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Electricity access and income inequality in South Africa: Evidence from Bayesian and NARDL analyses

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ABSTRACT

Access to modern energy services including electricity is fundamental to fulfilling basic social needs, driving economic growth and fueling human development, hence, the pathway out of poverty to prosperity. This study examined the impact of income level, inequality in the distribution of income and the control of corruption on access to electricity from 1990-2017 in South Africa, using Bayesian and nonlinear autoregressive distributed lag (NARDL) estimation approach. The long-run asymmetric effects of income level reveal a positive impact on electricity access, thus, validating the initial positive symmetric effect. While income inequality has positive effect on accessibility, corruption appears to hinder the roadmap towards achieving energy for all. Even though economic development is crucial to materialize access to electricity, yet, efficient and effective financing and investment climate alone are not enough to warrant energy security, but, right policies, good governance and institutional quality.

1. Introduction

The provision of energy services is essential for promoting employment, health and educational outcomes, the overall quality of public service and quality of life [1]. Many other authors and analysts argue that access to modern energy services is fundamental to fulfilling basic social needs, driving economic growth and fueling human development [2–4]. The statement on the importance of electricity is very instructive [5]:

> "Access to electricity is fundamental to opportunity in this age. It's the light that children study by; the energy that allows an idea to be transformed into a real business. It's the lifeline for families to meet their most basic needs. And it's the connection that's needed to plug Africa into the grid of the global economy. You've got to have power".

The State of the Electricity Access Report suggests that without access to electricity, the pathway out of poverty would be narrow and elongated. Energy is inextricably linked to every other critical sustainable development goals (SDGs) including, for example, health, food security, poverty reduction, and climate change [6]. It is however argued that energy deprivation is a leading contributor to morbidity, political unrest, and environmental instability [7]. Evidently, it gravely threatens the 'energy-haves' as well as the 'have-nots'. It is not surprising that many studies have been conducted to examine the effects of energy and electricity provision on economic growth [8,9] with just a few focusing on poverty and income inequality [10,11]. This gap of limited studies on income inequality-energy nexus and vice versa motivates our study. The objective of the study is to examine the effect of electricity access on income inequality in South Africa. With all the benefits associated with electricity access, the big question is how it impacts income inequality in South Africa. South Africa provides a perfect case as the most developed country in the SSA region with one of highest access to electricity. Yet, has very high-income inequality in the subregion and the world [12] after abolishing the Apartheid regime [13]. The authors observe that high inequality acts as a brake on poverty reduction.

The average access rate for SSA was 35% in 2014, while South Africa had 86% with the rural being 85% and urban 87% as of 2014. South Africa is strikingly different from other SSA countries because they exhibit urban bias in electrification as the ratio between urban-rural access to electricity is about 3.5 times. The SSA rural electrification rate is 14%, which is significantly lower than any other region [14–16]. Only Cape Verde (96%) Mauritius (100%) and Seychelles (98%) have a

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higher rate of electricity access [1]. Of the 634 million without access to electricity in SSA, only eight (8) million are in South Africa. It is not surprising therefore that the sixth round of the Afrobarometer report indicates that only 5% in South Africa suggest that access to electricity is not a problem [5]. A case study on South Africa is timely and necessary, because in 1993, only a third of the population (36%) had access to electricity [17], however, the dramatic increase to over 80% is worth examining, especially with respect to its effect on income distribution.

Studying the distributional effects is important because inequality is related to social vices in South Africa [18]. Some studies have also shown a high correlation between inequality and environmental pollution in South Africa [19,20]. Obviously, with one of the highest access to electricity and inequality levels, it is important to examine how access is impacting the distribution of income in the country to provide lessons for the neighbouring countries in the region. Electricity access is a condition for economic development, poverty alleviation and reducing inequalities [21], hence, a focus on income inequality is therefore in the right direction.

The motivation of the study stems from the energy justice literature which calls for the distribution of benefits and losses of energy services across all members of society regardless of one's status. A discussion of distributional impacts of electricity is important because of its negative effects [9,22] and the political economy implications. The political interest is associated with the view that reforms can be enforced more easily when they contribute to the social justice of society [23]. The issue of politics and political corruption has been noted as a big issue in the power sector in many African countries and more recently in South Africa. Accordingly, to improve the estimates in our model, we control for corruption in South Africa. This is consistent with previous findings that government ineffectiveness hinders electricity access in many developing countries [24]. To deal with this problem, we include the control of corruption variable to reduce any bias in the estimates. The variable for the control of corruption measures the transparency of the political system in recognizing the needs of different groups of people and more importantly how they participate in the decisions concerning the supply of energy. This helps to capture the three concepts (distribution, procedural, and recognition) espoused as key components of the energy justice framework [25,26]. To achieve the research objective, we employ Bayesian and nonlinear autoregressive distributed lag (NARDL) estimation techniques to examine the impact of electricity access on income inequality over the period 1990–2017.

The rest of the study is organized as follows. Section two presents a brief review of the literature after which the methodology employed is described. The results are then discussed, conclusions given, and policy implications offered.

2. Literature review

The energy - development nexus has become topical in recent times with contrasting results. Some studies show positive effects of electricity access while others suggest that the effect is either negative, negligible or even nonexistent. The World Bank [27] noted that energy access is at the heart of development because of the many benefits especially in SSA, including improved health care, school operations, economic development and air quality [17,28].

Electrification of poor communities has resulted in several additional benefits including the involvement of schools in evening adult education, and improved efficiency of school operations through the use of equipment, such as photocopiers and computers. An increase in rural electrification is associated with higher youth literacy rates by upgrading in-school and domestic learning facilities [14]. Access to electricity promotes development through job creation, improvement in education, and gender equality. The reduction in production and transaction costs through access to roads has been a key determinant of income convergence for the poorest regions [29]. In certain cases, electric street lighting may have contributed to reduced crime levels. This is evidential in the intermediate commodity role played by energy, therefore, progress on access to electricity is not just an end but as a means towards achieving other SDGs [21].

The benefits of electrification are associated with increased access to productive opportunities, through reducing transaction costs and thereby leading to industrial development, which helps to increase the value of assets of the poor and therefore reduces income inequality [30–32]. This effect is more pronounced if access is developed in regions that lack facilities and face resource constraints, as they may manage to exploit the new production possibilities [33]. Thus, improving access could improve human capital which then increases job opportunities and productivity [34,35]. On the contrary, if access improves in areas that are already abundant in physical and human capital, then infrastructure could adversely affect inequality.

Improving access to electricity is a key channel through which gender inequality is reduced — as households with access to electricity are able to free up time otherwise spent on cooking and lighting [36]. Gender-based inequality in education in Africa depends on electricity supply, access to water and improved sanitation [37]. The availability of basic services facilitates the execution of domestic chores, hence, free up time for girls and women to pursue educational opportunities. Accordingly, the progress of women in Africa is significantly retarded by the overburden of domestic chores [37]. The extra time could then be spent at work through self-employment or micro-enterprises. As noted, the excess time in many rural communities could enable additional agricultural and non-agricultural income-generating activities, and advance rural productivity [38]. Improving access to electricity enhances the welfare of both men and women but notes that the effect on gender parity is unclear and therefore calls for empirical studies to validate these findings [39].

Access to electricity is interconnected through complex causal relations with multiple dimensions of socio-economic development through income-generating activities, market production and revenues, household economy, local health and population, education, and habits and social networks [40]. However, when considering the impact of infrastructure countries where weak governance, distorted public investment choices, and corruption are a reality, the benefits of infrastructural expansion that result in higher growth are not necessarily equally shared and could result in increased inequality [32]. Thus, access to electricity has a positive impact on the distribution when supported by a balance in the overall economy [41]. At the micro-level, the creation of electricity-reliant firms in regions with access in rural Benin has been a clear positive effect of electrification [42], while in South Africa, 40% and 53% increase in small, medium and micro-enterprises uptake is attributable to the grid rollout [43]. A study demonstrated that 25% of households with electricity operated a home business compared to about 15% of households without electricity [44]. Complementary measures that sensitize firms about the implications of a grid connection are critical to program success [42]. On the other hand, the opposite effect that urban-rural income inequality is negatively related to electricity consumption does exist. Income disparity was found to negatively impact per capita electricity consumption in some regions [45]. However, the relationship between electricity access and income inequality depends on the level of development and is context-driven [46]. The benefits from improved access may have accrued more to the already rich in terms of better investment opportunities which leads to higher returns that translate into more consumption inequality [47]. Interestingly, the results show that improvement in expenditure on social services helps bring convergence through reduced interpersonal inequality.

The complex nature of the relationship between access and development indicates that the use of ordinary linear or predefined sets of relationship does not describe the relationship accurately ([48]; p.666). The simple deterministic relations between electricity access and development outcomes do not reflect reality ([49], p. 301) but the presence of multiple interface and feedback that shape outcome in electrification processes [15]. As long as a majority of people live below the poverty line, the potential for beneficial dynamics between electricity access and local business and industrial development would be very limited [50]. The nexus between electricity use and rural socio-economic development has dynamic components, which suggest that the nexus is characterized by complex feedback that can reinforce or balance impacts over time [51].

Though it is difficult to imagine real development without electrification, but the mere presence of electricity is by no means a guarantee for development. Various other conditions and services such as 'soft and hard infrastructure' must be present to stimulate economic growth and income generation [52]. There must be enabling environment or complementary actions for infrastructure more generally and electricity access more specifically to have the desired positive effect [11,48]. These supportive activities lead to a virtuous circle of development in the long-run, especially for the rural folk. In a related study, it was observed that the effect is dependent on more judicious planning, formulation, and evaluation of rural electrification programmes [53]. The socio-economic benefits of providing people with access to electricity in rural areas seemed to be overestimated. But poor institutions enhance the opportunities for private gain at the expense of provision of public goods which could result in a negative effect of the improved access [54]. Thus, political institutions play a critical role in electricity access – inequality nexus. Specifically, democracy such as strong opposition and effective institutions as intervening mechanisms — is associated with decreasing urban electrification inequality while increasing rural electrification [14].

Considering the studies reviewed, we contribute to the literature and global debate on universal electricity access by examining how both political and economic factors influence the electricity access – income inequality relationship in South Africa over the period 1990–2017. The methodology employed helps to reduce omitted variable bias, and endogeneity bias. Contrary to the frequentist estimation techniques which consider parameters as unknown nonetheless fixed quantities, the Bayesian techniques consider parameters as random quantities. Hence, it combines prior knowledge and evidence from the observed data producing credible results for statistical inferences. The data and methodology employed to achieve the research objectives are described next.

3. Materials and methods

In this section, we present the characteristics and source of data employed in the study, with a subsequent synopsis of the model estimation methods.

3.1. Data

To incorporate the concept of sustainable development and meet the research objectives, we adopt four data series based on the Sustainable Development Goals (SDGs) 7, 8, 10 and 16. According to SDG 7, ensuring access to modern, reliable, affordable and sustainable energy technologies is critical for the eradication of poverty through the improvements in health and wellbeing, food production, water supply, education, climate change mitigation and among others [55]. SDG 8 reveals that a sustained economic growth spurs per capita GDP and improves other sectors including energy, health, nutrition, environmental sustainability, thus, accelerates the agenda towards achieving sustainable development [55]. SDG 9 suggests that income inequalities affect the accessibility to other sectors such as health outcomes, energy, food and nutrition, education, water, and sanitation, hence, a decline in the distribution of income is critical for human development [55,56]. Bribery and corruption are global canker undermining development. According to SDG 16, a decline in the prevalence of bribery and corruption is a critical component of good governance and strong political institutions, thus, essential for sustainable development [55,56]. Table 1 presents a description of the study variables. Based on the above justification, the four data series include access to electricity, GDP per capita, Control of Corruption (used as a proxy for measuring corruption) adopted from World Bank [1], while GINI household disposable income is adopted from Solt [57]. Due to data availability, the model estimation of the study is based on a period spanning 1990-2017.

Table 1
Variable description.

Variable	Description	Unit
ELEACESS	Access to electricity (% of the population)	%
GDPPC	GDP per capita	current US$
GINI	GINI Disposable (Net)	Index
CORRUPT	Control of Corruption, Estimate	Index

Table 2
Descriptive statistical analysis of data series.

Statistic	CORRUPT	ELEAC	GDPPC	GINI
Mean	0.3094	75.23287	4684.857	57.8580
Median	0.3017	79.75	4219.377	58.3
Maximum	0.7329	90.8484	7976.466	59.3041
Minimum	−0.1156	57.6	2461.355	55.9
Std. Dev.	0.2785	10.0067	1653.617	1.18432
Skewness	0.0470	−0.3424	0.3955	−0.4028
Kurtosis	1.6485	1.6612	1.8338	1.6289
Jarque-Bera	1.6823	2.6383	2.3165	2.9505
Probability	0.4312	0.2674	0.3140	0.2287
Observations	22	28	28	28
Correlation				
CORRUPT	1			
ELEAC	−0.8708	1.0000		
GDPPC	−0.8117	0.7794	1	
GINI	−0.7566	0.9215	0.7245	1

3.2. Descriptive analysis

Prior to the model estimation, we examined the characteristics of the data series using descriptive statistical analysis presented in Table 2. Table 2 reveals that the mean estimate of corruption control is approximately 0.31. Corruption control is an estimate of governance and ranges from approximately −2.5 (weak) to 2.5 (strong) governance performance. Meaning that corruption control in South Africa is positively skewed, however, visible signs of weak performances have been exposed from 2012 to 2017. The average access to electricity is almost 75% of the population, thus, exhibiting a negative skewness, however, South Africa saw an appreciation of electricity access to almost 91% of the population in 2017. On per capita GDP, the average income level in South Africa is ~US$4,684, showing a significant increase within the past decades (positive skewness). South Africa's mean income distribution is around 58%, showing a decline in income inequality (negative skewness). The kurtosis statistic shows that all the data series exhibit a platykurtic distribution, hence, does not produce outliers. To test for normal distribution, the study adopted the Jarque-Bera test statistic. Evidence from the Jarque-Bera test in Table 2 reveals that the null hypothesis of the normal distribution cannot be rejected, thus, the variables are normally distributed. While the correlation coefficient reveals a negative association between corruption control and other variables, access to electricity exhibits a positive relationship with per capita GDP and income inequality.

3.3. Unit root test

The study performed augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests that the data series have unit root (follows a random walk). Both ADF and PP tests are based on the null hypothesis that the variables contain a unit root, against the alternative hypothesis

Table 3
Unit root tests.

Unit Root	ADF		PP	
	Level	1st Diff.	Level	1st Diff.
ELEAC	−0.8950	−9.0910	−0.6260	−9.3500
	[0.7895]	[0.0000]*	[0.8650]	[0.0000]*
GDPPC	−0.9130	−3.0640	−1.0840	−3.0410
	[0.7837]	[0.0293]*	[0.7212]	[0.0312]*
GINI	−0.7090	−3.1970	−0.7780	−3.1980
	[0.8445]	[0.0202]*	[0.8255]	[0.0201]*
CORRUPT	−1.1140	−3.1610	−1.1330	−3.1120
	[0.7093]	[0.0224]*	[0.7016]	[0.0257]*

[ ] denotes the p-value while * represents the rejection of the null hypothesis at 5% significance level.

that the data series were generated by a stationary process. While ADF employs additional lags of first-differenced variables [58], PP test adopts Newey-West standard errors to control for serial correlation in the regression [59]. Table 3 reveals that the null hypothesis cannot be rejected at a 5% significance level, however, rejected at first-difference. Meaning that the data series are integrated of order one [*I(1)*]. Thus, the data series fulfil the preconditions for testing cointegration using the autoregressive distributed lag (ARDL) bounds test.

3.4. Model estimation

Contrary to previous studies [60–63] that adopted the frequentist econometric models (i.e. where observed data are assumed to be random and estimation parameters are unknown but have fixed quantities), this study employed the Bayesian statistical analysis (i.e. it assumes that the observed data is fixed but the estimation model parameters are random). The Bayesian statistical analysis follows the Bayes rule which provides a formalistic approach of using both prior information and evidence from the data series.

The linear representation of the models can be expressed as:

$$\text{Model 1}: lnELEAC_t = \beta_1 lnGDPPC_t + \varepsilon_t \tag{1}$$

$$\text{Model 2}: lnELEAC_t = \beta_1 lnGDPPC_t + \varepsilon_t lnELEAC_t = \beta_1 lnGINI_t + \varepsilon_t \tag{2}$$

$$\text{Model 3}: lnELEAC_t = \beta_1 lnCORRUPT_t + \varepsilon_t \tag{3}$$

$$\text{Model 4}: lnELEAC_t = \beta_1 lnGDPPC_t + \beta_2 lnGINI_t + \varepsilon_t \tag{4}$$

$$\text{Model 5}: lnELEAC_t = \beta_1 lnGDPPC_t + \beta_2 lnCORRUPT_t + \varepsilon_t \tag{5}$$

$$\text{Model 6}: lnELEAC_t = \beta_1 lnGINI_t + \beta_2 lnCORRUPT_t + \varepsilon_t \tag{6}$$

$$\text{Model 7}: lnELEAC_t = \beta_1 lnGDPPC_t + \beta_2 lnGINI_t + \beta_3 lnCORRUPT_t + \varepsilon_t \tag{7}$$

$$\text{Model 8}: lnELEAC_t = \beta_1 lnGDPPC_t + \beta_2 lnGINI_t + \beta_3 lnCORRUPT_t + \beta_4 (lnGDPPC^{*}lnGINI)_t + \varepsilon_t \tag{8}$$

$$\text{Model 9}: lnGINI_t = \beta_1 lnELEAC_t + \beta_2 lnCORRUPT_t + \varepsilon_t \tag{9}$$

where *ln* denotes logarithmic transformation of the data series, β's are parameters to be estimated, ε represents the random error with a mean of zero and variance σ^2.

For brevity, the specification of the Bayesian linear regression (equations (1)–(9)) based on probability distribution employed in this study is expressed as:

$$y_t \sim N(\beta^T X_t, \sigma^2 I) \tag{10}$$

where y_t is the dependent variable (ELEAC) drawn from a probability distribution (normal Gaussian distribution), X_t is the matrix of the independent variables, β^T is the transposed weight matrix, σ^2 denotes the variance and I is the identity matrix, to give the model a multidimensional formulation.

The Bayesian linear regression model determines the posterior distribution $P(\beta|y_t, X_t)$ of the estimated model parameters generated from a probability distribution based on the inputs and outputs. The Bayes Theorem underpinning Bayesian statistical inferences can be mathematically expressed as:

$$P(\beta|y_t, X_t) = \frac{P(y_t|\beta, X_t)^{*}P(\beta|X_t)}{P(y_t|X_t)} \tag{11}$$

where $P(y_t|\beta, X_t)$ denotes the likelihood of the data series, $P(\beta|X_t)$ represents the prior probability information of the model parameters and $P(y_t|X_t)$ signifies the normalization constant. This model adopts non-informative priors for the model parameter estimation by assuming a normal distribution.

The Bayesian linear regression is implemented in this study using the adaptive random-walk Metropolis-Hastings algorithm available in Giordani and Kohn [64]; Roberts and Rosenthal [65].

After the Bayesian linear regression, the study examined the short- and long-run asymmetric effect of economic growth on access to electricity using NARDL regression model proposed by Shin et al. [66]. Because NARDL is an asymmetric extension of ARDL, the study presents the standard form of the ARDL approach, expressed as:

$$\Delta lnELEAC_t = \delta + \rho lnELEAC_{t-1} + \theta lnX_{t-1} + \sum_{j=1}^{p-1} \alpha_j \Delta lnELEAC_{t-j} + \sum_{j=0}^{q-1} \mu_j \Delta lnX_{t-j} + \varepsilon_t \tag{12}$$

where Δ denotes the first-difference operator, X represents the independent variables, δ represents the intercept, ρ and θ are the long-run coefficient parameters while α_j and μ_j are the short-run coefficient parameters to be estimated, p and q are the corresponding lags of *lnELEAC* and X, and ε denotes the error term in time t. The ARDL bounds testing is based on the null hypothesis of no level relationship ($\rho = \theta = 0$) against the alternative hypothesis of level relationship ($\rho \neq \theta \neq 0$). The ARDL bounds hypothesis is tested using the F-test proposed by Pesaran et al. [67]; however, this study further adopted approximate p-values by Kripfganz and Schneider [68] to corroborate the outcome of the critical values. According to Pesaran et al. [67]; the null hypothesis is rejected if the F statistic is more extreme than critical values for I(1) variables [if p-values < desired level for I(1) variables].

Contrary to the ARDL model which assumes all exogenous data series have a symmetric effect on the dependent variable, we employed NARDL model which assumes otherwise. The NARDL estimation method can be expressed as [66]:

$$\text{Model 10} - \text{I}: lnELEAC_t = \beta^{+} lnGDPPC_t^{+} + \beta^{-} lnGDPPC_t^{-} + u_t \tag{13}$$

where β^{+} and β^{-} are the asymmetric long-run parameters to be estimated, and u_t denotes the error process (i.e. deviations from the long-run equilibrium relationship with a stationary zero-mean).

The vector of the independent variable $lnGDPPC_t$ is decomposed as:

$$\text{Model 10} - \text{II}: lnGDPPC_t = lnGDPPC_0 + lnGDPPC_t^{+} + lnGDPPC_t^{-} \tag{14}$$

where $lnGDPPC_0$ represents a random initial value, $lnGDPPC_t^{+}$ and $lnGDPPC_t^{-}$ are the partial sum process exhibiting the changes (negative and positive) in $lnGDPPC_t$, expressed as:

Table 4
Results of ARDL and NARDL Bounds test for cointegration.

Bounds Test		Significance Level	10%		5%		1%		*p-value*	
		Critical Values	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
	ARDL									
lnELEAC = f(lnGDPPC, lnGINI, lnCORRUPT)	F	15.1070	3.5010	5.0230	4.6590	6.5320	8.1350	10.9600	0.0010	0.0030
lnGINI = f(lnELEAC, lnCORRUPT)	F	7.1050	3.841	5.172	5.064	6.693	8.587	11.020	0.019	0.042
lnELEAC = f(lnGDPPC$^+$, lnGDPPC$^-$)	*NARDL*									
	F_{PSS}	6.9564	2.1700	3.1900	2.7200	3.8300	3.8800	5.3000	–	–

$$\text{Model} \quad 10 - \text{III} \quad : lnGDPPC_t^+ = \sum_{j=1}^{t} \Delta lnGDPPC_j^+$$

$$= \sum_{j=1}^{t} \max \quad (\Delta lnGDPPC_j, \ 0) \tag{15}$$

$$\text{Model} \quad 10 - \text{IV} : lnGDPPC_t^- = \sum_{j=1}^{t} \Delta lnGDPPC_t^-$$

$$= \sum_{j=1}^{t} \min \quad (\Delta lnGDPPC_j, \ 0) \tag{16}$$

Equation (12) is then combined with the linear specification in equation (13) to obtain an ARDL asymmetric error correction model expressed as:

$$\text{Model} \quad 10 - \text{V} : \Delta lnELEAC_t = \delta + \rho lnELEAC_{t-1} + \theta^+ lnGDPPC_t^+ + \theta^- lnGDPPC_t^- + \sum_{j=1}^{p-1} \alpha_j \Delta lnELEAC_{t-j} + \sum_{j=0}^{q-1} \left(\mu_t^+ \Delta lnGDPPC_{t-j}^+ + \mu_t^- \Delta lnGDPPC_{j-t}^- \right) + \varepsilon_t \tag{17}$$

Where $\theta^+ = -\rho\beta^+$ and $\theta^- = -\rho\beta^-$, μ_t^+ and μ_t^- are the short-run adjustments towards positive and negative changes in $lnELEAC_t$. The NARDL model follows the same pathway for testing the null hypothesis ($\rho = \theta^+ = \theta^- = 0$) of no cointegration against the alternative hypothesis ($\rho \neq \theta^+ \neq \theta^- \neq 0$) of cointegration. The next step utilizes the Wald test to examine the long-run asymmetry ($\theta^+ = \theta^-$) and short-run asymmetry ($\sum_{j=0}^{q-1} \mu_{k,\ i}^+ = \sum_{j=0}^{q-1} \mu_{k,\ i}^-$). Finally, we test the disequilibrium following a positive or negative shock in $lnELEAC_t$ using the asymmetric dynamic multiplier effect on $lnELEAC_t$ with a percentage change in $lnGDPPC_t^+$ and $lnGDPPC_t^-$ expressed as:

$$\text{Model} \quad 10 - \text{VI} : m_h^+ = \sum_{j=0}^{h} \frac{\partial lnELEAC_{t+j}}{\partial lnGDPPC_t^+}, \ m_h^- = \sum_{j=0}^{h} \frac{\partial lnELEAC_{t+j}}{\partial lnGDPPC_t^-}, \ h = 0, \ 1, \ldots. \tag{18}$$

As $h \to \infty$, $m_h^+ \to \beta^+$ and $m_h^- \to \beta^-$, where β^+ and β^- represent the positive and negative long-run asymmetric coefficients.

4. Results and discussion

4.1. Cointegration

The unit root test results in Table 3 reveals that the data series has infinite mean and autocovariance and changes over time, hence, follow the first-difference stationary processes. Meaning that the variables are not covariance stationary and require the ARDL cointegration framework for model estimation and statistical inferences. Two data series are cointegrated if each of the series is integrated of order one but a linear combination of them is integrated of order zero. Table 4 presents the cointegration results of the ARDL and NARDL bounds testing approach. For the ARDL model, we utilized Pesaran, Shin, and Smith [67] bounds test via Kripfganz and Schneider [68] critical values and approximate p-values while the NARDL model is based on Shin et al. [66]. Table 4 reveals that both F and t statistics are more extreme than the critical values for *I(1)* variables at 1, 5, and 10% significance level, hence, rejecting the null hypothesis of no level relationship. Meaning that the variables under investigation are cointegrated (both symmetric and asymmetric cointegration).

Table 5
Results of Bayesian estimation approach.

Models	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
lnGDPPC	0.5133* [0.0027]			0.2695* [0.0542]	0.5242* [0.0069]		0.0962* [0.0807]	−2.6136* [0.8284]	
lnGINI		1.0626* [.0060]		0.5053* [0.1122]		1.0446* [0.0083]	0.8534* [0.1606]	1.1020* [0.1459]	
lnCORRUPT			−2.3764* [0.4349]		0.0538* [0.0397]	−0.0752* [0.0227]	−0.0505* [0.0299]	−0.0183* [0.0248]	0.0699* [0.0219]
lnGDPPC_lnGINI								0.6382* [0.1938]	
lnELEAC									0.9563* [0.0075]
Model Diagnostics									
σ^2	0.0146* [0.0043]	0.0155* [0.0045]	7.3672* [2.7801]	0.0078* [0.0023]	0.0194* [0.0074]	0.0070* [0.0030]	0.0067* [0.0029]	0.0038* [0.0015]	0.0064* [0.0026]
MCMC iterations	30,000	30,000	30,000	30,000	30,000	30,000	30,000	30,000	30,000
Burn-in	20,000	20,000	20,000	20,000	20,000	20,000	20,000	20,000	20,000
MCMC sample size	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Number of obs	28	28	18	28	18	18	18	18	18
Acceptance rate	0.4349	0.4429	0.4447	0.3790	0.3190	0.3524	0.3339	0.3476	0.3433
Efficiency	0.2076	0.2003	0.1818	0.1240	0.1035	0.1080	0.0694	0.0745	0.1119
Log (ML)	5.8946	5.6087	−51.7324	7.9496	−10.3754	−1.1279	−7.3418	−8.7488	−0.7572

Note: * denotes the rejection of the null hypothesis at 5% significance level, Marginal likelihood (ML) is computed using Laplace-Metropolis approximation; [ ] denotes Standard Deviation.

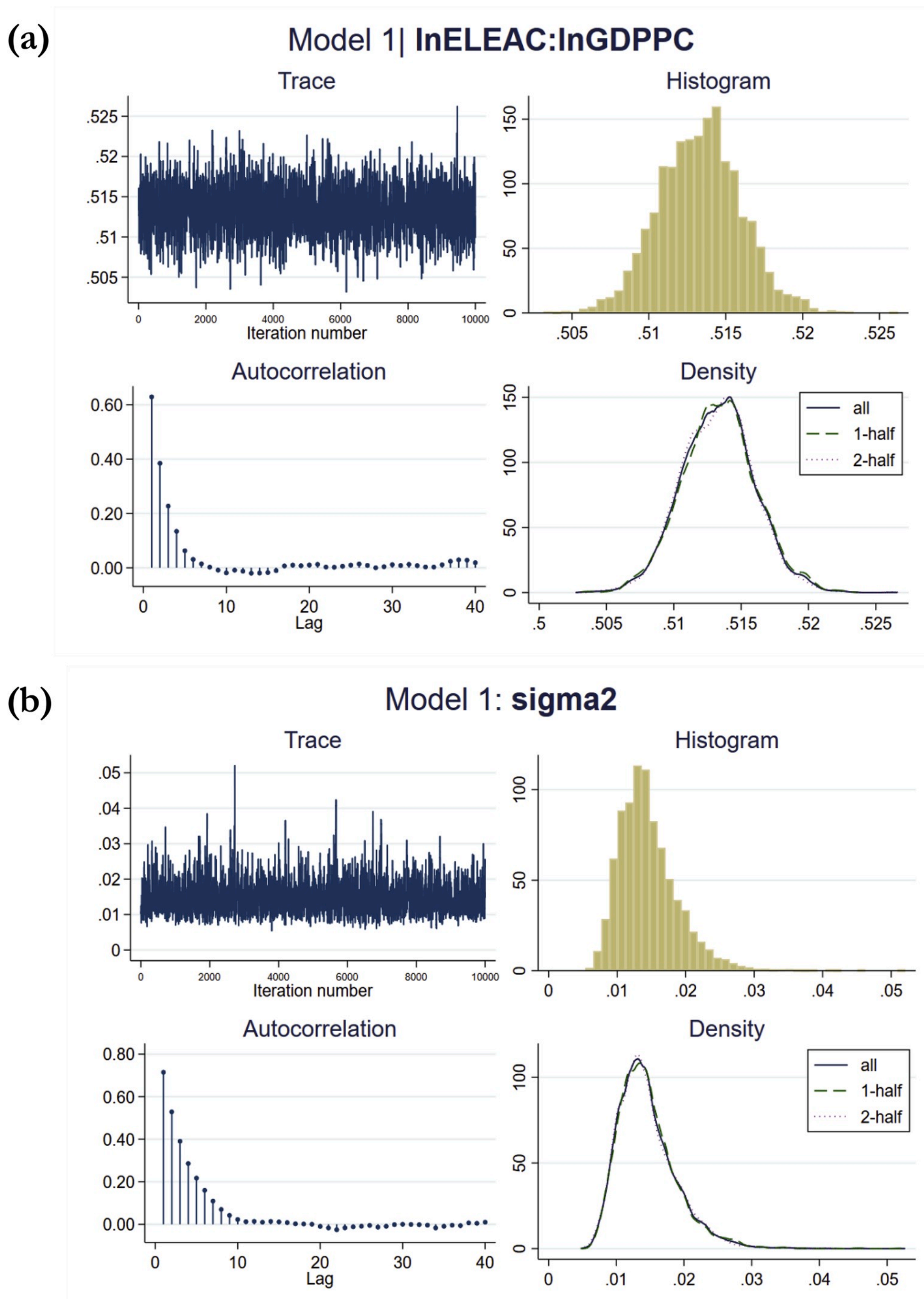

Fig. 1. Convergence plots of Model 1 (a) Nexus between access to electricity and income level (b) variance of the data.

4.2. Bayesian estimation results

The results of the Bayesian estimation approach using random-walk Metropolis-Hastings sampling for 8 models are presented in Table 5. Adaptive random-walk Metropolis-Hastings is a Markov chain Monte Carlo (MCMC) method capable of solving computing challenges with approximate sampling from posterior distribution effectively [69]. The Adaptive random-walk Metropolis-Hastings utilized noninformative prior, 30,000 MCMC iterations, burn-in periods of 20,000 and 10,000 MCMC sample size.

Four out of five models in Table 5 reveal a positive effect of increasing income levels on access to electricity. The results are corroborated by Bekun et al. [70]; Sarkodie and Adom [63]; Sarkodie et al. [71]. While Bekun et al. [70] found a positive impact of income levels on energy consumption in South Africa, Sarkodie and Adom [63]; Sarkodie et al. [71] found a positive effect of economic development on energy consumption in Kenya and Ghana. Poverty prevents accessibility and affordability to electricity and modern energy services [4]. Access to electricity has a long-standing of improving livelihoods — household income, investments, employment opportunities, well-being, and health outcomes, and cultural activities; improving food production — cultivating, harvesting, processing, preservation, and transportation; improving water productivity — desalination, filtering, water treatment and distribution, water harvesting, water recycling, and reuse, and wastewater treatment [55,72]. Thus, the lack of access to electricity and modern energy services, in turn, contributes to poverty and dampens

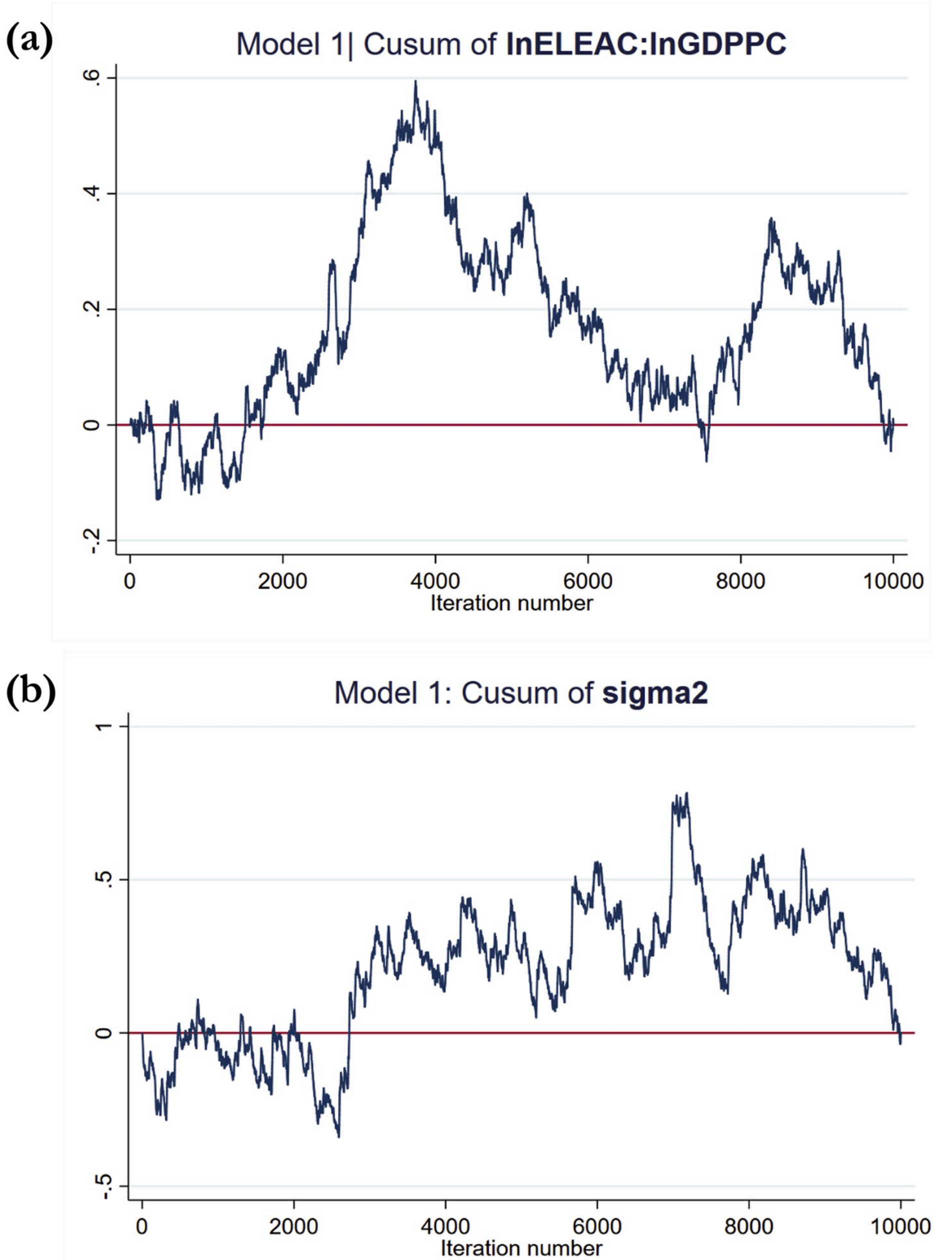

Fig. 2. Cusum plots of Model 1 (a) Nexus between access to electricity and income level (b) variance of the data.

economic development.

Income inequality has been established to affect access to electricity, especially in developing countries. According to DiSano [56]; inequality in the distribution of income has a long-term effect on economic development, as such, hinders human development. However, all the coefficients in the five estimated models reveal a significant positive effect of income inequality on access to electricity. The empirical results are in line with Sarkodie [73]; who revealed that South Africa is the only country in SSA with its household population above the poverty line (US $ 1.90/day). Thus, income inequality has no adverse effect on the accessibility of electricity in South Africa. The outcome is justified by the historical trend in access to electricity: according to the World Bank data, electricity access in South Africa grew from 59% in 1990 to 91% in 2017 [1].

Four out of five estimated coefficients in Table 5 reveals a negative relationship between access to electricity and corruption. In other words, a decline in access to electricity triggered by the rise in corruption translates into poor governance. The recent corruption brouhaha surrounding South Africa's monopolistic power supplier — Eskom, revealed how incompetence and corruption led to the power utility plummeting into dire financial difficulties resulting in interrupted power supply and decline in foreign and domestic investor confidence in the country's economy [74]. The Economic Times [75] reported that South Africa's treasury completed a probe of alleged corruption involving state Energy firm Eskom and Tegeta Exploration and Resources in a deal worth millions of dollars. According to a report by Trading Economics [76]; South Africa's business confidence dropped from over 50% in 2013 to a little over 35% in 2018. Imam et al. (2018) indicated that corruption abounds in the SSA energy sector which significantly reduces the technical efficiency of the sector and constrains efforts to increase access to electricity and national income. Trotter [14] has also noted that while electrification is possible in the absence of democratic institutions, rural electrification is more successful in sub-Saharan African countries with more democratic institutions.

Hence, the act of corruption (poor governance) hampers social intervention programs and access to basic needs including electricity, which is critical for human and sustainable development.

The nexus between access to electricity and the interaction between income level and income inequality shows a positive effect. Meaning that a combination of a rise in the level of income and inequality in income distribution does not depreciate accessibility to electricity and its services. Hence, income inequality has no negative impact on access to electricity when income levels appreciate.

Model 9 in Table 5 reveals a significant positive coefficient on both lnELEAC and lnCORRUPT. Meaning that access to electricity and corruption increase income inequality in South Africa. Our results reveal that access to electricity and corruption widens the income gap between the rich and the poor. Thus, accessibility to modern energy technologies including electricity may have benefited the wealthier in terms of better investment opportunities which leads to higher returns that translate into more consumption disparity. However, other studies report negligible effects of electricity access on the distribution of income. Palit & Bandyopadhyay [77] reported a negligible effect of electricity access on the distribution of income in India. The authors explain that this could be attributed to the focus on productive input in agro-industries and irrigation rather than as an infrastructure for changing the rural landscape and therefore not much on household electrification. The negligible effects have also been explained by Riva et al. [40] who revealed that merely providing access to electricity in the global south does not automatically translate into development. The World Bank highlighted that it is not enough to simply provide people with access to electricity and hope for local economic activity to pick up by itself. This is consistent with the literature that emphasizes that electricity access should always be accompanied and sustained by other enabling activities and services, in order to contribute to greater educational attainment, more business opportunities, and higher income at the local level [48,78].

The efficiency of the MCMC approach is measured by the corresponding acceptance rate. Acceptance rate closer to 0 or 1 means the MCMC fails to explore appreciable regions of the posterior distribution, while the latter represents the failure of the MCMC to explore the entire posterior region [79]. The model diagnostics in Table 5 reveal varying acceptance rate between 0.32 and 0.44 and efficiency between 7% and 21%. Roberts et al. [80] proposed an optimal acceptance rate of 0.234 and 0.45 for multivariate and univariate posterior distributions, respectively. Hence, the acceptance rate of the 8 models is within the asymptotically optimal range.

The validity of Bayesian inferences based on MCMC method using adaptive random-walk Metropolis-Hastings is examined using convergence diagnostics. Checking convergence diagnostics of MCMC is essential for model verification of the MCMC simulation. Statistical inferences are valid and unbiased if the Markov chain converges with corresponding samples drawn from the appreciable regions of the posterior distribution [79]. Although the selection of specified convergence criterion is inconclusive, yet, Brooks et al. [81]; Cowles and Carlin [82] propose methods for monitoring and assessing convergence diagnostics of MCMC. One approach proposed by Brooks et al. [81]; Cowles and Carlin [82] involves the inspection of the mixing and time trends of the individual parameters in single and multiple Markov chains. Thus, convergence diagnostic tests include the verification of Trace plots, Histogram plot, Autocorrelation plot, Density plot, and Cusum plot. For brevity, Figs. 1–2 depict convergence and cusum plots of Model 1, while graphical convergence diagnostics of the remaining models are presented in Appendix A. The trace diagnostic test plots the simulated parameter values against the number of iterations. A visual inspection of the trace plot of all the models shows the parameters have well-mixing chains traversing the posterior domain rapidly with nearly constant variance and mean. Apart from the acceptance rate, other criteria for assessing the efficiency of the MCMC approach is the degree of autocorrelation in the estimated sample. Samples mostly stimulated using random-walk Metropolis-Hastings MCMC method have highly correlated draws. Hence, an efficient MCMC has a small degree of autocorrelation. The autocorrelation plots of the estimated models confirm a well-mixing Metropolis-Hastings chain, thus, the autocorrelation plots become negligible rapidly. The histogram plots of the models appear to reveal a normal posterior distribution. The kernel density plots reveal a similarity between the estimated first and second halves of the sample and exhibit closeness to the overall estimated density. Yu and Mykland [83] also proposed the use of a graphical procedure to examine MCMC convergence of each estimated parameter using cumulative sums (cusum) plot. The cusum plot is essential to check for drifts in the Markov chain, hence, a perfect model without a trend and well-mixing parameters should have the cusum curve crossing the *x-axis*. The diagnostic test reveals that the cusum curve of all the models crosses the *x-axis* and exhibits a jagged trend denoting a faster mixing of the Markov chain. The convergence diagnostics of MCMC shows that all the models follow a typical Gaussian random-walk Metropolis-Hastings algorithm that has reached convergence.

Table 6
Electricity access-income level relationship using NARDL model.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\ln ELEAC_{t-1}$*	0.0117	0.0040	2.9535	0.0082[a]
$\ln GDPPC^{+}$**	−0.0885	0.0313	−2.8300	0.0107[b]
$\ln GDPPC^{-}_{t-1}$	−0.1687	0.0688	−2.4517	0.0241[b]
$\Delta\ln ELEAC_{t-1}$	−0.6933	0.1942	−3.5700	0.0020[a]
$\Delta\ln ELEAC_{t-2}$	−0.2593	0.1917	−1.3527	0.1920
$\Delta\ln GDPPC^{-}$	0.4150	0.1792	2.3155	0.0319[b]
ECT_{t-1}*	−0.0117	0.0024	4.8027	0.0001[a]
Long-run asymmetric effects				
$\ln GDPPC^{+}$	7.5501	3.2348	2.3340	0.0307[b]
$\ln GDPPC^{-}$	14.3953	8.1438	1.7676	0.0932[c]
Error Metrics				
R^2	0.6045	Durbin-Watson stat		1.9201
$\overline{R^2}$	0.5480	Log-likelihood		50.6550
[ ] regression	0.0348	AIC		−3.7324
Diagnostic Tests				
$\chi^2_H\, B-P-G$	0.6322	Prob. F(6,18)		0.7030
χ^2_{SC}LM	0.44846	Prob. F(2,17)		0.6460
χ^2_{FF}	1.7165	(1, 18)		0.2066
W_{LR}	9.8450	(1, 19)		0.0054

[a, b, c] denotes significance at 1%, 5% and 10%; $F_{PSS} = 6.96$ is above the 1% I(1) critical value (5.30) and $t_{BDM} = 2.95$ is above the 1% I(1) critical value (−3.66).
* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z); R^2 is the R-squared, $\overline{R^2}$ refers to Adjusted R-squared, [ ] is the standard error, $\chi^2_H\, B-P-G$ refers to Heteroskedasticity Test: Breusch-Pagan-Godfrey; χ^2_{SC}LM represents Breusch-Godfrey Serial Correlation LM Test; χ^2_{FF} means Ramsey RESET Test; and W_{SR} refers to Wald test of the additive short-run symmetry condition.

4.3. NARDL estimation results

En route to estimating the NARDL model presented in Table 6, the study first examined the symmetric effect using the ARDL approach. The NARDL model utilized an adjusted sample from 1993 to 2017 (i.e. included observations: 25 after adjustments) with maximum dependent lags of 3 using automatic selection. $\ln GDPPC^{+}$ and $\ln GDPPC^{-}$ were the dynamic regressors (1 lag, automatic) utilized in the conditional error correction regression model with no constant and no trend. The optimal model: ARDL (3, 0, 1) was selected using the Akaike info criterion (AIC) after the evaluation of 12 models. The estimated long-run coefficients on $\ln GDPPC^{+}$ and $\ln GDPPC^{-}$ reveals a negative impact on access to electricity with positive and negative changes in income level contrary to the Bayesian estimation results. Also, the short-run symmetry reveals the positive effect of a negative change in income level on access to electricity. However, the Wald test statistic (W_{LR}) rejects the null hypothesis of long-run symmetry. The long-run asymmetric effects of $\ln GDPPC^{+}$

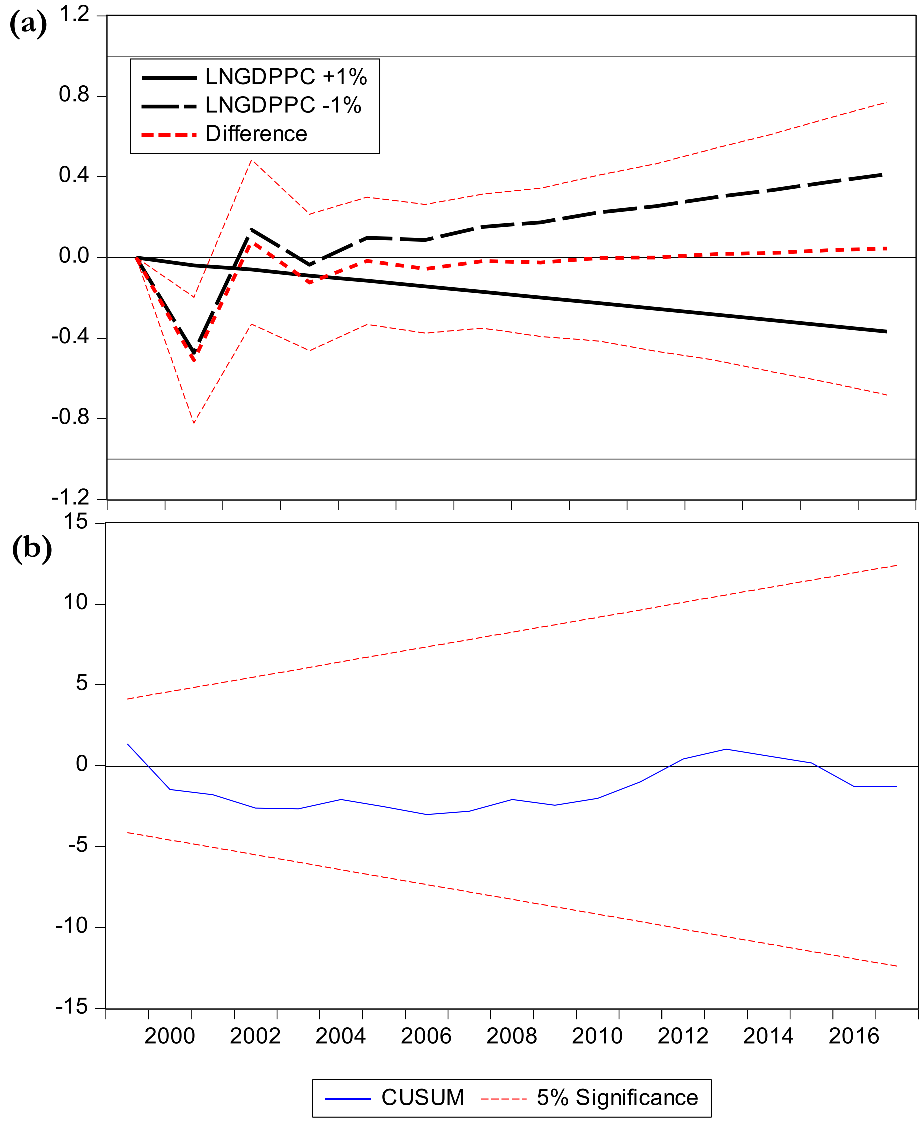

Fig. 3. Post estimation using graphical methods (a) Dynamic multiplier for electricity access-income level link (b) Cumulative sum test.

and lnGDPPC⁻ reveals a positive impact on access to electricity, hence, validating the initial positive effect via the Bayesian approach.

To validate the estimated NARDL model, we employed four diagnostic tests namely Durbin-Watson to test for the first-order autocorrelation, Breusch-Pagan-Godfrey to test for heteroskedasticity, Breusch-Godfrey LM to test for serial correlation and Ramsey RESET to test for the model's functional form. Table 6 reveals that the estimated model has no issues with autocorrelation, heteroskedasticity, serial correlation and misspecification. Fig. 3 (b) depicts the cumulative sum test for the estimated model. Fig. 3 shows that the CUSUM plot is within the 95% confidence level, signifying the stability of the estimated model.

The pattern of the dynamic multiplier is dependent on a combination of the speed of adjustment coefficient (error correction), long-run equilibrium parameters, and the estimated model dynamics. The dynamic multiplier is derived from equation (18) and shows the pattern of adjustment of access to electricity as it spreads to a new short- and long-run equilibrium following a positive or negative shock in income level. Fig. 3 (a) presents the asymmetric cumulative dynamic multiplier for electricity access-income level link. The black solid line in Fig. 3 (a) represents the shock in access to electricity after a positive change in income level while the black short-dashed line captures the shock in access to electricity after a negative change in income level. The red short-dashed line represents the asymmetry curve which captures the difference between the positive and negative changes in income level, with its corresponding 95% confidence interval for statistical inferences. It is observed in Fig. 3 (a) that the zero line is within the upper and lower band of the 95% confidence interval, as such, the asymmetric effect of income level is statistically insignificant at 5% level. The insignificant asymmetric curve reveals a negative impact of shocks in income level for a short period but turns positive in the long term, thus, confirming the positive impact of symmetric income level on access to electricity.

5. Conclusion

Access to electricity and its related energy services are essential for achieving sustained economic growth, improved livelihoods and quality of life. However, persistent access deficit exists in developing countries especially sub-Saharan Africa. IEA projects that 600 million of 674 million people without access to electricity will emerge from sub-Saharan Africa in 2030. Thus, the examination of the drivers and barriers of access to electricity is essential for energy policy formulation and enactment. The study examined the nexus between electricity access, control of corruption, and income inequality in South Africa. We employed data from 1990-2017 and utilized Bayesian and NARDL methods for model estimation. The study found a positive effect of increasing income levels on access to electricity. Affordability of modern energy services is a critical barrier to scaling-up solutions that improve access to electricity. Though renewable energy sources and decentralized energy systems like off-grid and mini-grid systems are cost-effective ways of improving electricity access. Yet, the upfront cost of most renewable energy off-grid systems is burdensome to consumers and higher than what they are willing to pay for access. Our study demonstrated that income inequality has a positive effect on access to electricity. In other words, inequality in the distribution of income does not hamper access to electricity in South Africa. On the contrary, we found a negative relationship between access to electricity and corruption, reflecting poor governance and institutional environment. Though economic growth is essential to materialize electricity for all concept, however, our study demonstrated that good governance, and institutional quality is critical to warrant energy security — availability, accessibility and affordability.

Declaration of interests

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esr.2020.100480.

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