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Link between household welfare and solar electricity demand in sub-Saharan Africa: A quantile approach

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ABSTRACT

This study investigates the link between household welfare and solar electricity demand in sub-Saharan Africa for the period between 2010 and 2019. Welfare was proxied by HDI, inequality in income, infant mortality, education, mobile phone subscriptions, internet users and unemployment rate. The study employed a Quantile regression with nonadditive fixed effects and the adaptive Markov Chain Monte Carlo optimisation method. The findings show that HDI has a negative and significant effect on solar electricity consumption at all quantiles except for the 30th quantile where the effect is positive. This implies that as welfare improves, consumers' demand for solar electricity declines due to a shift to other fuels or stacking of multiple fuels. Moreover, the findings show varying effects of inequality in income, education, mobile phone subscriptions, internet connectivity and unemployment rate on solar electricity demand at different quantiles. Lastly, the findings reveal that infant mortality has a negative effect on solar electricity demand across all quantiles. In overall, the findings imply that policy makers should develop strategies that will promote and incentivise solar electricity consumption across all income groups.

1. Introduction

The well-being of society, also known as welfare, has been challenged over the years, particularly in developing countries. Most developing countries are characterised by acute poverty and income inequality. This has been aggravated by the recent Covid-19 pandemic that has left society worse off [1]. As a result, there has been an increase in many inequalities across the world due to social instability and fragmentation, and a rise in authoritarianism [2]. The efforts of countries toward improving their citizens' welfare were first published by the UNDP in 1990 in the first Human Development Index (HDI) report. The UNDP introduced a human development indicator that advocates the welfare of people as the best indicator of economic development. In doing so the [3] argued that defining development goes beyond income and wealth but encapsulates the expansion of people's choices[1].

Recent reports of the HDI reveal that some African countries have made significant progress in human development. However, most African countries still have an HDI below the median, except for South Africa, Botswana, Algeria, and Libya which are classified as high human development countries [2]. The low level of human development has negative influence on the quality of life, particularly access to health, education, and energy. Some scholars have recently advanced the proposition that the HDI classification of an economy is highly correlated with the quality and level of energy consumption [4]. As such, countries with high HDI have most of the population with access to energy, whereas low HDI countries have most of the population without access to energy [5]. Also, low HDI countries heavily depend on biomass energy, with limited access to modern renewable energy technologies such as solar electricity [6,7]. In Nigeria and Rwanda respectively, solar electricity has the least consumption rate compared to other energy sources due to poor affordability of the appropriate technology [8]. This implies that welfare or human development factors influence the demand for energy, particularly renewable energy.

A few studies have attempted to analyse the relationship between welfare and solar electricity demand in developing countries. [9] examined the relationship between HDI and energy consumption in 93 countries and find a long-run inverse relationship between HDI and energy consumption, but a positive relationship with electricity consumption. Churchill et al. [10] examine the effect of income inequality on renewable energy sources in 19 nations and find a negative and

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[1] People's choices entail three essential components which are to lead a long and healthy life, acquire knowledge, and access to resources required for a decent standard of living [3].

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non-linear effect of income inequality on solar electricity. They also find that the effect becomes insignificant after a particular period. Liu et al. [11] analysed the impact of education and education expenditure on renewable energy consumption in BRICS economies and finds a positive and long run effect. However, the extent to which welfare influences solar electricity demand in SSA remains unknown.

According to the author's knowledge, no empirical investigation has been undertaken on the effects of welfare on solar electricity demand in SSA. Some of these studies provide evidence of the effect of welfare factors on total renewable energy consumption, although there are various renewable energy sources. Nevertheless, [10] evaluated the effects of income inequality on various renewable electricity sources. However, they focus on developed nations and did not extend the study to developing nations such as SSA. Also, they focus on income inequality and fail to expose the effect of other welfare factors that influence solar electricity consumption. This is a major gap because human development does not only entail income and wealth, but the expansion of people's choices too [3]. Narrowing this gap, is primarily important in SSA where human development is currently on a decline because of the recent Covid 19 pandemic, amongst others [12].

Therefore, understanding this relationship is important to policymakers in SSA for several reasons. Firstly, given the pressing need to address the region's poor rates of electricity access, information about this relationship provides a targeted approach to driving the adoption of solar technologies to attain the electrification targets outlined in the AU 2063 Agenda and the UN 2030 Agenda for Sustainable Development [13]. Secondly, it provides insight into the factors that drive or impede the realisation of the region's renewable energy investment goals, to contribute to improved energy access and poverty alleviation in the region. Lastly, it highlights the importance of improving the socio-economic landscape in the region to ensure easy and affordable access to modern sources of electricity by the region's population.

This study applied a robust estimation technique - Quantile regression with nonadditive fixed effects to examine the different effects of welfare along the distribution of solar electricity consumption. According to the authors' knowledge, there are no previous studies that have adopted the quantile regression technique to estimate the effects of welfare on energy. Quantile regressions are appropriate to this study because of their ability to estimate the quantile-specific effects of welfare on solar electricity consumption than conventional regression estimators such as the Ordinary Least Squares (OLS). The quantile specific effects are useful for policy makers to determine the adoption rate of solar electricity technologies by countries of different human development levels. This will ensure that policy makers adopt a targeted approach to formulation of policy aimed at promoting solar electricity demand. This estimation technique therefore addresses the research gap in solar electricity demand literature that has primarily relied on linear regression techniques that may not capture the effects of welfare in the different quantiles of solar electricity consumption. The study used data spanning from 2010 to 2019 and the findings indicate that welfare has significant effects on the demand for solar electricity. Therefore, policymakers should monitor the effects of welfare when promoting the transition to clean energy sources.

The study makes important contribution to literature. First, the study contributes to the literature on welfare and energy demand [4,5,6,7]. The study shows that in addition to HDI and income inequality as determinants for energy demand, education, health, information and communication technologies and unemployment are also determinants of energy demand, particularly in developing countries. Second, the study is closely related to [10], which investigates the effects of income inequality on renewable energy including the disaggregated sources of renewable energy (hydroelectricity, solar, wind and biomass and waste) in 17 countries. However, their study focused on developed nations powered by grid-connected renewable energy and boast of high electrification rates. This study focuses on SSA countries that has most of the population without access to electricity and rely on biomass fuels for energy. These countries make a good sample for this study because they are consumers of off-grid solar electricity and have poor access to clean and modern electricity. These countries have also contested with a low HDI and poor telecommunication infrastructure over the years, presenting significant challenges to economic growth.

The rest of the paper is structured into the following sections. Section 2 presents theoretical and empirical literature underpinning the study. Section 3 discusses the research methodology and data. Section 4 presents and discusses empirical results and Section 5 provides a conclusion and prospects for future studies.

2. Literature review

2.1. Theoretical literature

The study is underpinned by two consumer behaviour theories: energy ladder theory and fuel stacking theory. Some scholars also provide theoretical insight into the link between various welfare indicators and energy consumption in the subsequent section.

2.1.1. The energy ladder theory

The energy ladder theory holds that the income level of consumers explains the dynamics of energy use among households [14]. It outlines a three-stage fuel switching model, which has clean energy such as electricity and LPG at the top of the ladder, transition fuels such as coal, and kerosene at the second stage, and biomass fuels at the bottom and third stage [15]. The theory states that households start with total dependence on inferior fuels such as biomass, as their income increase, they use intermediate fuels such as coal and kerosene, and finally use clean and modern fuels such as electricity and gas [15]. However, this theory had policy limitations, especially in developing countries because households continue to demand biomass together with other sophisticated energy sources. Hence another household-level approach known as the fuel stacking or multiple fuel use theory had to be developed to capture the changes in energy consumption due to changes in the level of economic development in developing countries and this is known as the fuel stacking theory.

2.1.2. Fuel stacking theory

The fuel stacking theory also holds that once a household adopts modern fuels, they continue using traditional fuels partially. The reasons may be that households may use traditional fuels as insurance against modern fuels that are sometimes unreliable or increase significantly in cost [16]. Fuel stacking varies depending on the available energy sources, the purpose for which the energy source is used, and the geographic context [17]. In some contexts, fuel stacking is more relevant to cooking fuels than lighting fuels and sometimes more relevant to rural areas than urban areas. A review of empirical literature analysing the fuel stacking theory shows that households continue to use multiple fuels as their welfare improves, contrary to the argument advanced by the energy ladder [18].

2.2. Empirical literature

2.2.1. Human development and energy demand

The effect of HDI on energy consumption is mixed and inconclusive. Several studies have explored the link between human development and energy demand and include [19] that examined the link between per capita energy consumption and HDI in worldwide countries. Their results revealed that HDI had a significant effect on energy consumption in most countries and the effect was more significant in low HDI countries. This is mainly because in the early stages of development, countries tend to focus on growing income per capita, which leads to further environmental degradation. However, when the required income levels are accomplished, countries will shift their focus to promoting environmental sustainability [20]. [21] examined the link between HDI and energy consumption in 3-ASEAN countries (Indonesia, Malaysia, and Thailand). Their results revealed that HDI has a positive and significant effect on energy consumption across all those countries.

2.2.2. Income inequality and energy demand

Income distribution is one of the welfare factors influencing economic growth in developing countries because of its strong association with poverty [22]. Many scholars have confirmed the dire effects of income inequality on the environment where a widening of the income gap in societies increases carbon emissions, therefore, leading to environmental degradation [23]. Further, societies with high-income inequality may not support renewable energy technologies because such societies base their resource allocation on the price and costs of deploying the renewable energy technologies [24]. For example, income inequality has an insignificant effect on hydroelectricity, whereas the effect of income inequality on solar electricity, wind, and biomass is negative and significant. Dong et al. [25] also applied the GMM estimation technique to investigate whether the widening income gap in China impacts electricity consumption. The results reveal that the widening inequality gap has a negative impact on electricity consumption, implying that an increase in the income gap reduces electricity consumption in China.

2.2.3. Learning and energy demand

Learning influences consumer behaviour on environmental issues as consumers that have more knowledge of environmental issues have the willingness to pay a higher price for environmentally friendly products [26]. Education motivates individuals to use green energy technologies and observe environmental regulations because they become aware of the value of resource conservation and environmental preservation [27]. As a result, climate education has taken centre stage in many policy discussions, particularly energy policy discussions because of the impact of climate change on human development. Studies have examined the role of education on energy consumption include [27] who investigated the role of education on energy consumption and carbon emissions in China by applying the ARDL bounds testing approach. Their results showed that education had a negative impact on energy consumption, implying that policymakers should reinforce policies that create awareness about energy efficiency in China.

2.2.4. Health and energy demand

It is commonly assumed that a country's health policy reflects the state of the nation. This is because a quality healthcare system increases the stock of human capital required for higher productivity and income, thereby improving economic output [28]. Therefore, an investment in health is a welfare-enhancing activity.

Most studies have investigated the nature of the relationship and found that access to clean energy sources improves the health and welfare of the population [29,30]. However, the effect of population health on the demand for renewable electricity remains under-explored. According to the author's knowledge, there is only one study that investigated the effect of health outcomes on energy consumption. Youssef et al. [31] investigated the causality relationship between energy consumption and health outcomes in Africa. The study employed the panel VAR approach and found a bidirectional relationship between energy consumption and infant mortality. A possible explanation is that a decrease in infant mortality will lead to an improvement in the quality of human capital in these countries, therefore, improving productivity and output growth. As a result, energy consumption will increase as well.

2.2.5. ICT and energy demand

ICT is a tool for human development because it is used to seek information and communicate with others and this information becomes knowledge that contributes to human development [32]. ICT is also responsible for expanding human freedoms which leads to better efficiency in human activities [33].

Several empirical studies have examined the impact of ICT on electricity consumption, and these include [34] who found a positive and strong relationship between information communication technology proxied by mobile phone subscriptions and internet connections and electricity consumption in 67 global economies using the GMM estimation technique as well. This further confirms the need for deepening ICT capital in developing countries to improve energy access and consumption. [35] also examined the short and long-run effects of internet usage on electricity consumption in Australia using the ARDL bounds test for cointegration. The results showed that internet usage stimulates electricity consumption in Australia. Nadimi et al. [36] examined the effects of technology on energy consumption in 112 worldwide countries using the one-way analysis of variance (ANOVA). Their results showed that technology has significant positive effects on energy consumption per capita and the effects are more prevalent in developing countries than in developed countries.

2.2.6. Unemployment and energy demand

Economic theory does not provide conclusive results on the impact of unemployment, on energy consumption. [37] hold that there is an interdependent relationship between unemployment and renewable energy generation. [38] advance an inverse relationship between unemployment rate and energy consumption. They concluded that a low level of unemployment will lead to an increase in energy consumption and this effect is more evident in low-income countries.

3. Methodology

3.1. Data

The study used panel data of 15 SSA countries for the period between 2010 and 2019. This sample of countries was selected because they are high consumers of solar electricity, particularly off-grid solar technologies in SSA. The dependent variable is solar electricity demand proxied by solar electricity consumption per capita. The focus on solar electricity is motivated by that solar PV has the potential of boosting energy supply in the region due to high solar irradiation, the ease at which solar PV can be rapidly deployed compared to other power generation options and the falling costs of the technology. However, the installed capacity of solar PV in SSA is marginal and consumed primarily off-grid, except for South Africa and Egypt that have grid connected solar PV [39]. This poses a threat to the region's ability to meet the targets of the AU Agenda 2063 and the UN 2030 Agenda for Sustainable Development. Data on solar electricity consumption per capita was obtained from the Oxford Martin School at the University of Oxford. However, data for African countries is mainly available from 2010 to 2019, hence the period selected for this study.

The independent variable is welfare. It is proxied by various indicators including the HDI, inequality in income, infant mortality rate, government spending on education, mobile phone subscriptions, internet users and unemployment rate. The study adopts HDI as a measure of welfare instead of GDP because GDP measure income per capita and does not provide information about income distribution and quality of life, which are an important phenomenon in assessing welfare. Therefore, HDI remains a crucial measure of welfare.

Since the HDI only captures the human development aspect of welfare, instead of inequalities, poverty, government expenditure, etc., it is important to include other indicators that will provide a holistic view of the effects of welfare on solar electricity consumption, to get a broader view. Hence other indicators that have been included in the study. Data on the HDI and income inequality were obtained from the UNDP database published by the United Nations. Whereas data on infant mortality, mobile phone subscriptions, internet users, unemployment rate, CPI and urbanisation was sourced from the World Development Indicators database published by the World Bank.

3.2. Estimation technique

The study applied the Quantile regression with nonadditive fixed effects by [40,41] to estimate the effects of welfare on solar electricity consumption in SSA. The quantile regression with nonadditive fixed effects is ideal for this study because it does not separate the disturbance term and assumes a within-individual variation of the disturbance term. Therefore, the fixed estimates are not estimated, and the parameter estimates remain consistent even for short panels. Moreover, this estimation technique can examine heterogeneity and asymmetry of explanatory variables and further deal with heteroskedasticity because of its intensive and robust nature [42]. Also, due to the reverse causality between solar electricity consumption and welfare it means that there is endogeneity among the variables. The quantile regression with nonadditive fixed effects can deal with the endogeneity problem [43].

The quantile regression with nonadditive fixed effects uses the adaptive Markov Chain Monte Carlo (MCMC) method developed by [44] as an optimisation method. The MCMC optimisation method draws samples from a given or arbitrary probability distribution and these samples are used to estimate quantities related to the probability distribution. It is, therefore, superior to other optimisation methods such as the grid-searching optimisation method which uses a grid of values of substitution parameters that are pre-selected, and these values can include zero which is then used as a starting point for subsequent estimations and does not perform well when explanatory variables exceed two [45]. Whereas the unique feature of the adaptive MCMC method is that even in the presence of additional control variables, the nonadditive fixed effects method creates unconditional quantile treatment, thereby accommodating endogeneity and the addition of instruments and control variables [40,41,44].

Following the model by [40,46] the equation for the panel quantile regression with nonadditive fixed effects is expressed as:

$$Y_{it} = X'_{it}\beta\left(U^*_{it}\right),\ \ U^*_{it} \sim U(0,1) \tag{1}$$

where $t = 1\ldots$, T; $i = 1,\ldots$, n,

Y_{it} denotes the dependant variable, $X^{'}_{it}$ is a set of explanatory variables for country i at time t and are assumed to include a constant term. β represents an unknown parameter, whereas U^*_{it} is the non-separable disturbance term and it is a function of an individual fixed effect and an observable specific disturbance term. $U^*_{it} \sim U(0,1)$ and $X^{'}_{it}\beta(\tau)$ is increasing in quantile τ.

Therefore, the structural quantile function for Eq. (5) can be expressed as:

$$S_Y(\tau / d) = d'\beta(\tau),\ \ \tau\epsilon(0,1) \tag{2}$$

where the structural quantile function explains the quantile of the latent outcome variable $Y_d = d\beta(U^*)$ for randomly selected $U^* \sim U(0,1)$ and the fixed potential value of the treatment effect d.

Therefore, to estimate the effects of welfare on solar electricity demand, the panel quantile regression is expressed as:

$$SPV_{it}(\tau / \alpha_i, \delta_t, x_{it}) = \alpha_i + \delta_t + \beta_{1,\tau}HDI_{it} + \beta_{2,\tau}INC_{it} + \beta_{3,\tau}EDC_{it} + \beta_{4,\tau}MORT_{it} + \beta_{5,\tau}MOB_{it} + \beta_{6,\tau}INT_{it} + \beta_{7,\tau}UR_{it} + \beta_8 X_{it} + u_{it} \tag{3}$$

where SPV_{it} denotes per capita solar electricity consumption for country i at time t, τ denotes the quantile, α_i represents non-additive fixed effects, δ_t denotes the disturbance term, x_{it} represents the independent variables for individual countries i at time t. The independent variables are *HDI, INC, EDC, MORT, MOB, INT, UR* that denote the Human Development Index, inequality in income, government spending on education, infant mortality rate, mobile phone subscriptions, internet users and unemployment rate as explanatory variables. X_{it} represents the vector of control variables, including CPI, and urbanisation and these control variables were selected because a high inflation rate increases the price of goods thereby negatively affecting consumption [47]. On the other hand, an increase in urbanisation positively influences energy consumption [48]. u_{it} denotes the white noise. The estimation performs numerical optimization using the adaptive MCMC optimization method.

Eq. (3) can be simplified and re-written as:

$$SPV_{it} = \alpha_i + \beta_1 HDI_{it} + \beta_2 INC_{it} + \beta_3 EDC_{it} + \beta_4 MORT_{it} + \beta_5 MOB_{it} + \beta_6 INT_{it} + \beta_7 UR_{it} + \beta_8 X_{it} + u_{it} \tag{4}$$

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
SPV	150	0.893	1.717	0.004	10.841
HDI	150	0.490	0.061	0.331	0.601
INC	150	27.335	8.026	12.300	58.100
EDC	150	4.165	1.129	1.544	6.876
MORT	150	73.878	22.111	35.300	131.500
MOB	150	69.710	25.567	21.400	138.800
INT	150	13.884	10.006	0.800	46.800
UR	150	4.378	2.742	0.320	13.190
CPI	150	4.529	5.431	−3.233	27.283
URB	150	32.833	11.891	15.500	57.000

Notes: SPV=Solar PV per capita, HDI=Human Development Index, INC=Income inequality, EDC= Education, MORT=Infant mortality rate, MOB=Mobile phone subscription, INT=Internet users, UR=Unemployment rate, CPI=Consumer Price Index, URB=Urbanisation.

4. Empirical results

The summary of descriptive statistics for all the variables used in the study is presented in Table 1. Average solar electricity consumption per capita (SPV) was 0.893 kWh with minimum and maximum values of 0.004 kWh and 10.841 kWh, respectively. This indicates that in general the average level of solar electricity consumption is improving over the period from 2010 to 2019. The standard deviation is 1.717 kWh showing that most of the data points are far from the mean.

The independent variables, HDI had a mean of 0.490, a standard deviation of 0.061, and minimum and maximum values of 0.331 and 0.601, respectively. These statistics show an improvement in HDI over the 10 years from 2010 to 2019 and the variability of the data is generally far from the mean. The statistics also reveal that the average level of income inequality, infant mortality is still high in most countries in the sample. Further, the level of education and mobile phone subscription and has improved in SSA over the years, whereas internet connectivity and unemployment rate are still low.

Table 2 presents the pairwise correlation results. There is no evidence of multicollinearity among the variables, therefore, they are a good fit for this model. The statistics also show that HDI, inequality in income, education, mobile phone subscription, and internet users have a positive correlation with solar electricity consumption. Infant mortality, unemployment rate, CPI, and urbanization are negatively correlated with solar electricity consumption.

Table 3 and Table 4 show the unit root test results obtained from the Augmented Dickey Fuller – Fischer (ADF-Fischer) test and Phillips-

Table 2
Pairwise correlation matrix.

Variable	SPV	HDI	INC	EDC	MORT	MOB	INT	UR	CPI	URB
SPV	1.000									
HDI	0.201	1.000								
INC	0.135	0.545	1.000							
EDC	0.023	0.038	0.251	1.000						
MORT	−0.464	−0.712	−0.435	−0.187	1.000					
MOB	0.208	0.346	0.044	0.144	−0.101	1.000				
INT	0.465	0.560	0.271	−0.014	−0.480	0.611	1.000			
UR	−0.014	0.101	0.212	0.175	0.097	0.289	0.068	1.000		
CPI	−0.012	0.118	0.313	0.060	−0.260	−0.415	−0.154	0.124	1.000	
URB	−0.057	0.290	0.032	0.067	0.239	0.565	0.371	0.423	−0.344	1.000

Notes: SPV=Solar PV per capita, HDI=Human Development Index, INC=Income inequality, EDC= Education, MORT=Infant mortality rate, MOB=Mobile phone subscription, INT=Internet users, UR=Unemployment rate, CPI=Consumer Price Index, URB=Urbanisation.

Table 3
ADF-Fischer unit root test results.

Variables	Level	1st Difference	Order of Integration
SPV	1.000	0.000***	I(1)
HDI	0.000***	0.000***	I(0)
INC	0.000***	0.000***	I(0)
EDC	0.004***	0.000***	I(0)
MORT	0.000***	0.000***	I(0)
MOB	0.000***	0.000***	I(0)
INT	0.996	0.000***	I(1)
UR	0.856	0.000***	I(1)
CPI	0.016**	0.000***	I(0)
URB	0.964	0.000***	I(1)

Standard errors in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 %.
Notes: SPV=Solar PV per capita, HDI=Human Development Index, INC=Income inequality, EDC= Education, MORT=Infant mortality rate, MOB=Mobile phone subscription, INT=Internet users, UR=Unemployment rate, CPI=Consumer Price Index, URB=Urbanisation.

Table 4
PP-Fischer unit root test results.

Variables	Level	1st Difference	Order of Integration
SPV	1.000	0.000***	I(1)
HDI	0.000***	0.000***	I(0)
INC	0.000***	0.000***	I(0)
EDC	0.004***	0.000***	I(0)
MORT	0.000***	0.000***	I(0)
MOB	0.000***	0.000***	I(0)
INT	0.996	0.000***	I(1)
UR	0.856	0.000***	I(1)
CPI	0.016**	0.000***	I(0)
URB	0.965	0.000***	I(1)

Standard errors in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 %.
Notes: SPV=Solar PV per capita, HDI=Human Development Index, INC=Income inequality, EDC= Education, MORT=Infant mortality rate, MOB=Mobile phone subscriptions, INT=Internet users, UR=Unemployment rate, CPI=Consumer Price Index, URB=Urbanisation.

Peroni Fischer (PP-Fischer) test. The results show a combination of stationarity tests at levels and first difference for all the variables. The ADF-Fischer unit root results show that HDI, inequality in income, education, infant mortality, mobile phone subscriptions, and CPI are stationary at levels. However, solar electricity consumption, internet users, unemployment rate, and urbanisation are stationary at first differencing.

The PP-Fischer unit root test results are shown in Table 4. The results are consistent with the results of the ADF-Fischer unit root test results. These results show that the variables are integrated into the order I(0) and I(1). None of the variables are integrated into the order I(2), therefore all the variables can be used in this estimation.

Table 5 presents the quantile regression results based on the quantile regression with non-additive fixed effects at different quantiles ranging from the 10th quantile to the 90th quantile. The adaptive MCMC optimisation method's algorithm performed 1000 draws and dropped 100 draws and the acceptance rate was set at 0.5[2]. The estimation results show that HDI has a negative and significant effect on solar electricity consumption at a 1 % significance level, from the 10th to the 90th quantile except for the 30th quantile. This means that for every 10 % increase in HDI, ceteris paribus, solar electricity consumption will decrease by 7.12 % to 194.71 %. The effect is relatively strong in countries with low and high solar electricity consumption compared to countries with moderate solar electricity consumption.

However, for the 30th quantile, the effect of HDI on solar electricity consumption is positive and significant at a 1 % significance level. This implies that in the 30th quantile, a 10 % increase in HDI will increase solar electricity consumption by 4.09 %.

Furthermore, the effect of inequality in income on solar electricity consumption is negative and significant at a 1 % significance level for the 10th and 30th quantile. This means that as income inequality increases in these countries, solar electricity technologies become unaffordable, leading to a decrease in consumption. However, from the median to the 90th quantile, the effect on solar electricity consumption becomes positive and significant at a 1 % significance level. Also, the coefficients are close to zero at the lower quantiles and move away from zero at higher quantiles implying that the effect is stronger in countries with higher levels of solar electricity consumption.

Education has a negative and significant effect on solar electricity consumption at 1 % significance level in all quantiles except for the 80th quantile, which has a 10 % significance level. This implies that a 10 % increase in government spending on education will lead to a decrease in solar electricity consumption by 0.40 % to 4.83 %. This effect is pronounced in countries with low and high solar electricity consumption. On the other hand, the effect of infant mortality on solar electricity consumption is negative and significant at 1 % significance level, throughout the quantiles. This effect is stronger in countries with median to high solar electricity consumption.

Mobile phone subscriptions have a positive and significant effect on solar electricity consumption in all the quantiles except for the 70th and 80th quantiles. The effect is stronger up to the 60th quantile, after which the effect is insignificant and only becomes significant again in the 90th quantile. This implies that in countries with low levels of solar electricity consumption, mobile phones are used mostly to facilitate solar electricity transactions hence the increase in solar electricity consumption. Internet connectivity has a negative and significant effect on solar electricity consumption at 1 % and 5 % significance levels at the 10th and median quantiles respectively. However, the effect on solar

[2] This is the sequence of draws that the algorithm performs from the posterior distribution of the parameter [42].

Table 5
Quantile regression and DOLS estimation results.

Variable	10th Quantile	20th Quantile	30th Quantile	40th Quantile	Median	60th Quantile	70th Quantile	80th Quantile	90th Quantile	DOLS
HDI	−0.895***	−0.712***	0.410***	−1.132***	−1.850***	−4.404***	−6.332***	−18.646***	−19.471***	−23.057
	(0.004)	(0.132)	(0.007)	(0.342)	(0.098)	(0.350)	(0.072)	(3.384)	(0.840)	(52.739)
INC	−0.002***	−0.001	−0.002***	0.002	0.003***	0.007***	0.010***	−0.003	0.048***	0.224***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.006)	(0.005)	(0.063)
EDC	−0.043***	−0.040***	−0.055***	−0.094***	−0.117***	−0.143***	−0.186***	−0.124*	−0.483***	−1.308**
	(0.000)	(0.006)	(0.000)	(0.009)	(0.002)	(0.006)	(0.001)	(0.065)	(0.039)	(0.518)
MORT	−0.010***	−0.009***	−0.007***	−0.013***	−0.015***	−0.020***	−0.255***	−0.062***	−0.041***	−0.072
	(0.000)	(0.000)	(9.281)	(0.001)	(0.000)	(0.001)	(0.000)	(0.009)	(0.002)	(0.098)
MOB	0.001***	0.001**	0.002***	0.003***	0.005***	0.006***	0.006	0.002 (0.002)	0.006**	0.038
	(0.000)	(0.001)	(4.821)	(0.001)	(0.000)	(0.000)	(0.000)		(0.003)	(0.037)
INT	−0.001***	0.002	0.002***	0.002	−0.001**	0.013***	0.011***	0.085***	0.199***	−0.359***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.027)	(0.004)	(0.087)
UR	0.005***	0.001	0.009***	0.005**	0.008***	−0.011***	−0.003***	0.086***	−0.002	−0.102
	(0.000)	(0.005)	(0.000)	(0.002)	(0.001)	(0.003)	(0.001)	(0.023)	(0.010)	(0.447)
CPI	−0.002***	−0.007***	−0.007***	−0.011***	−0.006***	−0.008***	0.009***	−0.036***	−0.034***	−0.454***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)	(0.000)	(0.011)	(0.007)	(0.102)
URB	0.010***	−0.001	−0.011***	−0.010***	−0.008***	−0.002***	0.002***	0.018***	0.016***	0.151
	(0.000)	(0.001)	(0.000)	(0.002)	0.001	(0.001)	(0.000)	(0.008)	(0.002)	(0.358)

Standard errors in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 %.
Notes: SPV=Solar PV per capita, HDI=Human Development Index, INC=Income inequality, EDC= Education, MORT=Infant mortality rate, MOB=Mobile phone subscription, INT=Internet users, UR=Unemployment rate, CPI=Consumer Price Index, URB=Urbanisation.

electricity consumption is positive and significant at 1 % significance level at 30th, 60th, 70th, 80th and 90th quantiles.

Lastly, unemployment rate positively and significantly affects solar electricity consumption in the lower to median quantiles. However, from the 60th quantile, the effect is negative and significant, particularly for the 60th and 70th quantile.

4.1. Discussion and policy implications

This study examines the link between household welfare and solar electricity demand in sub-Saharan Africa. The relevant literature shows the influence of welfare on households' choices of energy fuels, either through an energy ladder hypothesis or fuel stacking approach. The consumption pattern of modern and clean renewable energy sources has been influenced by these hypotheses, however, there is a dearth of literature that provides sufficient insight into the actual effects. Therefore, this paper fills the gap and contribute to literature by examining the effects of various factors of welfare (HDI, inequality in income, education, health, ICT and unemployment) on solar electricity demand. First, the findings show that welfare has mixed effects on solar electricity demand. Firstly, an increase in household welfare, characterised by high HDI and low inequality in income negatively impact solar demand. This means as welfare improves, households demand other fuels, which leads to a decline in solar electricity demand. The findings can be explained through the fuel stacking theory [16,17,18] showing that households would use other fuels as insurance against the intermittency and high cost of solar electricity, therefore leading to a decline in solar electricity demand. For example, in Tanzania, [49] found that as welfare improves, household energy consumption pattern is characterised by the consumption of multiple fuels, therefore eroding the environmental and socio-economic benefits of using clean energy.

On the other hand, the findings reveal the energy ladder hypothesis, where solar electricity is used as a substitute to grid-based electricity as household welfare improves [15]. For example, [50] found that off-grid solar electricity remains costly to poor households, therefore any effort to improve access to energy by the poor should focus on grid-based electricity. These findings are aligned with extant literature [15,16,17,18] and in contradiction to the findings of [21], which introduces new knowledge in the study of the welfare-energy nexus. This finding has significant implications for developing countries because it reveals that the potential benefits of solar electricity in the transition to clean energy will not be realised as swiftly as envisioned. Therefore, policymakers should accelerate the development of policies that will stimulate the demand and access to solar electricity technologies.

However, the above cannot be said for the lower quantiles where if the welfare of households improves (increase in HDI and decrease in inequality in income), solar electricity demand increases. This finding holds in countries implementing energy access programmes through off-grid solar solutions and where grid-based electricity is unreliable. For example, Pakistan had implemented cash transfer programs and incentives that were aimed at improving household consumption of solar electricity. As a result, household welfare and solar electricity consumption increased simultaneously [51]. This implies that when policymakers should link human development objectives with solar electricity consumption targets to promote the use of clean energy sources.

Second, education, health (infant mortality) and unemployment negatively impact solar electricity demand across all quantiles. This finding is widely accepted in literature [11,27,29,38] and may happen when government's budget allocation to education institutions is minimal to develop programs aimed at promoting clean electricity technologies such as solar technologies [52]. On the other hand, when infant mortality is prevalent, labour force participation and productivity is negatively impacted, leading to poor economic growth and energy consumption, particularly clean energy sources whose adoption rates are still low [31]. Therefore, policymakers should promote policies and programs that will increase government support of solar electricity education and reduction of infant mortality to improve economic growth and solar electricity consumption.

Third, ICT positively impacts solar electricity demand, and this is widely accepted in extant literature [34,35,36]. The effect is two-pronged. First, since all ICT products require electricity to operate, therefore a rapid increase in the use of ICT products will lead to increasing demand for electricity [35]. Second, ICT enhances the shopping experience of consumers, therefore increasing the ease at which households purchase their solar electricity, which leads to increased consumption. The findings imply that policymakers should leverage the enhancing effect of ICT on energy consumption and deepen investments in ICT infrastructure, to enhance solar electricity consumption.

4.2. Robustness checks

To perform robustness checks, the study applied the panel Dynamic

OLS estimation technique developed by [53,54], with two leads and three lags, and R^2 is 0.946. The DOLS results in Table 5 are compared with the median results of the quantile regression.

For HDI, the DOLS results reveal a negative but insignificant effect of HDI on solar electricity consumption. These results are consistent with the main results even though the significance level is weak. Further, the results on income inequality, government expenditure on education, infant mortality, mobile subscription, internet usage and unemployment rate are consistent with the main results. Therefore, the DOLS results confirm the robustness and validity of the quantile regression results.

5. Conclusion and prospects for future research

The study examined the effects of welfare on the demand for solar electricity in 15 SSA countries for the period between 2010 and 2019, using the panel Quantile regression with non-additive fixed effects. The findings confirm that welfare has a significant impact on solar electricity demand, with HDI, inequality in income, education, and infant mortality revealing an inverse effect on solar electricity demand. ICT has mixed effect on solar electricity demand, with mobile phone subscriptions revealing a positive effect across all the quantiles, whereas internet connectivity shows a negative effect in the lower and upper quantiles. For policy makers, these results imply that solar electricity consumption may not swiftly yield the energy access benefits envisioned. There is a need for policymakers to increase the demand for solar electricity through pragmatic approaches of enhancing the welfare of society and strengthening the reliability and affordability of solar electricity technologies. Given the poor access to electricity in SSA, policy makers should seek to integrate renewable energy access targets into human development policies to promote the use of clean energy sources. For future research, scholars may apply causality econometric methods to model causality and bidirectionality of the welfare and energy nexus to expand the understanding of the relationship for effective policy formulation.

Ethics statement

As our research utilizes secondary data and does not involve direct engagement with human participants, formal ethical approval was not sought. However, the study complies with all ethical guidelines and standards for responsible research and publication.

CRediT authorship contribution statement

Andile Dube: Conceptualization, Data curation, Formal analysis, Investigation, Writing – original draft. **Roderick Crompton:** Supervision, Writing – review & editing. **Jones Odei-Mensah:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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