	2.97	−33.56	2.23	−7.85	1.09	−2.68	6.28	−21.60
2013	0.74	−1.33	2.99	0.67	2.08	−6.73	1.14	4.59	6.21	−1.11
2014	0.74	0.00	2.98	−0.33	1.94	−6.73	1.09	−4.39	6.01	−3.22
2015	0.83	12.16	3.35	12.42	1.96	1.03	1.15	5.50	6.46	7.49
2016	0.5	−39.76	2.01	−40.00	1.55	−20.92	0.39	−66.09	3.95	−38.85
2017	0.49	−2.00	1.9	−5.47	1.33	−14.19	0.22	−43.59	3.44	−12.91
2018	0.53	8.16	1.89	−0.53	1.28	−3.76	0.23	4.55	3.43	−0.29
2019	0.56	5.66	2.11	11.64	1.22	−4.69	0.2	−13.04	3.53	2.92
2020	0.45	−19.64	1.75	−17.06	1.23	0.82	0.2	0.00	3.22	−8.78
Average	**0.71**	**−6.23**	**2.80**	**−6.46**	**1.78**	**−5.61**	**0.68**	**−4.36**	**5.28**	**−6.31**
Annual Growth Rate (%)	**−59.09**	**-**	**−60.41**	**-**	**−48.54**	**-**	**−70.15**	**-**	**−57.01**	**-**

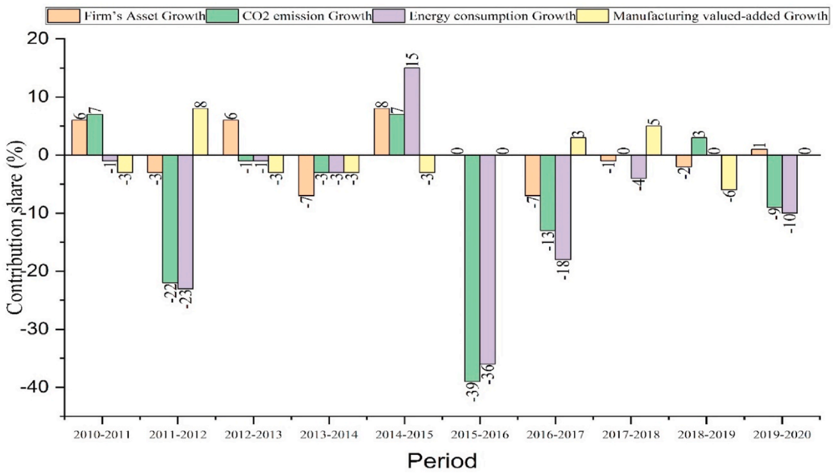

Fig. 3. Firm-level structural change.

3.2. *Yearly percentage share of emissions by energy sources across the periods*

Fig. 4 shows the yearly percentage share of energy consumption and the subsequent emissions from 2010 to 2020. The share of emissions by energy sources indicates that fuel (PMS) consumption produced nearly 30.84 $MtCO_2$, equivalent to 46.90 %, while diesel (AGO) and kerosene (HHK) produced 19.63 $MtCO_2$ and 7.51 $MtCO_2$, equivalent to 29.85 % and 11.41 % respectively. Additionally, the energy-related CO_2 emission from electricity was 7.79 $MtCO_2$ corresponding to 11.85 %. On the cumulative within the study period, the CO_2 emissions trend by subsectors is depicted in Fig. 5. The two subsectors that contributed the highest CO_2 emissions were the other manufacturing and chemical & pharmaceutical, estimated at 14.62 $MtCO_2$ and 14.61 $MtCO_2$, respectively. Food, beverages, tobacco, and Textile apparel/footwear contributed about 7.55 $MtCO_2$ and 6.63 $MtCO_2$, respectively, corresponding to 13.01 % and 11.43 % of the sector's overall emissions. However, Basic Metal and Iron & Steel (5.15 $MtCO_2$), Plastic & Rubber Products (2.99 $MtCO_2$), Agro-Allied (2.71 $MtCO_2$), Oil Refining (2.007 $MtCO_2$), and Pulp & Paper Products (1.76 $MtCO_2$) accounted for approximately 8.88%, 5.16 %, 4.66 %, 3.46 %, and 3.03 % of the sector's overall CO_2 emissions.

3.3. *Results of decomposition analysis of CO_2 emission changes*

3.3.1. *Overall sector decomposition from 2010 to 2020*

Table 4 presents the decomposition results of CO_2 emission changes in the manufacturing sector from 2010 to 2020. Changes in CO_2 emissions were affected by firm asset intensity, economic output, economic structure, energy intensity, energy mixes, and carbon emission coefficient. From Table 5, the CO_2 emissions decreased by 4.17 $MtCO_2$ between 2010 and 2020. The sector's growth in CO_2 emissions were attributed to the energy mix, firm asset intensity, and economic structure. The energy mix effect was the most

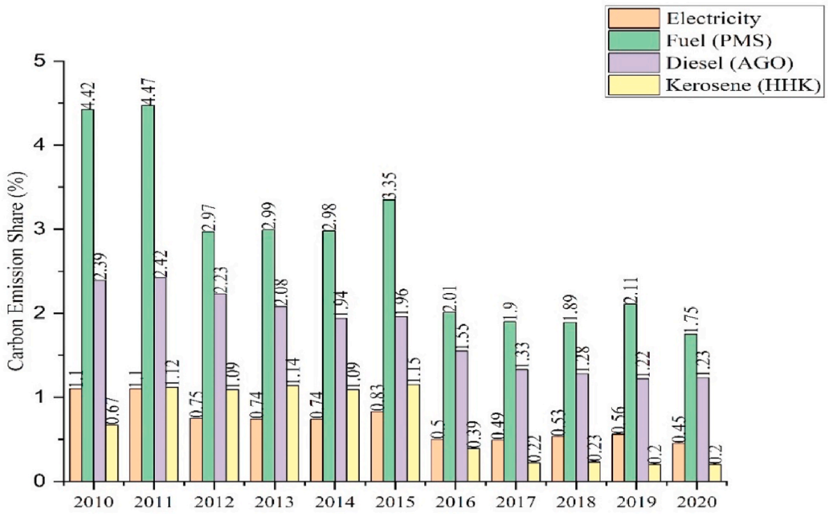

Fig. 4. Share of emission by fuel sources across the periods from 2010 to 2020.

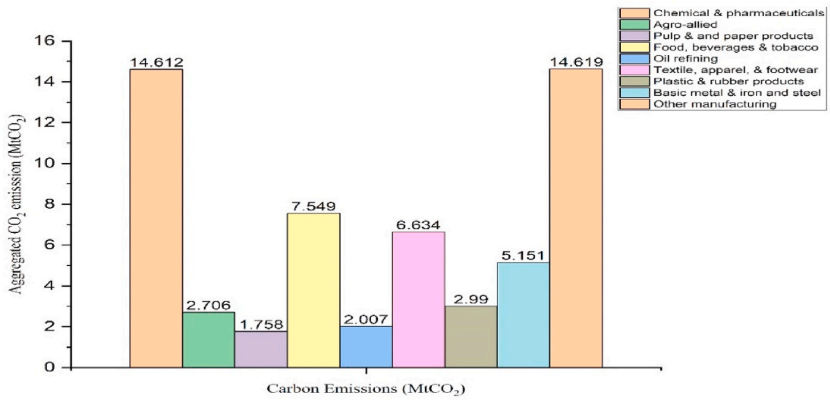

Fig. 5. Cumulative CO_2 emissions trend of manufacturing subsector (2010–2020).

Table 4
Decomposition results of CO_2 emissions in Nigeria's manufacturing sector. Unit: $MtCO_2$.

Period	Asset intensity effect	Economic output effect	Economic structure effect	Energy intensity effect	Energy mixes effect	Carbon emission coefficient effect	Total carbon emission change effect
2010–2011	0.42	−0.55	−0.01	0.08	0.54	0.03	0.51
2011–2012	−0.23	0.52	0.05	−2.18	0.17	0.00	−1.67
2012–2013	0.35	−0.45	0.00	0.05	−0.02	0.00	−0.07
2013–2014	−0.43	0.29	0.06	−0.10	−0.02	0.00	−0.19
2014–2015	0.44	−0.58	0.00	0.98	−0.41	0.00	0.44
2015–2016	0.02	−0.02	0.01	−2.23	−0.21	0.00	−2.43
2016–2017	−0.24	−0.12	−0.11	−0.25	0.21	0.02	−0.48
2017–2018	−0.02	0.24	0.04	−0.38	0.12	−0.04	−0.04
2018–2019	−0.06	0.17	0.07	−0.17	0.08	0.03	0.12
2019–2020	0.03	0.06	0.00	−0.44	0.04	−0.04	−0.35
2010–2020	**0.29**	**−0.42**	**0.11**	**−4.64**	**0.50**	**−0.01**	**−4.17**

significant driver that promoted CO_2 emissions accounted for approximately 0.50 $MtCO_2$. The results correspond to the studies of Safiullah et al. [19] and Calza et al. [15]. Other emission drivers that stimulated emissions include firm asset intensity and economic structure, which accounted for approximately 0.29 $MtCO_2$, and 0.11 $MtCO_2$, respectively. Likewise, throughout the study period, the emission driver that inhibited emissions was the energy intensity effect (−464 $MtCO_2$). However, economic output and carbon emission coefficient effects promoted emissions marginally. Periodically, most years demonstrated a decrease in CO_2 emissions, except

Table 5
Comparison of the results of CO_2 emission drivers ($MtCO_2$).

Period	EOPE		EIE		EME		CCE	
	[15]	Current study	[15]	Current study	[15]	Current study	[15]	Current study
1995–1996	30,617	–	−9130	–	1647	–	381	–
1996–1997	22,027	–	−37,588	–	−285	–	−88	–
1997–1998	20,944	–	−28,284	–	1974	–	−535	–
1998–1999	12,299		−23,778		2157		−88	
2000–2001	12,423	–	13,222	–	−1633	–	−1181	–
2001–2002	20,358	–	−8618	–	723	–	−795	–
2002–2003	33,367	–	−10,477	–	1011	–	260	–
2003–2004	53,342	–	−21,902	–	1011	–	809	–
2004–2005	66,172		−6633		−1011		−1841	
2005–2006	63,167	–	−6375	–	571	–	−2799	–
2006–2007	80,374	–	−41,373	–	2350	–	2063	–
2007–2008	91,938	–	−49,844	–	2350	–	−3767	–
2008–2009	55,929	–	−13,545	–	3109	–	−7651	–
2009–2010	64,620	–	−72,121	–	3109	–	8820	–
2010–2011	59,964	−0.55	−21,224	0.08	12,486	0.54	−5321	0.03
2011–2012	51,980	0.52	31,749	−2.18	892	0.17	1426	0.00
2012–2013	67,728	−0.45	−77,326	0.05	4882	−0.02	−11,155	0.00
2013–2014	67,986	0.29	−70,141	−0.10	3207	−0.02	−2776	0.00
2014–2015	53,940	−0.58	−38,151	0.98	2454	−0.41	−9556	0.00
2015–2016	40,256	−0.02	−44,795	−2.23	2454	−0.21	−907	0.00
2016–2017	–	−0.12	–	−0.25	–	0.21	–	0.02
2017–2018	–	0.24	–	−0.38	–	0.12	–	−0.04
2018–2019	–	0.17	–	−0.17	–	0.08	–	0.03
2019–2020		0.06		−0.44		0.04		−0.04
2010–2020	**-**	**−0.42**	**-**	**−4.64**	**-**	**0.50**	**-**	**−0.01**
1995–2015	**969,430**	**-**	**−536,334**	**-**	**43,334**	**-**	**−34,904**	**-**

EOPE = Economic output effect, EIE = Energy intensity effect, EME = Energy mix effect, CCE=Carbon coefficient effect.

from 2010 to 2011, 2014–2015, and 2018–2019.

3.4. Decomposition results of the subsectors

3.4.1. CO_2 emission changes in the chemicals and pharmaceuticals subsector

Fig. 6 shows the CO_2 emission trajectory for the Chemicals and Pharmaceuticals subsector. The CO_2 emissions decreased by 56 %, from 1.86 $MtCO_2$ in 2010 to 0.81 $MtCO_2$ in 2020, resulting in an annual reduction of −6.26 %. During this period, the economic production and energy intensity effects repressed emissions by −0.06 $MtCO_2$ and −1.22 $MtCO_2$, respectively. These findings disagree with Abam et al. [56]. The output of carbon emissions per unit increases with an increase in asset intensity effect. In light of this, the asset intensity increased emissions by nearly 0.14 $MtCO_2$ over the study period. In contrast, the growth in CO_2 emissions between 2017 and 2018 were influenced by variations in the energy mix and economic activity, while the asset intensity effect triggered the

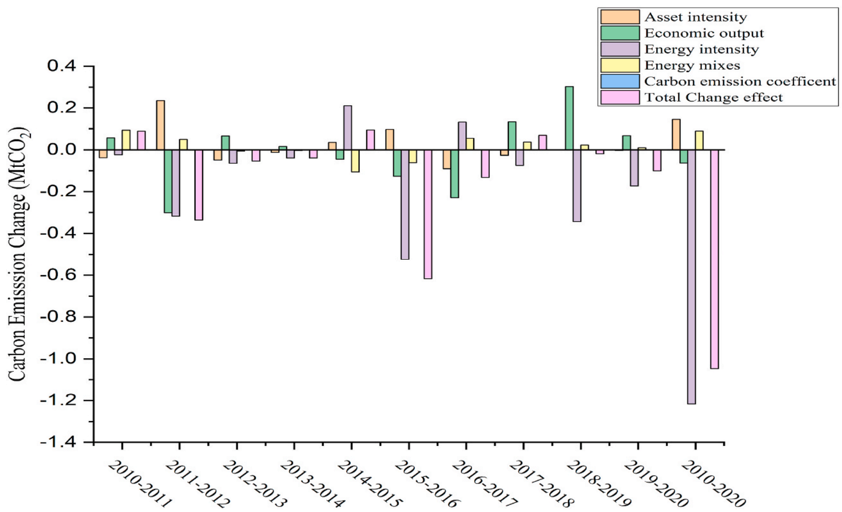

Fig. 6. CO_2 emission change in the chemicals and pharmaceuticals subsector.

emissions reduction from 2018 to 2019 and 2019–2020.

3.4.2. CO_2 emission changes in the agro-allied subsector

Fig. 7 presents the overall CO_2 emissions from the Agro-allied subsector, which declined from 0.38 $MtCO_2$ in 2010 to 0.06 MtCO2 in 2020 (−83 % reduction). The results show a remarkable net reduction in CO_2 emissions, calculated at approximately −0.318 $MtCO_2$ from 2010 to 2020. The decrease in CO_2 emissions are primarily promoted by the energy intensity effect. The asset intensity effect reduces CO_2 emissions by a negligible amount, estimated at −0.095 $MtCO_2$. However, the economic output increased emissions by 0.003 $MtCO_2$. The energy mix effect fluctuated across the period but had little influence on emissions. The CO_2 emissions decreased to varying degrees due to the effects of carbon emission coefficient, energy mix, and asset intensity. The latter is explained by the high penetration and utilization of renewable energy sources and the subsector's apparent lack of capitalization.

3.4.3. CO_2 emission changes in pulp & paper products subsector

The results of carbon emission changes in the pulp and paper products subsector are shown in Fig. 8. The overall CO_2 emissions decreased from 0.23 $MtCO_2$ in 2010 to 0.10 Mt CO_2 in 2020. The energy intensity effect is the most significant contributor to the reduction in carbon emissions, indicating that the energy efficiency strategy was effective. The economic output effect shows a decrease in carbon emissions by −0.05 $MtCO_2$. However, other drivers have growing propensities to promote emissions, for example, asset intensity (0.04 $MtCO_2$), energy mix (0.01 $MtCO_2$), and carbon emission coefficient (6.31×10^{-17} $MtCO_2$).

3.4.4. CO_2 emission changes in the food, beverages, and tobacco subsector

Fig. 9 shows the CO_2 emissions changes for the food, beverage, and tobacco subsector from 2010 to 2020. The CO_2 emissions decreased from 1.03 $MtCO_2$ in 2010 to 0.41 $MtCO_2$ in 2020, with a reduction and annual decline of 59 % and −6.61 %, respectively. The results indicate that the asset intensity, energy intensity, and economic output reduced emissions by 0.04 $MtCO_2$, 0.50 $MtCO_2$ and 0.18 $MtCO_2$, respectively. A marginal net increase in emissions of nearly 0.03 $MtCO_2$ was triggered by the changes in the energy mix. Nonetheless, the variations in the carbon emission coefficient had a negligible effect on CO_2 emissions during the study period. The values are calculated at -1.36×10^{-17} $MtCO_2$, which were extremely close to zero and thus insignificant. On the overall performance, the food, beverage, and tobacco subsector witnessed a net drop in CO_2 emissions of −0.61 $MtCO_2$ from 2010 to 2020.

3.4.5. CO_2 emission change in oil refining subsector

The variation in CO_2 emissions for the oil refining subsector is depicted in Fig. 10. All the emission values from the considered drivers were near zero. The overall emissions vary from 4.92×10^{-9} $MtCO_2$ in 2010 to 2.29×10^{-9} $MtCO_2$ in 2020 (53 % reduction), corresponding to 2.63×10^{-9} $MtCO_2$ in real terms. The combined effects of economic output and energy intensity calculated at -1.74×10^{-9} $MtCO_2$ and -1.21×10^{-9} $MtCO_2$ respectively, were responsible for the reduction in emissions. Nonetheless, the marginal emissions increase of 0.87×10^{-10} $MtCO_2$ observed during the study period was occasioned by the pooled effects of asset intensity and energy mix. Overall, the carbon emission coefficient did not influence any increase in emissions during the study period.

3.4.6. CO_2 emission change in the textile, apparel, and footwear subsector

The changes in CO_2 emissions in the textile, apparel, and footwear subsector is shown in Fig. 11. The subsector's CO_2 emissions

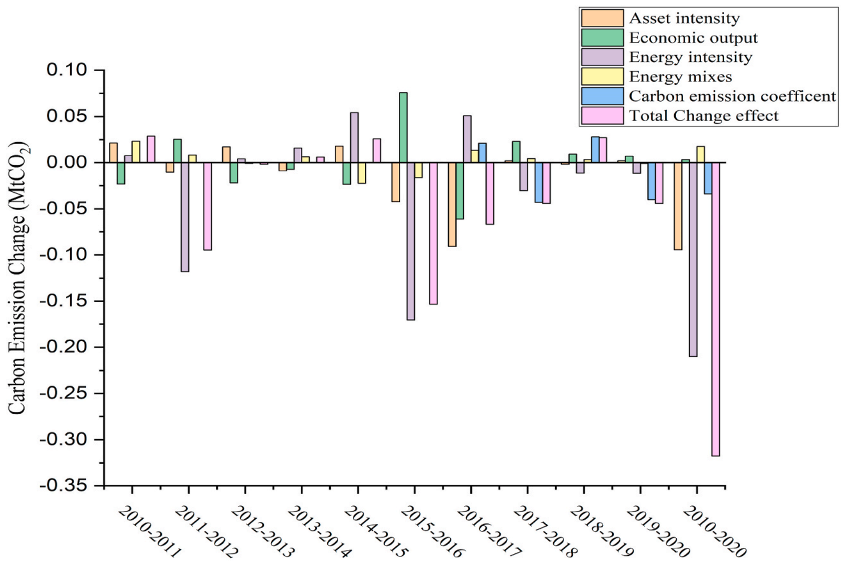

Fig. 7. CO_2 emission change in the agro-allied industry.

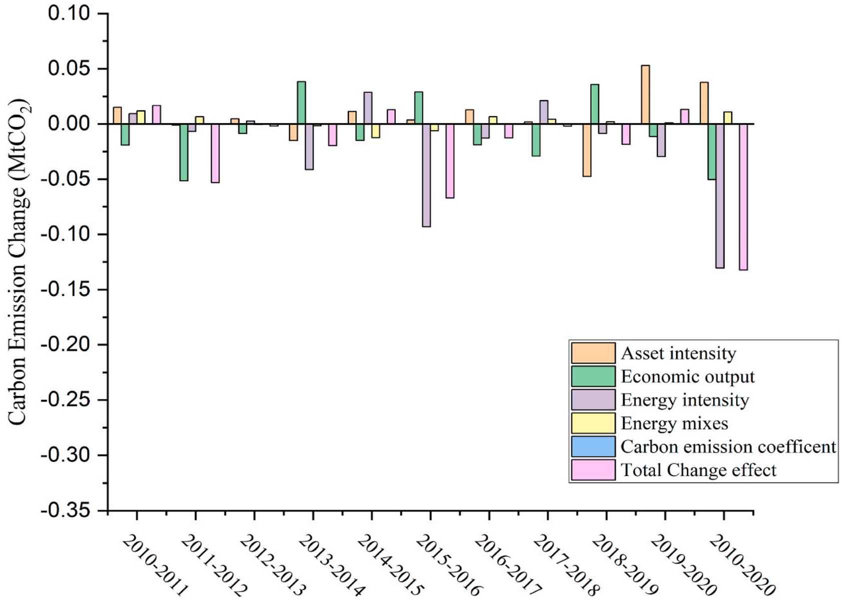

Fig. 8. CO_2 emission change in the pulp & paper products subsector.

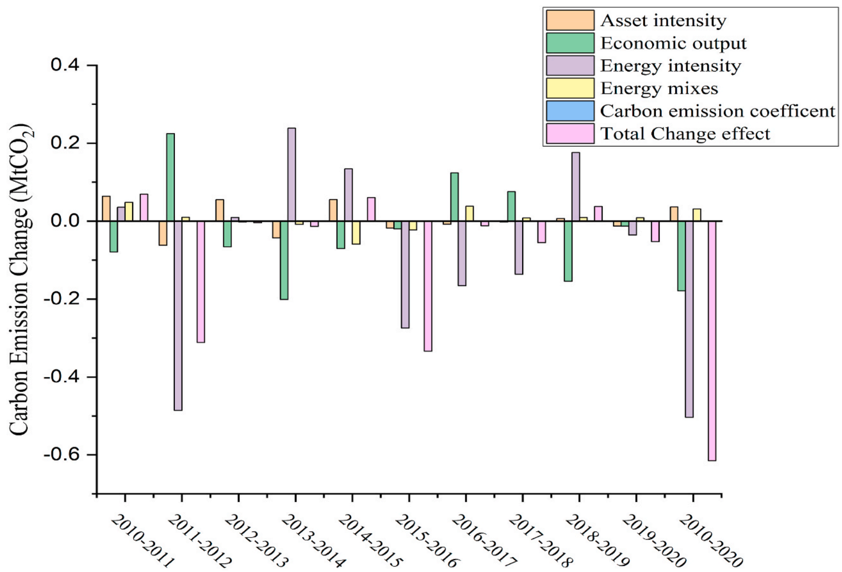

Fig. 9. CO_2 emission change in the food, beverages, and tobacco subsector.

decreased from 0.8 $MtCO_2$ in 2010 to 0.38 $MtCO_2$ in 2020. The decrease in energy intensity (−0.52 $MtCO_2$) was the main reason for emissions reduction. The emissions slightly increased from 2010 to 2011 and 2012–2013 due to high asset intensity. The subsector witnessed a decline in emissions from 2011 to 2012 and 2013–2014, which was attributed to low asset intensity. The effects of other drivers varied across the study period, and the decrease in energy intensity and a cleaner energy mix was responsible for the reduction in CO_2 emissions.

3.4.7. CO_2 emission change in other manufacturing

Fig. 12 depicts the variations of CO_2 emissions from the other manufacturing subsector from 2010 to 2020. The subsector experienced a 54 % decline in CO_2 emissions, with an average annual decrease of 5.84 %. The overall impact of the change in CO_2 emissions were negligible due to a decline in energy intensity and an increase in the energy mix. There was a slight negative trend in the carbon emission coefficient effect. However, carbon emissions were positively affected by economic output and asset intensity. Between 2010 and 2011, the subsector recorded a negative energy intensity effect of −0.07 $MtCO_2$, which indicates a decline in emissions brought by

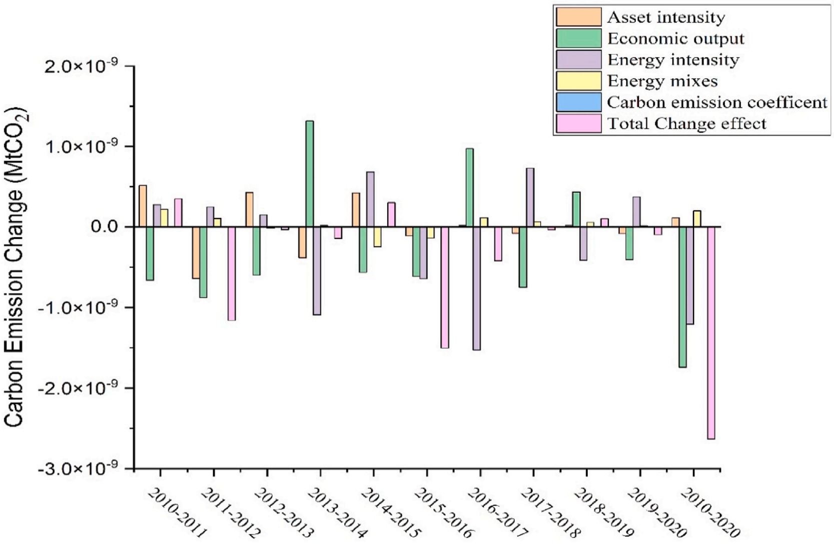

Fig. 10. CO_2 emission change in the oil refining subsector.

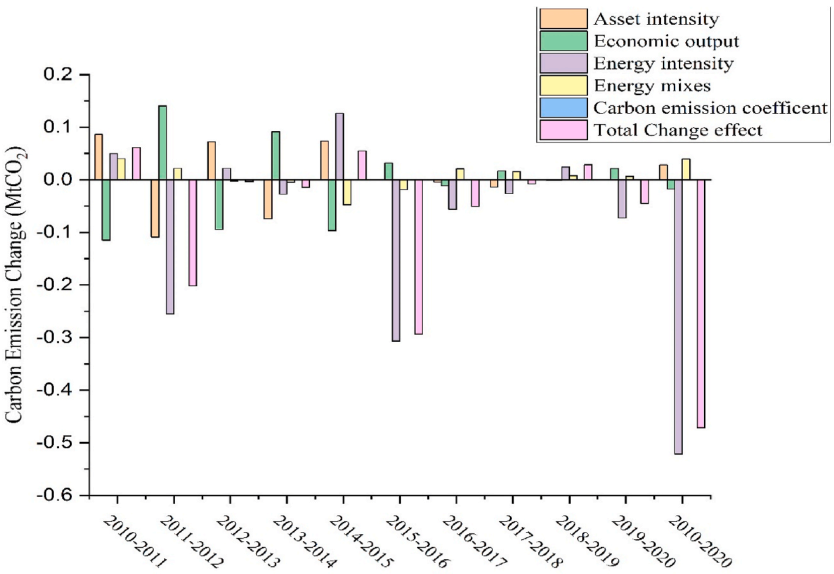

Fig. 11. CO_2 emission change in textile, apparel, and footwear.

energy efficiency. Similarly, the net energy intensity effect from 2010 to 2020 was negative (-1.42 $MtCO_2$), indicating a decrease in emissions brought by increased energy efficiency, whereas, in the same period, the net energy mix effect was positive (0.27 $MtCO_2$), showing a considerable growth in emissions due to changes in the energy mix. Conversely, emissions moderately increased by 0.06 $MtCO_2$ for the same period due to the combined effects of asset intensity and economic output.

3.4.8. CO_2 emission change in Plastic and rubber products

The plastic and rubber products subsector (Fig. 13) experienced a decline in CO_2 emissions from 0.38 $MtCO_2$ in 2010 to 0.16 $MtCO_2$ in 2020. From the results, the total net effect of all the factors influencing CO_2 emissions between 2010 and 2020 was -0.23 $MtCO_2$. Specifically, the asset intensity lowered emissions by -5.16×10^{-3} $MtCO_2$, followed by economic output and energy intensity, with respective values calculated at -0.23 $MtCO_2$ and -2.80×10^{-3} $MtCO_2$, respectively. However, the total emission trend indicates a positive value of 1.5×10^2 $MtCO_2$, which connotes a slight growth in CO_2 emissions triggered by the carbon emission coefficient and the energy mix effects.

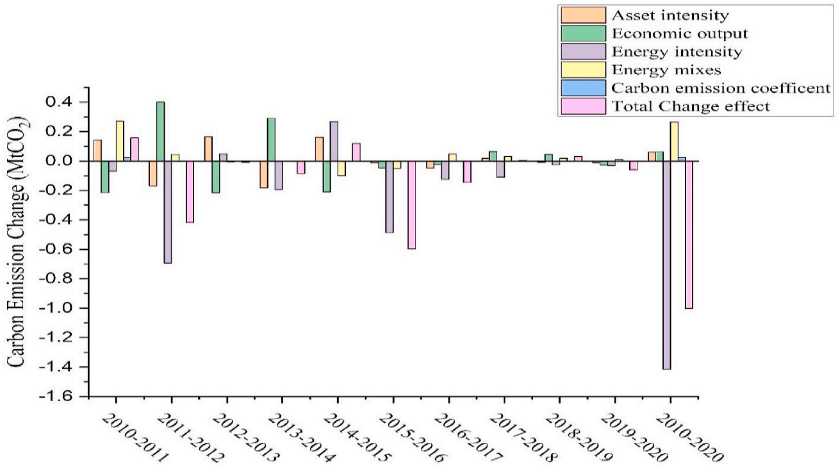

Fig. 12. CO_2 emission change in other manufacturing.

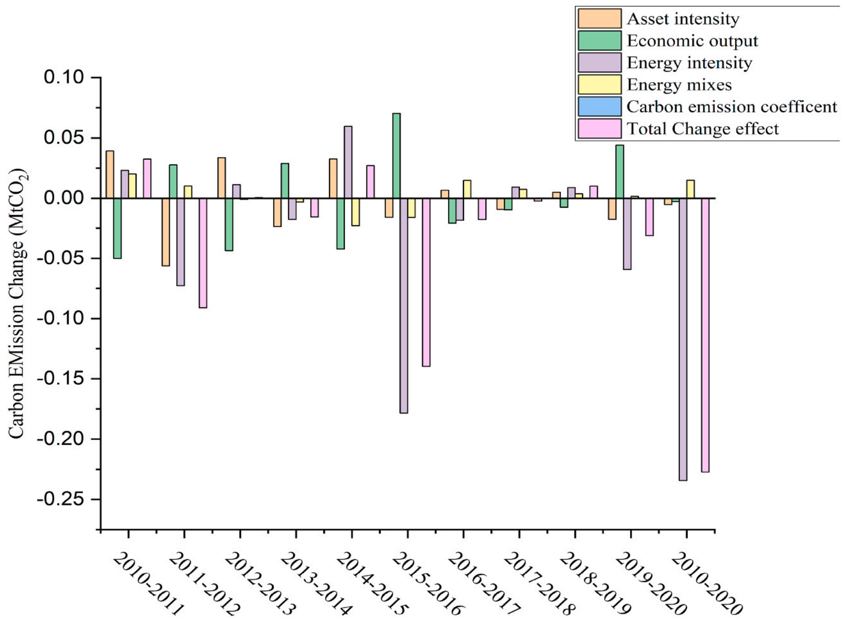

Fig. 13. CO_2 emission change in plastic and rubber products.

3.4.9. CO_2 emission change in basic metal & iron and steel

Fig. 14 shows changes in the trajectory of carbon emissions in the iron, steel, and basic metals subsector. The results show that the overall change in CO_2 emissions throughout the study period stood at 0.36 $MtCO_2$. The energy intensity and economic output reduced emissions by −0.41 $MtCO_2$ and −0.06 $MtCO_2$, respectively. The combined impact of energy mix and asset intensity increased CO_2 emissions by 0.03 $MtCO_2$ and 0.08 $MtCO_2$ in that order. Additionally, the subsector was impacted differently by the emission drivers. For example, a slight increase in CO_2 emissions between 2010 and 2011 were triggered by an increase in asset intensity. Likewise, a decrease in energy intensity from 2011 to 2012 resulted in a considerable decrease in emissions growth by (−0.23 $MtCO_2$). While the energy mix effect decreased emissions growth by −0.04 $MtCO_2$ between 2014 and 2015.

4. Study comparison and significance

4.1. Results comparison with previous studies

Based on the extended LMDI decomposition approach, the current study evaluates the associated CO_2 emissions drivers in Nigeria's manufacturing sector from 2010 to 2020. Calza et al. [15] used the same approach to examine CO_2 emissions in China's manufacturing

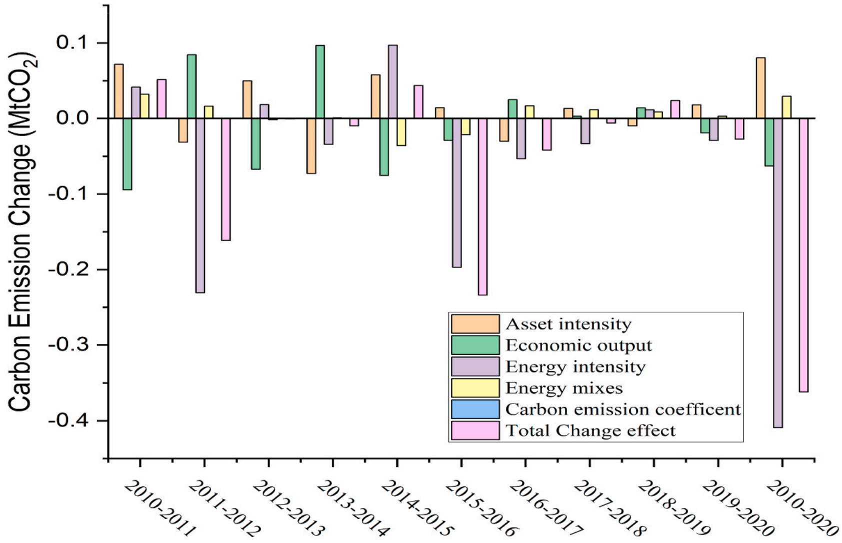

Fig. 14. CO_2 emission change in basic metal & iron, and steel.

sector between 1995 and 2015, with eight CO_2 emissions drivers. The five drivers applied in the current study are similar to those employed by Ref. [15]. Consequently, Table 5 presents the overall performance comparison of these drivers. In the current study, the EOPE had a significant inhibitive effect than [15]. This is ascribed to the slight economic growth observed in Nigeria during the first half of 2015. Nonetheless, Nigeria's manufacturing sector has been excluded from growth for a long time due to its low GDP contribution. The country's import rate contributes also to the inherent weakness of the domestic manufacturing sector. The country imports more manufactured goods with a low export rate of processed goods [57]. The Real GDP growth was 3.14 %, with the manufacturing sector contributing the least (−6.8 %) [55]. All these factors contributed significantly to the poor performance of the Nigerian manufacturing sector. In contrast, there is a slight discrepancy between the current investigations and Calza et al.'s [15] regarding the impact of energy intensity on CO_2 emissions. The reduction in conventional energy utilization must have decreased the country's energy intensity. Besides, the variations in energy intensity during this period must have been triggered by the drop in production capacity. From Table 5, both studies showed an increase in CO_2 emissions due to the energy mix effects. Similarly, while the study [39] employed a large data set, the current investigation used a small data set (time series), which may have caused the divergence in results. Nonetheless, in both studies, the results show that the emission coefficients facilitated the reduction in CO_2 emissions.

4.2. Novel driver: asset intensity and its impact on CO_2 emissions

Following the effects of the energy mix, the newly added driver, asset intensity, into the LMDI model increased the CO_2 emissions in the manufacturing sector. The latter indicates that the manufacturing sector contributes significantly to the rise in CO_2 emissions brought by asset-intensity investment, which is the principal engine of rising economic production. Additionally, this proposes that the manufacturing sector's emission levels were affected differently throughout the period depending on how the industrial assets advanced. The outcomes of this study support earlier research [15,58]. In this research, fixed asset investment was the key influencing driver of CO_2 emissions growth in China's manufacturing sector. However, this study's result differs from the previous disposition on "Cash-rich" firms [19,20].

4.3. The significance of the current study

The present study can be used as a reference for Nigeria's 2030 and 2060 net-zero emission targets. All the emission drivers are pivotal and broadly applicable for developing emission reduction strategies for Nigeria's manufacturing sector. The swift growth of CO_2 emissions in the industrial sector would inevitably occur due to economic expansion and reliance on conventional energy sources. Understanding the correlation between the development of the manufacturing sector and carbon emissions trends can assist in process optimization for adequate environmental policy [59]. The included driver, "asset intensity", was one of the indicators contributing to an increase in CO_2 emissions between 2010 and 2020. From 2019 to 2020, increased economic output and asset capitalization caused a rise in carbon emissions. Thus, results from this study can form a basis for developing policies for a low-carbon economy to advance energy efficiency and environmental sustainability.

4.4. Limitations of this research and direction of improvement

The current study only examined the evolution of carbon emissions in the sector at the firm level from 2010 to 2020. The study did not include data before 2010 due to data unavailability. However, the chosen variables represent the main factors, such as asset intensity, in exploring the key factors promoting carbon emissions at the firm level. Future efforts to examine capital structure and investment return as drivers of emissions at the firm level will be innovative.

5. Conclusion and policy recommendations

The growth of CO_2 emissions and the driving factors in the Nigerian manufacturing sector were studied at the firm levels from 2010 to 2020 using the addictive Logarithmic Mean Divisia Index (LMDI) decomposition method. The CO_2 emissions drivers comprise asset intensity, economic output effect, energy intensity, energy mix, and carbon emission factor. The results obtained indicate that CO_2 emissions declined from 7.49 $MtCO_2$ in 2010 to 3.22 $MtCO_2$ in 2020. Similarly, among the energy mix, electricity, fuel oil (PMS), diesel oil (AGO), and kerosene (HHK) accounted for 11.85%, 46.90%, 29.85%, and 11.41%, respectively, of the overall CO_2 emissions. Conversely, the decomposition results show that the energy mix, asset intensity, and economic structure effects were the primary drivers that stimulated CO_2 emissions, with estimated values of 0.50 $MtCO_2$, 0.29 $MtCO_2$ and 0.11 $MtCO_2$ respectively. In contrast, the energy intensity, economic output, and emission coefficient effects repressed CO_2 emissions by −4.64 $MtCO_2$, −0.42 $MtCO_2$, and −0.01 $MtCO_2$ respectively.

Furthermore, based on the study findings, the following are the primary policy recommendations for energy savings and emission reduction in the Nigerian manufacturing sector:

1. There is no apparent connection between asset intensity and economic productivity. The research indicates that the sector's underperformance was accompanied by declining fossil-fuel utilization. Consequently, to condense the adverse effects of asset-based emission growth and advance investment quality, investors should refrain from low-benefit production and blind investment. Besides, the manufacturing value-added of the sector requires considerable adjustment.
2. Despite Nigeria's energy endowment features, the short-term fossil-based energy mix is difficult to change, and the initiative to optimize the energy mix is lacking among industrial firms. Hence, for firms to profoundly reduce their dependence on conventional fuels and shift to green energy, the prices of fossil fuels should precisely mirror the cost of environmental externalities in the short run.
3. Finally, close attention to how energy intensity and carbon efficiency affect manufacturing carbon emissions is required. These research findings show that economic structure, energy structure, asset investment, and energy intensity have not completely reduced carbon emissions. Economic structure and energy structure had the least inhibitory effect of reducing emissions. The subsectors cannot completely replace the present production pattern dominated by fossil fuels. Therefore, accelerating strategies to support the decoupling development of the sector, in the long-run, might be to speed up the market-oriented restructuring of the energy pricing mechanism and incorporate the environmental cost of energy usage in energy prices [60].

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Fidelis I. Abam: Supervision, Conceptualization. **Oliver I. Inah:** Writing – original draft, Formal analysis. **Bethrand N. Nwankwojike:** Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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