Energy Aid, Energy Infrastructure and Energy Poverty in Sub-Saharan Africa

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Abstract
Despite continued efforts by the governments of developing countries to improve the supply of energy for household and industrial consumption, public investment in energy infrastructure remains low. This situation is further compounded by the rising prices of energy sources, such as crude oil and natural gas. In attempting to close the savings deficit gap, low-income countries have turned to wealthier nations and international aid institutions. However, despite receiving billions of dollars in foreign aid for energy, millions of people—particularly in Sub-Saharan Africa (SSA)—still lack access to modern energy services. Consequently, an analysis of the type and flow conditionality of aid effectiveness is both necessary and timely. This study examines the effectiveness of aid directed towards the energy sector, as well as the relative impact of energy aid and energy infrastructure endowment on energy poverty. It employs a Sequential (two-stage) Generalised Method of Moments (SGMM) dynamic panel model technique, using a short panel of 25 countries over the period 2002–2021. The findings suggest that energy aid is effective in equipping recipient countries with energy infrastructure, and that it reduces energy poverty both directly and indirectly through the improvement of energy infrastructure. The conditional analysis of aid flow and type reveals that the effectiveness of energy aid and its significant impact on energy poverty are more pronounced among 'orphans'—those countries receiving comparatively low volumes of foreign aid. Across all conditional variables, these orphans are predominantly situated in middle-income countries. It is therefore recommended that recipient countries, particularly those classified as low-income, avoid the diversion of energy aid into fungible channels as they pursue efforts to reduce energy poverty. The study's findings carry important implications for aid recipients, donor nations, and international interventionist institutions regarding the policy design and management of disbursed Official Development Assistance (ODA).

Keywords: *Darlings & Orphans, Energy aid, Energy Infrastructure Endowment, Energy Poverty*

1 Introduction

Access to energy is a foundational requirement for human well-being, underpinning basic household functions such as cooking and lighting, as well as industrial and commercial activities

(Foo et al., 2021). Yet, the global energy landscape faces persistent challenges, with energy poverty—defined as the inability of households to secure adequate, affordable, and reliable energy services—emerging as one of the most pressing issues (Birol, 2007; González-Eguino, 2015; Middlemiss et al., 2019; Munyanyi & Churchill, 2022). Sub-Saharan Africa (SSA) remains disproportionately affected, where approximately 600 million individuals lack electricity access and 970 million lack clean cooking technologies (International Energy Agency, 2017, 2022; United Nations, 2023). Recent global disruptions, notably the COVID-19 pandemic and Russia–Ukraine war, have further exacerbated these deficits, stalling progress toward universal energy access (Li, 2023). Foreign aid has emerged as a critical financing instrument for closing energy infrastructure gaps in developing countries, with increasing involvement from donors such as China—particularly via strategic platforms like the Belt and Road Initiative (Foo et al., 2021; OECD, 2022; Munyanyi & Churchill, 2022). While foreign development assistance is known to influence household-level welfare outcomes (Munyanyi & Churchill, 2022), its direct and indirect impact on alleviating energy poverty through targeted infrastructure interventions remains underexplored. Although studies such as Li (2023) provide evidence that aid improves access to clean energy and catalyses broader socioeconomic change, others highlight the risks of inefficiency and corruption—especially in the context of aggregate aid flows (Gondwe & Mbonigaba, 2022). Globally, progress in expanding access has been uneven. Between 2015 and 2021, electricity availability rose from 87% to 91%, yet over 675 million people—primarily in least developed countries and SSA—continue to live without reliable power, and 2.3 billion still rely on hazardous fuels for cooking (United Nations, 2023). Infrastructure-related costs, especially in sparsely populated rural areas, disincentivise utility expansion due to escalating marginal costs (Baldwin et al., 2015). Despite substantial aid allocations toward sustainable energy objectives (Satya & Sriram, 2022), access to modern energy services remains limited in many parts of Africa (Ouedraogo, 2017; IEA et al., 2021).

The academic literature has long recognised infrastructure's pivotal role in advancing trade, growth, and poverty reduction (World Bank, 1994; Limão & Venables, 2001; Adam & Bevan, 2006). However, few studies empirically examine how foreign aid influences infrastructure endowment—especially within the energy domain—with notable exceptions including Vijil and Wagner (2012), Donaubauer et al. (2016), and Donaubauer & Nunnenkamp (2016). Similarly, the conditional effectiveness of foreign aid has often been linked to absorptive capacity indicators such as institutional quality (Dollar & Levin, 2005; Abate, 2022), though recent conceptual frameworks also highlight the relevance of aid flow (Cohen et al., 2007) and aid type (Cordella & Dell'Ariccia, 2007). From the foregoing, the present study contributes to the literature by investigating the transmission mechanisms through which energy-targeted foreign aid affects energy poverty, with a particular focus on the role of aid flow, aid modality, and recipient income level. Using a dynamic panel model based on Kripfganz and Schwarz (2015), we examine how foreign energy aid affects the stock and quality of energy infrastructure and, through this endowment, influences energy poverty across 25 SSA countries from 2002 to 2021. By identifying the determinants most conducive to energy poverty reduction, the study provides evidence-based insights to support the design of more effective foreign aid interventions and inform broader energy policy strategies.

The subsequent sections of the article are presented in the following manner. Section 2 is dedicated to the review of relevant literature. Section 3 of the paper elucidates the empirical framework and techniques employed in this study, and the description of data and variables. The fourth section of

the paper focuses on presenting and discussing the estimation results. Finally, the fifth section presents the conclusions and recommendations.

2 Literature Review

This section is dedicated to the review of relevant literature on the effectiveness of foreign aid and the nexus between aid for energy sector and energy poverty. Moreover, a review of literature on the aid flow and type conditionalities of foreign aid effectiveness was also conducted.

2.1 Foreign Capital and Energy Infrastructure Financing: Stylized Facts

A prevalent stylized fact in energy infrastructure financing, particularly in developing regions, is the significant gap between the immense investment required for infrastructure development and the limited domestic financial capacity to meet these needs, necessitating substantial reliance on foreign aid and other external financial assistance. For instance, in the Common Market for East and Southern Africa (COMESA), there is an estimated annual infrastructure deficit of US$93 billion, with only about 48% (US$45 billion) mobilizable domestically, leaving a 52% financing gap that foreign aid is anticipated to help close, albeit over two decades (Gondwe & Mbonigaba, 2023). Similarly, in Sub-Saharan Africa, achieving universal electricity access by 2030 is estimated to cost approximately US$454 billion, averaging US$35 billion per year, an amount far exceeding the public finance capacity of these nations (Nguea et al., 2022). Developing economies, grappling with multifaceted challenges like rising poverty levels, income and health inequalities, and high unemployment, often find their internal revenue generation (e.g., through carbon taxes) insufficient to fund essential infrastructure, particularly for clean energy production, thereby reinforcing their dependence on overseas financial assistance (Villanthenkodath et al., 2022). This highlights a consistent pattern where foreign capital is crucial for bridging the financial shortfall in energy infrastructure development across the developing world (Gondwe & Mbonigaba, 2023; Nguea et al., 2022; Villanthenkodath et al., 2022).

2.2 Energy Aid, Infrastructure Endowment, and Energy Poverty: A Theoretical Review

The importance of foreign aid is laid out in the Sachs-Solow Model. Although Sachs et al. (2004) claim that most Sub-Saharan African (SSA) countries are trapped in a "poverty trap," they also argue that, ceteris paribus, capital should move from rich to poor countries due to higher potential returns. The traditional Solow growth model is based on the well-known neoclassical aggregate production function, and focuses on the immediate factors that contribute to economic growth:

$$Y = AtF(K, L) \tag{1}$$

where Y is real output, K is capital, L is the labour input, and At is a measure of exogenously determined "technology." The pro-aid group now has Sachs' persuasive arguments to rally around. Among the four primary lines of evidence and theory on foreign aid to Africa, as argued by Easterly (2005), two concern this study. The first is the scholarly responses to the funding deficit and/or Big Push models (see Masud & Yontcheva, 2005; Sachs, 2005). The second refers to ineffective aid, caused in part by dysfunctional donors and low-quality institutions (Svensson, 2000; Knack, 2001; Djankov et al., 2005).

Scholarly interest in the effectiveness of official development assistance (ODA) has produced mixed findings on its impact in developing contexts. Studies such as Collier and Dollar (2003), Basnet (2013), Headey (2008), and Ekanayake and Dasha (2010) suggest that aid promotes economic growth, while others—including Djankov et al. (2008) and Moyo (2009)—highlight adverse outcomes like corruption, dependency, and diminished output. This divergence has led to

a shift from assessing aggregate aid impacts to examining the relative efficacy of disaggregated aid types. Despite extensive macro-level analyses linking aid to growth and investment (Burnside & Dollar, 2000; Rajan & Subramanian, 2008), there remains limited empirical work on sector-specific impacts, particularly within the energy domain. Aid's transmission through capital accumulation and investment is supported by McPherson and Rakovski (2001), Gomanee et al. (2002), and Clemens et al. (2004), with emphasis on targeted interventions—e.g., infrastructure investment and budget support—yielding short-term growth benefits. However, little attention has been paid to how energy-targeted aid influences infrastructure endowment and energy poverty. This study addresses that gap by investigating the effectiveness of ODA disbursed to the energy sector and its impact on energy infrastructure and poverty in SSA, complementing emerging research by Munyanyi and Sefa (2022), Li (2023), and Wang et al. (2021), who begin to explore aid's role in alleviating household-level energy deprivation.

2.3 Influence of Aid Type and Aid Flow on Effectiveness of Aid

Building on theoretical insights from Cordella and Dell'Ariccia (2007) and Cohen et al. (2007), this study investigates the influence of aid flow and type on the effectiveness of energy-targeted foreign aid in Sub-Saharan Africa. Cordella and Dell'Ariccia advocate that budget support is best directed to relatively wealthy, development-oriented nations, while project aid suits poorer, less developmentally focused recipients. Similarly, Cohen et al. highlight donors' use of grants and concessional loans, noting the limitations of debt-financed aid in countries with weak institutions (Bulow & Rogoff, 2005; Odedokun, 2003). While loans may incentivise domestic revenue mobilisation, grants often reduce tax effort. Despite widespread interest in institutional quality as a determinant of aid effectiveness, few studies assess the impact of aid modality or flow—particularly in the energy sector. Addressing this gap, the study categorises recipient countries into "orphans" and "darlings" under loan, grant, project intervention, and budget support modalities, and examines how these interact with income level to shape the effectiveness of energy aid in improving infrastructure endowment and reducing energy poverty.

2.4 Empirical literature

Foo et al. (2021) empirically investigated the impact of Chinese foreign aid programs on reducing energy poverty in selected least developed ASEAN nations, specifically Cambodia, Lao PDR, Indonesia, Myanmar, and the Philippines, using panel data from 2000–2019. Their findings suggest a significant positive impact, indicating that Chinese aid helps reduce energy poverty, which they defined based on the percentage of the population with access to electricity. This assistance is highlighted as crucial for developing cleaner and more affordable energy, thereby improving citizens' access to modern energy services and enhancing living standards. They also indicate that China's role is particularly critical compared to aid from the United States and Japan. The study also notes that energy poverty negatively affects energy consumption, education, and per capita income in these households.

Li (2023) specifically examined the impact of Chinese foreign aid on energy poverty in 11 sub-Saharan African countries between 2000 and 2014, measuring energy poverty by access to clean cooking fuels and electricity, focusing on the accessibility dimension. Employing difference-in-differences estimations and propensity score matching, the study found that Chinese aid projects significantly improve access to clean cooking fuels in treatment areas of recipient countries, but do not show a robust impact on electricity access. Li (2023) further revealed that the effect of Chinese aid on energy poverty is heterogeneous across rural and urban areas, demonstrating a

positive and significant impact (i.e., reduction in energy poverty) in rural settings, while having limited effects in urban areas. This disparity is attributed to urban energy poverty being primarily an affordability issue, whereas rural areas face both accessibility and affordability challenges. The study identifies that Chinese aid directly impacts access through energy sector projects (e.g., biogas appliances) and indirectly improves access to clean cooking fuels by increasing employment and education levels in the recipient countries through economic and social aid.

Munyanyi and Churchill (2022) provided sub-national evidence from Senegal, demonstrating that foreign aid lowers the probability of energy poverty. Their analysis, using geo-referenced aid data and household information from five waves of the Demographic and Health Surveys (DHS) spanning 1994–2013, found that residing within a 25-km radius of an aid project reduces the likelihood of being energy poor by 3.3 percentage points. This finding was robust across various sensitivity checks, including different distance buffers, and types of aid such as production, social infrastructure, and economic infrastructure aid. Specifically, aid increased the likelihood of using clean cooking fuels by 0.4 percentage points, accessing electricity by 3.2 percentage points, and improved access to other energy-dependent appliances and communication means. The study identifies income poverty, education, and economic growth as key channels through which aid influences energy poverty. They noted that economic infrastructure aid (which includes energy) had a lower impact than social infrastructure aid, partly because economic infrastructure aid also includes sectors less directly related to household energy poverty, such as communication or transport.

In contrast to positive findings, Nguea et al. (2022), examining 36 African countries from 2000 to 2017, reported that foreign aid appears to have a negative impact that impedes access to electricity. Their findings also suggest that foreign aid increases urban-rural disparities in access to electricity. This study employed a two-step difference GMM estimation technique to assess the effects of foreign capital, including foreign aid, on electricity access. They conclude that governments should strengthen legal frameworks to overcome the negative effect of foreign aid on SDG7 attainment.

Gondwe and Mbonigaba (2023) specifically analyzed the impact of foreign aid on economic infrastructure development in the Common Market for East and Southern Africa (COMESA). Using the Blundell-Bond system generalized methods of moments, their results showed that foreign aid, on aggregate, has a net negative effect on infrastructure development, primarily due to corruption which compromises the utilization of grants. While loans were found to be positive and significant in influencing infrastructure development, grants had a diminishing effect, and overall, foreign aid was ineffective due to poor grant performance. The study highlighted that corruption in most COMESA countries is high, reflecting low levels of transparency and accountability.

Villanthenkodath et al. (2023) investigated the effects of aggregate foreign aid and energy aid inflows on renewable and non-renewable electricity production in selected BRICS countries (Brazil, India, China, South Africa) from 1995 to 2015. Their findings, using fully modified ordinary least square and dynamic OLS techniques, indicated that aggregate aid and energy aid inflows promote renewable electricity production. Conversely, they found that both aggregate aid and energy aid inflows reduce non-renewable electricity production, suggesting a positive impact on environmental sustainability through shifting energy sources. The study emphasized that economic growth and foreign direct investment also promote both types of electricity production, but specifically encourage renewable production more.

Wang et al. (2021) explored the impact of Official Development Assistance (ODA) on renewable energy development in 34 sub-Saharan African countries from 2005 to 2015 using a panel

threshold regression model. Their analysis revealed a non-linear impact of ODA on renewable energy development, particularly influenced by carbon dioxide emission intensity. They found that when CO2 intensity is high, the economy relies more on fossil energy, and aid funds might be diverted to traditional fossil energy industries, thus hindering renewable energy development. The study also noted that international assistance tends to be more inclined towards rural areas due to the needs of the rural population and international companies, influencing the distribution of renewable energy development.

While existing empirical studies have explored the direct impact of foreign aid—including energy-targeted aid—on outcomes such as access to clean cooking fuels and electricity, and its role in economic infrastructure or renewable energy development, the dynamic relationship between aid, infrastructure endowment, and energy poverty remains underexamined. Notably, Li (2023) and Munyanyi and Churchill (2022) link aid to energy poverty reduction, touching on both direct and indirect mechanisms. However, these studies do not explicitly model the intermediate step whereby aid improves the stock or quality of energy infrastructure (e.g., grid expansion, clean cooking technologies, household energy efficiency) as a pathway to poverty alleviation. Gondwe and Mbonigaba (2023) assess aid's effect on infrastructure but stop short of linking it to household energy deprivation. Likewise, Villanthenkodath et al. (2023) and Wang et al. (2021) address production-side impacts without tracing their transmission to household-level energy poverty indicators. A comprehensive study that models the full causal chain—from energy aid inputs to infrastructure endowment improvements and ultimately to energy poverty outcomes—would fill a critical gap and advance understanding of the conditions under which aid most effectively alleviates energy poverty.

3. Methodology

This section provides a short description of the models estimated and the choice of econometric technique in achieving the set objectives, Moreover, a brief discussion of the key variables of interest and the sources of data was also presented in this section.

3.1 Models and econometric technique

This study investigates the dynamic linkage relationship between energy aid, energy infrastructure endowment, and energy poverty. The novelty is that development assistant reduces energy poverty both directly and indirectly. While the effectiveness of energy aid in terms of energy infrastructure endowment is expected to increase generation, reduce distribution losses and reduce energy poverty on the one hand; the flow of foreign aid is expected improved per income and access to electricity due to increase in household income and public investment in physical capital on the one hand. Two models are estimated to provided empirical evidence to the arguments of this study. First, to examine the effectiveness of energy aid, we regress a set of variables. Following previous theoretical and empirical studies by Vijil and Wagner (2012), Donaubauer et al. (2016a), Donaubauer and Nunnenkamp (2016), and Maruta and Banerjee (2021) we estimated the following equation:

$$EDEV_{it} = \beta_0 + \beta_1 EDEV_{it-1} + \beta_2 EAPC_{it} + \beta_3 X_{it} + \varepsilon_{it} \qquad (2)$$

where $EDEV_{it}$ represent the energy infrastructure endowment of country *i* at time *t*; $EDEV_{it-1}$ represents lagged energy infrastructure endowment variable; $EODAPC_{it}$ is the Per Capita Energy Aid; X_{it} is a vector explanatory variables, and ε_{it} is the error term.

Moreover, to examine the relative effect of energy aid and energy infrastructure endowment on energy poverty to establish if aid can impact energy poverty through endowment of energy infrastructure, we again regress a set of variables. Following previous theoretical and empirical studies by Rodriguez-Alvarez et al (2021), Nguyen and Su (2021) we estimated the following equation:

$$EPOV_{it} = \beta_0 + \beta_1 EPOV_{it-1} + \beta_2 EAPC_{it} + \beta_3 EDEV_{it} + \beta_4 X_{it} + \varepsilon_{it} \quad (3)$$

where $EPOV_{it}$ represent energy poverty in country *i* at time *t*; $EPOV_{it-1}$ represents lagged energy poverty variable; $EAPC_{it}$ is the Per Capita Energy Aid; $EDEV_{it-1}$ is the energy infrastructure endowment; X_{it} is a vector explanatory variables, and ε_{it} is the error term.

The presence of a lagging dependent variable among the explanatory variables in each of the specified models (i.e., 2 and 3) implies a correlation problem between the lagging endogenous variable and the error term. This endogeneity bias is primarily due to the problem of reverse causality. The presence of such problems can lead to biased results when applying traditional estimation methods such as ordinary least-squares (OLS) estimators and fixed-effects estimators. To avoid this, the sequential two-stage GMM estimation methodology by Kripfganz and Schwarz (2015) was used in this study. In the context of dynamic panel models, generalized method of moments (GMM) estimators in the spirit of Arellano and Bover (1995), Blundell and Bond (1998) and Roodman (2009) are frequently employed. If the interest is on the coefficients of time-invariant regressors, the Arellano and Bond (1991) GMM estimator is not helpful because all time-invariant variables are removed by a first-difference transformation. To identify the coefficients of time-invariant regressors, the assumption that a sufficient number of regressors (or excluded instrumental variables) is uncorrelated with the unit-specific error component cannot be avoided. Incorrect assumptions about the exogeneity of some variables may cause inconsistency of all coefficient estimates. A sequential procedure can provide partial robustness to such misspecification. In a first stage, only the coefficients of time-varying regressors are estimated. In a second stage, the coefficients of time-invariant regressors are recovered.

Consider the dynamic panel data model with units i = 1, 2, ..., *N*, and a fixed number of time periods t = 1, 2, …, *T*, with $T \geq 2$:

$$y_{it} = \lambda y_{i,t-1} + \times'_{it}\beta + f_i'\gamma + e_{it}, \quad e_{it} = \alpha_i + u_{it} \quad (4)$$

where $\times_{it}$ is a $K_x \times 1$ vector of time-varying variables? The initial observations of the dependent variable, y_{i0}, and the regressors, x_{i0}, are assumed to be observed. f_i is a $K_f \times 1$vector of observed time-invariant variables that includes an overall regression constant, and α_i is an unobserved unit-specific effect of the *i-th* cross section. In a strict sense, α_i is called a fixed effect if it is allowed to be correlated with all of the regressor variables x_{i0} and f_i, and it is a random effect if it is independently distributed.

At the first stage, the time-invariant regressors under the unit-specific effects is subsumed and the coefficients of the time-varying regressors is estimated. At the second stage, the first-stage residuals are regressed on the time-invariant regressors. Both time-varying and time-invariant variables that are assumed to be uncorrelated with the unit-specific effects qualify as instruments at the second stage. The corresponding overidentifying restrictions are tested with the usual specification tests at the second stage. In general, the two-stage approach is neither restricted to models with a short time dimension nor to dynamic models. It has two main advantages compared

to the estimation of all parameters at once. First, the estimation of the coefficients of the time-varying regressors is robust to a model misspecification with regard to the time-invariant variables. Second, the researcher can exploit advantages of first-stage estimators that rely on transformations to eliminate the unit-specific heterogeneity such as first differences or forward orthogonal deviations.

The first stage model is

$$y_{it} = \lambda y_{i,t-1} + \times'_{it}\beta + \bar{\alpha} + \bar{e}_{it}, \quad \bar{e}_{it} = \bar{\alpha}_i - \bar{\alpha} + u_{it}, \qquad (5)$$

where $\bar{\alpha} = E[\bar{\alpha}_i]$. To obtain the first-stage estimates $\hat{\lambda}$ and $\hat{\beta}$ a transformation that eliminates the time-invariant unit-specific effects $\bar{\alpha}_i$ can be applied.

In the second stage, coefficients γ of the time-invariant variables is estimated based on the level relationship:

$$y_{it} - \hat{\lambda} y_{i,t-1} - \times'_{it}\hat{\beta} = f'_i\gamma + v_{it}, \quad v_{it} = \alpha_i + u_{it} - (\hat{\lambda} - \lambda)y_{i,t-1} - \times'_{it}\left(\hat{\beta} - \beta\right). \quad (6)$$

In particular, note the two additional terms in the error term v_{it} that are due to the first-stage estimation error. The second-stage GMM estimator was then set based on the moment conditions

$$E\left[Z'_{\gamma i}v_i\right] = 0. \qquad (7)$$

3.2 Data and variables

This section is dedicated to the discussion of the indicators used for measuring the key variables of interest in this study. For discussion of data (indicator, stylized facts) to understand the relationship between the variables of interest.

3.2.1 Energy Infrastructure Endowment Indicator

Our energy aid effectiveness outcome variable is the change in the recipient countries' endowment with energy infrastructure between two points in time. In contrast to the existing literature, we do not rely on just a few indicators to proxy the countries' endowment with energy infrastructure like electricity generation and distribution, or indexes like energy infrastructure development index by Donaubauer et al (2016) and the African Infrastructure Development Index (AIDI) by the African Development Bank (AfDB) (AfDB Statistics Department, 2018) that are constructed based on only some electricity generation and supply indicators. We recruited the energy productive capacity index as our indicator for energy infrastructure endowment. The energy productive capacity index by the United Nations Conference on Trade and Development (UNCTAD) (2021) is a sub-category of the productive capacity index that was developed in response to the resolution adopted by the Economic and Social Council on 24 July 2018 (United Nations, 2018). According to UNCTAD (2021), fostering productive capacities is a critical pre-requisite for achieving structural transformation, inclusive economic growth and sustainable development and is essential for building socioeconomic resilience, to withstand the negative consequences of external shocks. Unlike the infrastructure index by Donaubauer et al (2016b) that used energy generation capacity and reliability and quality of the national electrical power supply indicators in computing the index, the energy productive capacity index measures the availability, sustainability and efficiency of power sources. For this reason, it is composed by use and access to energy, losses in distribution and renewability of energy components and sources, and includes the GDP generated by each unit of oil to highlight further the importance of optimal energy systems. Unlike the energy infrastructure development index by Donaubauer et al (2016b) index that ranges between -1.78

and 3.40, our recruited energy infrastructure endowment indicator summarizes the state of energy productive capacities in economies worldwide by computing scores that range from 0 to 100. Figure 1 shows that energy productive capacity in SSA calls for concern. Energy productive capacity averaged 21.89 (i.e., only increasing from 18.21 to 25.78) in SSA as against 60.91 and 61.09 in Eastern and South-Eastern Asia and Western Asia and Northern Africa regions respectively between 2002 and 2021. Worthy of mention is that SSA has experienced the most remarkable improvement in energy infrastructure amongst all the region during this period. SSA growth rate in the energy productive capacity index stood at 29.37 per cent as against 12.38 per cent and 4.93 per cent in Eastern and South-Eastern Asia and Western Asia and Northern Africa regions respectively.



Figure 1: Energy Productive Capacity, 2002-2021.

3.1.2 Energy Poverty Indicator

The selection of energy poverty proxies in this study is mainly based on discussions by González-Eguino (2015) and Nguyen and Su (2022). Economic threshold, physical threshold, and technological threshold are known as the three main methods for assessing energy poverty; nevertheless, González-Eguino (2015) realizes that everyone has their limits. Based on the theoretical and empirical literature, energy poverty can be defined according to different proxies dependent on the availability of the dataset (Crentsil et al. 2019; Hassan et al. 2022; Apergis et al. 2022) including (i) a population that has access to clean fuels and technologies for cooking of the total population; (ii) percentage of urban population with access to electricity; (iii) percentage of rural population with access to electricity; (iv) percentage of the population that has access to electricity of the total population; (v) log of electric power consumption per capita; (vi) percentage of the losses during electric power transmission as a percentage of total electricity output; and (vii) percentage of renewable electricity output as a percentage of the total electricity output.

This study recruits the 'percentage of the population that has access to electricity of the total population' as the proxy for energy poverty. The data sourced from the World Bank Development Indicator (WDI) Database covered the period 2002-2021. It is crucial to note that an increase in these quantities implies a reduction in energy poverty. Figure 2 shows the proportion of access to

electricity in the total population between 2002 and 2021. We see that the part of the world's population without access to clean electricity was 8.59% in 2021, which means that almost 676.50 million people the world's population were without access to electricity. An average of 37.24 per cent of the total population has access to electricity (i.e., only increasing from 27.29 to 50.58 per cent) in SSA as against 95.93 and 95.62 per cent in Latin America & Caribbean and Middle East & North Africa respectively between 2002 and 2021. Worthy of mention is that SSA has experienced the most remarkable improvement in percentage of population with access to electricity amongst all the region during this period. SSA's growth rate in percentage of population with access to electricity stood at 46.04 per cent as against 5.73 per cent and 4.88 per cent in Latin America & Caribbean and Middle East & North Africa regions respectively.

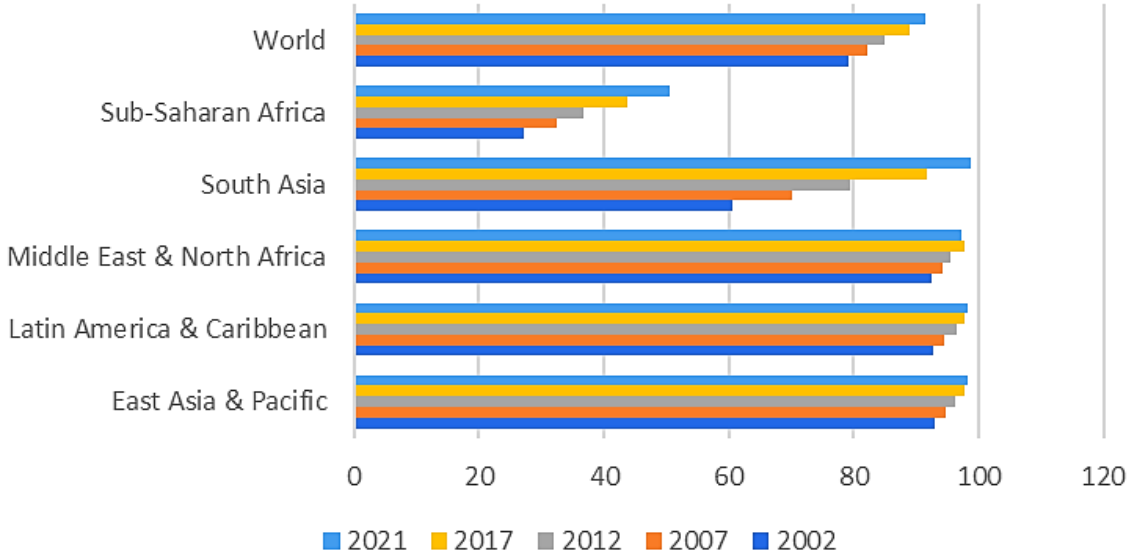


Figure 2: Percentage of Population with Access to Electricity, 2002-2021.

3.1.3 Energy Aid Indicator

Studies on aid effectiveness such as the present one should preferably use aid disbursements, rather than aid commitments (Michaelowa & Weber, 2007; Dreher et al., 2008). Commitments often do not lead to actual resource flows to the recipient country, or the actual flow may be considerably delayed. When it comes to sector-specific aid for energy, however, sufficiently long time series are available only for aid commitments. Sector-specific commitments are reported in OECD's Creditor Reporting System (CRS, available at: https://stats.oecd.org/Index.aspx?DataSetCode=crs1#). CRS statistics for earlier years suffer from underreporting, but this problem can reasonably be assumed to affect all sector-specific aid items to essentially the same extent (Michaelowa & Weber, 2007; Aldasoro et al., 2009). However, OECD's CRS started reporting disbursement data for sector-specific aid from the year 2002. Consequently, this study used disbursed aid for energy data covering the period 2002-2021. Moreover, to make better comparison and examine differential impacts between aid recipient countries, studies have suggested scaling foreign aid relative to specific recipient countries' indicators like population, real GDP, and GDP purchasing power parity (Maruta, 2018; Alemu & Lee, 2015; Agapova & Vishwasrao, 2020). We scaled aid to energy sector, measured at constant $USD 2015, in per capita term in which it is divided by the total population of the recipient countries.

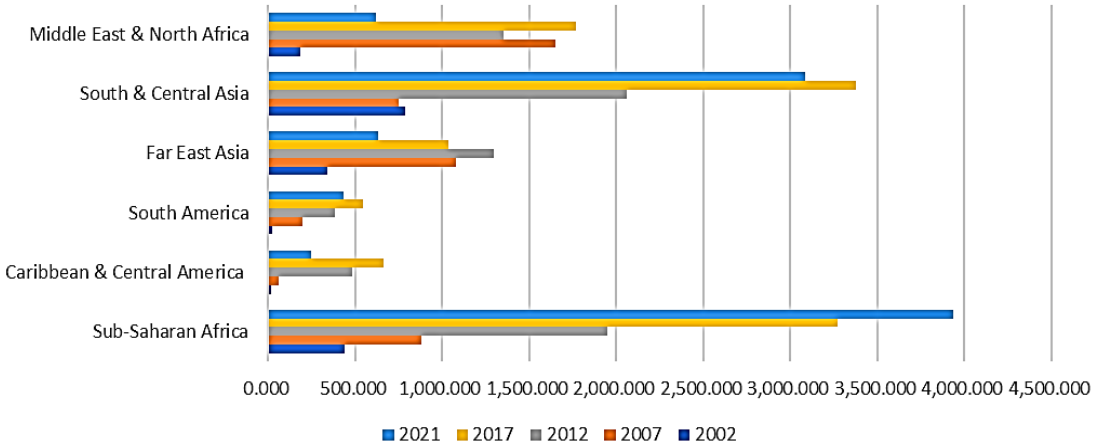
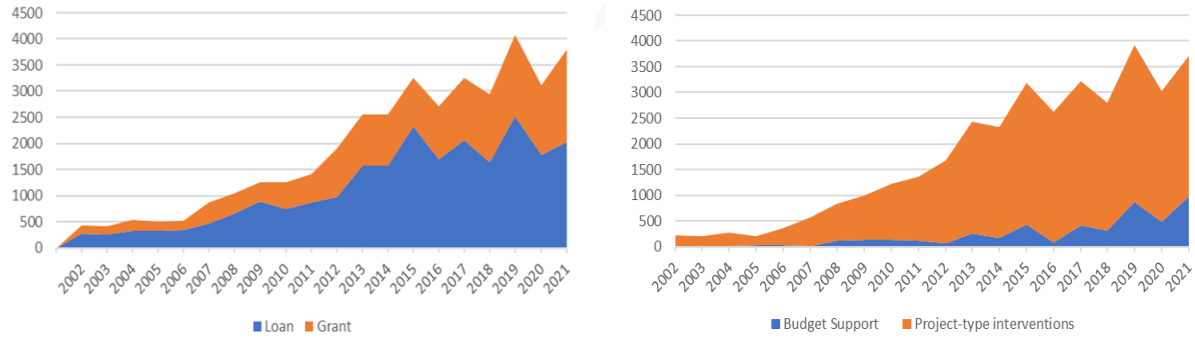


Figure 3: Disbursed Foreign aid for Energy Sector, 2002-2021.

Figure 3 shows the donors have disbursed more aid for the energy sector to SSA than any other regions of the world between 2002 and 2021; and next to SSA is the South and Central Asia. Aid disbursed for energy sector disbursed to SSA increased from 0.438 to 3.935 $US billion as against an increase from 0.784 to 3.088 $US billion between 2002 and 2021. Figures 3a and 3b shows the variation in the disbursement of aid flow (loan and grants) and types (budget support and project-type intervention) respectively to SSA during the period 2002-2021. Figure 3a shows that more grants were disbursed than loans (i.e., ratio 1: 1.54); as well as Figures 3b shows that donors favoured project-type intervention more than budget support as types of aid (i.e., ratio 1: 6.66).



vs Project-type Intervention

3.1.4 Control variables

To investigate the strong relationship between energy poverty and public expenditure, we control for other potential determining factors of poverty energy in our regression. Specifically, we consider the most used variable in the empirical theory: real GDP per capita or per capita income (growth). The Gini index is a proxy for income inequality (Ineq). Foreign direct investment net inflows (% of GDP) and trade (% of GDP) are proxy for FDI net inflows and trade openness (Trade), respectively. The general government's final consumption expenditure (% of GDP) is a proxy for measuring the overall level of government spending on goods and services that are consumed by the general public. The CO2 emissions are quantified in metric tons per annum of carbon emissions per capita (CO2). For the institutional quality (Instq) variable, we apply a set of institutional factors taken from the Worldwide Governance Indicators (WGI). In fact, five

indicators were selected, which are (i) voice and accountability, (ii) government effectiveness, (iii) regulatory quality, (iv) control of corruption, (v) political stability and absence of violence/terrorism, and (v) rule of law. These five indicators are collected, and their average is calculated to proxy for overall institutional quality (Instq) in Sub-Saharan African countries. The description of the other variables and data sources is set out in Table 1.

4. Results and discussion

4.1 Summary statistics

Table 1 shows the summary of the data sets. This table presents source of all variables, their units of measurement, means, standard deviations (overall, between and within countries), and minimum and maximum values. The statistical description of the variables is crucial to observe the distribution and variability of the studied variables. This is done to circumvent the likely problems associated with time series and cross-section data. All the variables display considerable variation both between and within countries, suggesting the use of panel estimation techniques, which allows the identification of the various parameters of interest, is reasonable. Moreover, the correlation coefficients are within suitable ranges and confirm the choice of both explanatory and instrumental variables. Moreover, Table 2 shows the correlation coefficients between all key variables which help to design the model and to confirm the choice of instruments. The result showed no threat of multicollinearity among variables as depicted in the correlation matrix. The highest correlation coefficient was 89.40% between energy productive capacity index (EIDEV) and energy poverty (EPOV). This was followed by the correlation coefficient between EIDEV and HDI (i.e., 81.8%) and between per capita energy aid and energy aid-real-GDP-ratio (i.e., 73.20%). These coefficients did not pose any serious threat of multicollinearity, especially since the link between them in this study is either that of a dependent-independent relationship or none. The strong correlation coefficient between per capita energy aid and the energy aid-to-real-GDP ratio provides a valid justification for employing the latter as an alternative measure of energy aid in the robustness check models.

Table 1: Summary statistics: annual data (2002–2021; observations=500).

Variable	Source	Measurement	Mean	Overall Std. Dev.	Between Std. Dev.	Within Std. Dev.	Min	Max
Energy Productive Capacity Index	UNCTAD	Index	22.197	14.26	13.941	4.052	1	59.994
Access to clean fuels and technologies for cooking	WDI	% of population	36.742	22.429	21.130	8.580	1.280	95.521
Energy Aid	OECD	US Dollars (in Millions)	46.23	64.60	35.410	54.469		
Per Capita Energy Aid	OECD/WDI	US Dollars (derived by dividing Energy Aid by population)	3.561	8.579	5.561	6.622	.001	121.493
Energy Aid- real-GDP-ratio	OECD/WDI	US Dollars (derived by dividing Energy Aid by GDP constant 2015)	.313	.474	.283	.384	0.00005	3.888
Institutional Quality	WGI	Estimate (derived by taking the average of the six governance indicators published by WGI)	-.626	.520	.509	.146	-1.675	.528
General government final consumption expenditure	WDI	% of GDP	13.101	5.082	4.584	2.300	.952	27.94
Human Development Index	UN	Index	.491	.087	.080	.037	.274	.736
Foreign direct investment, net inflows	WDI	% of GDP	4.39	6.3	3.573	5.236	-18.918	46.275
Domestic credit to private sector by banks	WDI	% of GDP	16.564	15.474	15.087	4.528	.002	70.382
Income inequality	WID	Index (bottom 50%)	.120	.026	.024	.010	.055	.182
Inflation	WDI	Consumer Price Index (%)	6.596	8.877	5.696	6.900	-8.975	108.897

CO2 emissions	WDI	Metric tons per capita	.681	1.49	1.514	.111	.03	8.447
Gross Capital Formation	WDI	% of GDP	23.688	10.038	7.391	7.132	6.699	79.401
Trade openness	WDI	% of GDP	63.751	24.288	21.603	11.872	16.352	156.862
Countries (*N* = 25)	Angola, Benin, Cabo Verde, Cameroon Chad, Congo, Democratic Republic of Congo, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Madagascar, Mali, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Tanzania, Uganda, and Zambia.							

Note: UNCTAD = United Nations Conference on Trade and Development; WDI = World Development Indicators; OECD = The Organization for Economic Co-operation and
Development; WBCP = World Bank Commodity Price Database; WGI = World Governance Indicator; UN = United Nations; WID = World Inequality Database
Source: Authors' computation, 2025

Table 2: The Results of Pairwise Correlations Analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) EIDEV	1.000													
(2) EPOV	0.894 (0.000)	1.000												
(3) EAPC	0.303 (0.000)	0.311 (0.000)	1.000											
(4) EAGDP	-0.020 (0.662)	0.043 (0.333)	0.732 (0.000)	1.000										
(5) INSTQ	0.583 (0.000)	0.529 (0.000)	0.355 (0.000)	0.184 (0.000)	1.000									
(6) GEXP	0.339 (0.000	0.209 (0.000	0.215 (0.000	0.102 (0.027	0.465 (0.000	1.000								

	)	)	)	)	)									
(7) HDI	0.818	0.788	0.298	0.058	0.554	0.290	1.000							
	(0.000	(0.000	(0.000	(0.200	(0.000	(0.000								
	)	)	)	)	)	)								
(8) FDI	-0.075	-0.094	0.076	0.115	-0.008	0.199	-0.069	1.000						
	(0.092	(0.036	(0.090	(0.010	(0.850	(0.000	(0.125							
	)	)	)	)	)	)	)							
(9) DCPS	0.775	0.666	0.372	0.092	0.736	0.616	0.702	0.002	1.000					
	(0.000	(0.000	(0.000	(0.039	(0.000	(0.000	(0.000	(0.958						
	)	)	)	)	)	)	)	)						
(10) INEQ	-0.404	-0.226	-0.003	0.162	-0.337	-0.475	-0.506	-0.092	-0.508	1.000				
	(0.000	(0.000	(0.940	(0.000	(0.000	(0.000	(0.000	(0.039	(0.000					
	)	)	)	)	)	)	)	)	)					
(11) CPI	0.051	-0.060	-0.099	-0.099	-0.121	-0.036	-0.014	0.059	-0.158	-0.065	1.000			
	(0.258	(0.180	(0.027	(0.027	(0.007	(0.434	(0.759	(0.188	(0.000	(0.145				
	)	)	)	)	)	)	)	)	)	)				
(12) CO2	0.652	0.542	0.005	-0.149	0.429	0.316	0.586	-0.077	0.709	-0.456	-0.018	1.000		
	(0.000	(0.000	(0.911	(0.001	(0.000	(0.000	(0.000	(0.085	(0.000	(0.000	(0.693			
	)	)	)	)	)	)	)	)	)	)	)			
(13) GCF	0.068	0.053	0.210	0.115	0.077	0.260	0.129	0.524	0.118	-0.116	0.023	-0.066	1.000	
	(0.137	(0.240	(0.000	(0.011	(0.091	(0.000	(0.005	(0.000	(0.009	(0.011	(0.609	(0.146		
	)	)	)	)	)	)	)	)	)	)	)	)		
(14) TOPEN	0.228	0.118	0.131	-0.026	0.001	0.397	0.201	0.423	0.205	-0.306	0.107	0.056	0.488	1.000
	(0.000	(0.008	(0.003	(0.567	(0.980	(0.000	(0.000	(0.000	(0.000	(0.000	(0.017	(0.208	(0.000	
	)	)	)	)	)	)	)	)	)	)	)	)	)	

Note 1: * and ** implies significance at 5% and 10% levels of significant errors respectively. **Note 2**: EIDEV= Energy Infrastructure Endowment (proxied by Energy Productive Capacity Index); EPOV = Energy Poverty (proxied by Access to clean fuels and technologies for cooking); EAPC = Energy Aid Per Capita; EAGDP = Energy Aid-real-GDP-ratio; INSTQ = Institutional Quality (measured by the average of the estimates of Control of Corruption, Voice and Accountability, Democratic Voice and Accountability, Government Effectiveness, and Regulatory Quality; GEXP = General government final consumption expenditure; HDI = Human Development Index; FDI = Foreign Direct Investment Inflow; DCPS = Domestic credit to private sector by banks; INEQ = Income inequality; CPI = Consumer Price Index (proxy for inflation); CO2 = CO2 emissions (proxy for environmental degradation; GCF = Gross Capital Formation (proxy for

total investment level); TOPEN = Trade openness (as a proxy for global integration).
Source: Authors' computation, 2025.

4.2 Panel cross-section dependency test (CD test)

The cross-sectional dependence (CSD) test represents an essential preliminary diagnostic in panel data analysis. Traditionally, models assume that error terms are cross-sectionally independent, particularly when the cross-sectional dimension (*N*) is large. However, empirical evidence suggests that cross-sectional dependence is a prevailing feature in macro-panel datasets and should not be overlooked (Adams & Klobodu, 2017; Beckmann & Czudaj, 2017; Pesaran, 2004, 2015). Ignoring this interdependence may lead to inefficient estimators and invalid statistical inference. The results of the Pesaran (2004, 2015) CD test, as reported in Table 3, confirm the presence of cross-sectional dependence, with the null hypothesis of independence rejected at the 1% significance level for the majority of the selected variables. Only institutional quality (INSTQ) and the Gini index (INEQ) failed to reject the null hypothesis. These findings underscore the importance of incorporating cross-unit lagged interdependencies into the model specification. Moreover, the observed cross-sectional dependence implies substantial heterogeneity in the interactions among variables across countries, indicating that analyses based solely on country-specific shocks may produce regionally biased conclusions.

Table 3: The Results of Pesaran (2004, 2015) Panel Cross-Sectional Dependence (CSD) Test.

Variable	CD Test Statistic	P-value	Decision
EIDEV	41.221***	0.000	Strong CSD
EPOV	68.865***	0.000	Strong CSD
EAPC	24.574***	0.000	Strong CSD
EAGDP	18.662***	0.000	Strong CSD
INSTQ	-0.275	0.783	Weak CSD
GEXP	2.632***	0.008	Strong CSD
HDI	74.034***	0.000	Strong CSD
FDI	3.394***	0.000	Strong CSD
DCPS	45.678***	0.000	Strong CSD
INEQ	0.391	0.696	Weak CSD
CPI	12.809***	0.000	Strong CSD
CO2	32.748***	0.000	Strong CSD
GCF	5.558	0.000	Strong CSD
TOPEN	3.893	0.000	Strong CSD

Note: (***), (**) and (*) indicates significant at 1%, 5% and 10% level respectively.
Source: Authors' computation, 2025.

4.3 Panel unit root tests

Table 4: The Results of Panel unit root tests results

Variables	**First generation**: Im-Pesaran-Shin (IPS)		**Second generation**: Pesaran's CADF		Order of Integration
	Levels	1st Diff.	Levels	1st Diff.	
EIDEV			-1.18	-6.25***	I (1)
EPOV			-1.19	-10.35***	I (1)
EAPC			0.88	-6.61***	I (1)
EAGDP			-1.85**		I (0)
INSTQ	-2.47***				I (0)
GEXP			0.51	-5.05***	I (1)
HDI			0.19	-3.55***	I (1)
FDI			-2.42***		I (0)
DCPS			-0.34	-5.41***	I (1)
INEQ	-2.40***				I (0)
CPI			-7.35***		I (0)
CO2			-2.23**		I (0)
GCF			-0.45	-7.59***	I (1)
TOPEN			-0.63	-4.35***	I (1)

Note: (***), (**) and (*) indicates significant at 1%, 5% and 10% level respectively.
Source: Authors' computation, 2025.

Since Pesaran's cross-sectional dependence (CSD) test revealed strong dependence across units for the majority of variables (twelve), indicating panel heterogeneity, and weak dependence for only two variables, the study proceeded to examine variable stationarity using panel unit root tests. For the twelve variables exhibiting strong cross-sectional dependence, the Pesaran CADF test—appropriate for heterogeneous panels—was employed. For the two variables with weak dependence, namely institutional quality (INSTQ) and the Gini index (INEQ), the Im, Pesaran and Shin (IPS) heterogeneous panel unit root test was used. As reported in Table 4, both INSTQ and INEQ were stationary at level according to the first-generation panel unit root tests. Table 4 also shows consistency in the second-generation heterogeneous panel unit root tests, with results indicating that eight variables were stationary after first differencing based on the Pesaran CADF test. Additionally, four variables—energy aid as a share of GDP (EAGDP), foreign direct investment (FDI), consumer price index (CPI), and carbon emissions (CO_2)—were stationary at level.

4.4 Energy aid effectiveness regression

To evaluate the effectiveness of energy aid across Sub-Saharan African (SSA) countries, we applied a sequential (two-stage) Generalised Method of Moments (GMM) regression approach (Kripfganz & Schwarz, 2015) across eleven model specifications (Table 5). The primary model indicates that per capita energy aid (0.026, $p < 0.05$), institutional quality (3.312, $p < 0.05$), and human capital development (41.630, $p < 0.01$) significantly enhance energy infrastructure endowment, confirming the overall effectiveness of aid in this domain. Diagnostic checks support the validity of instruments (Hansen J statistic $p = 0.47 > 0.05$) and reveal acceptable autocorrelation structure: first-order autocorrelation is present ($p = 0.01$), but no significant second- or third-order serial correlation was detected. Moreover, models assessing aid flow segmentation show that

energy aid is effective primarily among 'orphans'—countries receiving low volumes of loans and grants—with significant coefficients in model 2 (0.028, $p < 0.10$) and model 4 (0.022, $p < 0.01$), respectively. No significant effects are found among 'darlings'. Instrument validity and serial independence are confirmed across these models. Also, aid type analysis reveals similar patterns: both project-based and budget-support aid are effective amongst *orphan* recipients (models 6 and 8), yielding significant impacts (0.026 and 0.020, respectively; $p < 0.05$). These effects are absent among aid darlings. While most models pass the autocorrelation and Hansen tests, the project intervention orphans' model shows mild first-order autocorrelation. Lastly, income-level disaggregation suggests energy aid is effective only among middle-income SSA countries (model 10: 0.026, $p < 0.05$), with no observable impact in low-income settings. All instrument sets remain valid, and no concerning autocorrelation patterns were detected. In summary, these results emphasise the conditional nature of aid effectiveness, highlighting orphan-status and income-level as critical moderators. Policy implications underscore the need for more targeted, context-sensitive energy aid allocation strategies across SSA.

4.5 Impact of energy aid and energy infrastructure endowment on energy poverty

This study also assesses the relative impact of energy aid and energy infrastructure endowment on energy poverty across 25 Sub-Saharan African countries using a sequential (two-stage) GMM framework (Kripfganz & Schwarz, 2015). Eleven models were estimated (Table 6). In the baseline model, per capita energy aid (0.031, $p < 0.05$), energy infrastructure productive capacity (0.662, $p < 0.01$), and institutional quality (5.793, $p < 0.01$) positively influence energy poverty reduction, while CO_2 emissions exert a negative effect (-2.435, $p < 0.01$). Diagnostics confirm instrument validity (Hansen $p = 0.75 > 0.05$) and acceptable autocorrelation, with no significant second- or third-order serial dependence. Moreover, models examining how the volume of aid flow influence the effectiveness of energy aid show significant direct effects of energy aid on energy poverty among loan (0.036, $p < 0.01$) and grant orphans (0.033, $p < 0.01$), and indirect effects via infrastructure across orphan and grant darling groups. Aid type analysis reveals similar patterns: energy aid significantly improves energy poverty outcomes for project-based (0.031, $p < 0.01$) and budget-support orphans (0.032, $p < 0.05$), with infrastructure endowment significant across both orphan and darling configurations. Lastly, income-level analysis shows a direct positive impact of aid in middle-income countries (1.327, $p < 0.01$), and an indirect effect via infrastructure in low-income settings (1.038, $p < 0.01$), despite a slight negative direct aid effect (-0.679, $p < 0.10$) in the latter. Lastly, post-estimation tests across all models affirm joint instrument validity (Hansen $p > 0.05$) and no problematic serial correlation beyond the first order. The findings highlight the differentiated effectiveness of energy aid based on aid flow, modality, and income level, underscoring the importance of targeting absorptive capacity and governance dynamics in energy poverty reduction strategies.

Table 5: The Results of the estimated two-step system GMM Dynamic panel data models to examine the effectiveness of energy aid, dependent variable: *energy infrastructure endowment* (proxied by energy productive capacity index)

Variables	Main Model	**Energy Aid Flow**				**Energy Aid Type**				**Income level**	
		Loan - Orphan & Darling		Grant - Orphan & Darling		Project Intervention - Orphan & Darling		Budget Support Orphan & Darling		Low and Middle Income	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
L1_Energy Infra. Dev.	0.604*** (0.000)	0.696** (0.017)	-0.203 (0.539)	0.304 (0.323)	0.837*** (0.000)	0.830*** (0.000)	-0.057 (0.883)	0.415 (0.148)	-0.540 (0.694)	0.193 (0.671)	0.423 (0.114)
L2_Energy Infra. Dev.	0.014 (0.789)	-0.096* (0.078)	-0.068 (0.606)	-0.007 (0.928)	0.024 (0.815)	-0.105** (0.040)	-0.072 (0.605)	0.018 (0.739)	-0.227 (0.543)	-0.085 (0.514)	-0.024 (0.514)
Per Capita Energy Aid	0.026** (0.016)	0.028* (0.062)	-0.045 (0.503)	0.022*** (0.000)	-0.760 (0.214)	0.026** (0.095)	0.033 (0.871)	0.020** (0.016)	0.085 (0.461)	-0.010 (0.803)	0.027** (0.016)
Institutional Quality	3.312** (0.022)	4.557*** (0.000)	0.056 (0.994)	3.873*** (0.007)	8.141 (0.382)	3.918*** (0.000)	-32.299 (0.640)	4.134** (0.035)	-26.838 (0.744)	0.563 (0.748)	4.210* (0.072)
Govt. Expenditure	0.032 (0.632)	-0.125 (0.123)	0.067 (0.377)	0.047 (0.401)	-0.450 (0.159)	-0.112 (0.137)	-0.320 (0.622)	0.074 (0.185)	0.156 (0.715)	0.152* (0.062)	0.007 (0.929)
Human Dev. Index	41.630*** (0.001)	33.028** (0.040)	172.728** (0.012)	62.400*** (0.004)	- -	28.199* (0.067)	71.465 (0.400)	47.069* (0.058)	311.043 (0.369)	107.261 (0.369)	57.423*** (0.000)
Foreign Direct Invest.	0.014 (0.576)	-0.008 (0.518)	0.108 (0.192)	0.004 (0.747)	0.068* (0.052)	-0.007 (0.571)	0.131* (0.065)	0.008 (0.685)	0.162 (0.270)	0.0004 (0.980)	0.011 (0.683)
Credit to Priv. Sector	-0.024 (0.555)	0.020 (0.724)	-0.035 (0.362)	0.0004 (0.994)	1.173 (0.204)	0.014 (0.701)	1.116 (0.516)	0.008 (0.757)	-0.478 (0.405)	-0.027 (0.590)	-0.033 (0.555)
Trade Openness	-0.017 (0.313)	-0.018 (0.264)	-0.056** (0.010)	-0.016 (0.149)	-0.094** (0.023)	-0.006 (0.669)	-0.075 (0.240)	-0.009 (0.395)	-0.042 (0.267)	-0.002 (0.859)	-0.028** (0.017)
Constant	-9.042** (0.037)	-2.047 (0.712)	- 54.863** (0.024)	-10.944 (0.120)	6.515 (0.429)	-3.706 (0.351)	- 39.505** (0.045)	-8.068 (0.232)	-120.80 (0.493)	-36.30 (0.149)	-9.089* (0.079)
No. of countries/obs.	25/500	14/280	11/220	16/320	9/180	15/300	10/200	15/300	10/200	12/240	13/260
Sample period	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021

Hansen's J test (*p -value*)	0.47	0.39	0.95	0.73	1.00	0.67	1.00	0.57	1.00	0.82	0.89
AR (1) test (*p - value*)	0.01	0.05	0.77	0.11	0.09	0.04	0.93	0.12	0.56	0.44	0.06
AR (2) test (*p - value*)	0.33	0.77	0.06	0.72	0.98	0.82	0.99	0.66	0.63	0.76	1.00
AR (3) test (*p - value*)	0.22	0.41	0.05	0.36	0.33	0.38	0.79	0.85	0.59	0.71	0.25

Note 1: (***), (**) and (*) indicates significant at 1%, 5% and 10% level respectively. Note 2: (1) = Main Model (without influence); (2) = Loan Orphan Model; (3) = Loan Darling Model; (4) = Grant Orphan Model; (5) = Grant Darling Model; (6) = Project Intervention Orphan Model; (7) = Project Intervention Darling Model; (8) = Budget Support Orphan Model; (9) = Budget Support Darling Model; (10) = Low Income Countries Model; (10) = Middle Income Countries Model.
Source: Authors' Computation, 2025.

Table 6: The Results of the estimated two-step system GMM Dynamic panel data models to examine the relative impact of energy aid and energy infrastructure development on energy poverty, dependent variable: *percentage of population with access to electricity*

Variables	Main Model	**Energy Aid Flow**				**Energy Aid Type**				**Income level**	
		Loan – Orphan & Darling		Grant – Orphan & Darling		Project Intervention - Orphan & Darling		Budget Support Orphan & Darling		Low and Middle Income	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
L1_Energy Poverty	0.551*** (0.000)	0.605*** (0.000)	0.201 (0.783)	0.552*** (0.000)	0.514*** (0.000)	0.540*** (0.000)	0.502* (0.063)	0.677*** (0.000)	0.260 (0.541)	0.534 (0.100)	0.679*** (0.000)
L2_Energy Poverty	0.247*** (0.000)	0.222*** (0.000)	0.146 (0.407)	0.275*** (0.000)	0.097 (0.522)	0.274*** (0.000)	0.334 (0.220)	0.237*** (0.000)	0.163 (0.163)	0.236* (0.092)	0.250** (0.010)
Per Capita Energy Aid	0.031** (0.027)	0.036*** (0.000)	0.021 (0.835)	0.033*** (0.005)	-0.156 (0.306)	0.031*** (0.003)	-0.050 (0.812)	0.032** (0.017)	-0.365 (0.803)	-0.679* (0.064)	1.327*** (0.000)
Energy Infra. Dev.	`0.662*** (0.001)	0.522*** (0.000)	0.983 (0.259)	0.669** (0.026)	0.653*** (0.004)	0.540*** (0.004)	0.943** (0.014)	0.612*** (0.000)	0.247 (0.897)	1.038*** (0.001)	0.388 (0.203)

Institutional Quality	5.793** (0.012)	4.335 (0.133)	9.219 (0.358)	3.319 (0.161)	16.290* (0.083)	5.039** (0.036)	2.579 (0.965)	3.499 (0.346)	41.57 (0.728)	7.295 (0.363)	1.992 (0.517)
Income Inequality	23.060 (0.462)	50.514 (0.237)	-666.467 (0.807)	4.466 (0.852)	- -	40.483 (0.287)	- -	-15.756 (0.604)	- -	15.846 (0.987)	8.091 (0.866)
Inflation	0.001 (0.994)	0.010 (0.673)	-0.012 (0.935)	0.002 (0.942)	0.076 (0.224)	0.010 (0.647)	-0.061 (0.766)	0.038 (0.132)	0.047 (0.899)	0.022 (0.542)	- 0.089*** (0.001)
Govt. Expenditure	-0.098 (0.495)	-0.076 (0.558)	-0.238 (0.562)	-0.019 (0.892)	-2.925 (0.270)	-0.030 (0.832)	-0.328 (0.344)	-0.067 (0.603)	0.187 (0.932)	-0.027 (0.861)	-0.286 (0.280)
CO2 Emission	- 2.435*** (0.000)	-1.224 (0.702)	11.933 (0.912)	-2.705*** (0.000)	- -	-0.246 (0.945)	-0.769 (0.870)	- 3.343*** (0.000)	140.997 (0.782)	- 36.978** (0.041)	-2.229** (0.011)
Gross Cap. Formation	-0.026 (0.360)	-0.024 (0.241)	-0.096 (0.807)	-0.018 (0.439)	-0.033 (0.678)	-0.029 (0.175)	-1.092 (0.637)	-0.005 (0.862)	-0.327 (0.742)	-0.069 (0.177)	0.027 (0.462)
Constant	-1.440 (0.741)	-4.938 (0.351)	79.50 (0.776)	-3.793 (0.279)	44.999 (0.213)	-4.148 (0.361)	20.602 (0.388)	-1.952 (0.706)	-9.886 (0.908)	3.306 (0.978)	-0.558 (0.940)
No. of countries/obs.	25/500	14/280	11/220	16/320	9/180	15/300	10/200	15/300	10/200	12/240	13/260
Sample period	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021	2002-2021
Hansen's J test (*p -value*)	0.75	0.84	1.00	0.76	1.00	1.00	1.00	0.52	1.00	0.83	0.73
AR (1) test (*p - value*)	0.00	0.00	0.33	0.01	0.04	0.01	0.01	0.01	0.34	0.03	0.02
AR (2) test (*p - value*)	0.06	0.42	0.94	0.06	0.45	0.19	0.73	0.60	0.81	0.41	0.18
AR (3) test (*p - value*)	0.32	0.45	0.97	0.13	0.05	0.32	0.77	0.69	0.87	0.63	0.61

Note 1: (***), (**) and (*) indicates significant at 1%, 5% and 10% level respectively. Note 2: (1) = Main Model (without influence); (2) = Loan Orphan Model; (3) = Loan Darling Model; (4) = Grant Orphan Model; (5) = Grant Darling Model; (6) = Project Intervention Orphan Model; (7) = Project Intervention Darling Model; (8) = Budget Support Orphan Model; (9) = Budget Support Darling Model; (10) = Low Income Countries Model; (10) = Middle Income Countries Model.

Source: Authors' Computation, 2025.

4.6 Robustness check

We conducted robustness checks to assess the sensitivity of the findings to alternative measures of energy sector aid and to the use of a sub-sample of observations from the main models. The first set of checks involved employing the aid-to-real GDP ratio as an alternative proxy for foreign aid in both the aid effectiveness and energy poverty models (see Burnside and Dollar, 2000; Clemens et al., 2004; Collier and Dehn, 2001). Throughout the main analysis, we adopted per capita energy sector aid as the preferred measure (cf. Mishra and Newhouse, 2009; Dreher et al., 2008; d'Aiglepierre and Wagner, 2013). The findings reported in Tables 7 and 8 (see appendix) are qualitatively consistent with those in Tables 5 and 6, retaining identical signs and significance levels. A further set of robustness checks was conducted using a sub-sample of twenty (20) countries, having excluded five (5) statistical outliers. Two models were re-estimated: the energy aid effectiveness model and the energy poverty model. It is noteworthy that the results obtained using a sub-sample of twenty (20) countries remained consistent with those reported in Tables 5 and 6.

5. Conclusion and Recommendations

The effect of aid targeted to energy sector on energy infrastructure endowment and energy poverty; and the relative impact of energy prices and energy infrastructure endowment on energy poverty is assessed empirically within the framework of cross-country regressions for 25 recipient countries in SSA over the period 2002–2021. The study employed the sequential two-stage GMM (SGMM) model by Kripfganz and Schwarz (2015). The findings suggest that higher per capita energy sector aid significantly improves energy infrastructure endowment and reduces energy poverty. Moreover, while energy prices did not impact significantly on energy poverty, improvement of energy infrastructure endowment significantly reduces energy poverty. This study has also provided empirical evidence on the aid flow and type conditionalities of effectiveness of foreign aid for energy sector. per capita energy aid had a slight significant positive impact on energy infrastructure endowment among loan orphans; but significantly improve energy infrastructure endowment among orphans of grant, project-type intervention, budget support, and middle-income countries. Moreover, per capita energy aid significantly reduces energy poverty among orphans of loan, grant, project-type intervention, budget support, and middle-income countries. Worthy of mention is that energy infrastructure endowment significantly reduces energy poverty in majority (in exception of loan and budget support darling and middle-income countries) of the categories of aid flow, aid types, and income level countries examined. Further, these results are robust to the alternative measures of energy sector aid, and using as sub-sample of the observation used. While the results align with some findings, they are contrary to others. For example, the finding on effect of energy aid for on energy infrastructure align with the finding of Villanthenkodath et al (2023) but was contrary to the findings of Gondwe and Mbonigaba (2023) and Donaubauer and Nunnenkamp (2016). Also, the finding on aid effect on energy poverty align with that of Munyanyi and Sefa (2022) and Foo et al (2021) who found aid to significantly lowers energy poverty. The novelty in the study is the evidence of aid for energy having a direct and indirect impact on energy poverty, and the influence of the conditionalities of aid flow, aid type, income level of recipients of energy aid. Addressing energy poverty dilemma requires a multifaceted approach that considers all the interrelated factors. In unison, this study highlights the need to disaggregate aid to examine its effectiveness. Aid targeted to energy sector has significant contribution to achieving improvement in energy infrastructure endowment and reducing energy poverty in developing countries.

Drawing on the study's findings, economic policy should prioritise targeted energy-sector aid that enhances infrastructure endowment, particularly in Sub-Saharan African countries with limited aid inflows and middle-income status. Policymakers and donors should disaggregate aid by flow and modality—emphasising grants, project-based interventions, and budget support mechanisms—given their superior effectiveness in reducing energy poverty. Aid should be strategically directed toward infrastructure expansion. In countries with abundant energy resources and those with low electricity capacity alike, investment in infrastructure consistently proves beneficial, indicating that universal access goals require inclusive capital allocation. To ensure maximum development impact, energy aid should be accompanied by institutional capacity-building and targeted monitoring frameworks that reflect the direct and indirect transmission channels between aid, infrastructure, and household-level energy deprivation.

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Appendix

Table 7: The impact of energy aid on energy infrastructure development using alternative measures of energy aid and 80 percent of cross-section.

Variables	**Energy Aid-to-real GDP ratio**	**80 percent of cross-section (20 countries)**
	Model$_1$	Model$_2$
L1_Energy Infra. Dev.	0.573***	0.605***
	(0.001)	(0.006)
L2_Energy Infra. Dev.	0.018	-0.026
	(0.742)	(0.620)
Energy Aid	0.679***	0.026**
	(0.008)	(0.013)
Inst. quality	3.115**	4.567***
	(0.034)	(0.003)
Govt. Expenditure	0.030	0.053
	(0.646)	(0.535)
Human Dev. Index	41.071***	46.418**
	(0.001)	(0.013)
Foreign Direct Invest.	0.014	0.082**
	(0.586)	(0.015)
Credit to Priv. Sector	-0.020	-0.049
	(0.641)	(0.308)
Trade Openness	-0.016	-0.031
	(0.376)	(0.175)
Constant	-9.072**	-8.692
	(0.039)	(0.115)
Hansen J test (*p-value*)	0.4656	0.4329
AR (1) test (*p-value*)	0.0096	0.0289
AR (2) test (*p-value*)	0.3352	0.6481
AR (3) test (*p-value*)	0.3352	0.4630

Note: (***), (**) and (*) indicates significant at 1%, 5% and 10% level respectively.
Source: Authors' Computation, 2025.

Table 8: The relative impact of energy aid and energy infrastructure development on energy poverty using alternative measure of energy aid and 80 percent of cross-section.

Variables	**Energy Aid-to-real GDP ratio**	**80 percent of cross-section (20 countries)**
	Model$_1$	Model$_2$
L1_Energy Poverty	0.538***	0.587***
	(0.000)	(0.000)
L2_Energy Poverty	0.238***	0.256***
	(0.000)	(0.620)
Energy Aid	0.940*	0.038***
	(0.097)	(0.003)
Energy Infra. Dev.	0.620***	0.612***
	(0.002)	(0.003)
Institutional Quality	28.554	6.608**
	(0.303)	(0.030)
Income Inequality	3.746	31.013
	(0.941)	(0.351)
Inflation	0.010	-0.018
	(0.684)	(0.471)
Govt. Expenditure	-0.176	-0.144
	(0.199)	(0.449)
CO2 Emission	-2.695***	-2.228
	(0.002)	(0.003)
Gross Cap. Formation	-0.035	-0.053
	(0.288)	(0.127)
Constant	17.723	-2.158
	(0.433)	(0.632)
Hansen J test (*p-value*)	0.9575	0.6536
AR (1) test (*p-value*)	0.0005	0.0008
AR (2) test (*p-value*)	0.9476	0.0727
AR (3) test (*p-value*)	0.3776	0.4700

Note: (***), (**) and (*) indicates significant at 1%, 5% and 10% level respectively.
Source: Authors' Computation, 2025.

Total		**Loan**		**Grant**		**Project Intervention**		**Budget Support**		**Income Level**	
S/N	**Orphans**	S/N	**Orphans**	S/N	**Orphans**	S/N	**Orphans**	S/N	**Orphans**	**S/N**	**Low**

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15	Angola Benin Cabo Verde Cameroon Chad Congo Gambia Guinea Guinea-Bissau Madagascar Mali Namibia Niger Sierra Leone Zambia	1 2 3 4 5 6 7 8 9 10 11 12 13 14	Angola Benin Cabo Verde Cameroon Chad Congo DRC Gambia Guinea Guinea-Bissau Madagascar Namibia Niger Sierra Leone	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16	Angola Cabo Verde Cameroon Chad Congo Côte d'Ivoire Gambia Guinea Guinea-Bissau Madagascar Mali Namibia Niger Senegal South Africa Zambia	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15	Angola Benin Cabo Verde Cameroon Chad Congo Côte d'Ivoire Gambia Guinea Guinea-Bissau Madagascar Mali Namibia Niger Sierra Leone	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15	Cabo Verde Cameroon Chad Congo DRC Gambia Guinea Guinea-Bissau Madagascar Mozambique Namibia Sierra Leone South Africa Uganda Zambia	1 2 3 4 5 6 7 8 9 10 11 12	Chad DRC Gambia Guinea Guinea-Bissau Madagascar Mali Mozambique Niger Rwanda Sierra Leone Uganda
S/N	**Darlings**	**S/N**	**Darlings**	**S/N**	**Darlings**	**S/N**	**Darlings**	**S/N**	**Darlings**	**S/N**	**Middle (Upper & Lower)**
1 2 3 4 5 6 7 8 9 10	Côte d'Ivoire DRC Ghana Mozambique Nigeria Rwanda Senegal South Africa Tanzania Uganda	1 2 3 4 5 6 7 8 9 10 11	Côte d'Ivoire Ghana Mali Mozambique Nigeria Rwanda Senegal South Africa Tanzania Uganda Zambia	1 2 3 4 5 6 7 8 9	Benin DRC Ghana Mozambique Nigeria Rwanda Sierra Leone Tanzania Uganda	1 2 3 4 5 6 7 8 9 10	DRC Ghana Mozambique Nigeria Rwanda Senegal South Africa Tanzania Uganda Zambia	1 2 3 4 5 6 7 8 9 10	Angola Benin Côte d'Ivoire Ghana Mali Niger Nigeria Rwanda Senegal Tanzania	1 2 3 4 5 6 7 8 9 10 11 12 13	Angola Benin Cabo Verde Cameroon Congo Cote d'Ivoire Ghana Namibia Nigeria Senegal South Africa Tanzania Zambia