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Decomposition and drivers of energy intensity in Ghana

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ABSTRACT

Ghana's energy intensity trends point to a high energy use necessary to generate a unit of output. The country has also witnessed massive investment in energy infrastructure geared towards meeting its lower middle-income status and achieving universal access to energy. The logical question is: what is the contribution of the current economic and technical infrastructure level to the country's energy intensity? The current study addresses this question by employing the Logarithmic Mean Divisia Index I (LMDI) to decompose energy intensity in Ghana from 2000 to 2020 to examine its trends and sources. The impact of economic-technical factors on aggregate energy intensity in Ghana is then investigated with the aid of the ARDL estimation technique to unearth potential asymmetric and symmetric effects. The decomposition analysis indicates an oscillating pattern in energy intensity in Ghana promoted by structural effect and labour productivity respectively. The results suggest that renewable energy, rural electrification, and digitisation have a direct and secondary long-run asymmetric effect on aggregate energy intensity with labour productivity and household consumption working as the transmission channels. The study recommends the need for government to pursue clean and eco-friendly practices in its economic development agenda for a meaningful reduction in energy intensity.

1. Introduction

Energy use is crucial for economic growth. However, unsustainable use of energy is reported to hamper growth, human livelihood, and the environment threatening the achievement of the 7th sustainable development goal [1]. For this reason, achieving efficiency has become the central focus of public policy agenda as enshrined in the Kyoto Protocol [2]. The Intergovernmental Panel on Climate Change (IPCC) contends that energy use remains the key contributor to global warming, gradually pushing global temperatures above levels that can sustain life. This called for policymakers' attention to adopt coherent mitigating options to improve energy use and reduce greenhouse gas (GHG) emissions [3,4]. Subsequently, several policy attempts - informed by empirical evidence, have been applied to reduce GHG emissions amidst projections of growing energy demand from 2005 to 2030 by 18% [5,31].

Adom [6] and Tenaw [7] indicate that sub-Saharan Africa (SSA) countries achieved the least improvement in energy intensity from 2010 to 2017, with an annual rate of 1.3% energy intensity improvement compared to the world average of 2.2%. This has been attributed to the heavy reliance on primary energy requirements for economic activities, particularly for regional production and infrastructural development [8,9]. While existing policies are attempting to reduce energy intensity to ensure green economic growth, progress so far has been slow. The need for empirical investigations into the specific sectors that drive the variations in overall energy intensity using the decomposition approach has been emphasised in the literature [5,7].

Over the past decade, African countries, including Ghana, have been increasing investment in economic-technical factors such as renewable energy, rural electrification, industrialisation and digitisation. Increased provision and access to these factors will provide the needed infrastructure to spur the economies toward inclusive and sustained growth. The development of economic-technical infrastructure is expected to affect energy intensity and efficiency through productivity and consumption channels. Investment in the above infrastructure will trigger economic agents to exploit avenues and resources to innovate, develop

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capacities, and shift towards efficient production methods, thereby enhancing productivity. The increase in productivity reduces the intensity of resource use, including energy consumption. However, it is also plausible for the marginal increase in productivity to lead to a rise in energy consumption due to limited technical skills and know-how to develop energy-saving technologies. Hence, the implication of the increased investments in economic-technical factors on energy intensity on the continent is complex.

Although African countries are touted as the most vulnerable to the effect of climate change, limited empirical investigations into energy intensity trends and sources have focused on the African contexts. Huang [10] examined the effects of R&D activity and technology spillovers from international trade and openness, on energy intensity in China from 2000 to 2013. The study found that R&D activity, technological spillovers, and import are the primal factors in reducing energy intensity. Jimenez & Mercado [2] focused on 75 Latin American countries to measure trends in energy intensity from 1971 to 2010. The evidence showed that energy intensity would decrease between 40% and 50% as countries transition from low to middle-country status. Petrović et al. [11] found that within the EU, FDI affects intensity and efficiency. Focusing on the African context, Shahbaz et al. [12] explored the dynamic relationship between energy intensity and CO_2 emissions in 12 selected sub–Saharan African countries and found a positive correlation between energy intensity and CO_2 emissions. Adom [13] showed that technical factors such as FDI and industry structure have asymmetric effects on energy intensity in Nigeria. Adom & Kwakwa [14] examined the effect of FDI, urbanisation, trade structure, and technical characteristics of the manufacturing sector on energy intensity in Ghana. The evidence suggested that technological diffusion through trade significantly affects energy intensity. Adom [6] similarly reports that de-industrialisation since 1980 and a shift towards imports are the key factors driving the reduction in energy intensity in South Africa.

Although growing, the literature on energy intensity has been silent on the implication of renewable energy, rural electrification, industrialisation, and digitisation on energy intensity. Thus, we contribute to the existing literature in several ways: first, we focus on Ghana and use a decomposition method to understand Ghana's underlying sources of energy intensity. We decompose and examine the variations in energy intensity and sources across Ghana's economic sectors.

Secondly, we explore the economic-technical drivers of energy intensity in the country. Specifically, we examine the effect of renewable energy, rural electrification, industrialisation and digitisation on energy intensity. While Adom [13] examined the effect of industrialisation on energy intensity, the impact of renewable energy consumption, digitisation and rural electrification are ignored. Ghana has been committing resources to increase the share of renewable energy in total electricity generation mix which stood at 0.28% in 2020 as compared to 0.02% in 2013. In addition, Ghana currently has over 70% increase in rural electrification [29]. It is therefore important to grasp what this development implies for improvements in energy intensity and efficiency.

Furthermore, the government of Ghana has been investing heavily in digitising the economy; as part of efforts to achieve inclusive growth. The digital market is at its maturing stage; with total digital transactions valued in excess of GH500 billion (about $81 billion) in 2020 compared to the GH78 billion ($12.5 billion) in 2016 [32]. Improvement in digital infrastructure limits the demand for alternative high-end energy use infrastructure in ecosystems such as transport, banking, and industry. High use of digitisation is expected to lead to a reduction in demand for fuel, transaction cost, and energy combustion.

Third, the study examines the potential channels through which changes in technical factors affect energy intensity in Ghana such as labour productivity and household consumption on energy intensity. Productivity connotes the capacity of an economic unit to transform inputs into output. According to Ramachandran [15]; Ghana, like most sub-Saharan African countries, has witnessed a series of reforms since the 1980s to achieve structural transformation, however, labour productivity still remains low, particularly in the agricultural sector [16]. While the importance of labour productivity in the face of the rising population in SSA cannot be ignored, scientific investigation and understanding of its impact on energy intensity is lacking. Improving infrastructure through the provision of technical factors is expected to enhance labour productivity and output. However, if the level of labour productivity is stalled, then resource usage and efficiency in the productive sector will reduce; advancing substantial unfavourable effects on energy intensity. Similar to this, depending on the extent of environmentally conscious energy consumption practices in the household sector, household consumption may either operate as a preservative of energy usage or an accelerator of energy exploitation.

Fourth, contrary to previous studies, we test the symmetric and asymmetric effect of the economic-technical factors on energy intensity in Ghana. While several empirical studies have employed models that account for only symmetric effects, those investigating the asymmetric correlations between macroeconomic factors and energy intensity are limited. Adom [13]; Adom [6] explored the asymmetric effect of technology factors on energy intensity trends in the African context (i.e., Nigeria and South Africa respectively). This study utilises the nonlinear Autoregressive Distributed Lag (ARDL) bounds approach to assess the asymmetric effect of the determinants of energy intensity in Ghana.

The rest of the paper is structured as follows. Section 2 presents a contextual review of the energy sector in Ghana; whiles in Section 3 we describe the data source and study methodology. Section 4 reports and discusses the main results of the paper, while Section 5 focuses on the policy implications of the study findings.

2. Stylised facts on the energy sector in Ghana

In Ghana, energy insecurity has continued to be a perennial development affecting life and property. Until the commercial production of oil and gas in 2010, hydropower was the major source of Ghana's energy generation for decades [30]. However, over time, the percentage of hydropower generation in Ghana's total electricity generation mix has declined from 92% in 2000 to 36.2% in 2020; while thermal energy generation has increased from 8% to 63.6% over the same period [17]. This has increased the dependence on fossil fuels; particularly since 2013. Notwithstanding, the dominant use of fossil fuel, Ghana's total energy supply was made up of 36% of biomass in 2020; compared to 34% and 25% of oil and natural gas respectively in the same year. The yearly total electricity generation from 2010 to 2020 stands at 7.1%. Ghana has witnessed several periods of persistent and erratic electricity supply since 2001. The government has taken steps to improve the erratic power supply by signing several power agreements with independent power producers. Nonetheless, the power supply in the country remains erratic leading to an increased demand for wood and charcoal for cooking, as alternative sources of power supply such as LPG and solar energy are identified as costly. According to the 2021 Energy Commission report on wood fuel consumption in Ghana, the household sector accounted for 86.2% of biomass consumption in 2020 while the service and industry sectors consumed 4.4% and 9.37% respectively. According to the 7th round GLSS dataset (GLSS 7) 28.16% of households use charcoal, 46.48% use wood, and 18.37% use gas for cooking in Ghana.

These staggering statistics have contributed to the level of energy intensity in the country which was estimated to be 7.88 in 1990; but since 2000 has been declining steadily reaching as low as 3.57 in 2014. It however started crawling upwards afterwards; rising to about 3.85 in 2021. Aboagye [18] reveals that aside Ghana's energy intensity always exceeding the average for sub-Saharan Africa, Ghana's energy consumption has also been estimated to be higher than its total economic output. This raises concern about the country's capacity to achieve energy efficiency and sustainable growth in the midst of growing energy demand and perennial power crisis.

Ghana over the period has been committed to achieving the Sustainable Development Goal 7 (achieving universal access to affordable, reliable, sustainable and modern energy) by 2030. For instance, in terms of universal access to modern energy, Ghana has a rising national electricity access rate from 64.4% in 2010 to 85.6% in 2020 with 71.7% of the rural population connected to the national grid as of that same year, 2020. Also, since 2017 Ghana has been witnessing a 100% urban population electricity access rate although the yearly average of urban households with access to electricity since 2017 stands at 92.5% [29]. Ghana has also witnessed increased demand for LPG among rural and urban households for cooking; averaging a 1.9% yearly growth rate for urban households and 18.5% for rural households, between 2010 and 2020. In terms of renewable energy consumption, available data shows that approximately 40.4% of the total final energy consumption in 2020 was derived from renewables. Aboagye [18] notes that the slow progress towards achieving energy efficiency and SDG 7 can be attributable to inefficient energy pricing, inadequate financing of programmes aimed at energy conservation and efficiency, and limited public awareness of energy conservation measures. Ghana's effort to achieve SDG 7 has been supported by a number of legislative instruments including Energy Efficiency Standards and Labelling (Non-Ducted Air-conditioners and Self Ballasted Fluorescent Lamps) Regulations (2005); Energy Efficiency Standards and Labelling (Household Refrigerating Appliances) Regulations (2009), Renewable Energy Act (2011 [Act 832]) and the United Nation's funded Sustainable Energy for All (SE4All) project (2012).

3. Data and methodology

We used two sets of data for this study. For the first part of our study which involved decomposing energy intensity in Ghana, identifying its sources and sector trends; we relied on data from the 2021 Energy Commission annual report on the energy sector with data spanning 2000 to 2020. In the second part where we investigate the macroeconomic determinants of energy intensity in Ghana, the study uses annual time series data from 1990 to 2020 from the World Development Indicators (WDI) database. Series such as the energy intensity, industry value-added to GDP (a proxy for industrialisation), industry value-added per worker, (a proxy for labour productivity in industry), household final consumption, renewable energy consumption and the total number of mobile phone subscribers (a proxy for digitisation) were sourced from the database.

3.1. Decomposition method

According to Rodriguez, Pansera & Lorenzo [19] and Rodríguez [20]; the standard measurement of energy intensity, as it currently stands, is not a good measure of energy efficiency and could misguide policymaking on climate change and environmental sustainability. To this end, Rodríguez [20] suggested a new measure of intensity that incorporate energy per worker and labour per output to avoid bias results. Following the suggestion of Rodríguez [20]; we developed an extended measure of energy intensity that incorporates sectoral labour productivity, P_{it}, L_{it} energy use per worker, R_{it} and S_{it} V_{it} to capture the structural effect.

Ang [21] reveals that among the battery of decomposition methods, the Logarithmic Mean Divisia Index I (LMDI) is the most preferred method for policymaking.; due to its desirable properties including perfect decomposition, consistency in aggregation, path independency and an ability to handle zero values [7,22]. We adopted the multiplicative version of the LMDI method and begin decomposing total energy intensity by:

$$EI_t = \frac{E_t}{Y_t} = \sum\nolimits_{i=1}^{J} \left(\frac{Y_{it}}{Y_t} \times \frac{E_{it}}{L_{it}} \times \frac{L_{it}}{Y_{it}} \right) = \sum\nolimits_{i=1}^{J} S_{it} R_{it} P_{it} \tag{1}$$

where E_t gives the overall energy consumption in the country in time t and E_{it} is the share of sector's energy consumption in total energy consumption in time t. Similarly, Y_t and Y_{it} represent total national output and sector's output respectively in time t. L_{it} denotes sectoral labour employment in time t. The sector's share in total production is represented by S_{it}. Equation (1) suggests that variations in total energy intensity is the product sum of adjustments in economic activity (known as structure effect), changes in sector specific energy per worker (resource use efficiency effect), and labour per output (labour productivity effect) such that:

$$\Delta EI = S_{effect} \times R_{effect} \times P_{effect} \tag{2}$$

where S_{effect} gives the structure effect, R_{effect} is the resource use effect, and L_{effect} is the labour productivity effects. From Ang and Liu (2001), the multiplicative version of LMDI decomposes overall energy intensity to its component effects, such that:

$$S_{effect} = exp\left(\sum_{i=0}^{J} \frac{\left[\frac{\left(\frac{E_{it}}{Y_t} - \frac{E_{i0}}{Y_0} \right)}{\left(ln\frac{E_{it}}{Y_t} - ln\frac{E_{i0}}{Y_0} \right)} \right]}{\left[\frac{(EI_t - EI_0)}{(lnEI_t - lnEI_0)} \right]} \times ln\left(\frac{S_{it}}{S_{i0}} \right) \right) \tag{3}$$

$$R_{effect} = exp\left(\sum_{i=0}^{J} \frac{\left[\frac{\left(\frac{E_{it}}{Y_t} - \frac{E_{i0}}{Y_0} \right)}{\left(ln\frac{E_{it}}{Y_t} - ln\frac{E_{i0}}{Y_0} \right)} \right]}{\left[\frac{(EI_t - EI_0)}{(lnEI_t - lnEI_0)} \right]} \times ln\left(\frac{R_{it}}{R_{i0}} \right) \right) \tag{4}$$

$$L_{effect} = exp\left(\sum_{i=0}^{J} \frac{\left[\frac{\left(\frac{E_{it}}{Y_t} - \frac{E_{i0}}{Y_0} \right)}{\left(ln\frac{E_{it}}{Y_t} - ln\frac{E_{i0}}{Y_0} \right)} \right]}{\left[\frac{(EI_t - EI_0)}{(lnEI_t - lnEI_0)} \right]} \times ln\left(\frac{L_{it}}{L_{i0}} \right) \right) \tag{5}$$

Since agriculture, industry, service and residential sectors are important in the shares in final energy consumption, this study analysed energy intensity by sectors. Following Tenaw [7]; we used total household final consumption to represent economic output in the residential sector. We used the share of each sector's output to GDP to represent sectoral output; whereas sectoral value added at 2011 constant prices was used to measure sectoral value added in the agriculture, industry and service sector. National economic output on the other hand was measured in terms of GDP in PPP 2011 constant prices computed in millions of US dollars. In reference to labour, we used the share of each sector's employment in total employment except the residential sector where we used the total population. This means labour per output, for example, in the residential sector is measured as the inverse of household consumption per capita.

3.2. Model specification

We used renewable energy consumption (REC), industrialisation (IND), rural electrification (RRE) and digitisation as the main factors driving variations in total energy intensity. Further, the energy intensity level of primary energy (MJ/$2011 PPP GDP) was used to represent total energy intensity. Following Rodríguez [20]; we constructed an alternative measure of energy intensity by weighting the WDI energy intensity level of primary energy (MJ/$2011 PPP GDP) with labour per value-added and energy use per labour. This is referred to as "adjusted energy intensity". This shows greater variability and traces the average oscillations in energy consumption fairly; relative to the traditional WDI energy intensity measure (see Figure A in the appendix section). It also provides a granular view of intensity along energy efficiency aspects for more detailed understanding of how resource use and labour productivity drive changes in energy intensity in Ghana. We concentrate on the drivers of energy consumption trends to see how the results compare with the baseline regression (where WDI energy intensity is used as the dependent variable – Tables 3and4). This afforded the study the opportunity to test the robustness of the baseline results and also present alternative viewpoints to inform policy direction on energy consumption and intensity in Ghana. To trace the channels through which the technical and energy-related factors affect total energy intensity we introduce labour productivity (PROD), and household consumption (HC) in the modelling and estimate their pass-through effect. We considered the Shin et al. [24] nonlinear ARDL model to examine the determinants of energy intensity. We adopt this approach for three reasons. First, it allows us to capture asymmetries nonlinearly. Second, it has the additional ability to observe the path of asymmetric adjustment and the duration to equilibrium. Thirdly, with choice of appropriate lag orders and correct specification, the NARDL purges itself from residual serial correlations and perfectly deals with weak endogeneity of all independent variables [25]. This is because it possesses the desirable characteristics of the ARDL-based dynamic corrections associated in particular with the dynamic parametric framework proposed by Pesaran & Shin [26]. Following the specifications provided by Shin et al. [24]; we first consider the asymmetric cointegrating relationship:

$$y_t = \delta^+ x_t^+ + \delta^- x_t^- + \eta' w_t + u_t, \tag{6}$$

where y_t and x_t are I (0) and I (1) variables and represents the dependent and independent variables respectively. δ^+ and δ^- are the associated asymmetric long-run parameters. $x_t (= x_0 + x_t^+ + x_t^-)$ is a $k\times$ 1 vector of regressors decomposed and entering the model asymmetrically. x_t^+ and x_t^- are partial sum processes of positive and negative changes in x_t around the threshold of 0, defined as $x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} max(\Delta x_j, 0)$, and $x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} min(\Delta x_j, 0)$. w_t is a $g \times 1$ vector of other regressors entering the model symmetrically. By extension from the Pesaran et al. [23] ARDL framework, the long-run and short-run asymmetric error correction model (that is the asymmetric and nonlinear ARDL) is specified as follows:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \vartheta^+ x_{t-1}^+ + \vartheta^- x_{t-1}^- + \sum_{t=1}^{r} \gamma_i \Delta y_{t-i} + \sum_{i=0}^{s} \left(\theta_i^+ \Delta x_{t-i}^+ + \theta_i^- \Delta x_{t-1}^- + \theta_{w,i} w_{t-i} \right) + \varepsilon_t \tag{7}$$

where $\vartheta^+ = -\alpha/\delta^+$ and $\vartheta^- = -\alpha/\delta^-$ are long-run asymmetric parameters. There are four steps proposed by Shin et al. [24]. First, equation (8) is estimated, using OLS and using the bounds testing F_{PSS} statistic provided by Shin et al. [24]. Second, we check whether or not there is any long-run relationship between the variables of interest, y_t, x_t^+ and x_t^-, at their levels, by testing the null hypothesis ($H_n : \alpha_1 = \vartheta^+ = \vartheta^- = 0$). Third, we check for the existence of short-run asymmetry, using the null hypothesis that $H_n : \theta_i^+ = \theta_i^-$.

Table 2
Unit root test results.

	Levels		First Difference	
	Constant	Trend	Constant	Trend
WDI EI	−0.909	−2.272	−3.010***	−3.369**
Adjusted EI	−0.424	−2.102	−3.430***	−3.592**
Energy consumption	−0.947	−1.019	−3.266**	−3.313**
ln Renew	−3.534***	−2.485	−4.101***	−3.037***
ln Rural	0.171	−1.951	−5.348***	−5.622***
ln IVA	−1.693	−2.085	−2.605**	−4.718***
ln Consump	−0.149	−1.457	−5.412***	−5.271***
ln Industry	−3.646***	−3.952***		
ln Digital	−0.013	−0.846	−4.145***	−4.561***
ln Inv	−0.175	−1.962	−3.524***	−3.618**
ln Exchange	0.046	−0.726	−2.410**	−2.924*
ln M2	−1.161	0.196	−2.825***	−4.310***
ln RGDP	−0.908	−1.398	−3.388***	−3.600**
ln Deposit	−1.432	−2.141	−4.395***	−5.007***
ln Pcrdt	−0.310	−1.081	−3.476***	−3.950***
ln CO_2	0.869	−1.755	−4.774***	−5.989***

Note: *, **and *** represents significant at 10%, 5% and 1%. The critical values for DF-GLS test at 10%, 5% and 1% levels are −1.601, −1.950 and −2.655 for intercept and −2.890, −3.190 and −3.770 for trend respectively. The Schwarz Information Criteria (SIC) was used to select the optimal lag length.

Table 1
Summary Statistics and description of variables.

Variable	Description	Unit	Obs	Mean	Std. Dev.	Min	Max
Overall EI	Aggregate energy intensity – WDI estimate	Mega joules per constant 2011 purchasing power parity GDP. (MJ/$2011 PPP GDP)	32	5.453	1.720	3.737	7.889
Adjusted EI	Aggregate energy intensity	Weighted measure of WDI energy intensity measure by energy use per labour, inverse of labour productivity, value added per energy use consumed	32	8.705	2.824	2.132	14.019
Energy consumption	Energy use	kg of oil equivalent per capita	32	328.769	40.772	266.119	408.254
ln Renew	Renewable energy consumption	Percentage of total final energy consumption	32	4.090	0.235	3.737	4.418
ln Rural	Percentage of rural population with access to electricity	Percentage of rural population with access to electricity	32	2.932	1.186	0.459	4.249
ln IVA	Industry value added per worker – a proxy for labour productivity.	Output value from industry sector per worker at constant 2015 USD	32	23.112	1.227	21.377	25.366
ln Consump	Household final consumption	Value in current USD	32	23.336	0.963	22.114	24.578
ln Industry	Industry value-added	a percentage of GDP	32	−0.804	0.214	−1.398	−0.475
ln Digital	Mobile cellular subscription – a proxy for digitisation.	Number of mobile phone subscribers	30	14.089	3.624	5.991	17.527
ln Inv	Gross capital formation	Value in current USD	32	22.009	1.059	20.526	23.597
ln Exchange	Real effective exchange rate index	Index. 2010 = 100	32	−0.345	1.548	−3.423	1.722
ln M2	M2+ (broad money supply including foreign currency deposits)	Value in current Ghana Cedis	32	21.850	2.580	17.117	25.517
ln RGDP	Real GDP	GDP in PPP 2011 constant prices	32	24.870	0.375	24.267	25.590
ln Deposit	Deposit rate – the interest rate paid by commercial banks or financial institutions on cash deposits of account holders.	Rate (%)	31	2.770	0.432	2.184	3.577
ln Pcrdt	Domestic private sector credit	% of GDP	32	2.364	0.447	1.297	2.777
ln CO_2	CO_2 emissions (kt)	Kilotons of CO_2 emissions	32	8.949	0.587	7.848	9.687

Table 3
Asymmetric ARDL results – dependent variable: WDI energy intensity.

	NARDL (1)	NARDL (2)	NARDL (3)	NARDL (4)
ECM_{t-1}	−0.806 (0.240)***	−0.456 (0.136)***	−0.628 (0.166)***	−1.497 (0.105)***
X^{+}_{t-1}	2.272 (0.916)**	0.302 (0.070)***	0.054 (0.218)	−0.257 (0.060)***
X^{-}_{t-1}	1.001 (0.538)*	0.340 (0.093)***	0.144 (0.139)	−1.613 (0.818)***
ΔY_{t-1}	0.437 (0.217)*	−0.027 (0.216)	0.453 (0.239)*	0.017 (0.139)
ΔY_{t-2}	0.074 (0.187)	−0.624 (0.175)***		0.115 (0.127)
ΔX^{+}	0.670 (0.687)	−0.169 (0.169)	0.011 (0.011)	−0.220 (0.056)***
ΔX^{+}_{t-1}	−0.789 (1.118)	0.012 (0.059)	−0.062 (0.028)*	0.058 (0.079)
ΔX^{+}_{t-2}	−1.321 (0.957)		−0.021 (0.024)	−0.107 (0.035)***
ΔX^{-}	−0.025 (0.504)	0.054 (0.031)	0.113 (0.034)***	0.516 (0.262)*
ΔX^{-}_{t-1}	−0.363 (0.619)	−0.072 (0.044)	−0.021 (0.038)	0.312 (0.970)
ΔX^{+}_{t-2}	0.856 (0.502)	−0.323 (0.107)**	−0.020 (0.013)	0.268 (0.803)
ln Inv	0.038 (0.044)	0.032 (0.033)	0.015 (0.031)	
ln Exchange		−0.188 (0.044)***	−0.152 (0.070)**	−0.112 (0.025)***
ln M2	0.009 (0.044)	0.016 (0.007)*	0.153 (0.087)	
ln RGDP		−0.084 (0.036)**	−0.073 (0.037)*	−0.122 (0.038)**
ln Deposit	0 .101 (0.049) *	0.268 (0.061)***	0.204 (0.052)***	0.138 (0.056)**
ln Pcrdt		0.320 (0.071)***		
ln CO_2	0.155 (0.114)		0.390 (0.113)***	0.195 (0.079)**
Constant	0.142 (1.348)	1.134 (1.142)	1.388 (0.932)	3.901 (1.000)***
R-sq.	0.808	0.878	0.905	0.942
Adj. R-sq.	0.552	0.701	0.778	0.848
AIC	−100.699	−107.977	−121.009	−122.137
BIC	−77.455	−85.329	−97.765	−100.108
Log-likelihood	67.349	70.988	77.504	78.068
Prob > F	0.0248	0.0052	0.0001	0.0000
Observations	29	29	29	29

Note: *, ** and *** denote significant at 1%, 5% and 10% levels respectively. Standard Errors in Brackets. The shock variables examined in the selected models for NARDL (1–4) are the share of renewable energy, demand for rural electricity, industrialisation, and digitisation respectively. The null hypothesis for Jarque-Berra (JB) test is that errors are normal. The null hypothesis for the Breusch-Godfrey Serial Correlation LM test is that there is no problem of serial correlation. The null hypothesis for the Ramsey RESET test is that the model is correctly specified. And, the models pass all diagnostic tests.

For any short - run asymmetry to be established in Equation (9), the null hypothesis can also be expressed as $\sum_{i=0}^{n-1}\theta i^{+} = \sum_{i=0}^{n-1}\theta i^{-}$ for all $i = 1, 2, 3\ldots n$. Finally, we use the nonlinear, ARDL model in Equation (6) to derive two dynamic multipliers, m_h^{+} and m_h^{-}. These measure the cumulative dynamic adjustment effect of a unit change in x_t^{+} and x_t^{-} on y_t. Both are defined as $m_h^{+} = \sum_{i=0}^{h}\frac{\partial y_{t+1}}{\partial x_t^{+}}$, $m_h^{-} = \sum_{i=0}^{h}\frac{\partial y_{t+1}}{\partial x_t^{-}}$, with h = 0, 1, 2. From the model, as $h \to \infty$ then $m_h^{+} \to \alpha_1^{+}$ and $m_h^{-} \to \alpha_1^{-}$ respectively. To test the robustness of the nonlinear ARDL estimates, we also used the traditional ARDL model which focuses on symmetric interactions between the dependent and the independent variables. Generally, the ARDL (m, n) model is specified as:

$$y_t = \alpha_0 + \sum_{i=1}^{m}\alpha_i y_{t-i} + \sum_{i=1}^{n}\delta_i x_{t-i} + \varepsilon_t \tag{8}$$

Table 4
Asymmetric model diagnostic statistics – dependent variable: WDI energy intensity.

	NARDL (1)	NARDL (2)	NARDL (3)	NARDL (4)
L_X^{P} f-stat	2.820*** 16.38	0.662** 7.221	−0.117 0.708	−0.093*** 99.46
L_X^{N} f-stat	−1.243** 4.876	−0.746*** 9.971	0.001 0.000	1.437** 5.237
Wald-LR	9.661 [0.009]***	0.605 [0.453]	0.852 [0.374]	4.614 [0.017]**
Wald-SR	0.663 [0.431]	14.34 [0.003]***	2.684 [0.127]	4.507 [0.024]**
F_PSS	3.831	11.095	7.151	20.191
CHSQ-SC	14.28 [0.283]	3.311 [0.855]	23.18 [0.056]	10.02 [0.529]
CHSQ-HET	0.164 [0.700]	0.190 [0.663]	0.035 [0.852]	0.047 [0.827]
CHISQ-FF	2.218 [0.204]	1.230 [0.324]	1.736 [0.229]	1.479 [0.301]
CHSQ-NOR	2.741 [0.254]	0.827 [0.661]	0.533 [0.766]	2.585 [0.275]

NOTES: L_Y^{+} and L_Y^{-} denote the long-run coefficients associated with positive and negative changes of output, respectively. W_{LR} refers to the Wald test for long-run symmetry while W_{SR} denotes the Wald test for short-run symmetry condition [23]. 5% critical values for F_PSS are −3.23 and 4.35 for k = 3 and k = 2, respectively. The shock variables examined in the selected models for NARDL (1–4) are the share of renewable energy, demand for rural electricity, industrialisation, and digitisation respectively. The null hypothesis for Jarque-Berra (JB) test is that errors are normal. The null hypothesis for the Breusch-Godfrey Serial Correlation LM test is that there is no problem of serial correlation. The null hypothesis for the Ramsey RESET test is that the model is correctly specified. And, the models pass all diagnostic tests.

Where y_t and x_t represents the dependent and independent variables respectively. Re-parametrising equation (10) to include both the short run and long run correlations between the variables, and following Tenaw [7]; the ARDL model is reformulated as:

$$\Delta y_t = \alpha_0 - \rho(y_{t-i} - \delta x_{t-i}) + \sum_{i=1}^{m-1}\gamma_i \Delta y_{t-i} + \omega \Delta x_t + \sum_{i=0}^{n-1}\theta_i \Delta x_{t-i} + \varepsilon_i \tag{9}$$

Where $\Delta y_t = y_t - y_{t-1}$. γ_i and θ_i gives the short run estimates of the lagged dependent and independent variables respectively. is the short run estimate of the independent variable. The speed of adjustment is represented given by $\rho = 1 - \sum_{i=1}^{m}\gamma_i$; while the long run coefficients, $\delta = \sum_{i=1}^{m}\delta_i/\rho$.

4. Empirical results and discussion

4.1. Energy intensity decomposition

We first estimated aggregate energy intensity at the national level and then disentangled the overall energy intensity with respect to the subsectors of residential, agriculture, service and industry. The results presented in Table A1 in the appendix section shows that generally energy intensity has been oscillating for most periods; rising from 2000 to 2006 and declining sharply onwards from 2006 to 2020 (Fig. 1). The trends in energy intensity are defined significantly by structural effect and labour productivity effect respectively. In addition, it is observed that overall energy intensity was stronger in 2005–2006, 2011–2012, and 2012–2013 periods. These periods were also characterised strong economic growth; with the source of intensity traced to the industry and the residential sectors. Moreover, resource use plays a modest role in Ghana's energy intensity trends. Closer scrutiny reveals that Ghana has witnessed two significant peak periods of energy intensity including 2005–2006 and then 2012–2013.

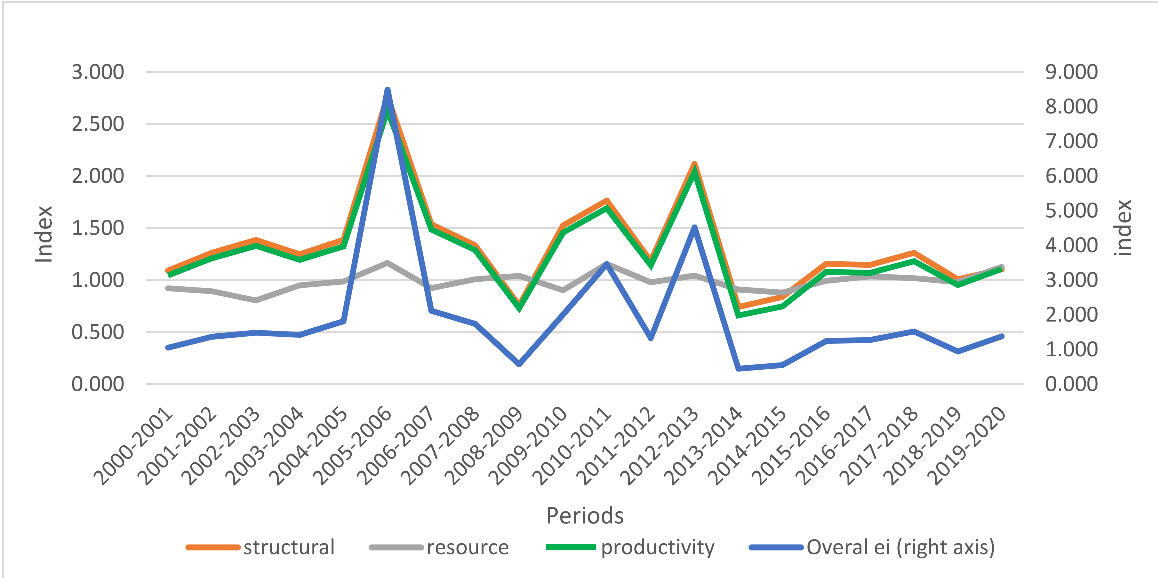

Fig. 1. Decomposition of overall Energy Intensity in Ghana
Source: Authors' own computation.

4.2. *Sectoral Energy Intensity Trends*

The energy intensity trends in the agriculture, industry, service and residential subsectors are displayed in Table A2 in the appendix section. Fig. 2 provide a graphical illustration of the changes in energy intensity for the four sectors. The results show that energy intensity in the industry and residential sectors are high respectively. The general trend shows that residential sector contribution to overall energy intensity was stronger from 2000 to 2007 but was overtaken by the industrial sector from 2007 to 2013. Trends in agriculture sector energy intensity shows a level trend driven largely by structural effect and labour productivity. In the service sector, however, energy intensity largely oscillates driven structural effect, labour productivity and resource use efficiency. The residential energy intensity has also been oscillating driven by resource use and structural effect respectively when it is rising but by labour productivity and structural change when adjustment in energy intensity is downward-sloping. Further, it is observed that adjustment in intensity in the industry sector has been strong, peaking in 2004–2005, 2010–2011 and 2012–2013.

4.3. *Econometric results*

The description and summary statistics of all the variables used in the econometric analysis are presented in Table 1. The study included the following macroeconomic covariates in the estimation; investment, CO_2 emissions, real GDP, exchange rate and private sector credit growth, deposit rate and M2+. All the variables are in their natural logs.

4.3.1. *Diagnostic tests (Unit root test, cointegration, stability test results)*

The study adopted the Dickey-fuller generalised least square method to conduct the unit root test (DF-GLS) due to its superior properties in small sample size data set. As reported on Table 2, the series became

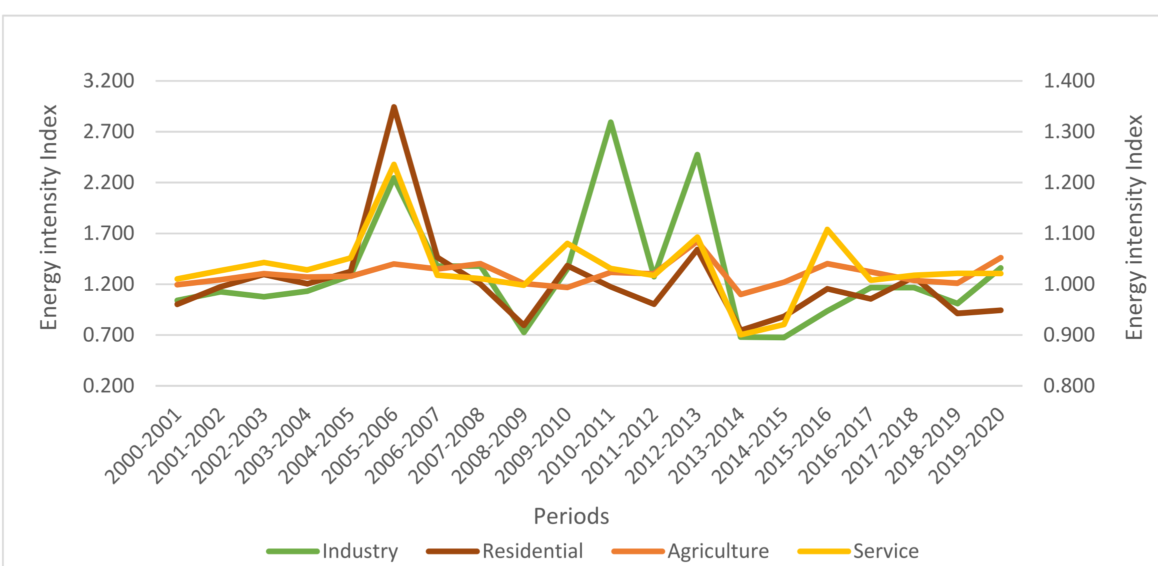

Fig. 2. Sectoral Energy Intensity Trends in Ghana.
Source: Authors' own computation.

stationary after first difference. We then used the ARDL bounds cointegration test to evaluate the existence of long-run relationships. Our test results show that the F-bound test and T-bound test values were greater than the *I (1)* critical values confirming the existence of stable long-run equilibrium relationship among the variables (See Tables 3–8). Our diagnostic test results show that our models do not suffer from heteroscedasticity, autocorrelation or serially correlated error terms (Tables 3–8). The Hansen parameter stability test results also revealed that the coefficients are stable over time (see Table A3 and A4 in the appendix section).

Table 5
Asymmetric ARDL results – dependent variable: Adjusted WDI energy intensity.

	NARDL (1)	NARDL (2)	NARDL (3)	NARDL (4)
$\_ECM_{t-1}$	−0.569 (0.126)***	−0.688 (0.301)**	−0.734 (0.256)***	−0.569 (0.059)***
$\_X^{+}_{t-1}$	0.425 (0.156) ***	−0.560 (0.154)***	0.482 (0.561)	1.264 (0.364) ***
X^{-}_{t-1}	0.632 (0.308) **	−1.325 (0.787)**	−2.321 (1.852)	1.016 (0.536) **
ΔY_{t-1}	−1.125 (0.362)***	0.232 (0.365)	0.236 (0.232)	0.264 (0.394)
ΔY_{t-2}	−0.045 (0.011)***	0.451 (0.256) *		0.601 (0.156) ***
ΔY_{t-3}	−0.121 (0.009)**			
ΔX^{+}	1.101 (0.536) **	−0.922 (0.046)***	−1.201 (0.661)**	−0.488 (0.291)*
ΔX^{+}_{t-1}	−0.364 (0.310)	−0.645 (0.459)*	−1.526 (0.521)***	1.369 (0.892)
ΔX^{+}_{t-2}	−0.810 (0.309)**	−0.895 (0.251)***	−1.009 (0.458)**	−0.500 (0.311)
ΔX^{+}_{t-3}	−1.256 (0.456)***	−0.326 (0.129)**		
ΔX^{-}	−0.559 (0.639)	−0.582 (0.331)*	0.892 (0.621)	1.183 (0.711) *
ΔX^{-}_{t-1}	−0.899 (0.331)**	1.369 (0.892)	1.005 (0.694) *	1.059 (0.429) **
ΔX^{-}_{t-2}	−1.260 (0.502)**	0.661 (0.672)	0.268 (0.358)	0.593 (0.091) ***
ΔX^{-}_{t-3}	−0.457 (0.402)			
ln Exchange		−1.156 (0.159)***	−1.477 (0.552)**	−1.261 (0.360)***
ln RGDP		−0.852 (0.401)*	−0.482 (0.102)***	−1.202 (0.159)***
ln Deposit	0.412 (0.213) **		0.963 (0.236) ***	
ln Pcrdt				−0.596 (0.126)***
ln CO_2	1.362 (0.891) *		0.702 (0.202) ***	0.530 (0.072) ***
ln Consump	0.569 (0.265) ***	0.808 (0.523) *	0.531 (0.222) **	0.361 (0.108) *
ln IVA	−0.303 (0.089)***	−0.963 (0.458)**	−0.351 (0.189)*	
ln Crude			−0.362 (0.115)**	−0.854 (0.968)
Constant	1.926 (0.892) **	−2.556 (0.452)***	−3.932 (1.028)***	1.301 (0.691) **
R-sq.	0.991	0.935	0.870	0.962
Adj. R-sq.	0.966	0.816	0.718	0.894
AIC	−50.701	32.821	15.391	28.391
BIC	−26.762	48.962	38.921	50.365
Log-likelihood	38.321	15.691	5.294	18.361
Prob > F	0.000	0.000	0.000	0.000
Observations	29	29	29	29

Note: *, ** and *** denote significant at 1%, 5% and 10% levels respectively. Standard Errors in Brackets. The shock variables examined in the selected models for NARDL (1–4) are the share of renewable energy, demand for rural electricity, industrialisation, and digitisation respectively. The null hypothesis for Jarque-Berra (JB) test is that errors are normal. The null hypothesis for the Breusch-Godfrey Serial Correlation LM test is that there is no problem of serial correlation. The null hypothesis for the Ramsey RESET test is that the model is correctly specified. And, the models pass all diagnostic tests.

Table 6
Asymmetric model diagnostic statistics – dependent variable: Adjusted WDI energy intensity.

	NARDL (1)	NARDL (2)	NARDL (3)	NARDL (4)
L_X^P f-stat	12.026*** 20.08	10.021** 15.02	9.362** 19.69	10.641*** 11.26
L_X^N f-stat	−8.059*** 22.36	−4.209*** 23.31	−1.691 0.826	13.020** 16.361
Wald-LR	12.31 [0.000] **	9.632 [0.001] ***	22.06 [0.001] ***	6.394 [0.003] ***
Wald-SR	0.282 [0.107]	14.190 [0.001]*	10.258 [0.000]**	2.369 [0.004] **
F_PSS	56.456	14.561	10.118	20.101
CHSQ-SC	11.261 [0.269]	15.698 [0.452]	19.362 [0.636]	19.660 [0.202]
CHSQ-HET	0.009 [0.990]	0.008 [0.848]	0.601 [0.440]	0.695 [0.411]
CHISQ-FF	0.326 [0.789]	2.361 [0.364]	0.897 [0.569]	1.019 [0.459]
CHSQ-NOR	2.326 [0.285]	1.025 [0.615]	3.442 [0.377]	0.105 [0.802]

NOTES: L_Y^+ and L_Y^- denote the long-run coefficients associated with positive and negative changes of output, respectively. W_{LR} refers to the Wald test for long-run symmetry while W_{SR} denotes the Wald test for short-run symmetry condition [23]. 5% critical values for F_PSS are −3.23 and 4.35 for k = 3 and k = 2, respectively. The shock variables examined in the selected models for NARDL (1–4) are the share of renewable energy, demand for rural electricity, industrialisation, and digitisation respectively. The null hypothesis for Jarque-Berra (JB) test is that errors are normal. The null hypothesis for the Breusch-Godfrey Serial Correlation LM test is that there is no problem of serial correlation. The null hypothesis for the Ramsey RESET test is that the model is correctly specified. And, the models pass all diagnostic tests.

4.3.2. *Nonlinear ARDL estimation results*

The nonlinear ARDL model was used to examine the effect of economic-technical factors on energy intensity in Ghana from 1990 to 2020. We partitioned our results into three. First, we examine the dynamic effect of economic-technical factors on energy intensity accounting for asymmetric effect (Tables 3–8). Second, we explored the pass-through effect of economic technical factors on energy intensity (Table A5 – A8 in the supplementary appendix), through the household consumption, and labour productivity channels. Finally, we test the robustness of the results by employing a revised measure of energy intensity that incorporates resource use efficiency and productivity (Tables 5and6); and energy consumption as another dependent variable to explore the effect of the economic-technical factors (see Tables 7and8). Second, we employed the traditional ARDL (see Table A3-A4 in the online appendix).

Starting from the models with asymmetric effects (Table 3), it is identified that in the long run dynamic adjustments in renewable energy consumption and rural electrification, tend to have significant effect on energy intensity in Ghana. On the other hand, both negative and positive changes in digitisation have a negative and significant effect on energy intensity in the long run. Table 4 supports the observed long run asymmetric effect of renewable energy consumption and digitisation on energy intensity. The evidence however reveals that excluding industrialisation, all the economic-technical factors have a long run impact on energy intensity.

We found that exchange rate has a significant negative effect on energy intensity. As expected, an increase in real GDP was also found to have a negative effect on energy intensity. However, an increase in the deposit rate has a significant positive effect on energy intensity. The result also shows that an increase in private sector credit increases aggregate energy intensity. The positive response of energy intensity to private sector growth underscores the need for more policy focus of

Table 7
Asymmetric ARDL results – dependent variable: Energy consumption.

	NARDL (1)	NARDL (2)	NARDL (3)	NARDL (4)
$\_ECM_{t-1}$	−0.344 (0.146)**	−0.485 (0.184)**	−0.638 (0.191)***	−1.475 (0.217)***
$\_X^{+}_{t-1}$	0.216 (0.135)	−0.057 (0.091)	−0.079 (0.078)	−0.151 (0.027)***
X^{-}_{t-1}	0.175 (0.067)**	−0.336 (0.054)***	0.002 (0.113)	−2.777 (0.955)**
ΔY_{t-1}	−0.309 (0.401)	−0.631 (0.173)***	0.119 (0.201)	0.162 (0.136)
ΔY_{t-2}	−0.443 (0.398)	−0.494 (0.138)***		0.078 (0.136)
ΔY_{t-3}	−0.261 (0.216)			
ΔY_{t-4}	0.437 (0.209)*			
ΔX^{+}	0.997 (0.568)	0.081 (0.059)	−0.122 (0.065)*	−0.217 (0.057)***
ΔX^{+}_{t-1}	0.756 (1.378)	0.221 (0.057) ***	0.051 (0.055)	−0.006 (0.089)
ΔX^{+}_{t-2}	0.441 (1.007)	0.107 (0.061)	−0.012 (0.055)	0.129 (0.036) ***
ΔX^{+}_{t-3}	2.286 (0.961)*	−0.045 (0.031)		
ΔX^{-}	1.127 (0.515)*	−0.047 (0.031)	0.189 (0.059) ***	−1.094 (0.095)***
ΔX^{-}_{t-1}	0.677 (0.205)***	0.248 (0.076) ***	0.046 (0.068)	0.058 (0.944)
ΔX^{-}_{t-2}	1.335 (0.583)*	0.349 (0.061) ***	0.060 (0.055)	0.286 (0.802)
ΔX^{-}_{t-3}	−0.385 (0.583)	0.260 (0.082) **		
ln Exchange		−0.167 (0.107)	−0.092 (0.035)**	−0.119 (0.029)***
ln RGDP		−0.056 (0.039)	−0.048 (0.024)**	−0.081 (0.039)*
ln Deposit	0.110 (0.049)*		0.116 (0.031) ***	
ln Pcrdt				0.264 (0.073) ***
ln CO_2	−0.276 (0.125)*		0.137 (0.069) *	0.169 (0.079) *
ln Consump	0.197 (0.076)*	0.299 (0.108) *	0.258 (0.098) **	0.364 (0.133) **
ln IVA	−0.097 (0.043)*	- 0.023 (0.008)**	−0.099 (0.032)***	
ln Crude			−0.055 (0.017)**	−0.062 (0.013)***
Constant	−5.181 (3.411)*	5.246 (2.612)	2.439 (1.356) *	0.921 (0.165) ***
R-sq.	0.935	0.925	0.881	0.946
Adj. R-sq.	0.729	0.782	0.732	0.850
AIC	−107.806	−114.049	−111.598	−118.675
BIC	−82.644	−90.723	−90.283	−97.286
Log-likelihood	73.903	75.024	71.799	76.337
Prob > F	0.034	0.004	0.002	0.001
Observations	29	29	29	29

Note: *, ** and *** denote significant at 1%, 5% and 10% levels respectively. Standard Errors in Brackets. The shock variables examined in the selected models for NARDL (1–4) are the share of renewable energy, demand for rural electricity, industrialisation, and digitisation respectively. The null hypothesis for Jarque-Berra (JB) test is that errors are normal. The null hypothesis for the Breusch-Godfrey Serial Correlation LM test is that there is no problem of serial correlation. The null hypothesis for the Ramsey RESET test is that the model is correctly specified. And, the models pass all diagnostic tests.

existing energy efficiency programmes on the private sector; particularly small and medium scale enterprises. The result also suggests that a rise in CO_2 emissions increases in energy intensity.

The plots demonstrating the dynamic adjustment of overall energy intensity to positive and negative shocks to economic-technical factors for the long-run are not identical (see Figure B in the appendix section).

Table 8
Asymmetric model diagnostic statistics – dependent variable: Energy consumption.

	NARDL (1)	NARDL (2)	NARDL (3)	NARDL (4)
L_X^P f-stat	6.276* 4.357	−0.117 0.297	−0.125 1.275	0.102*** 29.2
L_X^N f-stat	−5.076** 4.915	0.693*** 10.89	−0.003 0.000	1.882*** 13.49
Wald-LR	21.701 [0.011]**	12.91 [0.006] ***	0.872 [0.369]	12.1 [0.007] ***
Wald-SR	0.433 [0.535]	18.34 [0.002] ***	13.769 [0.006]***	10.42 [0.042] **
F_PSS	5.144	14.081	7.151	18.421
CHSQ-SC	14.94 [0.185]	14.21 [0.221]	8.272 [0.602]	12.02 [0.344]
CHSQ-HET	0.105 [0.745]	2.242 [0.124]	0.158 [0.691]	0.669 [0.413]
CHISQ-FF	2.137 [0.274]	2.508 [0.133]	6.398 [0.138]	0.731 [0.570]
CHSQ-NOR	1.173 [0.556]	0.305 [0.858]	1.033 [0.597]	0.216 [0.898]

NOTES: L_Y^+ and L_Y^- denote the long-run coefficients associated with positive and negative changes of output, respectively. W_{LR} refers to the Wald test for long-run symmetry while W_{SR} denotes the Wald test for short-run symmetry condition [23]. 5% critical values for F_PSS are −3.23 and 4.35 for k = 3 and k = 2, respectively. The shock variables examined in the selected models for NARDL (1–4) are the share of renewable energy, demand for rural electricity, industry value added per worker, industrialisation, private consumption and digitisation respectively. The null hypothesis for Jarque-Berra (JB) test is that errors are normal. The null hypothesis for the Breusch-Godfrey Serial Correlation LM test is that there is no problem of serial correlation. The null hypothesis for the Ramsey RESET test is that the model is correctly specified. And, the models pass all diagnostic tests.

4.3.3. *Test of macroeconomic transmission mechanism*

Next, we examine the potential pass-through of economic-technical drivers into energy intensity using labour productivity and household consumption. We conducted this investigation by decoupling the effect of economic-technical factors on energy intensity and scrutinised the contribution of the pass-through elasticity of each factor on the overall energy intensity. We measure the pass-through elasticity as the product of the cumulative dynamic adjustment effect of a unit change in each technical factor on consumption and labour productivity and the aggregate dynamic effect of consumption and labour productivity on energy intensity. This gives the percentage of pass-through. This is represented mathematically as:

$$P_{ath} = \frac{\sum\sum \frac{\partial g_{t+i}}{\partial x_t} \bullet \frac{\partial y_{t+i}}{\partial g_t}}{\sum \frac{\partial y_{t+i}}{\partial x_t}} \times 100 \tag{10}$$

The evidence revealed that a 1% reduction in the share of renewable energy in total energy consumption will cause a 1.5% reduction in labour productivity (Table A5-A8: supplementary appendix). However, in the short-run period, industry value added per worker is more sensitive to positive shocks to renewable energy consumption. The dynamic effect of labour productivity on energy intensity is also stronger in the long-run period than the short run and implies that the transmission effect of renewable energy consumption on labour productivity is significant. The degree of pass-through suggest that 13.23% of the impact of negative changes in renewable energy consumption on overall energy intensity is transmitted through the labour productivity channel. This reduces to 6.48% for every 1% positive change to the technical factor.

Similarly, the results revealed that electrification and digitisation have a significant relationship with labour productivity. Positive dynamic changes in digitisation exhibited a stronger effect on labour productivity. The pass-through effect is also found to be significant in the long run period with 11% of the impact of positive shocks to digitisation on energy intensity transmitted through labour productivity. However, the effects of positive and negative adjustment in rural electrification on overall energy intensity are significantly transmitted through labour productivity with a pass-through elasticity of 8% and 9% respectively. Additionally, the evidence suggests a significant effect of positive changes in renewable energy consumption and rural electrification on consumption in the long run period; whereas the positive and negative changes in digitisation also significantly influence household consumption. The effect of shocks to technical factors on consumption in the short run is insignificant.

4.3.4. Robustness checks

We tested the robustness of the results by using energy consumption and an adjusted energy intensity measure. The results as displayed on Tables 5–8 were generally consistent with the baseline results. As shown in Tables A3-A4 in the supplementary appendix section, the results are largely similar to the main results; suggesting that our results are robust to model specification.

5. Discussion and concluding remarks

This work examined the primary sources and determinants of energy intensity in Ghana. The study provided the energy intensity decomposition analysis using the multiplicative LMDI over the period, 2000–2020. This was subsequently unpacked to inspect sectoral energy intensity decompositions over the same sample period. The nonlinear ARDL and traditional ARDL models were then applied to investigate the impact of renewable energy consumption, industrialisation, rural electrification and digitisation on aggregate energy intensity. The transmission effects of the macroeconomic economic-technical factors on labour productivity and household consumption were also examined in this present study. The decomposition analysis results revealed that aggregate energy intensity has an oscillating structure.; with the residential and industry sector as key sources of intensity.

Focusing on the impact of economic-technical factors, the evidence suggests an asymmetric dynamic effect of renewable energy consumption, digitisation and rural electrification in the long and short run periods. The evidence also shows the importance of labour productivity and household consumption to overall energy intensity since they act as channels through which renewable energy consumption, digitisation and rural electrification exert an indirect effect on overall energy intensity. The study recommends that government's development agenda must focus on producing an eco-friendly infrastructure. Government intention to introduce electric trains, improve public transport system, build solar and wind energy infrastructure has so far remained rhetoric. Rather there is an increasing reliance on thermal energy and fossil fuel. As a result, existing expansion in technical infrastructure such as rural electrification and industrialisation drive lacks adequate energy-saving technology platforms that can yield significant reduction in energy intensity. There should be a conscious energy saving approach in the development of economic-technical infrastructure that allow citizens to access green innovation products at less cost. Government efforts at promoting the use of clean and modern energy at the household level such as the promotion of liquified petroleum gas and the use of energy-efficient fluorescent bulbs should be improved.

Interestingly, increasing energy prices is driving down adoption over the years. It behoves on government to not only increase awareness, but pursue a local content policy in the production and distribution of some of these energy-saving technologies to drive down prices and revive uptake. Government subsidies will be needed to build up these infrastructures in order to encourage adoption of energy-saving products while also enhancing access. In order to successfully secure sufficient supply of energy-saving infrastructure that will reduce global warming, developing and low-income countries, such as Ghana, would need a long-term policy emphasis on building a resilient renewable energy ecosystem, [27]. Globally, developing nations account for a modest and decreasing portion of the world's overall production and use of renewable energy [28]. Several developing countries including Ghana have an underdeveloped renewable energy sector despite efforts to achieve the SDG 7. The government of Ghana recently passed the Ghana's Renewable Energy Master Plan (REMP) in 2019 with the intention to incentivise private sector investment in green technology and advance the country's movement towards energy transition. Until now, there has been a slow progress in its implementation. A key provision in the REMP which requires government to provide tax and import exemptions to private energy developers in renewable energy production is laudable and must be realised.

6. Limitation and suggestion for future research

Even though this study contributes immensely to both literature and policy issues, it is not without some limitations. First, the study failed to incorporate the issue of energy transition and estimate its impact on energy intensity in Ghana. Even though the study includes renewable energy in the estimation, it could not categorize the major types of renewable energy, their spatial distribution and the structural decomposition of energy intensity. This will provide a guide to effectively assess how energy transition issues impact energy intensity.

Second, this study could not include trade, an important variable that determines energy intensity and its decomposition. Owning to the importance of trade in economic growth, it is expected its interaction with growth can lead to a reduction in energy intensity and therefore influence trade policy toward the production and exports of non-energy intensity commodities. Thus, future studies should consider including these variables to unearth and provide a broad understanding of the drivers of energy intensity in Ghana.

Authors contributions

All authors (Eric Fosu Oteng-Abayie, John Bosco Dramani, Frank Adusah Poku, Kofi Amanor, and Jonathan Dagadu Quartey) have equally contributed at each stage of developing the manuscript, including the topic, problem statement, literature reviews, methodology, data collection and analysis, and conclusions, each of us made some substantial contributions.

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.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esr.2023.101090.

Appendix

Table A1
Decomposition of Ghana's energy intensity from 2000 to 2020

	Overall EI	Structural Effect	Resource use Effect	Labour productivity Effect
2000–2001	1.054	1.093	0.922	1.047
2001–2002	1.370	1.264	0.895	1.211
2002–2003	1.486	1.387	0.806	1.330
2003–2004	1.422	1.249	0.951	1.196
2004–2005	1.819	1.389	0.988	1.326
2005–2006	8.497	2.767	1.166	2.633
2006–2007	2.116	1.539	0.925	1.487
2007–2008	1.739	1.336	1.010	1.290
2008–2009	0.576	0.757	1.042	0.731
2009–2010	2.007	1.526	0.903	1.457
2010–2011	3.461	1.767	1.158	1.692
2011–2012	1.328	1.186	0.979	1.144
2012–2013	4.525	2.120	1.045	2.042
2013–2014	0.448	0.743	0.911	0.662
2014–2015	0.552	0.839	0.880	0.748
2015–2016	1.247	1.159	0.995	1.081
2016–2017	1.274	1.147	1.037	1.070
2017–2018	1.523	1.263	1.020	1.182
2018–2019	0.944	1.009	0.980	0.954
2019–2020	1.382	1.104	1.129	1.108

Source: Authors' own computation based on data from the Energy Commission – Ghana and World Development Indicators.

Table A2
Decomposition of sectoral energy intensity from 2000 to 2020

	Agriculture	Service	Industry	Residential
2000–2001	0.999	1.010	1.041	1.003
2001–2002	1.009	1.027	1.126	1.174
2002–2003	1.021	1.043	1.077	1.296
2003–2004	1.014	1.028	1.132	1.204
2004–2005	1.016	1.052	1.286	1.324
2005–2006	1.040	1.236	2.246	2.944
2006–2007	1.030	1.018	1.378	1.465
2007–2008	1.041	1.011	1.378	1.200
2008–2009	1.001	0.998	0.725	0.795
2009–2010	0.994	1.080	1.352	1.382
2010–2011	1.024	1.031	2.793	1.174
2011–2012	1.021	1.017	1.274	1.004
2012–2013	1.085	1.093	2.475	1.542
2013–2014	0.980	0.901	0.679	0.747
2014–2015	1.004	0.921	0.676	0.883
2015–2016	1.040	1.108	0.936	1.155
2016–2017	1.024	1.008	1.168	1.056
2017–2018	1.007	1.017	1.168	1.272
2018–2019	1.002	1.021	1.010	0.914
2019–2020	1.052	1.021	1.361	0.945

Source: Authors' own computation based on data from the Energy Commission – Ghana and World Development Indicators.

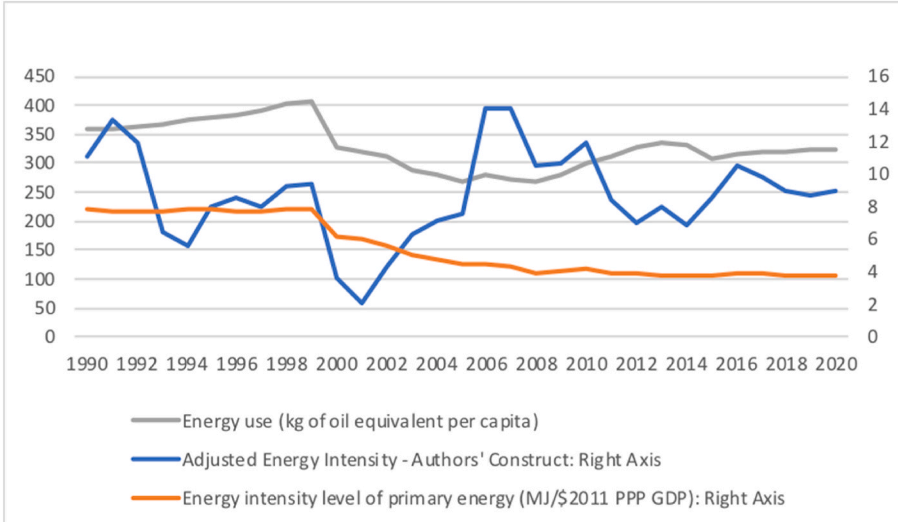

Fig. A. Trends of energy consumption, WDI energy intensity and adjusted energy intensity

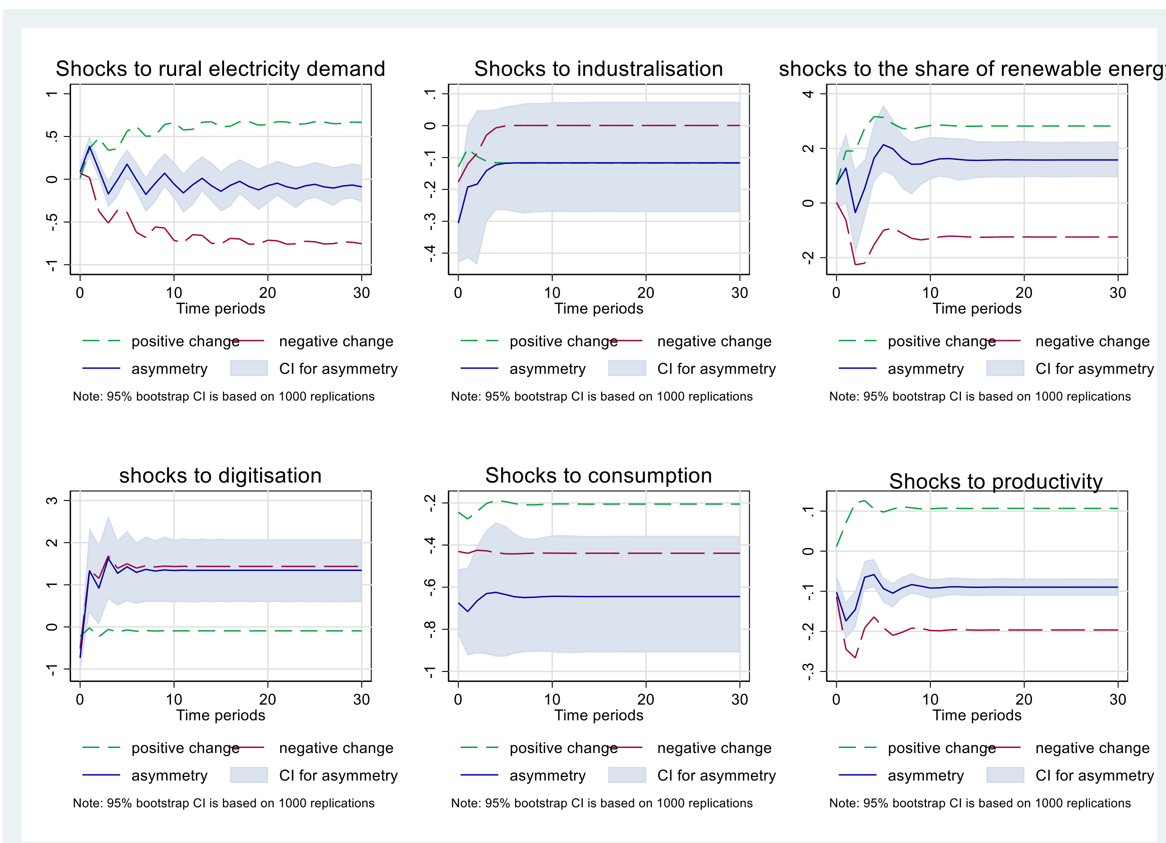

Fig. B. Plot of dynamic multiplier adjustment of energy intensity to shocks to economic-technical factors (Models: NARDL 1–6)

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