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Energy poverty and public health: Global evidence

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ABSTRACT

The impacts of energy poverty on a range of development goals have been widely examined in the literature; however, how energy poverty affects public health has yet to be studied. Using annual data for a broad panel of 175 countries over the period 2000 to 2018, this paper investigates the effect of energy poverty on public health. To identify the causal effect of energy poverty on public health and tackle the issue of endogeneity, we rely on Oster's (2019) bound analysis and the system generalized method of moments (GMM) estimation. Our results show that energy poverty has a detrimental effect on public health. We also find that living standards can serve as a channel through which energy poverty influences health, and that countries with higher standards of living weaken the negative effect of energy poverty on public health. Our results are robust across various specifications and measures of health indicators. Our findings have important implications for policies in public health and transitions to renewable energy.

1. Introduction

With over a billion people around the world considered to be lacking basic access to electricity (IEA, 2017), energy poverty stands as one of the major problems facing global communities. Despite improvements, researchers expect that this challenge will continue beyond 2030, with approximately 674 million people still needing access to electricity. Energy poverty has been described as the absence of sufficient access to modern energy required to meet certain basic tasks such as cooking and lighting (Sovacool, 2012; Sovacool et al., 2012). Accordingly, one of the key factors that differentiates energy-poor households from energy non-poor households is the level of access to and consumption of energy (Barnes et al., 2011; Bridge et al., 2016). Factors such as limited and inconsistent electricity supply, high prices and faulty energy infrastructure may lead to energy poverty and affect every aspect of livelihood (Bhattacharyya, 2012). Following pressure exerted on the United Nations (UN) member states by bodies concerned with energy poverty, a commitment to secure access to services of modern energy for all by 2030 is underway. In line with this, the Sustainable Development Goal for energy (SDG 7) highlights important objectives for 2030, to: "(i) ensure universal access to modern energy services; (ii) increase the share of renewable energy in the global energy mix substantially; and (iii) double the global rate of improvement in energy efficiency". As such, addressing energy poverty has become an increasingly significant agenda for research and practice in developing and developed nations (González-Eguino, 2015; DellaValle, 2019).

Researchers have begun to recognize that energy impacts a range of development goals at the micro and macro levels (Modi et al., 2005; González-Eguino, 2015). In particular, access to affordable and reliable energy contributes to adequate standards of living. For example, energy access has been shown to significantly affect income (Bridge et al., 2016). Others have assessed the impact of energy poverty on various key development dimensions, such as education (Oum, 2019), gender (Ruchi, 2015; Listo, 2018), and subjective wellbeing (Awaworyi Churchill et al., 2020), as well as a variety of other socio-economic dimensions (see Bhattacharyya, 2012 for a review). This literature implies that any effort to tackle the problems of access to and consumption of energy may have a considerable impact. However, the understanding of how energy poverty impacts specifically on public health across countries has yet to be widely examined (González-Eguino, 2015; Jessel et al., 2019; Awaworyi Churchill and Smyth, 2021). This study fills this gap by examining the implications of energy poverty for public health.

Public health is a key focus of sustainable development policies in all economies (Basch, 2014; Bernstein et al., 2015). A healthy society contributes to economic development and greater wellbeing (Bernstein et al., 2015). Researchers have been looking for various factors that will

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help us to understand what constitutes a healthy population. The World Health Organization (WHO) defines health as "a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity." Public health comprises diverse elements, such as physical health, emotional and psychological wellbeing, and overall mental health. In essence, public health is crucial to the development of society. In ensuring adequate public health, many sectors of a country's economy play important and diverse roles, with the common aim of making citizens healthy and happy. Public health is therefore what people do as members of a nation, community, or society to create an atmosphere where essential conditions exist to make everyone healthy (DeSalvo et al., 2017). It is noteworthy that public health contributes essentially to subjective wellbeing, which is increasingly becoming an important metric to gauge progress (Thomson et al., 2017). That is to say that individuals are happier when they are healthier (Biggs et al., 2010). Wellbeing encompasses several dimensions: standards of living, life satisfaction, and personal growth (Trudel-Fitzgerald et al., 2019). How healthy an individual feels could be influenced by such factors as education, housing, transportation, and economic development (DeSalvo et al., 2017).

Yet, while creating access to affordable energy is considered a key strategy to improving public health, studies that have made theoretical and empirical inroads into explaining the relationship between energy poverty and health have focused predominantly on European countries (e.g., Kahouli, 2020; Llorca et al., 2020; Oliveras et al., 2021; Recalde et al., 2019; Rodríguez-Álvarez et al., 2019; Thomson et al., 2017). Using cross-sectional data from European countries, Thomson et al. (2017) find that the physical and mental health conditions among energy-poor households are considerably worse than non-energy poor households. In their study of 21 European countries, Welsch and Biermann (2017) find that increases in energy prices cause a decline in individual wellbeing. Awaworyi Churchill et al. (2020) use cross-sectional data from Australia and find fuel poverty significantly reduces wellbeing.

The few studies originating from developing countries that explore the connection between energy poverty and health mirror these findings. Using the Economic Consumption Survey from Lao PDR, Oum (2019) finds a negative relationship between energy poverty and household health status. Similarly, Zhang et al. (2019) conducted an econometric analysis on the association between the lack of energy access and health in China using household survey data from 2012 to 2016, confirming energy poverty negatively affects health. The findings of these studies indicate that adequate and affordable energy is vital to ensuring household health. In other words, energy poverty, which arises from social, economic and environmental factors, has considerable implications for public health.

The purpose of this study is to examine the impact of energy poverty on public health in a way that takes into account diverse global health and economic contexts. We argue that energy is a crucial determinant of public health, and thus lack of adequate energy, defined as energy poverty, has significant implications for health. Given the extent to which energy poverty varies by geographical location, level of economic development, and types of energy, we conduct this research using cross-country panel data.

Our study seeks to make a number of contributions to the current literature on energy poverty and public health. First, the relationship between energy poverty and public health is rarely explored in the energy literature; thus, we contribute by providing new robust evidence on the extent to which energy poverty impacts public health to extend the current literature. Second, to the best of our knowledge, this is the first study that utilizes cross-country panel data to investigate the relationship between energy poverty and public health. While the prior empirical research on energy poverty predominantly focuses on household-level analysis (see e.g., Alem and Demeke, 2020; Barnes et al., 2011; Lin and Wang, 2020; Sambodo and Novandra, 2019), our use of cross-country panel data is more useful for policy formulation, because we can control for individual unobserved factors that cofound the relationship between energy poverty and health. Moreover, we investigate any remaining biases that cannot be removed by the fixed effect model, by adopting Oster's (2019) bound estimate to overcome the issue of unobservable selection. Our third contribution is that we propose a simple, multidimensional measure of public health that includes crude death rate, total life expectancy and life expectancy by gender. Our findings show that energy poverty has a detrimental effect on public health.

The remainder of this paper is structured as follows. The next section explains the data and outlines the empirical strategies used in this study. Section 3 reports the statistical findings of the study. Section 4 provides robustness tests. Section 5 conducts the mechanism analysis, and Section 6 concludes the paper.

2. Data and methodology

Energy poverty is caused by a combination of factors ranging from the lack of availability of certain energy types to the lack of affordability for available energy due to low income and high usage costs (Boardman, 2010). As such, researchers have used both objective and subjective measures in investigating energy poverty at the household level. For example, in examining the impact of ethnic diversity on household energy poverty in Australia, Awaworyi Churchill and Smyth (2020) use a panel data of household expenditure, ability to heat homes and a multidimensional poverty index to find a positive association between ethnic diversity and energy poverty. Rodríguez-Álvarez et al. (2019) explore the effects of fuel poverty on wellbeing in Europe using micro-level data. Their study employs stochastic frontier techniques and an approach grounded in consumer theory and reliant on 'a primal representation of individual's preferences using indifference curves' (Rodriguez-Alvarez et al., 2019, p. 22). The authors advocate for developing a broad definition of fuel poverty that can be used by the member states of the European Union to recognize fuel poverty as a policy issue. Similarly, Thomson et al. (2016) argue for the importance of developing a broader definition of fuel poverty for all EU countries. Nussbaumer et al. (2012) propose the use of a Multidimensional Energy Poverty Index (MEPI) as a more effective tool for understanding the incidence and intensity of energy poverty. However, Pachauri and Spreng (2011) note that it is often only at the micro level that the causal associations of both subjective and objective measures of energy poverty can be addressed directly, indicating macro-level energy poverty measures may consider other measurement indicators.

Previous studies in the energy poverty literature have defined energy poverty in terms of access to energy services, highlighting that without access to modern energy, households will depend on traditional biomass resources, such as animal dung, crop residues and wood (Avila et al., 2017; Bazilian et al., 2010; Li et al., 2014; Njiru and Letema, 2018). In discussions around energy poverty, researchers often indicate the lack of access to modern energy in developed and developing countries remains a significant challenge for households across the world (Khanna et al., 2019; Charlier and Kahouli, 2019; Bridge et al., 2016). For example, Njiru and Letema (2018). in assessing energy poverty in rural Kenya using access to electricity as the main indicator, find that low access to electricity is the main cause of energy poverty.

Therefore, to alleviate energy poverty, the level of access to modern energy services, such as electricity, is fundamental (Culver, 2017). We measure energy poverty based on the proportion of a population that has access to electricity. Our measure of energy poverty is consistent with the energy accessibility approach reflecting the supply-side perspectives at a macro level of measurement (Pereira et al., 2010; Baquié and Urpelainen, 2017; Chakamera and Alagidede, 2018; González-Eguino, 2015), which captures the percentage of the population that have access to modern energy such as electricity. Here, it is argued that energy-poor countries tend to have a high percentage of the population with limited or no access to modern energy services, such as electricity and sources other than biomass for cooking and home heating (González-Eguino, 2015; IEA, 2017). The present study employs cross-country panel data to understand the relationship between energy poverty and public health at the macro level.

2.1. Data

We use annual panel data over the period 2000 to 2018 for 175 countries (see list of countries in Table A1 of Appendix). The data for this study are obtained from the World Development Indicators (WDI) database of the World Bank. Table 1 presents the summary statistics. Table 1 shows large variations in the key variables across countries. As can be seen from Table 1, the percentage of population with access to electricity ranges from 1.24% to 100%. This suggests that not all countries or areas have equal access to electricity, and the level of access can be informative of the development level of the country. The average life expectancy is 70.02 years with a standard deviation of 9.12. Significant variations in life expectancy are also found across gender groups. Specifically, female and male life expectancies at birth are 72.54 and 67.59 years, respectively. The average mortality rate is 37.83 per 1000 live births with a tremendous variation in mortality rates across countries.

2.2. Empirical methodology

We begin with our basic econometric model that relates public health indicators with the electrification rate:

$$Health_{it} = \beta_0 + \beta_1 Electricity_{it} + \beta_2 \boldsymbol{X}_{it} + \varepsilon_{it} \tag{1}$$

Table 1
Summary statistics.

Variable	Obs.	Mean	Std.Dev	Min	Max
Death rate, crude (per 1000 people)	2657	8.46	3.34	1.13	20.43
Access to electricity (% of population)	2657	78.74	30.66	1.24	100
Real GDP per capita, PPP (constant 2011 international $)	2657	18,920.53	19,935.45	630.70	115,256
School enrolment, primary (% gross)	2657	103.22	13.66	32.36	150.79
Fertility rate, total (births per woman)	2657	2.90	1.52	0.98	7.68
Domestic private health expenditure (% current health expenditure)	2657	41.11	18.66	1.20	86.44
Life expectancy at birth, total (years)	2656	70.02	9.12	42.52	85.42
Life expectancy at birth, female (years)	2656	72.54	9.55	44.60	86.80
Life expectancy at birth, male (years)	2656	67.59	8.86	40.42	84.10
Mortality rate, under-5, total (per 1000 live births)	2657	37.83	40.91	2	224.80
Mortality rate, under-5, female (per 1000 live births)	2657	35.05	38.69	1.90	220.40
Mortality rate, under-5, male (per 1000 live births)	2657	40.47	43.04	2.20	228.90
Access to clean fuels and technologies for cooking (% of population)	2377	62.94	38.07	0.29	100
Trade (% of GDP)	2541	87.24	46.88	0.17	408.36
FDI (as a ratio of GDP)	2641	0.06	0.18	−0.58	4.49
Urban population (% of total population)	2657	55.56	22.97	8.25	100

where the subscript $i = 1, 2, \ldots, N$ represents countries; $t = 1, 2, \ldots, T$ refers to the time span in years; $Health_{it}$ stands for public health indicators such as crude death rate and life expectancy; $Electricity_{it}$ denotes electrification rate; $\boldsymbol{X}_{it}$ is a vector of control variables including per capita real GDP, primary school enrolment, total fertility rate and private health expenditure; and ε_{it} denotes the idiosyncratic error term. Our variable of interest is *Electricity*, thus, β_1 captures the effect of the electrification rate on public health. All of the data series are converted into the form of logarithms so that the parameters of our model have an interpretation as elasticities. Moreover, the transformation can also help to solve issues that are related to distributional properties of our variables since there are substantial measurement differences.

As a benchmark exercise, we first use ordinary least-squares (OLS) and fixed effect models to estimate Eq. (1). Although using the fixed effect model can control for time-invariant heterogeneity, time-varying heterogeneity could remain that is not fully controlled for by the set of variables in $\boldsymbol{X}_{it}$. Therefore, we use the bound estimates proposed by Oster (2019) to assess the amount of bias that the omitted unobservable factors would cause. To perform bound analysis, Oster's (2019) method utilizes two pieces of information. First is the relative degree of selection on observed and unobserved variables (i.e., value of δ). In the present study, following the suggestion of Oster (2019), we set the value of δ equal to one. Second is the theoretical maximum R^2 (defined as R^2_{max}) from a hypothetical regression where all observed and unobserved variables are included. Following the suggestions based on the randomized-trial results of Oster (2019), we set R^2_{max} equal to $Min\left\{1, 1.3\widehat{R}^2\right\}$, where $\widehat{R}^2$ can be obtained from the fixed effect regression with controls. The identified set (or bounds) $[\widehat{\beta}, \beta^*(R^2_{max}, \delta = 1)]$ is given by $[\widehat{\beta}, \beta^*\left(Min\left\{1, 1.3\widehat{R}^2\right\}, \delta = 1\right)]$, which contains the true estimate. The parameter β^* can be estimated as $\widehat{\beta} - (\dot{\beta} - \widehat{\beta})\frac{R^2_{max} - \widehat{R}^2}{\widehat{R}^2 - \dot{R}^2}$, where $\dot{\beta}$ and $\dot{R}^2$ are from the fixed effect regression without controls, while $\widehat{\beta}$ and $\widehat{R}^2$ can be obtained from the fixed effect regression with controls. Results of the bound analysis are easy to interpret. According to Oster (2019), if the bounded set does not include zero, the true effect of each treatment on the dependent variable then is not zero. Hence, estimation results of the fixed effect model are robust.

Another estimation problem that can lead to bias in the usual estimators is measurement error. It is rarely acknowledged that although panel data tend to increase measurement error bias, commonly used estimations, such as fixed effects, worsen the bias (Solon, 1985; Kao and Schnell, 1987). Therefore, our study may confront an endogeneity issue arising from measurement error. To handle measurement error bias, we use the system generalized method of moments (GMM) estimation. The first difference of Eq. (1), which is used in the GMM model, is:

$$\Delta Health_{it} = \beta_1 \Delta\, Electricity_{it} + \beta_2 \Delta\, \boldsymbol{X}_{it} + \Delta\varepsilon_{it} \tag{2}$$

The system GMM method combines Eqs. (1) and (2). Specifically, both the lagged differences of the regressors in the level equation and lagged level values of the regressors in the difference equation are used as instruments to overcome the issue of endogeneity. Moreover, the system GMM model can provide consistent estimates that are asymptotically efficient and robust to arbitrary heteroscedasticity.

3. Empirical results and discussion

3.1. Preliminary analysis

Prior to the regression results, we first show some scatter plots and time series properties of our data series as preliminary analyses. Panel A of Fig. 1 illustrates a negative relationship between access to electricity and crude death rate, while Panel B shows a positive correlation between electrification rate and life expectancy. In fact, the percentage of

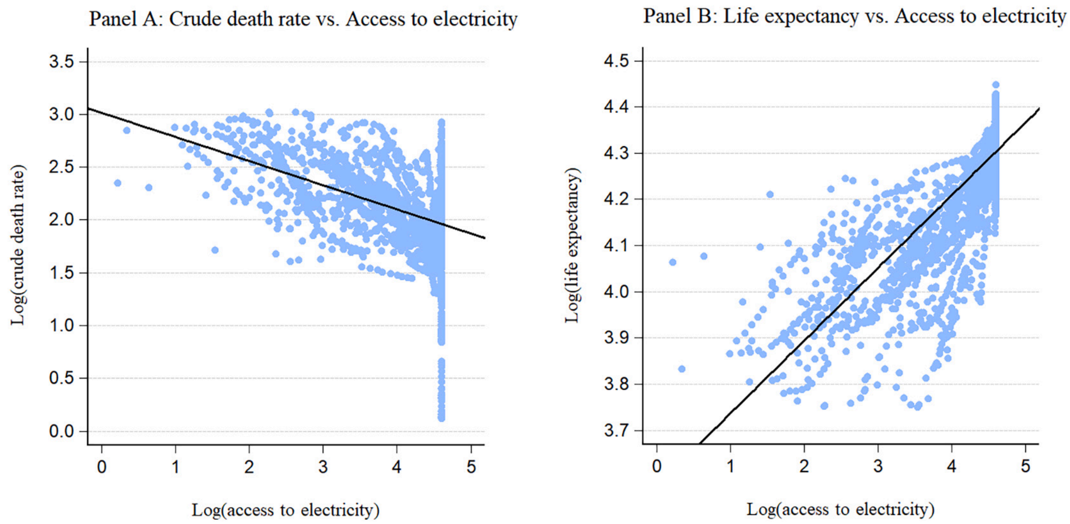

Fig. 1. Association between health indicators and access to electricity.

population with access to electricity is strongly correlated with health indicators, such that the fitted lines are close to linear. In Sections 3.2, 3.3 and 3.4, we estimate the impact of energy poverty on public health using different empirical strategies.

Prior to implementing the panel cointegration test, we first conduct panel unit root tests. We apply three conventional panel stationarity tests: the Im et al. (2003) test, the Maddala and Wu (1999) test and the Choi (2001) test. Notice that the latter two tests are different from the Im et al. (2003) test, in the sense that different lag lengths are selected for each individual augmented Dickey-Fuller (ADF) regression and they are developed specifically for the unbalanced panel data. Table 2 presents the results of panel unit root tests. We can see that most of our variables are nonstationary at level. In particular, the test statistic of Maddala and Wu (1999) indicates that all the data series are nonstationary. When all the data series are first differenced, the test statistic of all the three unit root tests show that all the variables are stationary.

Table 2
Panel unit root test results.

Variables	Test		
	Im et al. (2003)	Maddala and Wu (1999)	Choi (2001)
Level			
Crude death rate	−1.234	0.560	−0.617
Life expectancy at birth, total	−9.200***	−1.553*	−8.193***
Life expectancy at birth, female	−10.961***	−1.606*	−9.947***
Life expectancy at birth, male	−11.311***	−0.153	−8.648***
Access to electricity	1.647	4.202	−0.693
Real GDP per capita	2.734	2.882	2.574
School	−8.252***	1.119	−0.666
Total fertility rate	1.037	3.801	2.719
Private health expenditure	−1.182	−1.088	−4.001***
1st difference			
Crude death rate	−20.693***	−15.138***	−16.311***
Life expectancy at birth, total	−32.206***	−4.561***	−15.540***
Life expectancy at birth, female	−29.514***	−4.833***	−16.990***
Life expectancy at birth, male	−36.166***	−6.031***	−15.142***
Access to electricity	−11.160***	−20.123***	−47.261***
Real GDP per capita	−19.452***	−18.457***	−20.798***
School	−18.751***	−2.162**	−18.559***
Total fertility rate	−16.123***	−11.957***	−11.642***
Private health expenditure	−5.059***	−16.576***	−32.292***

Note: *, ** and ***indicate significance at the 10%, 5% and 1% levels, respectively.

To examine whether there is a long-term effect between electrification rate and public health, we then use the Pedroni (2004) and Kao (1999) cointegration tests. It is worth noting that all data series need to be integrated to the same order prior to conducting cointegration tests since all of our variables, as shown in Table 2, are I (1). The cointegration analysis therefore can be performed to investigate the long-term association between access to electricity and public health. Table 3 reports the results of the Pedroni (2004) and Kao (1999) cointegration tests. The panel Phillips-Perron (PP), panel ADF, group PP and group ADF test statistics indicate that the null hypothesis of no cointegration is rejected at the 5% significance level or better. Moreover, based on the Kao (1999) test statistic, the null hypothesis of no cointegration is also rejected at the 1% significance level. Hence, our results of the panel cointegration tests indicate that there is a long-term impact of access to electricity on public health.

3.2. *Benchmark results*

We begin our analysis with OLS estimation. The results of the OLS model are presented in Table 4. We can see that there is a strong negative statistical relationship between crude death rate and access to electricity with a coefficient of −0.24 that is statistically different from zero at the 1% significance level. The results in columns (2) to (4) reveal that the electrification rate has a positive influence on life expectancy at birth. More specifically, a 1% increase in the electrification rate leads to a 0.07% increase in life expectancy. Overall, our results from the OLS model indicate that access to electricity has a statistically and economically important impact on public health.

Although the OLS estimates are suggestive of the correlation between access to electricity and public health, they may inflate the true effect of access to electricity on public health due to the presence of omitted variables and not taking consideration of time-invariant variables with time-invariant effects. To solve these issues, we include country and year fixed effects when estimating the baseline model. Table 5 presents the fixed effect estimates from Eq. (1). Column (1) of Table 5 shows that the coefficient of access to electricity is negative and statistically significant at the 1% level, suggesting energy poverty has a negative impact on health. The results in columns (2) to (4) show that an increase in the percentage of populations with access to electricity causes an increase in life expectancy where the effect is stronger for women. In particular, on

Table 3
Pedroni (2004) and Kao (1999) cointegration test results.

Method	Statistic	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Pedroni residual cointegration test	Panel v statistic	0.276	−1241.037	−1238.467	−1241.400
	Panel rho-statistic	7.475	1.832	1.802	1.873
	Panel PP statistic	−1.481**	−39.478***	−39.460***	−39.721***
	Panel ADF statistic	−4.530***	−27.367***	−27.204***	−27.469***
	Group rho statistic	12.800	8.765	8.926	8.676
	Group PP statistic	−5.029***	−59.226***	−58.946***	−60.915***
	Group ADF statistic	−3.412***	−24.833***	−25.020***	−25.576***
Kao residual cointegration test	ADF stat	−4.038***	−8.780***	−9.018***	−8.388***

Note: ** and ***indicate significance at the 5% and 1% levels, respectively.

Table 4
Access to electricity and public health, OLS estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to electricity	−0.236***	0.068***	0.069***	0.067***
	(0.010)	(0.003)	(0.003)	(0.003)
Real GDP per capita	−0.065***	0.078***	0.072***	0.084***
	(0.010)	(0.003)	(0.003)	(0.003)
School	−0.303***	0.071***	0.071***	0.072***
	(0.024)	(0.007)	(0.007)	(0.007)
Total fertility rate	0.139***	−0.048***	−0.057***	−0.040***
	(0.021)	(0.006)	(0.006)	(0.006)
Private health expenditure	0.064***	−0.021***	−0.020***	−0.021***
	(0.011)	(0.003)	(0.003)	(0.003)
R^2	0.12	0.75	0.77	0.71
Obs.	2657	2656	2656	2656
No. of countries	175	174	174	174

Note: ***indicates significance at the 1% level.

Table 5
Access to electricity and public health, fixed effect estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to electricity	−0.223***	0.059***	0.061***	0.056***
	(0.057)	(0.014)	(0.015)	(0.015)
Real GDP per capita	−0.029	0.033***	0.035***	0.031***
	(0.042)	(0.010)	(0.010)	(0.010)
School	−0.278***	0.060***	0.060***	0.060***
	(0.075)	(0.020)	(0.020)	(0.021)
Total fertility rate	0.164**	−0.021	−0.033**	−0.010
	(0.081)	(0.017)	(0.016)	(0.018)
Private health expenditure	0.048	−0.012	−0.012	−0.012
	(0.040)	(0.010)	(0.010)	(0.010)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.49	0.70	0.69	0.70
Obs.	2657	2656	2656	2656
No. of countries	175	174	174	174

Note: All regressions include year and country fixed effects. Robust standard errors are in parentheses. ** and ***indicate significance at the 5% and 1% levels, respectively.

average, a 1% increase in the percentage of population with access to electricity can lead to an increase in total life expectancy at birth of about 0.06%. Looking at the effect by gender, a 1% increase in access to electricity is associated with 0.061% and 0.056% rise in female and male life expectancy, respectively. Our results also show that real per capita GDP and schooling have significant positive effects on public health.

3.3. Bounding values and omitted variable Bias

Although fixed effect models are appealing as they controls for the time-invariant determinants of public health and energy poverty, it is far from trivial to identify the causal effect of energy poverty on public health. In particular, the fixed effect estimator is inconsistent if there are time-varying omitted factors that affect energy poverty and public health. To address the issue of omitted variable bias, we adopt the Oster (2019) bound analysis.

The intuitive argument often made in the literature is that omitted variable bias must be limited if a coefficient remains stable after the inclusion of observed controls. Nevertheless, Oster (2019) points out that the value of R^2 also needs to be considered, because the coefficient may remain stable after adding uninformative controls. The Oster (2019) approach enables us to bound the omitted variable bias, hence partially identify causality by comparing 'uncontrolled'[1] and

[1] An uncontrolled regression refers to the regression equation that only includes the key variable of interest (*Electricity* in our case), as well as any observed uninformative covariates.

'controlled'[2] regressions under a set of assumptions about the relationship between observable and unobservable selection.

We conduct the bound analysis separately for different health indicators used in this study. Table 6 reports the bounds of values for β from the fixed effect model with full controls. For ease of comparison, column (1) reproduces the controlled-effect estimates in Table 5. The bound estimates are presented in column (2) of Table 6. We can see that the identified bounds of all the estimates in column (1) do not include zero, suggesting that our fixed effect estimates are robust to the potential omitted variable bias. Furthermore, we can also consider the width of bound estimates. In particular, the estimated 0.22% reduction in crude death rate caused by a 1% rise in electrification rate is robust, but the bound is slightly larger at −0.34%. The Oster (2019) bounding analysis therefore indicates the existence of causality between access to electricity and crude death rate, but of a marginally larger size than that presented in Table 5 after taking into account the potential omitted variable bias. We obtain similar conclusions for all the other health indicators.

3.4. System GMM estimation

Another drawback of fixed effect model is that they can lead to biased coefficients due to measurement errors. We therefore use the GMM method to further tackle the issue of endogeneity that is likely to arise from measurement errors. Since the cross-sectional dimension of our data is larger than the time-series dimension (i.e., larger N, smaller T), we employ the system GMM method specifically developed for this type of data set. The method utilizes the level of lagged variables in difference regressions and the level of lagged difference in level regressions as instruments to solve the endogeneity issue. Following Roodman (2009), we treat access to electricity as endogenous and control variables as exogenous. Notice that this results in fewer observations and a lower power of regression estimates. To solve this issue,

Table 6
Oster (2019) bound estimates.

	(1) Controlled effect	(2) Identified set
	$\hat{\beta}$ (S.E.)	$[\hat{\beta}, \beta^*\left(Min\left\{1, 1.3\hat{R}^2\right\}, \delta = 1\right)]$
Panel A: Crude death rate		
Access to electricity	−0.223***(0.057)	[−0.342, −0.223]
Obs.	2657	
$\hat{R}^2$	0.49	
Panel B: Life expectancy at birth (total)		
Access to electricity	0.059***(0.014)	[0.059, 0.122]
Obs.	2656	
$\hat{R}^2$	0.70	
Panel C: Life expectancy at birth (female)		
Access to electricity	0.061***(0.015)	[0.061, 0.122]
Obs.	2656	
$\hat{R}^2$	0.69	
Panel D: Life expectancy at birth (male)		
Access to electricity	0.056***(0.015)	[0.056, 0.121]
Obs.	2656	
$\hat{R}^2$	0.70	

Note: The results in column (1) are reproduced from Table 5. Robust standard errors are reported in parentheses. ***indicates significance at the 1% level.

we employ the forward orthogonalization procedure of Arrellano and Bover (1995) to reduce observation losses caused by differencing, and the collapsing method of Holtz-Eakin et al. (1988) to limit the number of instruments.

The GMM estimation is valid when the crucial assumption of the exclusion restriction holds, $E(X'\mu) = 0$. That is, the explanatory variables are treated as being exogenous and, hence, are uncorrelated with the error term in the second-stage regression. Furthermore, to ensure the moment conditions used in the model are valid, the estimator requires no serial correlation in the first-difference errors at an order higher than one. Therefore we report the second-order autoregressive, AR(2) test. We also report the Hansen test of over-identifying restrictions. The null hypothesis of the Hansen test is that over-identifying restrictions are valid. Hence, rejecting the null hypothesis means that either our model or instruments need to be reconsidered. We can see that both the AR(2) test and the Hansen test presented in Table 7 suggest there is insufficient evidence to reject the null hypothesis. Specifically, the p-value for the second-order serial correlation test is greater than 10% in all specifications, indicating that we cannot reject the null hypothesis of no second-order serial correlation at the conventional statistical significance levels, with cut-off points at 1%, 5% and 10%. In addition, the Hansen test cannot reject the null hypothesis of the validity of the over-identifying restrictions at the 1%, 5% and 10% significance levels. Overall, both the AR(2) test and the Hansen test of over-identifying restrictions appear to be satisfied, suggesting that our system GMM estimates are consistent and efficient.

The system GMM results presented in Table 7 imply that access to electricity has a significant negative impact on public health. In particular, after controlling for other determinants of public health indicators, we find that 1% rise in access to electricity causes a fall in the crude death rate of about 0.62% per 1000 population. Similarly, a 1% increase in electrification rate leads to an increase in life expectancy at birth by around 0.21%. One plausible interpretation of these findings is that without electricity access, households could inhale emissions from burning kerosene for lighting (Lam et al., 2012). Our results are consistent with the most recent studies of Oliveras et al. (2021) and Awaworyi Churchill and Smyth (2021) who demonstrate that energy poverty negatively affects people's health and wellbeing. Private health expenditure is another variable that significantly impacts population health. Table 7 shows that larger private health expenditure is negatively related to life expectancy. This finding is also consistent with Deshpande et al. (2014) who find a negative relationship between healthcare spending and life expectancy. They argue that this is due to the quality of health care expenditure. Specifically, countries spend less efficiently on healthcare tend to have lower life expectancy.

4. Robustness check

In this section, we perform five sets of robustness tests. First, we estimate our benchmark model with the instrumental variable (IV) estimation strategy proposed by Lewbel (2012). Second, we test the robustness of our benchmark model using an alternative measure of public health. Third, we examine the sensitivity of our OLS results by employing different measures of energy poverty. Fourth, we divide our data sample into five regional groups based on the World Bank's classification. Last, we investigate how our benchmark regression results vary by including more control variables.

4.1. Estimation using Lewbel (2012)

As a further robustness check on the system GMM estimates, we adopt the instrumental variable approach proposed by Lewbel (2012). Lewbel's (2012) method is appealing as it can provide IV estimates when there is a lack of other sources of identification, such as external IVs. Following Lewbel (2012), we construct instruments based on heteroscedasticity in error terms. The constructed instruments can be used as a

[2] A controlled regression stands for the benchmark model, such as Equation (1) in the main text, which includes the main variable of interest, and all control variables in X.

Table 7
Access to electricity and public health, system GMM estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to electricity	−0.618***	0.213***	0.190***	0.273***
	(0.151)	(0.046)	(0.041)	(0.055)
Real GDP per capita	−0.014	0.014	0.013	0.009
	(0.055)	(0.014)	(0.012)	(0.017)
School	−0.227	−0.041	−0.015	−0.120
	(0.190)	(0.079)	(0.072)	(0.085)
Total fertility rate	−0.613***	−0.012	−0.042	0.057
	(0.149)	(0.034)	(0.030)	(0.042)
Private health expenditure	0.074	−0.040**	−0.037**	−0.045**
	(0.047)	(0.017)	(0.015)	(0.019)
Obs.	2657	2656	2656	2656
No. of countries	175	174	174	174
AR(2) *p*-value	0.40	0.46	0.36	0.56
Hansen test *p*-value	0.11	0.14	0.14	0.11

Note: ** and ***denote statistically significant at the 5% and 1% levels, respectively.

valid IV if no suitable external instruments can be found (Lewbel, 2012). We briefly describe the method below:

$$Y_1 = X^{'}\beta + Y_2\gamma + \varepsilon_1, Y_2 = X^{'}\alpha + \varepsilon_2 \tag{3}$$

where ε_1 and ε_2 denote the error terms; Y_1 refers to the dependent variable (i.e., indicators of public health); Y_2 stands for the endogenous variable, that is, percentage of population with access to electricity in our case; and X is the vector of explanatory variables. To solve the endogeneity issue in the absence of external instruments, Lewbel (2012) develops an identification strategy utilising information contained in heteroscedasticity of ε_2. With the assumption that $E(\boldsymbol{XX}')$ is non-singular and $E(\boldsymbol{X}\varepsilon_1) = E(\boldsymbol{X}\varepsilon_2) = 0$, $Cov(\boldsymbol{Z}, \varepsilon_1, \varepsilon_2) = 0$ and $Cov(\boldsymbol{Z}, \varepsilon_2^2) \neq 0$, where Z equals X or a subset of the elements of X, the instruments are constructed as $\left(\boldsymbol{Z} - \overline{\boldsymbol{Z}}\right)\widehat{\varepsilon_2}$, where $\overline{\boldsymbol{Z}}$ stands for the mean of Z. The key identifying assumption in Lewbel's (2012) approach is that the regressors are uncorrelated with heteroscedastic errors.

Table 8 reports the results of Lewbel's (2012) model with internal instruments only. The coefficients of access to electricity remains statistically significant at the 1% level in all regressions, confirming the negative impact of energy poverty on public health. Column (1) of Table 8 shows a negative relationship between access to electricity and crude death rate. Specifically, a 1% rise in electrification rates can lead to a fall in crude death rates by 0.24%. Columns (2) to (4) show that an increase in access to electricity is associated with an increase in life expectancy. We can see that the coefficient of *School* is statistically significant at the 1% level, indicating that countries with higher primary school enrolment rates are more likely to have lower crude death rates. This is consistent with our benchmark results, as well as the findings of Winkleby et al. (1992) and Cutler and Lleras-Muney (2010), who argue that early childhood education is beneficial for health outcomes. The coefficient on real GDP per capita has the expected sign in all specifications and is statistically significant at the 1% level, suggesting that an increase in the level of per capita income can result in improvements to public health.

4.2. *Alternative measures of public health*

To examine the robustness of our benchmark model, we measure public health using the mortality rate for children under five years old. Results are presented in Table 9. We can see that coefficients on access to electricity are all negative and statistically significant at the 1% level, suggesting that access to electricity has a negative influence on mortality rates. Specifically, a 1% increase in access to electricity results in a

Table 8
Lewbel (2012) IV estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to electricity	−0.237***	0.052***	0.050***	0.055***
	(0.019)	(0.006)	(0.005)	(0.006)
Real GDP per capita	−0.115***	0.037***	0.032***	0.043***
	(0.019)	(0.003)	(0.002)	(0.003)
School	−0.519***	0.053***	0.063***	0.041***
	(0.055)	(0.014)	(0.014)	(0.015)
Total fertility rate	−0.463***	−0.088***	−0.112***	−0.061***
	(0.044)	(0.008)	(0.008)	(0.009)
Private health expenditure	0.028*	−0.019***	−0.020***	−0.018***
	(0.014)	(0.003)	(0.003)	(0.003)
R^2	0.28	0.77	0.80	0.73
Obs.	2657	2656	2656	2656
No. of countries	175	174	174	174
Hansen J stat	29.98	32.59	31.32	33.16
Hansen J p-value	0.09	0.05	0.07	0.04

Note: Robust standard errors in the parenthesis. * and ***denote statistically significant at the 10% and 1% levels, respectively.

Table 9
Access to electricity and mortality rate, OLS estimates.

	Mortality rate	Mortality rate (female)	Mortality rate (male)
Access to electricity	−0.125***	−0.136***	−0.160***
	(0.017)	(0.017)	(0.017)
Real GDP per capita	−0.891***	−0.892***	−0.890***
	(0.016)	(0.016)	(0.016)
School	−0.070*	−0.082**	−0.058
	(0.041)	(0.041)	(0.040)
Total fertility rate	0.219***	0.241***	0.200***
	(0.036)	(0.036)	(0.036)
Private health expenditure	0.120***	0.120***	0.118***
	(0.018)	(0.018)	(0.018)
R^2	0.83	0.84	0.83
Obs.	2657	2657	2657
No. of countries	175	175	175

Note: *, **, and ***indicate significance at the 10%, 5% and 1% levels, respectively.

Table 10
Access to clean energy and public health, OLS estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to clean energy	−0.107***	0.024***	0.026***	0.023***
	(0.011)	(0.003)	(0.003)	(0.003)
Real GDP per capita	−0.090***	0.084***	0.078***	0.090***
	(0.012)	(0.003)	(0.003)	(0.004)
School	−0.403***	0.110***	0.110***	0.110***
	(0.025)	(0.007)	(0.007)	(0.007)
Total fertility rate	0.243***	−0.076***	−0.085***	−0.067***
	(0.024)	(0.007)	(0.007)	(0.007)
Private health expenditure	0.104***	−0.031***	−0.030***	−0.032***
	(0.012)	(0.003)	(0.003)	(0.003)
R^2	0.09	0.71	0.74	0.67
Obs.	2377	2376	2376	2376
No. of countries	172	171	171	171

Note: ***indicates significance at the 1% level.

decrease in mortality rates by 0.13%. This is consistent with our benchmark estimation results.

4.3. Alternative measures of energy poverty

Next, we estimate our benchmark model using access to clean energy, which is measured by the percentage of total population primarily using clean fuels and technologies for cooking to proxy energy poverty. Table 10 shows that our main results are robust to using this alternative measure. The results reported in Table 10 indicate that energy poverty has a detrimental effect on public health and this effect is stronger for women. These findings are consistent with the claim that shifting to clean cooking fuels lowers health risks associated with inhaling noxious emissions from traditional cook stoves (Smith et al., 2014). Furthermore, this risk is likely to affect women to a greater extent because of common gender roles related to household chores such as cooking (Rao and Pachauri, 2017). Through women's empowerment, access to clean energy can enhance population health. Specifically, modern cook stoves free up women's time otherwise spent on collecting fuel or firewood toward productive activities, and consequently improve their income and health (Acheampong et al., 2021).

4.4. Dividing data sample into different regional groups

Importantly, since structural characteristics differ widely across the regions of the world, one cannot simply compare the electrification rate and conclude that a country with higher percentage of people with access to electricity is "doing better" in population health. Taking this concern into consideration, we divide our sample into five regional groups on the basis of the World Bank's classification: East Asia and Pacific (EAP), European and Central Africa (ECA), Latin America and the Caribbean (LAC), Middle East and North Africa (MENA) and Sub-Saharan Africa (SSA). Results are presented in Tables 11a to 11e. We can see that, only for countries in the ECA region, some coefficients on access to electricity become statistically insignificant or even change the sign. In all the other four sub-samples, signs of coefficients on access to electricity are as expected and almost all of them are also statistically significant at 1% significant level, which is consistent with our benchmark estimation results.

4.5. Adding more controls

In the last robustness check, we include more control variables in our benchmark model. First, as in Philip et al. (2013), we add trade openness[3] to our benchmark regression. The logic is as follows. On the one hand, trade openness can enhance economic growth, which further provides greater sums for households to improve their standard of living and for government to spend more on public health. On the other hand, trade liberalization increases global diffusion of knowledge (so called 'knowledge spillover') and products that improve public health.

[3] Trade openness is the sum of exports and imports of goods and services as a share of GDP. Data are sourced from the World Development Indicators (WDI).

Table 11a
Access to electricity and public health (EAP region), OLS estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to electricity	−0.161***	0.032***	0.033***	0.031***
	(0.014)	(0.004)	(0.004)	(0.004)
Real GDP per capita	−0.036**	0.066***	0.065***	0.067***
	(0.015)	(0.004)	(0.004)	(0.004)
School	−0.248***	0.089***	0.089***	0.090***
	(0.034)	(0.008)	(0.008)	(0.009)
Total fertility rate	0.087**	−0.050***	−0.047***	−0.055***
	(0.041)	(0.010)	(0.010)	(0.010)
Private health expenditure	−0.006	−0.014***	−0.013***	−0.015***
	(0.014)	(0.003)	(0.003)	(0.003)
R^2	0.32	0.78	0.76	0.78
Obs.	377	376	376	376
No. of countries	27	26	26	26

Note: ** and ***indicate significance at the 5% and 1% levels, respectively.

Table 11b
Access to electricity and public health (ECA region), OLS estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to electricity	1.211	−0.363*	−0.212	−0.548**
	(0.877)	(0.217)	(0.177)	(0.267)
Real GDP per capita	−0.043***	0.080***	0.069***	0.091***
	(0.013)	(0.003)	(0.002)	(0.004)
School	−0.288***	−0.007	−0.017	0.0003
	(0.059)	(0.015)	(0.012)	(0.018)
Total fertility rate	−0.080**	0.025***	0.014**	0.036***
	(0.031)	(0.007)	(0.006)	(0.009)
Private health expenditure	0.045**	0.011**	0.010***	0.013**
	(0.019)	(0.005)	(0.004)	(0.006)
R^2	0.02	0.72	0.79	0.63
Obs.	798	798	798	798
No. of countries	47	47	47	47

Note: *, ** and ***indicate significance at the 10%, 5% and 1% levels, respectively.

Table 11c
Access to electricity and public health (LAC region), OLS estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to electricity	−0.534***	0.068***	0.100***	0.041***
	(0.087)	(0.012)	(0.012)	(0.013)
Real GDP per capita	0.120***	0.030***	0.032***	0.029***
	(0.024)	(0.003)	(0.003)	(0.004)
School	0.054	−0.034***	−0.029***	−0.038***
	(0.068)	(0.009)	(0.009)	(0.010)
Total fertility rate	−0.126**	−0.088***	−0.067***	−0.107***
	(0.052)	(0.007)	(0.007)	(0.008)
Private health expenditure	0.005	−0.015***	−0.016***	−0.012***
	(0.026)	(0.004)	(0.003)	(0.004)
R^2	0.08	0.43	0.42	0.41
Obs.	440	440	440	440
No. of countries	30	30	30	30

Note: ** and ***indicate significance at the 5% and 1% levels, respectively.

Second, as suggested in Burns et al. (2017), we include foreign direct investment (FDI)[4] and urbanization[5] in our estimations. The rationale is FDI can enhance economic growth, raises wage levels and improves working conditions. These factors could in turn affect access to healthcare; hence, FDI is beneficially related to public health. Urbanization is another factor that could be associated with public health. Urbanization is a driver of FDI inflows, indicating its confounding effect in the context of FDI and health.

Table 12 presents the regression results. We can clearly see that our benchmark regression results hold. In regard to the new control variables, we find that urbanization has a positive effect on public health. This is likely due to the many opportunities provided by urban living such as potential access to better health care. Moreover, the coefficients on trade openness and FDI are insignificant, indicating that these two variables may have little influence on public health across countries.

5. What is driving the results?

In this section, we explore standard of living as a potential channel through which energy poverty affects public health. We use the generally accepted measure, real GDP per capita, to proxy standard of living. It is widely acknowledged that energy is an important factor of

[4] We measure FDI as net inflows of foreign direct investment divided by GDP. Data are in current US dollar and are obtained from the WDI database.

[5] Urbanization is measured by the proportion of people who live in urban areas. Data are retrieved from the WDI database.

Table 11d
Access to electricity and public health (MENA region), OLS estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to electricity	−0.152	0.153***	0.146***	0.159***
	(0.108)	(0.022)	(0.022)	(0.023)
Real GDP per capita	−0.089***	0.058***	0.054***	0.062***
	(0.034)	(0.006)	(0.006)	(0.007)
School	−0.348***	0.073***	0.067***	0.085***
	(0.075)	(0.016)	(0.015)	(0.017)
Total fertility rate	0.476***	−0.062***	−0.067***	−0.058***
	(0.038)	(0.008)	(0.008)	(0.008)
Private health expenditure	0.148***	−0.019***	−0.017***	−0.020***
	(0.023)	(0.005)	(0.005)	(0.005)
R^2	0.23	0.51	0.48	0.57
Obs.	240	240	240	240
No. of countries	17	17	17	17

Note: ***indicates significance at the 1% level.

Table 11e
Access to electricity and public health (SSA region), OLS estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to electricity	−0.168***	0.050***	0.051***	0.048***
	(0.019)	(0.006)	(0.006)	(0.006)
Real GDP per capita	−0.051	0.060***	0.056***	0.064***
	(0.037)	(0.013)	(0.013)	(0.013)
School	−0.264***	0.059***	0.062***	0.057***
	(0.045)	(0.015)	(0.015)	(0.015)
Total fertility rate	0.940***	−0.328***	−0.327***	−0.330***
	(0.090)	(0.031)	(0.031)	(0.031)
Private health expenditure	0.092***	−0.033***	−0.033***	−0.033***
	(0.026)	(0.009)	(0.009)	(0.009)
R^2	0.21	0.30	0.37	0.23
Obs.	642	642	642	642
No. of countries	44	44	44	44

Note: ***indicates significance at the 1% level.

Table 12
Access to electricity and public health, adding more controls, OLS estimates.

	Crude death rate	Life expectancy at birth (total)	Life expectancy at birth (female)	Life expectancy at birth (male)
Access to electricity	−0.282***	0.081***	0.082***	0.079***
	(0.011)	(0.003)	(0.003)	(0.003)
Real GDP per capita	−0.014	0.063***	0.059***	0.068***
	(0.011)	(0.003)	(0.003)	(0.003)
School	−0.277***	0.060***	0.061***	0.060***
	(0.024)	(0.007)	(0.007)	(0.007)
Total fertility rate	0.053**	−0.025***	−0.035***	−0.015**
	(0.021)	(0.006)	(0.006)	(0.006)
Private health expenditure	0.055***	−0.021***	−0.020***	−0.021***
	(0.011)	(0.003)	(0.003)	(0.003)
Trade openness	0.007	0.001	0.0005	0.002
	(0.006)	(0.002)	(0.002)	(0.002)
FDI	−0.001	−0.001	−0.0003	−0.002
	(0.010)	(0.003)	(0.003)	(0.003)
Urbanization	−0.263***	0.077***	0.069***	0.087***
	(0.038)	(0.010)	(0.010)	(0.010)
R^2	0.13	0.72	0.75	0.68
Obs.	2526	2525	2525	2525
No. of countries	169	168	168	168

Note: ** and ***indicate significance at the 5% and 1% levels, respectively.

Table 13a
Effect of access to electricity on the potential channel.

Dependent Variable	Real GDP per capita
Access to electricity	0.329***
	(0.018)
Controls	Yes
R^2	0.68
Obs.	2657

Note: ***indicates significance at the 1% level.

production. According to International Renewable Energy Agency (2018), access to energy raises productivity of business, which therefore improves living standards. Furthermore, it well accepted that countries with higher standards of living are associated with improved health outcomes.

To investigate whether standard of living is a potential channel, we use an approach that is consistent with previous studies (e.g., Awaworyi Churchill et al., 2019). For standard of living to qualify as a potential channel, two conditions need to be satisfied. First, real GDP per capita needs to be correlated with access to electricity. Table 13a presents the relationship between access to electricity and real GDP per capita. Our results suggest that access to electricity significantly enhances standard of living. Specifically, access to electricity is associated with a 0.33% increase in real GDP per capita.

Second, the inclusion of real GDP per capita as an additional covariate in the regression linking access to electricity to public health indicators should decrease the magnitude of the coefficient on access to electricity or render it statistically insignificant. The results are reported in Tables 13b and 13c. Columns (2, 5) of Tables 13b and 13c show that with the inclusion of real GDP per capita as an additional covariate, the

Table 13b
Effect of access to electricity and the potential channel on public health (crude death rate and total life expectancy).

Dependent Variable	Crude death rate			Life expectancy at birth (total)		
Access to electricity	−0.257***	−0.236***	−0.920***	0.095***	0.068***	0.141***
	(0.010)	(0.010)	(0.076)	(0.003)	(0.003)	(0.022)
Real GDP per capita		−0.065***	−0.499***		0.078***	0.121***
		(0.010)	(0.049)		(0.003)	(0.014)
Access to electricity× Real GDP per capita			0.095***			−0.020***
			(0.010)			(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2657	2657	2657	2656	2656	2656
R^2	0.12	0.12	0.11	0.74	0.75	0.74

Note: ***indicates significance at the 1% level.

Table 13c
Effect of access to electricity and the potential channel on public health (female and male life expectancy).

Dependent Variable	Life expectancy at birth (female)			Life expectancy at birth (male)		
Access to electricity	0.094***	0.069***	0.133***	0.095***	0.067***	0.146***
	(0.003)	(0.003)	(0.022)	(0.003)	(0.003)	(0.023)
Real GDP per capita		0.072***	0.110***		0.084***	0.133***
		(0.003)	(0.014)		(0.003)	(0.015)
Access to electricity× Real GDP per capita			−0.009***			−0.011***
			(0.003)			(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2656	2656	2656	2656	2656	2656
R^2	0.77	0.77	0.77	0.68	0.71	0.70

Note: ***indicates significance at the 1% level.

coefficient on access to electricity reduces in magnitude. Our findings indicate that standard of living serves as a potential channel through which access to electricity impacts public health.

As a further check on our mediation (potential channel) results, we also examine whether standard of living moderates the relationship between access to electricity and public health. In doing so, we augment Eq. (1) to include the interaction term between access to electricity and real GDP per capita. Columns (3, 6) of Tables 13b and 13c show that the interaction term is negative and statistically significant at the 1% level. Our results indicate that standard of living also moderates the relationship between access to electricity and public health. To be more specific, the relationship between access to electricity and population health is lower in countries with higher living standards.

6. Conclusion

This study contributes to the growing body of literature on the impacts of energy poverty. Specifically, we examine the impact of energy poverty on public health. Energy, although essential to public health, is rarely given attention. It could be considered the lifeblood of all economic activities across individual, household, and national fronts. Several studies have examined the extent to which energy poverty affects important socio-economic variables or dimensions, such as education, wellbeing, and gender. The literature on the specific impact of energy poverty on public health, however, is sparse. Focus, so far, has been on the impacts of energy poverty on health and wellbeing in European countries, with very few studies conducted in developing countries or countries outside Europe. This paper contributes to the literature by examining the impact of energy poverty using multiple public health indicators, including crude death rate and life expectancy. We use annual data for a sample of 175 countries over the period 2000 to 2018, which allows us to control for unobservable factors that differ across countries or over time.

Our main finding is that energy poverty has a significant negative effect on public health. This general conclusion is robust across alternative measures or specifications of public health, different periods, and other sensitivity checks. Moreover, we find that living standard is a channel through which energy poverty affects public health. We also find that standard of living plays a moderating role in the relationship between energy poverty and public health, such that countries with higher living standards dampen the negative effect of energy poverty on public health. We believe our study will help researchers and policy makers to develop alternative strategies to address the issues raised here. Based on our findings that the inability to access modern energy such as electricity can have a detrimental impact on public health, it is imperative that policy makers take steps to facilitate household access to electricity and work toward making it affordable for all people. Our claim is based on the premise that the lack of access to electricity pressures households to use traditional sources of energy, such as wood and charcoal, which have severe impacts on the health of the population. Policy-wise, directing state-sponsored programs to focus on providing access to modern energy services in collaboration with other important stakeholders may lead to the implementation of strategic measures aimed at improving public health and environment.

Overall, our study findings, drawn from rich data from multiple counties, emphasize the importance of improving access to electricity. By devising policies that address access to energy, policy makers will be able to impact broader issues of public health and socio-economic outcomes. This impact, in turn, can help to promote a wider perspective of energy poverty as a global challenge, rather than a challenge confined to particular geographic settings. Hence, the policy actions can include integrated efforts to formulate governance processes and practices that build the capacity of community organizations and local authorities to facilitate more efficient access to modern energy, particularly in areas where households use traditional energy sources that increase public health risks. As such, we hope that people working in the field will consider emerging energy alternatives such as solar and wind energy, which deliver public health improvements as well as more comprehensive and context-specific energy access to society. Researchers and policy makers may need validated and comparative evidence on energy strategies and their impacts, not only in relation to creating access to energy but also public health. Thus, we hope that our study will serve as a key source of information when creating robust policy frameworks to address energy poverty and the promotion of public health.

Declaration of conflict of interest

The authors declare no conflict of interest.

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Appendix A. Data appendix

This appendix provides the list of countries used in the study.

Table A1
List of countries.

Country	World bank country code	Country	World bank country code
Afghanistan	AFG	Angola	AGO
Albania	ALB	United Arab Emirates	ARE
Argentina	ARG	Armenia	ARM
Antigua and Barbuda	ATG	Australia	AUS
Austria	AUT	Azerbaijan	AZE
Burundi	BDI	Belgium	BEL
Benin	BEN	Burkina Faso	BFA
Bangladesh	BGD	Bulgaria	BGR
Bahrain	BGR	Bahamas	BHS
Belarus	BLR	Belize	BLZ
Bolivia	BOL	Brazil	BRA
Barbados	BRB	Brunei Darussalam	BRN
Bhutan	BTN	Botswana	BWA
Central Africa Republic	CAF	Canada	CAN
Switzerland	CHE	Chile	CHL
China	CHN	Cote d'Ivoire	CIV
Cameroon	CMR	Congo, Dem. Rep.	COD
Congo, Rep.	COG	Colombia	COL
Comoros	COM	Cabo Verde	CPV
Costa Rica	CRI	Cyprus	CYP
Czech Republic	CZE	Germany	DEU
Djibouti	DJI	Dominica	DMA
Denmark	DNK	Dominican Rep.	DOM
Algeria	DZA	Ecuador	ECU
Egypt	EGY	Spain	ESP
Estonia	EST	Ethiopia	ETH
Finland	FIN	Fiji	FJI
France	FRA	Micronesia, Fed. Sts.	FSM
Gabon	GAB	United Kingdom	GBR
Georgia	GEO	Ghana	GHA
Guinea	GIN	Gambia	GMB
Guinea-Bissau	GNB	Equatorial Guinea	GNQ
Greece	GRC	Grenada	GRD
Guatemala	GTM	Guyana	GUY
Honduras	HND	Croatia	HRV
Hungary	HUN	Indonesia	IDN
India	IND	Ireland	IRL
Iran	IRN	Iraq	IRQ
Iceland	ISL	Israel	ISR
Italy	ITA	Jamaica	JAM
Jordan	JOR	Kazakhstan	KAZ
Kenya	KEN	Kyrgyz Republic	KGZ
Cambodia	KHM	Kiribati	KIR
St. Kitts and Nevis	KNA	Korea Republic	KOR
Kuwait	KWT	Lao PDR	LAO
Libya	LBY	St. Lucia	LCA
Sri Lanka	LKA	Lesotho	LSO
Lithuania	LTU	Luxembourg	LUX
Latvia	LVA	Morocco	MAR
Moldova	MDA	Madagascar	MDG
Maldives	MDV	Mexico	MEX
Marshall Islands	MHL	North Macedonia	MKD
Mali	MLI	Malta	MLT
Myanmar	MMR	Montenegro	MNE
Mongolia	MNG	Mozambique	MOZ
Mauritania	MRT	Mauritius	MUS
Malawi	MWI	Malaysia	MYS

(*continued on next page*)

Table A1 (*continued*)

Country	World bank country code	Country	World bank country code
Namibia	NAM	Niger	NER
Nigeria	NGA	Nicaragua	NIC
Netherlands	NLD	Norway	NOR
Nepal	NPL	New Zealand	NZL
Oman	OMN	Pakistan	PAK
Panama	PAN	Peru	PER
Philippines	PHL	Palau	PLW
Papua New Guinea	PNG	Poland	POL
Portugal	PRT	Paraguay	PRY
Qatar	QAT	Romania	ROU
Russian Federation	RUS	Rwanda	RWA
Saudi Arabia	SAU	Sudan	SDN
Senegal	SEN	Singapore	SGP
Solomon Islands	SLB	Sierra Leone	SLE
El Salvador	SLV	Serbia	SRB
Sao Tome and Principe	STP	Suriname	SUR
Slovak Republic	SVK	Slovenia	SVN
Sweden	SWE	Eswatini	SWZ
Seychelles	SYC	Chad	TCD
Togo	TGO	Thailand	THA
Tajikistan	TJK	Timor-Leste	TLS
Tonga	TON	Trinidad and Tobago	TTO
Tunisia	TUN	Turkey	TUR
Tanzania	TZA	Uganda	UGA
Ukraine	UKR	Uruguay	URY
United States	USA	Uzbekistan	UZB
St. Vincent and the Grenadines	VCT	Vietnam	VNM
Vanuatu	VUT	Samoa	WSM
South Africa	ZAF	Zambia	ZMB
Zimbabwe	ZWE		

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105423.

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