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Too big to be ignored: How energy poverty undermines productive efficiency

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ABSTRACT

Productive efficiency has far-reaching implications on the direction of economic growth and welfare. While this has led to an expansive literature on the drivers of productive efficiency, this literature has proceeded without considering the role of energy poverty. Yet, energy poverty affects productive efficiency on several fronts. This paper fills this knowledge gap, u. sing a sample comprising 100 developing countries for the period 2000–2017. W e found robust evidence suggesting that energy poverty negatively affects productive efficiency—i.e., energy-poor countries become productively inefficient. Further analysis in the paper revealed that this negative effect persists largely across regions and is not sensitive to cross-country differences in income level. We also found that the negative effect of energy poverty on productive efficiency becomes more pronounced at a higher level of productive efficiency. We discuss the policy implications of our findings.

1. Introduction

In this paper, we focus on the potential effect of energy poverty on productive efficiency. Energy poverty—by which we mean lack of access to affordable and reliable energy sources for all—is arguably the worst form of deprivation as its presence is inextricably intertwined with other forms of deprivation. Closely knitted to this view, Karekezi et al. (2012) note that the nexus between energy poverty and economic poverty is similar as people who lack access to cleaner and affordable energy are often trapped in a re-enforcing cycle of deprivation. Among others, this is because they are compelled to use significant amounts of their limited income on energy costs. More recently, the World Economic Forum [WEF] (2021) opined that the goal of leaving no one behind and eradicating global poverty must be preceded by intentional efforts to end energy poverty. The European Union and its member countries have also pushed for the recognition of energy poverty as a distinct form of material hardship for households that extends beyond, and overlaps with, the domains of monetary poverty and other types of material deprivation (Tirado-Herrero, 2017).

Despite the vicious cycle energy poverty triggers, it remains perversive across the world as more than 750 million people have no access to electricity and 2.6 billion people continue to lack access to clean cooking technologies (WEF, 2021). Furthermore, forecasts based on prevailing trends show that by 2030, about 670 million people will be without access to electricity and 2.1 billion people will still lack access to clean cooking energy (International Energy Agency, 2022; Sy and Mokaddem, 2022; Huang et al., 2022). The picture is more austere in developing countries. World Bank 2020 statistics indicated that 48.2 percent of the population in Sub-Saharan Africa still lacks access to electricity, while 41.4 (54.6) percent of the population in low-income (least developed) countries still lacks access to electricity (World Bank, 2023). This preponderance and pervasiveness of energy poverty have led to an expansive literature examining its effect on economic growth (see Ghali and El-Sakka, 2004; Shahidur et al., 2010; Doğanalp et al., 2021; Zhao et al., 2022). While these studies are suggestive of a detrimental effect of energy poverty on economic growth, the negative consequences of energy poverty on economic growth lie not only in its direct impact but the implicit mechanism through which it affects economic growth—undermining productive efficiency.

Considering countries as decision-making units (DMU), a country is productively efficient, if it can produce the maximum amount of output using the least number of resources or inputs such as labor and capital.

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The importance of attaining this feat cannot be overemphasized. Productive efficiency can lead to lower prices as well as increase the volume and variety of output which has a strong effect on economic growth, the standard of living, and overall welfare. The gains of lower prices and increased variety emanate jointly from the fact that productive efficiency is associated with optimal resource allocation and cost minimization in the production process. On the one hand, resource optimization results in higher levels of output with the same number of resources. This means that more goods and services are available for consumption, leading to higher levels of overall welfare. Increased output can also lead to economic growth, creating more job opportunities and improving the overall well-being of the society. On the other hand, cost minimization results in lower production costs, which, other things equal, are pushed to the consumer in the form of lower prices for goods and services. Alternatively, the lower costs can also translate into producing different products at the same time and ultimately, expand the varieties. In line with the forgoing, Ndubuisi and Owusu (2023) note that productively efficient countries compete effectively in the global market, while Danquah and Ouattara (2015) note that productive efficiency enhances productivity and economic growth and is responsible for differences in productivity amongst countries.

These growth and development benefits associated with productive efficiency have resulted in an expansive literature on its drivers (Ayuso and Rodríguez, 2004; Jayasuriya and Wodon, 2005; Danquah and Ouattara, 2015; Salas-Velasco, 2018; Das and Drine, 2020; Ndubuisi et al., 2022; Ndubuisi and Owusu, 2023). However, to our best knowledge, this literature is yet to consider the role of energy poverty. The primary objective of this paper is, therefore, to fill this knowledge gap. Energy poverty affects productive efficiency on several fronts as without access to a reliable and steady energy supply, industries (including the agricultural sector that depends on energy, say, for storing and processing harvested produce among other things) may struggle to operate efficiently. More specifically, energy poverty can affect productive efficiency directly through increased production costs, limited operational hours, reduced productivity, and hindered adoption or application of technological innovation. For instance, firms that lack reliable and steady access to energy may experience disruptions in their operations, which can result in production delays, quality debasement, equipment downtime, increased production costs, decrease production output, and reduced overall operational efficiency. It can also hinder a firm's ability to adopt energy-efficient technologies, such as automated machinery or computerized systems, which can improve efficiency and competitiveness.

In addition to these direct effects of energy poverty on productive efficiency, it can also indirectly affect it through its effect on income, human capital, and innovation. On the one hand, the impact of these variables on productive efficiency has been examined in the literature and available evidence suggests they are important for productive efficiency (see Ayuso and Rodríguez, 2004; Danquah and Ouattara, 2015; Salas-Velasco, 2018; Das and Drine, 2020). On the other hand, some studies have also examined how these variables are determined by energy poverty. Available evidence indicates they are seriously negatively affected by energy poverty (see Shahidur et al., 2010; Doğanalp et al., 2021; Banerjee et al., 2021). For instance, as energy-poor societies rely on expensive alternatives, such as diesel generators or other inefficient sources of energy, it significantly reduces profit margins and limits the resources available for investment in other productivity-enhancing activities. Energy poverty can impact human capital accumulation by affecting access to basic services such as healthcare, education, and clean water. As per innovation, as energy poverty limits access to and the use of modern machinery and equipment, entrepreneurs may face challenges in implementing innovative solutions and technologies.

Against this backdrop, we assemble country-level indicators of energy poverty and productive efficiency across 100 developing countries for the period 2000–2017 to study the impact of energy poverty on productive efficiency. To our best knowledge, this is the first study to examine such a relationship. We recur to the approach of computing productive efficiency using the data envelope analysis (DEA) (see Ndubuisi et al., 2022; Ndubuisi and Owusu, 2023; Mensah et al., 2023). The approach uses linear programming to compute an index measuring the efficiency level of a country relative to a virtual production function frontier which is considered the best practice. In this case, productively efficient countries are those operating on the production frontier and have an efficiency score of one, while productive inefficient countries are below the frontier and have an efficiency score of less than one.[1] Inspired by recent developments in the literature (see Chaudhry and Shafiullah, 2021; Barkat et al., 2023), we compute country-specific time-varying dummy indicators of energy poverty. As per the estimation strategy, we employ the Tobit model as it enables us to address the bounded nature of our outcome variable—i.e., productive efficiency. However, another crucial empirical challenge our analysis faces is endogeneity arising mainly due to reverse causality and omitted variable bias. In light of the daunting task associated with finding a valid external instrument to address these endogeneity concerns, we recur to two alternative approaches that provide causal evidence without necessarily requiring an external instrument. This includes the Lewbel instrumental variable (IV) method and the differenced generalized methods of the moment (differenced GMM) developed by Lewbel (2012) Lewbel (2012)Lewbel (2012) and Arellano and Bond (1991), respectively.

Our results show a robust evidence indicating that energy poverty significantly undermines productive efficiency. In particular, our result indicates that a full eradication of energy poverty, which corresponds to a discrete jump of the energy poverty index from the maximum value of one to the minimum value of zero, is associated with an estimated increase of the productive efficiency by almost 5.7 percent in the long run. We extend our analysis in two directions to explore possible heterogeneities in our baseline results. First, we explore how our results vary across regions and income levels. Second, we examine how our results vary across different levels of productive efficiency. We found that the productive inefficiency induced by energy poverty persists across regions and is not sensitive to differences in income level. In this case, the call to end energy poverty is a call to all as the world is increasingly more interdependent, and poor outcomes in another country may adversely affect all. Finally, we find that the negative effect of energy poverty on productive efficiency becomes more pronounced at a higher level of productive efficiency, implying that the call for greater efficiency must emphasize eliminating energy poverty in all its form and entirety.

This paper is related to the broader literature on the effect of energy poverty on economic growth and development using cross-country data (see Ghali and El-Sakka, 2004; Shahidur et al., 2010; Doğanalp et al., 2021; Zhao et al., 2022). On the one hand, our study deviates from these studies in that we focus on productive efficiency which is an important determinant of economic growth (Ndubuisi and Owusu, 2023). On the other hand, our study contributes to this broader literature by documenting one of the causal pathway energy poverty negatively affects economic growth. Along this line, our paper relates as well as contributes to the incipient literature on the drivers of productive efficiency. To date, this literature has paid predominant attention to the role of human capital, trade, ICT, institutions, and market distortions (Ayuso and Rodríguez, 2004; Jayasuriya and Wodon, 2005; Danquah and Ouattara, 2015; Salas-Velasco, 2018; Das and Drine, 2020; Ndubuisi et al., 2022; Ndubuisi and Owusu, 2023). We extend this literature by providing novel evidence on the role of energy poverty and how such effect varies across regions, income levels, and productive efficiency levels.

More broadly, our study is also related to the growing literature on the social and economic development implication of energy (in-)efficiency. This literature has among others highlighted the link between energy poverty and energy efficiency, noting that they are interlinked

[1] It follows that the productive efficiency variable range from zero to one.

(Li et al., 2021; Dong et al., 2022). We extend this literature by documenting a causal link between energy poverty and productive efficiency, and by extension energy (in-)efficiency and productive efficiency since energy poverty and efficiency are inextricably intertwined. Finally, our study relates to the firm-level literature that studies how firm performance is negatively affected by energy inefficiency, electricity shortage, and energy crisis (Montalbano and Nenci, 2019; Xu et al., 2022; Xiao et al., 2022). We contribute to this literature by providing country-level evidence on how such firm-level outcomes lead to an economy-wide effect in terms of country-level productive inefficiency.

The rest of this paper is structured as follows: the next section presents the research design, describing the study's data, model specification, and empirical strategy. Section three presents and discusses the study's findings, while section four concludes.

2. Research design

2.1. Data and computation of variables

The two most important variables for our analysis include the indicators of energy poverty and productive efficiency. Beginning with the former, there is currently no universally accepted measure. Some of the factors driving this include the multifaceted nature of energy poverty and the corresponding limited availability of comparable cross-country data on energy-related variables that are required to compute the index. This has led to energy poverty being operationalized in different ways in the literature, with the measurement varying from micro to macro studies. Within the macro literature where our work is best situated, however, most studies recline to variables on access to clean fuels and modern technologies for cooking and access to electricity (Banerjee et al., 2021; Nguyen and Nasir, 2021; Chaudhry and Shafiullah, 2021; Nguyen and Su, 2022; Barkat et al., 2023). We follow this tradition, employing four indicators that are related to energy poverty as in Barkat et al. (2023). The indexes include i) share of the total population with access to electricity, ii) share of the total population with access to clean fuels and technologies for cooking, iii) share of rural population with access to electricity; and iv) share of urban population with access to electricity. We source these variables from the World Development Indicator (WDI). For some of the few missing data points, we use the original data points to extrapolate and intraplate to reduce missing observations.[2]

Using these four variables, the computation of the energy poverty index we use in our analysis proceeds in two steps. In line with the multifaceted nature of energy poverty, Churchill and Smyth (2020) propose a composite index as an alternative to using a single indicator to proxy energy poverty. We opt for this approach. Therefore, the first step entails using the above four variables to compute a single composite index. We achieve this by employing the Principal Component Analysis—a widely received approach of transforming sets of indicators into a smaller set of linear factors. The process entails data matrix construction, standardized variables creation, correlation matrix calculation, determination of eigenvectors, and then principal components selection (Asongu, 2015; Pradhan et al., 2017; Ndubuisi et al., 2021). We extract the first principal component which has the highest eigenvalue of 3.6 and represents about 90 percent of the information. This choice is informed by the standard in the literature to use the principal components with an eigenvalue greater than one (Asongu, 2015; Ndubuisi et al., 2021). As a second step, inspired by Chaudhry and Shafiullah (2021), we use the median of the first principal component from step 1 as a cutoff, resulting in an indicator variable that takes the value of one for countries with values below the cutoff and zero otherwise. Accordingly, countries with a value of one in a period are energy poor in that period, while countries with a value of zero in a period are energy-rich in that period. In this case, the variable is a time-varying dummy indicator. Our empirical analysis relies on this indicator variable. In the robustness checks, we employ two additional indicators. First, we employ an energy poverty indicator that is based on the average of the four variables instead of the PCA. Second, following Chaudhry and Shafiullah (2021), we use an indicator of energy intensity. For completeness, we also reduce the data into a dummy that takes the value of 1 for observations below the sample median and one for observations that are equal to or above the sample median. The variable is obtained from the UN Statistics Division.[3]

As per productive efficiency, we recur to the approach of computing productive efficiency using the data envelope analysis (DEA) (see Ndubuisi et al., 2022; Ndubuisi and Owusu, 2023; Mensah et al., 2023). The DEA is a non-parametric approach used to distinguish countries that are on the global production frontier from those lagging. In this case, countries operating at the global frontier are productively efficient, while those below the frontier are productively inefficient. The method achieves this by using a linear programming method to endogenously compute a virtual production efficient frontier which it then uses to derive a country-specific indicator that captures each country's distance to the frontier. The country-specific indicator, can thus, be used in a reduced-form equation, enabling us to identify possible factors such as energy poverty that explain its variations. The DEA model is subdivided into two: the input-oriented DEA and the output-oriented DEA. As noted by Ndubuisi and Owusu (2023), the choice of the two is more of a researcher's discretion and has little or no strong statistical underpinning. We employ the output-based approach and compute the productive efficiency index under two assumptions as in Ndubuisi et al. (2021): (i) output is produced by labor and capital inputs, and (ii) there is free disposability of inputs and outputs. More formally, given an output level y and a set of inputs x, our computation of an output-oriented productive efficiency using the DEA entails solving the following linear programming problem;

$$max_{\theta,\tau}\theta \tag{1}$$

Subject to:

$$\sum_{i=1}^{I} y_{iq}\tau_i \geq y_{iq}\theta_q, q = 1, \ldots, Q$$

$$\sum_{i=1}^{I} x_{ij}\tau_i \leq x_{ij}, j = 1, \ldots, J$$

$$\lambda_i \geq 0$$

From equation (1), x_i is a column vector containing labor and capital, while y_i is the i-th country (out of I) output level. j and q inequalities capture the free disposability of inputs and output and represent the j th inputs and q th output for countries, respectively. λ is $I \times 1$ a vector with the intensity coefficient, implying that the linear problem is solved I times to obtain a value of θ for each country in the sample. Since we are interested in the output-based efficiency measure, the value of θ that solves the linear program problem that gives the productive efficiency index for each country i in time t is computed as $1/\theta$ with the inverse being the efficiency score that varies between zero and one. If $\theta_i = 1$, the country is on the frontier and current inputs cannot be reduced (proportionally). Conversely, the country is below the frontier if $\theta_i < 1$. We source original data for capital, labor, and output used to compute the index from the Penn World Table (PWT). We use all the countries in the dataset to compute the index after which we selected observations for only developing countries. Our decision to use a global sample to compute the index rather than the subsample of developing countries we

[2] Specifically, we perform a linear interpolation using the "*ipolate*" and "*epolate*" routine in STATA for interpolation and extrapolation.

[3] https://unstats.un.org/unsd/envstats/qindicators.

are interested is because the best frontier defined by the DEA is determined by the countries. In this case, we may be capturing a local frontier (when we use a subsample of developing countries) rather than a global frontier which occurs when our sample comprises mostly all countries in the world. We are more interested in how energy poverty undermines a country's productiveness and competitiveness relative to the world rather than within a region.

In addition to the variables described above, we control for other variables in our empirical analysis to minimize potential omitted variable bias. Specifically, we source data on natural resource capital and government final consumption as a share of GDP from the UNCTAD, Mobile Broadband from the WDI, financial market from the IMF database, and institutional quality from the World Governance Indicator. For the latter we use the product of the indexes of "rule of law" and "control for corruption", enabling us to jointly capture the institutional aspect of expropriation and contract enforcement. Besides addressing issues related to omitted variable bias, the inclusion of these variables is guided by the literature on productive and technological efficiency (see Danquah and Ouattara, 2015; Das and Drine, 2020; Ndubuisi et al., 2022, 2023). Table 1 provides a basic summary of descriptive statistics of these variables. Our final sample comprises an unbalanced sample of 100 developing countries, for the period 2000–2017. The outcome variable—i.e., productive efficiency—as reported in the table ranges between 0.06 and 1 which is within the bounds of the variables as previously defined. The three energy poverty indicators are also within bounds, with zero indicating energy-rich countries and one indicating energy-poor countries.

2.2. Model specifications and estimation strategies

To examine the nexus between energy poverty and productive efficiency, the baseline equation that guides our analysis is the following:

$$\psi_{it} = \beta_1 Energy\_poverty_{it} + Z_{it}\gamma + \delta_i + \delta_t + \nu_{it} \qquad (2)$$

where ψ_{it} is the country's i's productive efficiency level at period t, and $Energy\_poverty_{it}$ is an indicator variable that takes the value of 1 if a country is energy poor and 0 if the country is energy-rich. β_1 is the parameter of interest, measuring the impact of energy poverty on productive efficiency. We expect it to be negative and statistically significant, implying that energy poverty reduces productive efficiency. Z_{it} is a vector of time-varying country characteristics as discussed in the previous section. To further reduce the potential biases that may result from unobserved country heterogeneities and time shocks, we include full sets of country (δ_i) and year (δ_t) dummies. More specifically, the former absorbs unobserved time-invariant country-specific characteristics such as culture, geography, and initial institutional quality while the latter absorbs time-specific shocks such as the global financial crises that are common across countries. Finally, ν_{it} is the error term.

Concerning our estimation strategy, we first estimate equation (2) using the two-way panel fixed-effects method. However, the equation has two characteristics that require careful consideration to avoid biased estimation. The first is that the outcome variable is by construction, censored between zero and one, implying that the mere adoption of linear estimation methods leads to model misspecification and dubious statistical inference. To address this concern, past studies employ the Tobit regression which is by design best suited for models where the outcome variable is censored (see Ji and Lee, 2010; Ndubuisi and Owusu, 2023). Against this backdrop, we employ the Tobit regression as our preferred estimation strategy although we show the results of the panel fixed effect. The second concern with the baseline model is that of endogeneity concern, especially those resulting from omitted variable bias and reverse causality. Indeed, part of the problem associated with omitted variable bias is addressed by the control variables and dummies controlled in our model. Nevertheless, one cannot entirely rule out the possibility of country-specific time-varying confounding factors. Further, although we argue that energy poverty drives productive efficiency, skeptics may argue otherwise: productively inefficient countries lack the wherewithal to improve their energy and are therefore energy poor. In this case, alluding that energy poverty causes productive efficiency calls for a more formal way of addressing endogeneity issues.

One of the conventional ways to address such endogeneity issues is through the two-stage least square (IV-2SLS) method, wherein the endogenous explanatory variable is corrected with an external instrument. However, finding a valid external instrument is a daunting task. As an alternative, we recline to two approaches that provide causal evidence without necessarily requiring an external instrument. They include the Lewbel instrumental variable (IV) method and the differenced generalized methods of moment (differenced GMM) developed by Lewbel (2012) and Arellano and Bond (1991), respectively. Unlike the conventional IV approach requiring an external instrument, the Lewbel (2012) IV approach exploits heteroskedasticity present in the model to generate sets of instruments that it uses to identify the endogenous explanatory variable. Nevertheless, the method also offers options of including external instruments where available with Baum and Lewbel (2019) noting that such an approach improves the model's efficiency. Inspired by this, we include a period lag of energy poverty as an additional instrument. A similar approach while implementing the Lewbel approach is adopted by Ndubuisi et al. (2021, 2022) and even in conventional IV methods (see Flachaire et al., 2014). As per the difference-GMM, the approach identifies the endogenous explanatory variable by exploiting its lagged values. To apply the difference-GMM, we re-specify equation (2) into its dynamic form and time difference the dynamic equation to remove the country fixed-effects as described in equation 3

$$\psi_{it} = \alpha\Delta\psi_{i,t-1} + \beta_1\Delta Energy\_poverty_{it} + \Delta Z_{it}\gamma + \Delta\delta_i + \Delta\delta_t + \Delta\nu_{it} \qquad (3)$$

Table 1
Basic summary descriptive statistics.

	Observation	Mean	Std. Dev.	Minimum	Maximum
Productive Efficiency	1800	0.4086	0.2013	0.0648	1.0000
Energy Poverty (1)	1800	0.5000	0.5001	0.0000	1.0000
Energy Poverty (2)	1800	0.5000	0.5001	0.0000	1.0000
Energy Poverty (3)	1800	0.4977	0.5001	0.0000	1.0000
Institutional Quality	1800	0.6102	0.6340	−0.19800	3.2776
Financial Development	1800	0.1094	0.1578	0.0000	0.7043
Government Consumption	1780	2.5536	0.3777	−0.0494	3.7723
Mobile Broadband	1793	57.0021	46.3828	0.0000	190.525
Natural Resource	1777	54.9801	8.2971	14.6077	96.6857

Note: This table reports the basic summary statistics of the variables used in our analysis. All variables are in levels except government consumption which is in the log. Productive efficiency is computed using the data envelop analysis (DEA). The index is a relative efficiency measure defined as the distance between the country's efficiency score and the global efficiency score in a given period; Energy poverty indicators are country-specific time-varying dummy indicator that takes the value of one for those periods a country is considered energy poor, and zero for those periods the country is considered energy-rich. Energy poverty 1 is based on the sample median cutoff of a synthetic index that is based on an extracted first principal component of four variables on access to electricity, clean fuels, and modern technologies for cooking. Energy poverty 2 is based on the sample median cutoff of a synthetic index that is based on the unweighted average of these four variables on access to electricity, clean fuels, and modern technologies for cooking. Energy poverty 3 is based on the sample median cutoff of energy intensity.

From equation (3), all variables and subscripts are as previously defined. Further, $\Delta\delta_i = 0$ and $\psi_{i,t-1}$ is a period-lagged value of productive efficiency for country *i*. Successful application of the method relies on the following orthogonality condition: $E(\psi_{i,t-s}\Delta\nu_{it}) = 0$ for $t = 3, \ldots T$ and $2 \leq s \leq T-1$, wherea $\psi_{i,t-s}$ are suitable lags of the dependent variable. Although we employ the difference-GMM to address the endogeneity issue, it is important to note that it does not address the boundary problem discussed earlier. Therefore, while we employ it to show the robustness of our results, we still consider the Tobit regression as our preferred estimator.

In addition to examining the linear relationship between energy poverty and productive efficiency, we extend our analysis to explore possible heterogeneities that may arise due to cross-country differences and differences in the distribution of productive efficiency. Beginning with the former, such analysis can help us to underpin whether our baseline finding is a global phenomenon or driven by country or group specificities. To this end, we test such heterogeneity by focusing on cross-country income-level differences but also present results for three sub-regions in the appendix. To test the income-level difference, we augment the baseline Equation with an indicator variable of income level, and an interaction variable comprising the indicators of energy poverty and income level. The income level variable we compute is based on a sample mean cut-off of real GDP per capita.[4] The resulting index takes the value of zero for countries that lie above the sample mean (and by definition is considered developing countries at higher income level) and one for countries that either lie on or below the sample mean (and by definition is considered developing countries at lower income level).

Concerning the extended analysis on the heterogeneity arising from the distribution of productive efficiency, we employ the quantile regression. Two objectives underpin the analysis. The first is that estimation of the baseline equation using the methods described above only provides an average effect of energy poverty on productive efficiency which may obscure tailor-made policies. Second, is that the approach is robust to outliers and sample heterogeneity as well as more flexible on assumptions about the parametric distribution of the error term (Greene, 2003). Along this line, it is safe to consider it as providing a robustness check to the earlier methods we discussed. Equation (4) provides a more general formulation of the quantile model that guides our empirical analysis.

$$Quant(\mathbb{Q}_{it}|Z_{it}) = Z_{it}\varphi + \mu_{it} \tag{4}$$

From equation (4), $\mathbb{Z}_{it} = Energy\_poverty_{it} + Z_{it}$, $\mathbb{Z}_{it}$ is, therefore, a vector of exogenous variable as described for Equation (2) affecting the distribution of the outcome variable. φ is the parameter to be estimated corresponding to ϑ^{th} conditional quantile of the productive efficiency where $0 < \vartheta < 1$. Accordingly, the ϑ^{th} quantile estimator of productive efficiency is obtained by solving for the optimization problem expressed as follows[5]:

$$\min_{\vartheta\in\Theta}\left[\sum_{i:\mathbb{Q}_i\geq\mathbb{Z}_{it}\varphi}\vartheta|\mathbb{Q}_i - \mathbb{Z}_{it}\varphi| + \sum_{i:\mathbb{Q}_i<\mathbb{Z}_{it}\varphi}(1-\vartheta)|\mathbb{Q}_i - \mathbb{Z}_{it}\varphi|\right] \tag{5}$$

3. Result and discussion

3.1. Main result: energy poverty and productive efficiency

Table 2 shows the results on the effect of energy poverty on productive efficiency. Columns 1 and 2 show the panel fixed effect results, with column 1 showing the results when we only control for time and fixed effects while column 2 shows the result when we introduce other control variables. The estimated coefficient of energy poverty turns out negative and statistically significant in both cases, implying that energy poverty reduces productive efficiency. As indicated in Section 2, the bounded nature of the outcome variable calls for an alternative estimation that addresses this concern. In line with our discussion in that section, columns 3 and 4 show the Tobit regression. In both cases, the estimated coefficient of energy poverty remains negative and statistically significant, implying that our result is not sensitive to the choice of estimation strategy.

Concerning the control variables, the results for mobile broadband and institutional quality are consistent with Ndubuisi et al. (2022). Particularly, the positive coefficient for mobile broadband highlights the importance of technology for productive efficiency, while that of institutional quality highlights the importance of good governance and rule of law that encourages entrepreneurship. The estimated coefficient of financial development is also positively associated with productive efficiency, highlighting the importance of a well-functioning and developed financial market that engenders the (re)allocation of capital and knowledge accumulation which are both important for productive efficiency. Along this line, the result is in line with Ang (2011) who found that financial development facilitates the accumulation of new ideas. The negative estimated coefficient of natural resources is suggestive of the resource curse hypothesis and is in line with the results of Sachs and Warner (2001) and Ndubuisi et al. (2022). Finally, government consumption is surprisingly positive since a large government may act as a tax on private economic activities, which in turn, is expected to reduce productive efficiency. Nevertheless, if government consumption goes more into public investments, it may improve productive efficiency, and not reduce it. Our result points to the direction of the latter.

Next, columns 5 and 6 in Table 2 show the IV results. Particularly, column 5 shows the results obtained when we implement the Lewbel IV method, while column 6 shows the results generated from the difference GMM. The signs of the estimated coefficient in both columns are consistent with those obtained panel Fixed effect and Tobit regression model. Importantly, the estimated coefficients are also statistically significant at the conventional significance level. The second to the last column of the Table shows the Kleibergen-Paap rk Wald F statistics for the Lewbel estimation, while the last column of the table shows the p-*value* of the Hansen overidentification restriction test for the Lewbel IV and the difference GMM. The F-test score is above the rule of thumb of 10, implying that the internally generated instruments are relevant—-that is, they are strongly correlated with energy poverty. The p-*value* of the Hansen overidentification restriction test for the Lewbel IV and the difference GMM, on the other hand, is statistically insignificant implying that the internally generated instruments are orthogonal to the error terms—that is, they are uncorrelated with the error term. These put together, indicate the internally generated instrument are valid and thus lend credence to our IV model. In this case, the results presented in Table 2 jointly suggest that productive efficiency is negatively associated with energy poverty, and this effect is not sensitive to endogeneity issues, say, due to omitted variables bias and reverse causality.

In Table 1A in the appendix, we show additional results when we employ alternative indicators of energy poverty. Estimations are achieved with the Tobit regression which is our preferred estimator. First, columns 1 and 2 show the results when we use the average of the energy indicators in computing the energy poverty, instead of the first principal component. Columns 3 and 4 on the other hand show the result when we use energy intensity as a measure of energy poverty. Across all the columns, the estimated coefficient of energy poverty remains negative and statistically significant. These additional results further indicate that the negative association between energy poverty and productive efficiency is not susceptible to how we measure energy poverty. On this premise, to quantify the size of the estimated effects of energy poverty on productive efficiency, we follow Prati et al. (2013) to compute the long-term multiplier. This approach, particularly, captures the dynamics

[4] The real GDP and population variables that are used to compute the series are drawn from the Penn World Table.

[5] We implement the quantile regression using the Stata routine “xtqreg”.

Table 2
Energy poverty and productive efficiency.

	FE-Model		Tobit Model		Lewbel-IV	Diff-GMM
	(1)	(2)	(3)	(4)	(5)	(6)
Productive Efficiency (lag)						0 .7727*** (0.004)
Energy Poverty	−0.0865*** (0.019)	−0.0598*** (0.018)	−0.0193*** (0.007)	−0.0112* (0.007)	−0.0891*** (0.021)	−0.0442*** (0.004)
Institutional Quality		0.1966*** (0.025)		0.0755*** (0.011)	0.1921*** (0.025)	0.1168*** (0.0059)
Financial Development		0.3918*** (0.093)		0.1744*** (0.030)	0.3378*** (0.091)	0.0794*** (0.009)
Government Consumption		0.1169*** (0.038)		0.0289** (0.013)	0.1259*** (0.038)	0.1555*** (0.011)
Mobile Broadband		0.0022*** (0.000)		0.0005*** (0.000)	0.0016*** (0.000)	0.0007*** (0.000)
Natural Resources		−0.0115*** (0.003)		−0.0015 (0.001)	−0.0123*** (0.003)	−0.0087*** (0.005)
Constant	−1.0516*** (0.044)	−0.8811*** (0.169)	0.4019*** (0.020)	0.3660*** (0.066)		
No. Of countries	100	100	100	100	100	100
No. Of Observations	1800	1774	1800	1774	1677	1577
R-squared	0.854	0.874	–	–	0.538	–
Kleibergen-Paap rk Wald F statistic	–	–	–	–	26.64	–
Hansen p-value	–	–	–	–	0.482	0.99

Note: Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.
Regression results contain unreported year and country dummies. The difference-GMM results are obtained using the two-step. Except for the Tobit models, the outcome variables in the respective columns are in log.

in the outcome variable when energy poverty moves down from its highest value (1) to its lowest value (0). Using the difference-GMM results reported in Table 2, we found that a full eradication of energy poverty, which corresponds to a discrete jump of the energy poverty index from the maximum value of one to the minimum value of zero, is associated with an estimated increase of the productive efficiency by almost 5.7 percent in the long run.[6]

The evidence that energy poverty reduces productive efficiency is consistent with our expectations. Energy poverty can reduce productive efficiency by either slowing down or disrupting production. It also negatively impacts workers' morale and productivity and makes it difficult for firms to optimally recombine resources. Besides these direct channels, energy poverty can indirectly affect productive efficiency through its negative effect on human capital accumulation, income, and innovation which are strong predictors of productive efficiency. For instance, Banerjee et al. (2021) and Amin et al. (2020) provide evidence indicating a negative effect of energy poverty on income and human capital accumulation. Beyond the evidence these studies provide, our finding indicates that the negative effect of energy poverty may be more profound given the importance of productive efficiency. Among others, productively efficient countries compete effectively in the global market as they can increase the complexity of their export bucket, target and serve high-growth markets, and ultimately, increase the incomes and welfare of citizens (Yang et al., 2021; Ndubuisi and Owusu, 2023). Our result highlights how energy poverty impedes this prospect by undermining a country's production structures and economic competitiveness. Along this line, our finding is in line with the broader literature that documents a negative association between energy poverty and economic development (Shahidur et al., 2010; Doğanalp et al., 2021; Banerjee et al., 2021), while documenting a potentially new channel through which energy poverty affects economic development.

[6] This is computed as the product of the coefficient of energy poverty and the inverse of the coefficient of the period lag of productive efficiency.

3.2. Heterogeneous effects: energy poverty and productive efficiency

Thus far, our analysis has focused on the average effect of energy poverty on productive efficiency. In this section, we expand our analysis to explore possible heterogeneities that may arise due to cross-country differences and differences in the distribution of productive efficiency levels. Table 3 presents the result where we consider potential heterogeneity arising from income-level differences across countries in our sample. Across the columns in Table 3, the estimated coefficient of energy poverty remains negative and mostly statistically significant. However, the interaction variable, which captures the differential effect of energy povertyacross the two income-level groups, is statistically insignificant across the entire columns in the table. This implies that the negative effect of energy poverty on productive efficiency is not sensitive to income level. Put differently, the productive efficiency of lower-income developing countries that are energy poor is as much affected as the productive efficiency of higher-income developing countries that are energy poor. This evidence appears to be consistent with anecdotal evidence from South Africa. Particularly, although the country can be considered a higher-income developing country, its energy crisis is beginning to have severe macroeconomic negative consequences similar to what has been observed in lower-income developing countries for decades.

Next, in Table A2 in the appendix, we further show results for three sub-regions including Africa (see columns 1 and 2), Asia and Pacific (see columns 3 and 4), and the Middle East and Central Asia (see columns 5 and 6). Our identification of countries in either of these regions follows the IMF regional classification. As per the estimation strategy, we recur to the Tobit regression which is our preferred estimator. We find that the estimated coefficient of energy poverty turns significantly negative across the columns in the Table. The only exception to this is Asia and the Pacific where the coefficient albeit negative is statistically insignificant at the conventional significance level.

Finally, Table 4 presents the panel quantile regression results to better understand the effect of energy poverty along the different distributions of productive efficiency. The estimated coefficient of energy poverty is consistently negative across the quantiles. However, it only becomes statistically significant at the conventional significance level

Table 3
Income-level Difference: Energy poverty and productive efficiency.

	FE-MODEL		Tobit Model		Lewbel-IV	Diff-GMM
	(1)	(2)	(3)	(5)	(7)	(8)
Productive Efficiency (lag)						0.784***
						(0.004)
Energy Poverty	−0.1115***	−0.0629**	−0.0131	−0.0011	−0.0841**	−0.0398***
	(0.031)	(0.029)	(0.009)	(0.008)	(0.034)	(0.006)
Energy Poverty × Income	0.0315	0.0010	−0.0063	−0.0114	0.0138	0.0090
	(0.035)	(0.033)	(0.010)	(0.010)	(0.038)	(0.006)
Institutional Quality		0.1955***		0.0761***	0.1923***	0.0982***
		(0.025)		(0.012)	(0.025)	(0.006)
Financial Development		0.3944***		0.1739***	0.3430***	0.0402**
		(0.093)		(0.030)	(0.092)	(0.017)
Government Consumption		0.1175***		0.0283**	0.1264***	0.1228***
		(0.038)		(0.013)	(0.038)	(0.006)
Mobile Broadband		0.0022***		0.0005***	0.0016***	0.0007***
		(0.000)		(0.000)	(0.000)	(0.000)
Natural Resources		−0.0115***		−0.0015	−0.0122***	−0.0076***
		(0.003)		(0.001)	(0.003)	(0.001)
Income	−0.0095	−0.0160	0.0097	0.0106	−0.0118	−0.0156**
	(0.028)	(0.028)	(0.009)	(0.008)	(0.028)	(0.007)
Constant	−1.0467***	−0.8733***	0.3965***	0.3632***		
	(0.048)	(0.170)	(0.021)	(0.066)		
No. Of Countries	100	100	100	100	100	100
No. Of Observations	1800	1774	1800	1774	1677	1577
R-squared	0.854	0.874			0.538	
Kleibergen-Paap rk Wald F statistic					15.051	
Hansen p-value					0.409	1.00

Note: Standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.10.
Regression results contain unreported year and country dummies. The difference-GMM results are obtained using the two-step. Except for the Tobit models, the outcome variables in the respective columns are in log.

Table 4
Energy poverty and productive efficiency.

	Q = 0.05	Q = 0.2	Q = 0.35	Q = 0.5	Q = 0.65	Q = 0.8	Q = 0.95
Energy Poverty	−0.0186	−0.0396	−0.0555***	−0.0699***	−0.0826***	−0.0936***	−0.1103***
	(0.040)	(0.0274)	(0.020)	(0.017)	(0.020)	(0.025)	(0.035)
Institutional Quality	0.1908***	0.1983***	0.2040***	0.2091***	0.2137***	0.2176***	0.2235***
	(0.056)	(0.038)	(0.027)	(0.024)	(0.028)	(0.035)	(0.048)
Financial Development	0.4732**	0.4184***	0.3769***	0.3393***	0.3061***	0.2773**	0.2339
	(0.215)	(0.146)	(0.106)	(0.094)	(0.108)	(0.135)	(0.187)
Government Consumption	0.1016	0.1152**	0.1255***	0.1348***	0.1431***	0.1502***	0.1610**
	(0.080)	(0.054)	(0.039)	(0.035)	(0.040)	(0.050)	(0.070)
Mobile Broadband	0.0046***	0.0044***	0.0043***	0.0041***	0.0040***	0.0039***	0.0038***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Natural Resources	−0.0046	−0.0074*	−0.0095***	−0.0114***	−0.0130***	−0.0145***	−0.0167***
	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)

Note: ***p < 0.01, **p < 0.05, *p < 0.10.

from the 35th decile, suggesting that the effect of energy poverty is conditional on a certain level of productive efficiency. At lower levels of productive efficiency—i.e., from the 5th decile to the 20th decile—, energy poverty exerts no significant effect. From the 35th decile, wherein it starts exerting a statistically significant effect, the magnitude of the effect increases monotonically as we move from that decile to the higher decile. In this case, while energy poverty negatively affects productive efficiency, this effect is more pervasive at higher productive efficiency.

4. Conclusion and policy implications

Productive efficiency is widely acknowledged as an important source of economic growth and development, with some scholars even suggesting that differences in productive efficiency explain the difference in productivity amongst countries. Accordingly, there is now a growing body of literature on the drivers of productive efficiency aimed at identifying relevant social and economic factors that policymakers must improve to become productively efficient and as well as reap the associated gains. However, this literature has proceeded to date without due consideration of the role of energy poverty although the latter affects productive efficiency on several fronts. This paper filled this knowledge gap in by examining how energy poverty affects productive efficiency.

Using a sample comprising 100 developing countries for the period 2000–2017, we found robust evidence suggesting that energy poverty reduces productive efficiency—i.e., energy poor countries become productively inefficient. By extension, this implies these countries lose out from the gains of being productively efficient such as lower prices, and increased output and variety that are growth and welfare-enhancing. Moreover, we also found suggestive evidence that factors such as stronger institutional quality that engenders economic exchange, financial market development that reallocates capital to their most productive use, and mobile broadband that engenders buyer-supplier matching as well as help firms access quality inputs and knowledge are enablers of productive efficiency. Finally, we extended our analysis in two directions to explore possible heterogeneities that may arise due to cross-country income-level and regional differences, and differences in the distribution of productive efficiency levels. We found that the productive inefficiency induced by energy poverty persists across regions and is not sensitive to differences in income level. In this case, the call to end energy poverty is a call to all as the world is increasingly more interdependent, and poor outcomes in another country may adversely affect all. Further, we found that the productive efficiency effect of energy poverty becomes more pronounced at a higher level of productive efficiency, implying that the call for greater efficiency must emphasize eliminating energy poverty in all its form and entirety.

From a policy perspective, our findings highlight an important channel through which energy poverty undermines economic growth and development that is too big to be ignored because the performance of other drivers of economic growth and development depends on it. Along this line, our result calls for a more concerted effort and proactive measures at the local, national, and regional levels to address issues of energy poverty to avoid further escalating the problem of economic underdevelopment. Different options are already presented in the literature. Among others, this includes eco-efficiency labeling and education that encourages the culture of energy efficiency, expanding investment in energy infrastructure, and adopting alternative renewable and green energy sources. Our objective here is not to evaluate the efficiency and effectiveness of these strategies as we believe the path to energy prosperity entails adopting an energy mix and a mix of policy strategies. In this case, the above-mentioned strategies can be pursued in tandem and not apart. We also believe they are in a large part doable if the right political will, financial commitment, and economic incentives are in place. Given the financial circumstance of developing countries, however, we do recognize that achieving them should not only be a prerogative of the national government but also a thing of public-private partnership. In this case, liberalizing the energy sector to encourage foreign direct investment, decentralizing the national energy grid to provide opportunities for localized (including home and community) production and a shift toward a smart grid are all policy options that need careful consideration. In considering these strategies, effort must also be made that they are climate-friendly. The contribution of the energy sector to climate change is well-established in the literature. As the global call to a low-carbon future intensifies, policy makers must ensure that the effort to address energy poverty does not come at a cost that jeopardizes the global effort toward a low-carbon future.

Going forward, our study and its findings form a premise for different research directions future studies can consider. For instance, although we only document the net effect of energy poverty on productive efficiency, we highlighted various channels this effect comes about. As data becomes readily available, future studies can formally test these various channels empirically, highlighting the most relevant and how this differs across regions, and income and technology levels. Such analysis can either be a stand-alone exercise or serve as a premise for a more formal theoretical model that links energy poverty to productive efficiency. Currently, we lack such models and given the strong link between energy poverty and productive efficiency we document, the need for such models to constructively guide how we think about such a relationship cannot be overemphasized. Finally, our energy poverty index does not consider power outages. Although data limitation informed this choice, anecdotal evidence highlights the preponderance of power outages in developing countries, which can ultimately result in productive inefficiency. As cross-country data becomes readily available, future studies can empirically test the linear relationship between power outages and productive efficiency as well as how power outage influences the nature of the relationship between access to energy and productive efficiency.

CRediT authorship contribution statement

Gideon Ndubuisi: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – review & editing, Visualization. **Yuni Denis:** Methodology, Writing – review & editing. **Christian Urom:** Conceptualization, Writing – review & editing. **Ilyes Abid:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

No conflict of interest statement.

Data availability

Data will be made available on request.

Appendix

Table 1A
Alternative Indicators: Energy poverty and productive efficiency

	(1)	(2)	(3)	(4)
Energy Poverty	−0.0249***	−0.0150**	−0.0249***	−0.0208**
	(0.008)	(0.007)	(0.008)	(0.008)
Institutional Quality		0.0756***		0.0752***
		(0.011)		(0.011)
Financial Development		0.1756***		0.1681***
		(0.030)		(0.031)
Government Consumption		0.0293**		0.0280**
		(0.013)		(0.013)
Mobile Broadband		0.0005***		0.0005***
		(0.000)		(0.000)
Natural Resources		−0.0015		−0.0014
		(0.001)		(0.001)
Constant	0.4020***	0.3664***	0.4213***	0.3809***
	(0.020)	(0.066)	(0.021)	(0.066)
No. Of Observations	1800	1774	1800	1774

Note: Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.
Regression results contain unreported year and country dummies. Estimation in each column is achieved using the Tobit model.

Table A2
Regional Analysis: Energy poverty and productive efficiency

	Africa		Asia & Pacific		Middle East & Central Asia	
	(1)	(2)	(3)	(4)	(5)	(6)
Energy Poverty	−0.1303***	−0.0680***	−0.0171	−0.0151	−0.1547***	−0.1491***
	(0.015)	(0.017)	(0.013)	(0.013)	(0.024)	(0.024)
Institutional Quality		0.0622***		0.0983***		0.1170***
		(0.017)		(0.021)		(0.017)
Financial Development		0.0357		0.1783***		0.1541***
		(0.173)		(0.066)		(0.042)
Government Consumption		0.0369**		0.0673		0.0578***
		(0.015)		(0.042)		(0.021)
Mobile Broadband		0.0022***		0.0008***		−0.0008***
		(0.000)		(0.000)		(0.000)
Natural Resources		−0.0019		0.0023		−0.0052*
		(0.001)		(0.003)		(0.003)
Constant	0.5159***	0.3664***	0.3195***	−0.0021	0.2259***	0.2962*
	(0.030)	(0.102)	(0.035)	(0.212)	(0.024)	(0.152)
Observations	666	663	306	303	306	294

Note: Standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.10.
Regression results contain unreported year and country dummies. Estimation in each column is achieved using the Tobit model.

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