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Climate shocks, adaptive mechanisms and household energy transition in Uganda

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Abstract
Nearly 41% of the global populace depends on unclean fuels for cooking. As a result, about 4 million premature deaths connected to household air pollution are registered annually. Worryingly, over 2.1 billion people are estimated to continue using unclean fuels by 2030 if no strong policy actions are taken to alter the status quo. Climate parameters including; temperature, solar radiation, wind, and moisture have been widely touted as having an impact on multidimensional energy poverty, their effect on household energy consumption and subsequent transition to cleaner fuels is seldom investigated in Uganda. The purpose of this study is to investigate the effect of climate shocks, and adaptation mechanisms on household energy transition in Uganda. The study adopted a panel data methodology employing an ordered logit model with random effects to estimate the effect of climate shocks and adaptation mechanisms on household fuel transition from high to low-pollutant cooking fuels in Uganda. The findings revealed that climate shocks, adaptation mechanisms significantly affect household energy transition in Uganda. The study recommended that policies aimed at enhancing detection and report of early warning signs should be emphasized. Furthermore, investing in an insurance scheme especially for people living in climate shock prone areas can help households to cope up with shocks are eventually transition to clean cooking fuels.

Keywords Climate shocks (JEL Q54) · Traditional fuels (JEL Q42) · Transitional fuels (JEL Q42) · Modern fuels (JEL Q42) · Adaptation mechanisms (JEL Q54)

1 Introduction

1.1 Background of the study

The adverse consequences of climate shocks such as drought, floods, and severe weather events are felt with greater frequency and intensity, particularly in low-developing economies [1, 2]. The global temperature has already jumped more than 1.1 °C beyond the preindustrial average [2]. This has led to extreme heat and severe storms causing serious harm to the lives, and livelihoods [2]. Sub-Saharan African countries are among the most hit by climatic deviations [1, 3]. Climate

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shocks have a negative effect on economic growth. While the impact of temperature shocks have a lasting reduction on real gross domestic product (GDP), droughts and storms are even more explosive [2]. Moreover, high temperatures have greater damage and subsequent reduction on economic growth in developing countries [4]. Climate shocks affect and lower agricultural productivity which has serious effect on food prices. The destruction of infrastructure such as connecting roads to the markets by floods prove detrimental to economic growth [2]. Climate shock (floods, drought and storms) are a threat to fragile global ecosystems [5]. In some regions, more than 2/3 of water capacity is lost due to extreme and prolonged drought [5].

Nearly 41% of the global populace depends on unclean fuels for cooking. As a result, about 4 million premature deaths connected to household air pollution are registered annually [6]. Worryingly, over 2.1 billion people are estimated to continue using unclean fuels by 2030 if no strong policy actions are taken to alter the status quo [7]. Climate parameters including; temperature, solar radiation, wind, and moisture have been widely touted as having an impact on multidimensional energy poverty [8]. In numerous studies [9–11], temperature and rainfall are reported to influence residential energy consumption. What is not reported in the literature is whether the same weather parameters can influence household decisions to switch from unclean to clean fuels. Similarly, little has been explored on the effectiveness of different adaptation mechanisms that households employ when such shocks occur. Households respond to climate shocks differently but most commonly, households consider income diversification, agroforestry and taking new employment [12].

According to Kang and Reiner and Blázquez et al. temperature hurts a household's electricity consumption, meaning that household electricity consumption decreases as temperatures rise [13, 14]. Kang and Reiner further reported that rainfall was positively associated with household electricity consumption [13]. Whereas this is empirically tested, we note that those studies depict the situation in the developed economies away from sub-Saharan Africa where the weather conditions are different. As in other sub-Saharan Africa (SSA) countries, both the frequency and intensity of climate shocks are increasing in Uganda [15].

Since 1960s, the average temperatures in Uganda are estimated to have increased by 1.3 °C. The minimum temperatures and maximum temperatures have increased by 0.5–1.2 °C and 0.6–0.9 °C respectively. Significant reduction in rainfall is also reported [15]. Ugandan government has prioritized transitioning households to using clean fuel alternatives for cooking [16]. The focus areas as stipulated in National Development Plan-NDPIII-2020/21–2024/25 are; reducing the share of biomass fuel for cooking from 88% in 2018 to 50% and increasing the share of clean fuels for cooking from 15 to 50% by 2025. Secondly, increase the uptake of Liquefied Petroleum Gas (LPG) from 1% in 2018 to 8%. In recent developments, the government plans to implement the parish development model, and the switch to clean fuels is one of the key issues that the model is meant to address [17]. This, in a way, contributes greatly to the reduced greenhouse gas emissions.

Although several studies have been conducted to determine the drivers of household energy transition in Uganda, the effect of climate shocks and adaptation mechanisms on transition is one area that remains unexploited. Studies investigating the effect of the weather parameters (climate shocks) on household fuel transition are sparse, anecdotal, and at best speculative. Using a panel data from Uganda Bureau of statistics, this study intended to fill this knowledge gap by modelling the effect of different climate parameters (floods, drought, landslides among others) adaptation mechanisms on household energy transition in Uganda.

2 Literature review

2.1 Theoretical review

The transition from traditional to modern cooking fuel in literature is conceptualized as a 3-stage straight forward process. Stage one presents firewood as the dominant source of cooking fuels for households, step two is marked with the emergence of transitional fuels such as kerosene and charcoal [18]. Lastly, the third step is characterized by the developed markets in which there are rising incomes thus facilitating the switching to LPG and Electricity [19, 20]. Household energy transition studies are often anchored on energy ladder hypothesis [20]. The theory posits that with the rise in the household income, households abandon traditional cooking fuels and adopt modern fuels. Unfortunately, this approach has been criticized for being economic-centric because it over looks other factors that influence cooking fuel decisions. The role of resilience in determining whether households can switch to and sustain the use of modern fuels after suffering from different shocks such as climate shocks and economic shocks can based be explained using resilience theory. In this study, we attempt to integrate energy ladder and resilience theories to explain the connection between economic aspects and resilience in household energy transition.

2.1.1 Energy ladder theory

The energy ladder theory emerged in 1970s and was later developed by Hosier and Dowds in 1987 [21]. The energy ladder was developed based on the relationship between income and the use of modern fuels for cooking [19]. It ranks fuels into inferior and superior categories. Electricity and LPG are considered superior while firewood, plant wastes and animal wastes are categorized as inferior fuels. The energy ladder has since been used in explaining household fuel use in developing countries [22]. The theory assumes that all forms of fuels are available and that, there is a universal set of fuel preferences by the households. The theory further assumes that households will choose to move up the ladder as soon as they can afford to do so [23, 24] while simultaneously dropping inferior fuels. The theory assumes linear progression such as the household socioeconomic status improves, the household abandons inferior cooking fuels and adopts modern ones for cooking.

Primarily, three steps are documented in the energy ladder theory. First is the collective and or widespread dependence on traditional biomass and other solid fuels. These are normally defined as wood and other plant and animal wastes [21]. The poor households burn wood and other wastes to provide energy for cooking. The second step is characterized by households switching to transitional fuels (mostly kerosene and coal. The final step involves households switching to cleaner (modern) fuels such as electricity and liquified petroleum gas, biogas and natural gas [20, 25]. The main strength of this theory is the ability to explain the relationship between fuel consumption and income.

However, the energy ladder theory has met with several criticisms. For example, Heltberg and Masera et al. disagree with the assumption of linear progression [23, 25]. They argue that households will not automatically drop traditional fuels as soon as their socioeconomic status improve. Masera et al. argue that switching is not a unidirectional process since some households tend to switch back to traditional fuels [23]. Thus, the energy ladder theory can only provide a limited view of reality. Households are faced with a multitude of factors beyond income that influence consumption decisions that can be explained by theories other than the energy ladder.

2.1.2 Resilience theory

Resilience first emerged as a theory in 1970s when child psychologists identified that some children showed good responses despite facing childhood trauma and adversity [26, 27]. Later Holling's article laid the groundwork for what became known as resilience theory [28]. The central focus of resilience theory is the notion of the ability of the system to bounce back from the negative effect of a shock [27]. It is not the nature of the adversity or stressors that is most important but rather how to deal or cope with it [27].

Resilience encompasses the capacity to adapt to stressors that impede the normal functioning of any unit or organization [27]. Adversities such as shocks create damage and losses that destabilize the normal functioning of the household and therefore households need to learn to be resilient through adaptation. Resilience enables households to maintain normal functioning when life stressors such as weather shocks, death of the main breadwinner, and so forth occur [29].

It should be noted that resilience is about a system being able to return to its original state in terms of consumption levels, health, and investment after experiencing shocks such as natural disasters and, the death of breadwinners among others. In summary, resilience involves the extent to which the original impact of the shock is dampened so that the household does not experience the shock in its fullness [30]. Despite the benefits proposed by resilience theory, some scholars argue that not all forms of adversities or stressors need resistance. Drawing from the definition of resistance by UNISDR, includes "the ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions", its rather important to develop mitigation strategies rather than struggling to absorb, accommodate the hazard [31]. Furthermore, in the context of poverty, loss of job among others resilience may not be the solution but rather think of ways of getting out of poverty through seeking employment and investment opportunities.

2.2 Empirical literature review

2.2.1 Shocks and adaptation mechanisms

Weather-related shocks due to climate change have become predominant over the past few decades. The impact is alarming especially in those low-developing economies located in sub-Saharan Africa [32]. Climate projections especially for African regions show an average temperature upsurge of 3 to 4 °C by the end of the twenty-first century [32]. This calls for adaptation/coping mechanisms to enable households to cope with challenges caused by weather shocks [33]. Adaptation mechanisms or coping strategies are needed to help households respond to such an upsurge in temperatures that normally result in unfavorable conditions [34]. Unfortunately, in many cases households have not been well equipped to respond adequately to the shocks caused by abrupt changes in climate. While there are a range of adaptation mechanisms households can rely on to respond to climate shocks, a majority of them are informal. For instance, dependence on social local networks have proved to be less reliable due to recurrent nature of climate shocks in some regions [35]. The continued dependence of households on informal adaptation mechanisms to mitigate shocks if left un attended could lead to significant socioeconomic costs [35]. Skoufias noted that the use of informal adaptation mechanisms more so reliance on support from family members and friends, sale of assets, sending children to live with relatives is ineffective because climate shocks affect households simultaneously [36]. He further advances that the recurrent nature of climate shocks should a matter of policy rather than individual household coping mechanisms because in the end, households become vulnerable and can no longer cope with the impact of climate change.

Households have a variety of ex-ante and post coping mechanisms and hence it is import for households to know which strategy provides greater resilience during and after the calamity. For instance, Barrett and Constas believe that building human capital through education tends to be associated with better resilience [37]. Boka advances that access to climate information, more so, early warning and access to climate change coping mechanisms helps to boost household resilience across the areas prone to climate related calamities [38]. There is therefore need to evaluate different adaptation and coping mechanisms to identify which ones can be emphasized for households to mitigate the impact of climate shocks.

Shocks are unpredictable events that can have dramatic effects on the performance of the economy, industry, or even households [1]. Vulnerability to, for example, climate shocks and economic shocks can exacerbate poverty, food insecurity, and incidences of disease among others [39]. Over time, researchers have further reported that once households are trapped in a poverty trap without any chance of Aid, they can no longer escape from it thus remaining poor and unable to resist climate and economic shocks [40].

Similarly, Que et al. noted that frequent heat shocks lower agricultural revenues thus exacerbating energy poverty among the households [41]. Relatedly, Paudel found forest fires are negatively associated with clean energy consumption among households [42]. He also noted that an increase in forest fires led to the decline in energy expenditures among households. Feeny et al. after investigating the connection between shocks (temperature) and energy poverty noted that beyond reducing agricultural output, temperature shocks also caused multidimensional poverty among households in Vietnam [43]. Earlier studies by Barreca et al. linked shocks (high temperatures) to energy poverty [44]. They noted extreme temperatures can raise the demand for electricity appliances hence leading to high prices beyond the reach of poor households. Although this is not directly connected to income, the fact that the demand for such appliances, increases, their price is forced to go higher making it impossible for households with low income to afford them [44]

In related studies, Wang et al. investigated the consequence of health shocks on households in China [45]. They found out that unexpected health shocks induce a large and long-lasting deterioration of an individual's physical and mental health. The study findings further revealed that shocks reduce household incomes and net assets thus raising the likelihood of poverty among households. The fact that shocks reduce incomes and force households to fall into poverty, shows why eventually such households will rely on unclean fuels for cooking. As stated in the energy ladder hypothesis, the choice of cleaner sources of fuel is highly correlated with income growth. Where there is a fall in income due to uncertainties, the likelihood of picking cleaner fuels for cooking diminishes. A similar study titled "Quantifying vulnerability to poverty in the drought-prone lowlands of Ethiopia" by [46]. The findings revealed that shocks plunge households into poverty. Recently, Wang et al. also noted that shocks play a role in plugging households into poverty thus reducing the households ability to afford cleaner fuels for cooking [45]. Shibia also noted that review of institutional frameworks to manage uncertainties, use of market-based measures such as financial instruments are necessary to reduce the effect of shocks [35].

In summary, most scholarly work has focused primarily on the effect of economic factors while paying less attention to non-economic factors such as climate shocks and adaptation mechanisms. Similarly, the focus on linear progression as proposed by the energy ladder theory does not reflect the dynamic nature of household energy transition especially under conditions of uncertainties such as climate, economic and other shocks. In this study, we also note that households face a myriad of challenges including shocks but the role of resilience in promoting the much-needed household energy transition from high to low polluting fuels has not been extensively explored in literature. Finally, reviewed studies mostly relied on cross-section data. Owning to the continuous nature of climate shocks, longitudinal data provides a better option for analysis of climate shocks and household energy transition.

3 Materials and methods

3.1 Data and variables

This study adopted mixed methods approach combining qualitative and quantitative data. For qualitative data, three rounds of Uganda National Panel Surveys, 2015/16, 2018/19, and 2019/20 data collected by Uganda Bureau of Statistics were used to model the effect of climate shocks and adaptation mechanisms on household energy transition in Uganda. In 2009, The Uganda National Panel Survey set out to track and interview 3123 households. These households were distributed in 322 Enumeration Areas (EAs) selected out of the 783 EAs that had been visited by the National Household Survey (UNHS) in 2005/06. The distribution of the EAs covered by the 2009/10 UNPS was such that it was it included all 34 EAs within Kampala and 72 EAs (58 rural and 14 urbans) in all the four regions (Northern, Central but excluding Kampala, Western and Eastern). This panel dataset contains an assortment of the socioeconomic variables and energy consumption at household level. The socioeconomic variables collected include; housing information, age, marital status, income, water and sanitation. Information on energy use included; types of fuels used for cooking, cooking technologies, cost of fuels, kitchen space and the time of stove used.

Information on shocks such as; drought, floods, soil erosion, landslides, loss of employment by the principal income earner, injuries and deaths caused by accidents, increased crop pests and coping mechanisms were also collected. Just like many other panel datasets, the problem of attrition exists where some households dropped off the panel study. To manage the challenges that might arise due to attrition, the analysis was restricted to only the households that were visited in all three waves used in this study. The study considered data collected between, 2016–2020. This period was chosen because the data collected within this period was inspected and found to contain the key variables that inform decisions for energy use among households and it is a nationally representative (i.e., covering all four regions—Northern, Eastern, Central, and Western) sample. Primary qualitative data was collected and the responses were used to validate the findings from the secondary quantitative data.

3.2 Theoretical model

Utility maximization problem theorem [47] is used to derive the theoretical model to explain household demand for cooking fuels. Household utility is maximized subject to a set of socioeconomic and non-socioeconomic constrains. Households are assumed to have preferences which can be described by means of a utility function [48]. According Varian, a rational consumer (household) will choose the most preferred bundle from a set of feasible alternatives [49]. Consider a household faced consumption bundles in set M where M refer to cooking fuel alternatives. The household is assumed to have preferences on the consumption of alternatives in bundle M i.e., households rank the alternatives in bundle based on their desirability. In this study, we assume that households have characteristics to order the bundle a in m in M. This ranking gives rise to a utility function that the household wishes to maximize as presented in Eq. 1:

$$U(m) = U(m1, \dots mn) \tag{1}$$

Households are faced with budget constraint. Therefore, from the consumption of items $mi, i = 1, \dots n$, households are required to choose values of $m1, \dots mn$ that satisfy the budget constraint and give larger values of $U(m1, \dots, mn)$ than other values of m1, …mn from the consumption possibilities. The budget constraint specifies the expenditure X based on the prevailing market price P. With P1, ….pn being the prices of n commodities, the utility maximization can be expressed as in Eq. 2.

$$MaxU(m) subject\ to\ pimi = X \tag{2}$$

A household cooking fuel utility function can be derived from the constrained utility function in Eq. 2 above by extending to capture non-economic factors. This approach was used by Browning et al. and Waweru and Mose [48, 50]. The set of non-economic factors included in this study include, climate shocks, marital status, level of education, household size and the age of the household head. Beyond price and the level of income, cooking fuel type is chosen by household based on its attributes such as convenience, food taste, level of emission and access. The theoretical model that incorporates both economic and non-economic factors in this study follows Pundo and Fraser [51] approach and can be expressed in Eq. 3:

$$U^{*} = U\Big[Mw(Pw, Pa, Y, \Omega)Ma(Pw, Pa, Y, \Omega)\Big] \tag{3}$$

where $U^{*}(Pw, Pa, Y, \Omega)$ is the maximum attainable utility, *Mw* is the units of cooking fuel type purchased, *Pw* is the price of cooking fuel type chosen, *Pa* is the price of alternative cooking fuels, Y is the household income, Ω is the set of other factors that influence household fuel choice, *Ma* is the Units of alternative cooking fuels purchased by the household.

Therefore, Eq. 3 presents the theoretical model that incorporates the non-socioeconomic factors that influence household decisions on the type of fuel to be used for cooking.

3.3 Study variables

The cooking fuels were grouped based on the energy ladder theory [52, 53]. Fuels are grouped as traditional (firewood, dung, and plant wastes), transitional (Kerosene and charcoal) and modern (Electricity, LPG, and biogas). The independent variables are climate shocks and household characteristics while the dependent variable is the type fuel used for cooking. Transition takes place when households choose to shift from traditional fuels to modern cooking fuels. Table 1 shows the definition of the study variables and the measurement scale.

3.4 Empirical model and estimation strategy

To study and model household energy transition, it was necessary to provide a method for categorizing different fuels used by households for cooking into categories. To do this task, an energy ladder framework was adopted and used to group the fuels into 3 distinct categories. The multiple ordinal levels for cooking fuel in households (i.e., j "0, 1 and 2") where 0 is traditional fuels, 1 is transitional fuels and 2 is modern fuels which were obtained from the energy ladder. This classification necessitated the application of the ordered logit model for analysis.

$$y_{it}^{*} = \beta' X_{it} + \varepsilon_{it} \tag{4}$$

where y_{it}^{*} is the latent energy transition level for household ($i = 0, 1, 2, \ldots$ n); X_{it} is the vector of the observed explanatory variables for household *i* (shocks and adaptation mechanisms) that affect household energy transition; β is the corresponding matrix of the coefficients of the regression to be estimated (i.e., $\beta_1, \beta_2 \ldots .\beta_n$) and ϵ_{it} denotes the error terms which must be independently and identically standard for logistic distribution.

The latent propensity y_{it}^{*} is mapped to observed energy transition level y_{it} through the threshold $\mu_j(\mu_0 = -\infty$ and $\mu_2 = \infty)$ as shown in Eq. 5.

$$y_{it} = \begin{cases} 0 \text{ if } -\infty \le y_{it}^{*} \le \mu_1(\text{Traditional fuel}) \\ 1 \text{ if } \mu_1 \le y_{it}^{*} \le \mu_2(\text{Traditional fuels}) \\ 2 \text{ if } \mu_2 \le y_{it}^{*} \le \infty(\text{Modern fuels}) \end{cases} \tag{5}$$

where μ_1 and μ_2 were the threshold values to be estimated together with β. The following probabilities were then predicted;

Table 1 Definition and measurement scale of the study variables

Variable	Definition	Scale	Coding
Fuel type	Type of energy fuel a household uses for cooking	Nominal	1 = Traditional, 2 = transition, and 3 = modern
Climate shocks	Extreme weather conditions that cause damage to live environment and other ecosystems [2]	Binary	1 = if a household experienced climate shock, 0 = otherwise
Economic shocks	Unexpected exogenous disturbance that has significant impact on the economic system [54]	Binary	1 = if a household experienced economic shock, 0 = otherwise
Household income	Household income is a flow that enables consumption and contributes to changes in household wealth or net worth [55]	Ratio	Amount of money in UGX earned per month
Household size	No of occupants living together one household [56]	Ratio	No of household occupants
Age of household head	Years of age of the head of the household [56]	Ratio	Age in years
Location (urban)	Household located either in urban or rural area	Nominal	1 = if a household is located in urban and 0 otherwise
Region	Household located in either western, central eastern of northern part of Uganda	Nominal	1 = Central, 2 = Eastern, 3 = Northern, and 4 = Western
Marital status	The nature and type of marriage for the household head	Nominal	1 = Married polygamously, 2 = Divorced / Separated, 3 = Widow/Widower, 4 = Never married
Education level	The level of education attained by the household head	Nominal	1 = No formal education, 2 = Primary level, 3 = Secondary level, 4 = Secondary, and 5 = Tertiary

$$
\begin{aligned}
Prob(y_1 = 1|X_{it}) &= F(\hat{\mu}_1 - X_{it}\hat{\beta}) \\
Prob(y_2 = 2|X_{it}) &= F(\hat{\mu}_2 - X_{it}\hat{\beta}) - F(\hat{\mu}_1 - X_{it}\hat{\beta}) \\
Prob(y_3 = 3|X_{it}) &= 1 - F(\hat{\mu}_2 - X_{it}\hat{\beta})
\end{aligned} \tag{6}
$$

where F(.) is the cumulative function using the following mathematical formula

$$F(Z) = \frac{exp(Z)}{1 + \exp(Z)} \tag{7}$$

The empirical models were presented based on the study hypothesis as follows:

a. Household energy transition = f (shocks, household income, household size, age of the household head, marital status, and education level of the household head).

$$
\begin{aligned}
HET_{it} = \propto_0 &+ \beta_1\text{climate}_{it} + \beta_2\text{economic}_{it} \\
&+ \beta_3\text{others}_{it} + \beta_4\text{INCOM}_{it} \\
&+ \beta_5\text{HSIZE}_{it} + \beta_6\text{Age}_{it} \\
&+ \beta_7\text{Mstatus}_{it} + \beta_8\text{EDLEV}_{it} + \varepsilon_{it}.
\end{aligned} \tag{8}
$$

b. Household energy transition = f (adaptation, household income, household size, age of the household head, marital status, and education level of the household head).

$$HET_{it} = \propto_0 + \beta_1\text{adaptation}_{it} + \beta_2\text{INCOM}_{it} + \beta_3\text{HSIZE}_{it} + \beta_4\text{Age}_{it} + \beta_5\text{Mstatus}_{it} + \beta_6\text{EDLEV}_{it} + \varepsilon_{it} \tag{9}$$

where $P_r(Y_{it}=j)$ is the probability of choosing fuel in any of the two fuel categories other than the base category and i is the individual household. INCOM is the household income, HSIZE is the household size, Mstatuss is the marital status of the household head while EDLELV and ε are the education level of the household head and error terms respectively.

4 Findings

4.1 Descriptive statistics

This study sought to determine the effect of shocks and adaptation mechanisms on household energy transition in Uganda.

4.1.1 Shocks and coping mechanisms

The number of households that experienced climatic, economic, and other shocks as shown in Table 2. The findings show that only 805 households out of 2975 experienced climate shocks in 2016. This number increased to 1106 in 2018 but later dropped to 1003 in 2020. The findings also indicate that overall 326 and 1090 households experienced economic and other shocks respectively.

The findings also show that only 2.11% of the households that experienced shocks were able to cope with the situation in 2016. In 2018 and 2020, the number of households that managed to cope with the shocks reduced to 1.92% and 1.86% respectively. This finding reveals that a majority of the households that experienced shocks both climate and other shocks did not apply any mitigation strategy against the effect of the shocks. Households' inability to cope with the effects of shocks could dent household's efforts to transition to modern fuels for cooking.

4.1.2 Energy fuels used for cooking in Uganda

The cooking energy mix in Uganda is dominated by traditional and unprocessed biomass as shown in Fig. 1. In 2016, about 2189 households used traditional/primitive fuels such as firewood, sawdust, dung, and plant wastes for cooking. While about 516 households used transition fuels like charcoal and kerosene, only 11 households used modern fuels such

Table 2 Shocks & coping ability (adaptation mechanisms)

	2016	2019	2020	Total
Shocks				
Climate shocks	805	1106	1003	2914
Economic shocks	69	113	69	326
Other shocks	236	428	426	1090
Ability to cope				
Able to cope, %	2.11	1.81	1.86	1.92
Unable to cope, %	97.89	98.19	98.14	98.08

Source: Authors own computation based on the UNPS data—2016, 2018 & 2020

as electricity and liquified petroleum gas for cooking in 2016. There was a slight increase in the number of households using traditional fuels for cooking from 2189 in 2016 to 2268 in 2019.

There was no significant change in the number of households using transition and modern fuels for cooking in 2020. In Uganda, over 80.9% of the population lives in rural areas with limited access to cleaner cooking alternatives [57]. This could explain why there is a high dominance of firewood as cooking fuel among households. Generally, of the 94% of households that predominantly use biomass for cooking, about 73% use firewood while about 21% use charcoal. Only about 5.3% use electricity, LPG, and biofuels for cooking [57, 58]. The availability of biomass as a monetary-cost-free alternative cooking fuel is one of the key factors driving over dominance of traditional fuels for cooking. This has consequences on household energy transition among Ugandan households especially to households with low income levels.

4.2 Pre-estimation diagnostics

4.2.1 Multicollinearity test

To determine whether or not the regressors are highly correlated, the study conducted a multicollinearity test. There are several techniques used to detect multicollinearity. In this study Variance Inflation Factor (VIF) was used to check for multicollinearity [59]. The purpose was to detect how much the independent variable are correlated. Hair et al. emphasized that when VIF is below 5, there is no threat of multicollinearity among the regressors [60]. The VIF is calculated as indicated in Eq. 10.

$$\mathrm{VIF} = \frac{1}{1 - \mathbf{R}^2} = \frac{1}{\mathrm{Tolerance}} \tag{10}$$

where tolerance is the inverse of the VIF. The lower the tolerance, the more likely that multicollinearity exists among the independent variables [59]. VIF = 1 is an indication that the independent variables are moderately related to each other. The VIF value between 5 and 10 (VIF ≥ 5 to 10) shows high correlation [60]. Multicollinearity occurs in multiple regression models when two or more predictor variables are highly correlated, meaning they contain similar information about the variance within the dependent variable. This can make it difficult to ascertain the individual effect of each predictor on the dependent variable.

Fig. 1 Energy fuels used for cooking in Uganda

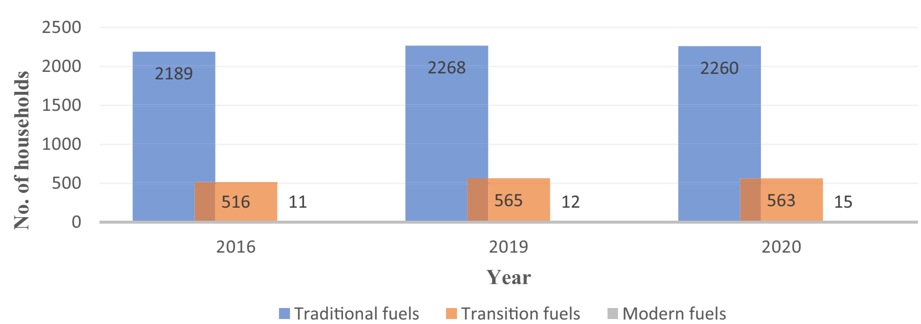

Table 3 Multicollinearity test results

Independent variables	Variance inflation factor	1/VIF
Climate shocks	1.10	0.905971
Economic shocks	1.01	0.992531
Other shocks	1.02	0.982982
Coping strategy	1.06	0.943870
Household income	1.49	0.671326
Household size	1.28	0.780650
Age of household head	1.11	0.900303
Location (urban)	1.24	0.808434
Region	1.07	0.934029
Marital status	1.17	0.851815
Education level	1.27	0.787134
Mean VIF	1.17	

Source: Authors' computations using the UNPS 2016/2017; 2017/2018 and 2019/2020

Table 4 Pearson correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Energy1	1											
Climate	−0.1975	1										
Economic	−0.0077	0.0060	1									
Others	−0.0353	0.0182	0.0280	1								
Cope	−0.0473	0.2126	0.0372	0.1009	1							
Income	0.2576	−0.0905	0.0402	0.0054	−0.0114	1						
Size	−0.2379	0.0884	0.0010	0.0119	0.0248	0.3160	1					
Age	−0.1194	0.0101	−0.0016	0.0462	0.0223	0.1247	0.0574	1				
LOC	0.5791	−0.1847	0.0017	−0.0401	−0.0462	0.2839	−0.1311	−0.0311	1			
REG	−0.2301	0.1307	−0.0134	−0.0432	0.0213	−0.1228	0.0391	−0.0532	−0.1459	1		
MS	0.1121	−0.0521	0.0474	0.0129	0.0042	−0.1287	−0.2335	0.2088	0.0826	−0.1568	1	
EDUC	0.3293	−0.0988	−0.0062	−0.0398	−0.0287	0.3362	−0.0954	−0.1229	0.2901	−0.0514	−0.0956	1

*Correlation is significant at a 5% significant level

Source: Author's computation using UNPS data—2016, 2018 & 2020

Source: Authors' computations using the UNPS 2016/2017; 2017/2018 and 2019/2020

EF Energy fuel, *LOC* location, *REG* region, *MS* marital status, *EDUC* education

The findings for both VIF and correlation analysis are presented in Table 3. The test results show a mean VIF of 1.17 with all the VIF values for the independent variables ranging between 1.02 to 1.49. The general rule of thumb is that the VIF values exceeding 5 are signs of serious multicollinearity among the regressors. Since the test results in Table 3 show a mean VIF of 1.17 which is far below 5 as recommended by Hair et al. it implies an absence of multicollinearity among the regressors [60].

To confirm the results obtained using the VIF, a correlation matrix was used, and the results are presented in Table 4. The correlation results indicated that the correlation values for each independent variable were less than 0.58 0r (0.0 ≤|r|≤ 0.58), implying a weak correlation between the regressors. This therefore indicates that the regressors used in the estimation showed no multicollinearity.

4.2.2 Normality test

The normality assumption means that the collected data follows a normal distribution, which is vital for the parametric assumption. To check whether the data used in this study follows a normal distribution, a Shapiro-Wilks test was adopted and used to test for normality [61]. Shapiro-Wilks test is specified as in Eq. 11.

$$W = \frac{\left(\sum_{i=1}^{n} \alpha_i x_{(i)}\right)^2}{\sum_{i=1}^{n} \left(x_i - \overline{x}\right)^2} \tag{11}$$

where W is the test statistic while x_i and $\overline{x}$ are the ordered sample values and the sample mean respectively. The reference point is the W test statistic. The rule is that the closer the W statistic to 1, the more evidence there is, that the sample comes from a normally distributed population. The results of the Shapiro–Wilk W test for normal data show that most of the variables show a normal distribution of the data. Table 5 shows the normality test results.

4.3 Post-estimation tests

4.3.1 Hausman test

To decide between fixed or random effects models, a Hausman test [62, 63] was run to determine which model is appropriate for estimating the effect of shocks and adaptation mechanisms (coping strategies) on household energy transition in Uganda.

Hausman test evaluates whether the model uses appropriate estimators (random effect estimator and the fixed effect estimator). It compares the two estimators to determine whether the difference between them is statistically significant. The test statistic follows a chi-squared distribution under the null hypothesis [64, 65]. The Hausman test can be expressed mathematically as below:

Given that fixed effects and random models can be defined as:

$$\left.\begin{aligned} \mathcal{Y}_{it} &= \alpha_i + \beta \mathrm{X}_{it} + \mu_{it} \\ \mathcal{Y}_{it} &= \alpha + \beta \mathrm{X}_{it} + \left(\mu_i + \mu_{it}\right) \end{aligned}\right\} \tag{12}$$

Table 5 Shapiro–Wilk W test for normal data results

Independent variables	Obs	W	V	Z	Prob > z
Energy fuel	8,399	0.99575	18.187	7.728	0.00000
Climate shocks	8,639	0.99933	2.935	2.871	0.00205
Economic shocks	8,639	0.99391	26.724	8.761	0.00000
Other shocks	8,639	0.99846	6.750	5.092	0.00000
Coping strategy	8,639	0.98956	45.800	10.197	0.00000
Household income	8,589	0.99249	32.780	9.304	0.00000
Household size	8,601	0.97448	111.516	12.568	0.00000
Age of household head	8,623	0.97181	123.463	12.841	0.00000
Location (urban)	8,617	0.99946	2.360	2.290	0.01102
Region	8,617	0.99725	12.052	6.637	0.00000
Marital status	8,621	0.97538	107.788	12.478	0.00000
Education level	7,135	0.96995	111.517	12.502	0.00000

Source: Authors' computations using the UNPS 2016/2017; 2017/2018 and 2019/2020

Source: Authors' computations using the UNPS 2016/2017; 2017/2018 and 2019/2020

Obs denotes observations, *W* denotes Wilk statistic, *V* denotes variance- covariance matrix, *Z* Denotes vector of difference between the two estimators where α_i and α are the individual specific effect and the common intercept respectively. B is the vector of coefficients. μ_i is the individual-specific random effect and μ_{it} is the error term. Hausman test statistic computed by estimating the parameters from both fixed and random models as shown in equation two (13):

$$\hat{d} = \hat{\beta}_{FE} - \hat{\beta}_{RE} \tag{13}$$

where $\hat{d}$ is the difference between the estimators. The variance of the difference is computed as shown in Eq. 14.

$$\hat{V}\left(\hat{d}\right) = \hat{V}\left(\hat{\beta}_{FE}\right) - \hat{V}\left(\hat{\beta}_{RE}\right) \tag{14}$$

where V is the variance of the difference. Therefore, the Hausman test statistic is given as in Eq. 15:

$$\mathrm{H} = \hat{d}, \left(\hat{V}\left(\hat{d}\right)\right)^{-1}\hat{d} \tag{15}$$

Table 6 presents the results of the Hausman test. The chi-squared test is statistically significant at a 0.05% significance level (Prob > chi2 = 0.0000). This implies that the null hypothesis is rejected in favor of the alternate.

Table 6 Hausman test results

	Coefficients			
	(b)	(B)	(b-B)	
	FE-results	RE-results	Difference	Std. Err
Shocks and coping strategy				
Climate shocks	−0.0131558	−0.0359047	0.0227489	0.0022168
Economic shocks	−0.0106391	−0.0355006	0.0248615	0.0038714
Other shocks	−0.0041798	−0.0103449	0.0061651	0.0022187
Coping strategy	−0.008316	−0.0063487	−0.0019673	0.0032355
Household characteristics				
Household income	0.0146369	0.0849129	−0.070276	0.0051447
Household size	−0.0095828	−0.0260286	0.0164458	0.0017488
Age of household head	−0.0000705	−0.0031222	0.0030518	0.0009944
Location (urban)	0.0511825	0.2904406	−0.2392581	0.0079339
Region	−0.1079966	−0.0572309	−0.0507657	0.0358068
Marital status				
Married polygamously	0.0019061	−0.0000443	0.0019503	0.0107625
Divorced/separated	−0.0092169	0.0356038	−0.0448208	0.0143177
Widow/widower	0.0326144	0.0453548	−0.0127405	0.0212212
Never married	0.018706	0.1728432	−0.1541373	0.0226748
Education level				
Primary	−0.0481094	0.0423663	−0.0904756	0.0400278
Secondary	−0.0498786	0.1144511	−0.1643297	0.0429319
Post-secondary	−0.0454569	0.1676885	−0.2131454	0.0449975
University	−0.0789741	0.2800369	−0.359011	0.0529646

b = Consistent under H0 and Ha; obtained from regression

B = Inconsistent under Ha, efficient under H0; obtained from regression

Test of H0: Difference in coefficients not systematic

chi2(13) = (b − B)'[(V_b − V_B)^(−1)](b − B) = 1074.13

Prob > chi2 = 0.0000

FE Fixed effect, *RE* Random effects

4.3.2 Specification: Ramsey RESET Test

To ascertain whether the model was properly specified, the Ramsey RESET specification test was conducted. The findings from the Ramsey RESET specification test indicate that the coefficients on all powers of the predicted values are jointly significant at a 5% level of significance. This implies that the functional form of the estimated model is properly specified and has no omitted variables.

4.4 The marginal estimated effects and the qualitative responses.

To estimate the effect of shocks and adaptation mechanisms on household energy transition in Uganda, an ordered logit model was used. The marginal effects generated from the ordered logit regression are presented in Table 7. These findings were validated using the responses from the primary qualitative data. The results show the effect of shocks and adaptation mechanisms on household energy transition after controlling household head and other household characteristics.

The results show that climate shocks have a positive effect on the use of traditional fuels for cooking but a negative effect on the use of transitional and modern fuels for cooking. Specifically, the findings indicate that a unit increase in the occurrence of climate shocks leads to a 5.81% increase in the use of traditional fuels for cooking while reducing the probability of households switching to transitional and modern fuels by − 5.56% and − 0.25%, respectively. This implies that the increased occurrence of climate shocks such as floods, landslides, and drought, a is a hindrance to household energy transition. Modern fuels have a cost implication due to the attached price. Households that experience climate shocks find it difficult to transition to cleaner fuels, especially after the property damage and economic disruptions arising from extreme weather events. As a result, poorer households revert to using traditional fuels that typically have no

Table 7 Estimated marginal effects of shocks on household energy transition

	Traditional fuel		Transition fuel		Modern fuel	
	dy/dx	SE	dy/dx	SE	dy/dx	SE
Shocks						
Climate shocks	0.0581***	(0.012)	− 0.0556***	(0.011)	− 0.0025***	(0.000)
Economic shocks	0.0392***	(0.019)	− 0.0375***	(0.018)	− 0.0017	(0.000)
Other shocks	0.0118	(0.011)	− 0.01139	(0.010)	− 0.0005	(0.000)
Household characteristics						
Household income	− 0.0779***	(0.007)	0.0746***	(0.006)	0.0033***	(0.000)
Household size	0.0290***	(0.002)	− 0.0278***	(0.002)	− 0.0012***	(0.000)
Age of household head	0.0029***	(0.000)	− 0.0028***	(0.000)	− 0.0001***	(0.000)
Location (urban)	− 0.2039***	(0.008)	0.1952***	(0.008)	0.0087***	(0.001)
Region	0.0423***	(0.004)	− 0.0405***	(0.004)	− 0.0018***	(0.000)
Marital status						
Married polygamously	− 0.0053	(0.012)	0.0051	(0.011)	0.0002	(0.000)
Divorced/separated	− 0.0252	(0.014)	0.0242	(0.0143)	0.0009	(0.000)
Widow/widower	− 0.0503***	(0.017)	0.0482***	(0.016)	0.0021***	(0.000)
Never married	− 0.1362***	(0.034)	0.1288***	(0.032)	0.0074***	(0.002)
Education level						
Primary	− 0.0275	(0.055)	0.0368	(0.054)	0.0007	(0.000)
Secondary	− 0.0993	(0.056)	0.0969	(0.055)	0.0025***	(0.001)
Post-secondary	− 0.1389***	(0.057)	0.1348***	(0.056)	0.0040***	(0.001)
University	− 0.1973***	(0.064)	0.1903***	(0.063)	0.0070***	(0.002)
Observations	6951		6951		6951	
No. of households	2676		2676		2676	

Robust standard errors in brackets

Marginal effect coefficients in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The reference category for education is no schooling and for marital status is monogamous marriage

Source: Authors' computations using the UNPS 2016/2017; 2017/2018 and 2019/2020 monetary cost. Additionally, extreme weather conditions can disrupt the power grid, forcing even households that rely on grid power for cooking to practice energy stacking, a practice associated with partial transition.

The study findings show that economic shocks have a significantly positive effect on the use of traditional fuel but negatively affect the use of transitional fuels. For modern fuels, the findings indicate a non-significant effect. Specifically, the result reveal that a unit increase in the occurrence of economic shocks increases the likelihood of a household relying on traditional fuels for cooking by 3.95% while reducing the likelihood of switching to transitional fuel for cooking by 3.7%. Economic shocks, including loss of income and sudden rises in commodity price, have implications for household energy transition. This means that with an increase in household economic shocks, households with limited income will not be able to afford cleaner cooking fuels. Consequently, these households will continue relying on freely collected firewood from forests for cooking.

These results were further elaborated by the following qualitative responses;

"…when mudslides happened in our area, all was destroyed. We had to run to the nearby camps. In the camps only, food items were given which were not even enough. Everybody had to look for firewood around for cooking because the little help given could not be split to buy charcoal for cooking".

"……… The problem here is the constant increase in price of LPG. I used to use LPG to cook soft food like preparing tea and warming food when it was UGX45,000/=. Recently the price has short to UGX 62,500/=. I stopped using it".

The study findings are supported by earlier scholars. For instance, Genoni reported that when shocks occur, households are often compelled to limit their expenditure to only key consumption items [66]. In extreme circumstances, however, even such critical expenditure is either postponed or suspended altogether. This leaves households with the only option of collecting firewood and other traditional forms of energy sources to meet cooking energy needs. Amondo et al. reported that extreme weather conditions can affect agriculture output [67]. Thus, households that entirely depend on depleted agriculture will languish in poverty and therefore unable to afford cleaner cooking options.

Similarly, Nchofoung in his recent study on oil price shocks and energy transition in Africa, noted that an increase in price shocks is associated with trade deficits, currency value loss, an increase in inflation, and subsequently a fall in economic activity [68]. Thus, an increase in inflation leads to an increase in modern energy prices, causing a fall in demand for modern cooking fuels. An increase in the price of modern fuels would therefore lead to an increase in the demand for non-clean (traditional fuels) which are almost free in most parts of Uganda.

Among the control variables, the marginal effects show that a 1% increase in household income is associated with a -7.79% decrease in the use of traditional fuels but increases the likelihood of using transitional fuels and modern fuels by 7.46% and 0.33% respectively. For household size, the marginal effects show that an increase in the household size by one (1) member is likely to increase the likelihood of relying on traditional fuels for cooking by 2.9% but reduces the likelihood of using transitional fuels by − 0.28% and − 0.01% respectively.

Location-wise, the findings show that relative to rural location, a household being located in an urban area reduces the likelihood of relying on traditional fuels for cooking but increases the likelihood of using transitional fuels and modern fuels by 19.5% and 0.87% respectively. The marginal effects on marital status showed that widow/widower and single status had a significant effect on household energy transition. Specifically, households headed by widower/widow relative to other status, had -5.03% reduced chances of relying on traditional fuels for cooking but had increased likelihood of transition to transitional and modern fuels by 4.82% and 0.021% respectively. Households being headed by unmarried heads reduced the probability of using traditional fuels for cooking by − 13.2% but increased the probability of using transition and modern fuels by 12.9% and 0.74% respectively.

Regarding the education status of the household head, the results revealed that the likelihood of using modern fuels for cooking increased by 0.25% if the household head attained a secondary level of education. Compared with households' heads without formal education, attainment of post-secondary education reduced the likelihood of relying on traditional fuels by − 13.89% but increased the likelihood of transitioning to transition and modern fuels by 13.48% and 0.4% respectively. University education reduces the probability of the household using traditional fuels by − 19.73% and increases the likelihood of using transitional and modern fuels by 19% and 0.7% respectively.

Overall, the results suggest that climatic and economic shocks have a significant effect on household energy transition in Uganda. Table 8 presents the marginal estimates of the effect of the adaptation mechanism on household energy

Table 8 Estimated marginal effects of adaptation mechanisms on household energy transition

	Traditional fuel		Transition fuel		Modern fuel	
	dy/dx	SE	dy/dx	SE	dy/dx	SE
Shocks and adaptation						
Adaptation mechanism	0.0575***	(0.028)	– 0.0556***	(0.028)	– 0.0019***	(0.001)
Household characteristics						
Household income	– 0.1126***	(0.007)	0.1089***	(0.007)	0.0037***	(0.000)
Household size	0.0340***	(0.002)	– 0.0329***	(0.002)	– 0.0011***	(0.000)
Age of household head	0.0031***	(0.000)	– 0.0030***	(0.000)	– 0.0001***	(0.000)
Marital status						
Married polygamously	– 0.0048	(0.012)	0.0047	(0.012)	0.0001	(0.000)
Divorced/separated	– 0.0638***	(0.017)	0.0616***	(0.016)	0.0021***	(0.000)
Widow/widower	– 0.0854***	(0.019)	0.0824***	(0.018)	0.0030***	(0.000)
Never married	– 0.1832***	(0.039)	0. 1744***	(0.037)	0.0087***	(0.002)
Education level						
Primary	– 0.0547	(0.048)	0.0541	(0.047)	0.0007	(0.000)
Secondary	– 0.1623***	(0.048)	0.1592***	(0.049)	0.0030***	(0.000)
Post-secondary	– 0.2085***	(0.049)	0.2038***	(0.050)	0.0047***	(0.000)
University	– 0.2943***	(0.062)	0.2852***	(0.060)	0.0091***	(0.002)
Observations	6951		6951		6951	
No. of households	2676		2676		2676	

Robust standard errors in brackets

Marginal effect coefficients in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The reference category for education is no schooling and for marital status is monogamous marriage

Source: Authors' computations using the UNPS 2016/2017; 2017/2018 and 2019/2020

transition in Uganda. The findings show that the adaptation mechanism has a significant effect on household energy transition in Uganda. Specifically, relative to households without adaptation mechanisms, the likelihood of using traditional fuels increased by 11.26% for households that applied adaptation mechanisms but reduced the likelihood of using transitional and modern fuels by – 5.56% and – 0.19% respectively. These findings were further supplemented by qualitative responses as below:

> *"….. Here in Sironko, there was a time when we had terrible mudslides. We received help in terms of posho and blankets for some time. But at that time even people who had some money, they also used that money for medication and buying other necessary household utensils since what we had was destroyed. So, what the government and other agencies give is not enough. In fact, when we get it, the little money we have can now be diverted to other things other than clean cooking fuels".*

This finding implies that the more households continue to apply the adaptation mechanisms available to them, the more they continue consuming traditional fuels rather than cleaner fuels. This could be because the nature and type of the available adaption mechanisms are insufficient to propel households to transition to cleaner cooking fuels in Uganda. These findings are in line with the assertion of the resilience theory. Resilience theory recognizes that adversities such as shocks create damage and losses that destabilize the normal functioning of the household and therefore households need to learn and adapt accordingly [29].

It is expected that households should have mechanisms to cope with disasters (shocks) such as climate and economic shocks. In this case, households are expected to have the capacity to anticipate and prepare to be able to lessen the effect of shocks and continue thriving [69]. There is therefore need to encourage households to build capacity to absorb, accommodate, and lessen the effect of the shocks. They should build capacity to bounce back to the original position after suffering from the shock.

The study findings also agree with what earlier scholars reported. For instance, Arthur et al. noted that adaptation mechanisms play a key role in mitigating the effects of energy insecurity among small and medium enterprises in Ghana [70]. It suffices therefore to note that adaptation leads to resilience. Lama et al. reported that the occurrence of shocks increases vulnerability among households. This explains why households must learn to not only adapt but instead build capacity to reduce the effect of the shocks [71].

5 Conclusion and policy recommendations

This paper assessed the effect of shocks (climate and economic) and adaptation mechanisms on household energy transition in Ugandan households. The study findings established that shocks significantly affect household energy transition in Uganda. Specifically, climate shocks and economic shocks significantly affect household energy transition in Uganda. The occurrence of shocks increased the likelihood of households relying on traditional fuels for cooking but reduced the likelihood of switching to modern or cleaner of modern fuels for cooking. Similarly, the occurrence of economic shocks such as loss of income, and sudden increases in fuel prices in the market reduce the likelihood of switching to modern fuels but instead confine households to using traditional fuels that are presumed to be free of cost.

This study adopted a theoretical pluralism approach, combining energy ladder and resilience theories to explain the impact of climate shocks and adaptation mechanisms on household energy transition in Uganda. The combination of the two theories gave a better understanding of climate shocks, adaptation mechanisms and household energy transition. From the resilience theory perspective, households need to build resilience to respond and cope up with the climate shocks. The analysis from the data used in this study indeed confirm that coping mechanisms have an effect on household energy transition. Our findings add climate shocks and adaptation on to the existing literature on the antecedents of household energy transition in Uganda.

The findings show a significant association between climate shocks, adaptation mechanisms and household energy transition in Uganda. Climate shocks such as floods and landslides normally cause sudden power blackouts especially when the floods and landslides cause a collapse in the electric poles of the grid. This means that when the grid households use the grid electricity for cooking will not have access to electricity thus looking for the available alternatives of which one of them is traditional fuels. Secondly, floods and landslides normally cause a collapse of bridges and other road networks thus leading cut-off of the supply of cleaner alternatives like liquified petroleum gas.

This finding offers policy direction. Policies aimed at improving coping mechanisms will go a long way in helping households' transition to clean energy fuels for cooking. Policies aimed at enhancing the ability to detect and report warning sign s by investing in early warning signs are critical in enabling households prepare and deal with climate shocks.

Secondly, policies aimed at investing in an insurance scheme especially for people living in climate sock prone areas rather than on off response by government may be more sustainable and can help households to cope up with shocks are eventually transition to clean cooking fuels.

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Data availability The data that was used for analysis to generate the findings of this study are obtained from world bank living measurements. The panel data was collected by Uganda bureau of statistics on households. The link to the data is given below; https://microdata.worldbank.org/index.php/home. Also the data analysis files are available and the authors are at liberty to provide them whenever its needed.

Declarations

Ethics approval and consent to participate Not applicable.

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References

1. Tapsoba R, Diallo Y. Climate shocks and domestic conflicts in Africa. IMF Work Pap. 2022;2022(250):1. https://doi.org/10.5089/9798400227066.001.
2. Cevik S. Eye of the storm: the impact of climate shocks on inflation and growth. 2023. https://doi.org/10.5089/9798400241307.001.
3. IMF. WP/20/243 perfect storm: climate change and tourism the authors would like to thank. IMF; 2020.
4. Burke M, Tanutama V. Climatic constraints on aggregate economic output. National Bureau of Economic Research; 2019.
5. Naceur M'barek Ben SRM. Overview of the climate change impact on the environment and humanity; 2024. www.multidisciplinaryarticle.net
6. Al-delaimy WK, Ramanathan V, Change C, Pollution A. Health of People, Health of Planet and Our Responsibility. In: Health of People, Health of Planet and Our Responsibility. 2020. https://doi.org/10.1007/978-3-030-31125-4.
7. W. IEA, IRENA, UNSD, WorldBank. Tracking SDG7: the energy progress report. 2023. www.worldbank.org
8. Shourav MSA, Shahid S, Singh B, Mohsenipour M, Chung ES, Wang XJ. Potential impact of climate change on residential energy consumption in Dhaka City. Environ Model Assess. 2018;23(2):131–40. https://doi.org/10.1007/s10666-017-9571-5.
9. Aroonruengsawat A, Auffhammer M. Impacts of Climate Change on Residential Electricity Consumption: Evidence from Billing Data; 2011. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Impacts+of+Climate+Change+on+Residential+Electricity+Consumption+Evidence+from+Billing+Data#1
10. Krese G, Prek M, Butala V. Analysis of building electric energy consumption data using an improved cooling degree day method. Stroj Vestnik/J Mech Eng. 2012;58(2):107–14. https://doi.org/10.5545/sv-jme.2011.160.
11. Campagna LM, Fiorito F. On the impact of climate change on building energy consumptions: a meta-analysis. Energies. 2022;15:354.
12. Zakari S, Ibro G, Moussa B, Abdoulaye T. Adaptation strategies to climate change and impacts on household income and food security: evidence from Sahelian region of Niger. Sustainability. 2022. https://doi.org/10.3390/su14052847.
13. Kang J, Reiner DM. What is the effect of weather on household electricity consumption? Empirical evidence from Ireland. Energy Econ. 2022;111: 106023. https://doi.org/10.1016/j.eneco.2022.106023.
14. Blázquez J, Fuentes-Bracamontes R, Manzano-Gonzalez B. A road map to navigate the energy transition. Oxford Inst. Enery Stud. 2019. https://www.oxfordenergy.org/wpcms/wp-content/uploads/2019/10/A-road-map-to-navigate-the-energy-transition-Insight-59.pdf?v=04c19fa1e772
15. World Bank. Climate risk country profile—Uganda. 2020. p. 36. www.worldbank.org
16. National Planning Authority (NDPIII) 2020/21–2024/25. Third national development plan (NDPIII) 2020/21–2024/25. Natl Plan Auth. 2020. p. 1–310. http://envalert.org/wp-content/uploads/2020/06/NDP-3-Finale.pdf
17. Ministry of Local Government. Implementation guidelines for PARISH DEVELOPMENT MODEL Implementation Guidelines for PARISH DEVELOPMENT MODEL MINISTRY OF LOCAL GOVERNMENT The Republic of Uganda. 2021. https://www.masindi.go.ug/sites/default/files/Implementation_Guidelines_for_FOR__PARISH_MODEL_OPERATION%5B1%5D.pdf, https://www.kasese.go.ug/wp-content/uploads/2021/09/Implementation-Guidelines-for-FOR-PARISH-MODEL-OPERATION.pdf
18. Barnes DF, Krutilla K, Hyde WF. The urban household energy transition. Urban Househ Energy Transit. 2010. https://doi.org/10.4324/9781936331000.
19. Leach G. The energy transition. Energy Policy. 1992;20(2):116–23. https://doi.org/10.1016/0301-4215(92)90105-B.
20. Hosier RH, Dowd J. Household fuel choice in Zimbabwe. An empirical test of the energy ladder hypothesis. Resour Energy. 1987;9(4):347–61. https://doi.org/10.1016/0165-0572(87)90003-X.
21. Kowsari R, Zerriffi H. Three dimensional energy profile: a conceptual framework for assessing household energy use. Energy Policy. 2011;39(12):7505–17. https://doi.org/10.1016/j.enpol.2011.06.030.
22. Atanassov B. Socio-cultural dimensions in household cooking energy choice: implications for energy transition in Catembe, Mozambique Acknowledgments. 2010. p. 95. www.humangeo.su.se
23. Masera OR, Saatkamp BD, Kammen DM. From linear fuel switching to multiple cooking strategies: a critique and alternative to the energy ladder model. World Dev. 2000;28(12):2083–103. https://doi.org/10.1016/S0305-750X(00)00076-0.
24. Schilmann A, et al. Just and fair household energy transition in rural Latin American households: are we moving forward? Environ Res Lett. 2021;16(10): 105012. https://doi.org/10.1088/1748-9326/ac28b2.
25. Heltberg R. Fuel switching: evidence from eight developing countries. Energy Econ. 2004;26(5):869–87. https://doi.org/10.1016/j.eneco.2004.04.018.
26. Norman G. Stress, competence and development: continuities in the study of schizophrenic adults, children vulnerable, and search for stress- resistant children. Am J Orthopsychiatry. 1987. https://doi.org/10.1111/j.1939-0025.1987.tb03526.x.
27. Masten ANNS, Best KM, Garmezy N. Resilience and development : Contributions from the study of children who overcome adversity. Dev Psychol. 1990;2(1990):425–44.
28. Holling C. Resilience and stability of ecological systems. Annu Rev Ecol Syst. 1973;4(1973):1–23.
29. Kaplan CP, Turner S, Norman E, Stillson K. Promoting resilience strategies: a modified consultation model. Soc Work Educ. 1996;18(3):158–68. https://doi.org/10.1093/cs/18.3.158.

30. Mahdiani H. The dark side of resilience. Advers Resil Sci. 2021. https://doi.org/10.1007/s42844-021-00031-z.
31. UNISDR. Terminology on disaster risk reduction. UNISDR; 2009.
32. Abid M, Ali A, Raza M, Mehdi M. Ex-ante and ex-post coping strategies for climatic shocks and adaptation determinants in rural Malawi. Clim Risk Manag. 2020;27: 100200. https://doi.org/10.1016/j.crm.2019.100200.
33. Bryan E et al. Adapting agriculture to climate change in Kenya: Household and community strategies and determinants. World bank's Adapt. Smallhold. Agric. to Clim. Chang. Kenya 2016. 2011. p. 5–30.
34. Pörtner BRHO, Roberts DC, Tignor M, Poloczanska ES, Mintenbeck K, Alegría A, Craig M, Langsdorf S, Löschke S, Möller V, Okem A. IPCC, 2022: climate change 2022: impacts, adaptation, and vulnerability. In: Contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change; 2021. https://doi.org/10.1017/9781009325844.Front.
35. Shibia AG. Households coping mechanisms and resilience to the impacts of droughts and floods in Kenya. 2020. http://www.kippra.org
36. Skoufias E. Economic crises and natural disasters: coping strategies and policy implications. World Dev. 2003;31(7):1087–102. https://doi.org/10.1016/S0305-750X(03)00069-X.
37. Barrett CB, Constas MA. Toward a theory of resilience for international development applications. Proc Natl Acad Sci U S A. 2014;111(40):14625–30. https://doi.org/10.1073/pnas.1320880111.
38. Boka GT. Measuring resilience to climate change in Ethiopian. 2017.
39. IPCC. Climate change 2014 synthesis report. 1992. https://doi.org/10.1080/00139157.1992.9931432.
40. Barrett CB, Carter MR. The economics of poverty traps and persistent poverty: empirical and policy implications. J Dev Stud. 2013;49(7):976–90. https://doi.org/10.1080/00220388.2013.785527.
41. Que ND, et al. How temperature shocks impact energy poverty in Vietnam: mediating role of financial development and environmental consideration. Environ Sci Pollut Res. 2022;29(37):56114–27. https://doi.org/10.1007/s11356-022-19672-3.
42. Paudel J. Beyond the blaze: the impact of forest fires on energy poverty. Energy Econ. 2021;101: 105388. https://doi.org/10.1016/j.eneco.2021.105388.
43. Feeny S, Trinh TA, Zhu A. Temperature shocks and energy poverty: findings from Vietnam. Energy Econ. 2021;99: 105310. https://doi.org/10.1016/j.eneco.2021.105310.
44. Barreca A, Clay K, Deschenes O, Greenstone M, Shapiro JS. Adapting to climate change: the remarkable decline in the US temperature-mortality relationship over the Twentieth Century. J Polit Econ. 2016;124(1):105–59. https://doi.org/10.1086/684582.
45. Wang Y, Jin Z, Yuan Y. The consequences of health shocks on households: evidence from China. China Econ Rev. 2023;79: 101969. https://doi.org/10.1016/J.CHIECO.2023.101969.
46. Temesgen Y, Ketema M, Ademe A. Rural households vulnerability to covariate and idiosyncratic shocks using multilevel longitudinal model: evidence from Ethiopia. Heliyon. 2022;8(10): e10968. https://doi.org/10.1016/j.heliyon.2022.e10968.
47. Gregory SA, Christine Conway M, Sullivan J, Gregory SA. Econometric analyses of nonindustrial forest landowners: is there anything left to study? J For Econ. 2003;9(2):137–64. https://doi.org/10.1078/1104-6899-00028.
48. Waweru D, Mose N. Household fuel choice in urban Kenya: a multinomial logit analysis. Financ Internet Q. 2022;18(2):30–41. https://doi.org/10.2478/fiqf-2022-0011.
49. Varian HR. Intermediate microeconomics a modern approach, 8th edition, vol. 01; 2017.
50. Browning M, Crossley TF, Weber G. Asking consumption questions in general purpose surveys. Econ J. 2003;113(491):540–67. https://doi.org/10.1046/j.0013-0133.2003.00168.x.
51. Pundo MO, Fraser GCG. Multinomial logit analysis of household cooking fuel choice in rural Kenya: the case of Kisumu district. Agrekon. 2006;45(1):24–37. https://doi.org/10.1080/03031853.2006.9523731.
52. Karimu A. Cooking fuel preferences among Ghanaian Households: an empirical analysis. Energy Sustain Dev. 2015;27:10–7. https://doi.org/10.1016/j.esd.2015.04.003.
53. Choumert-Nkolo J, Combes Motel P, Le Roux L. Stacking up the ladder: a panel data analysis of Tanzanian household energy choices. World Dev. 2019;115:222–35. https://doi.org/10.1016/j.worlddev.2018.11.016.
54. Mar XAM, Collinao P. Banco Central de Chile Documentos de Trabajo Central Bank of Chile Working Papers. Banco México Doc. Investig. 2006–11; 2001.
55. OECD. Household income & poverty; 2014. http://webcache.googleusercontent.com/search?q=cache:vbjIVwT5cfAJ:www.epu.gov.my/en/socio-economic/household-income-poverty&num=1&hl=en&strip=0&vwsrc=0
56. UBOS. The national service delivery survey 2021; 2022. www.ubos.org.
57. UBOS-UNHS. Uganda National Survey Report 2019/2020 released—Uganda Bureau of Statistics; 2020. https://www.ubos.org/uganda-national-survey-report-2019-2020-released/
58. Ogwok J, Naluwagga A, Abbo MS, Tesfamichael M. Uganda's cooking energy sector: a review. 2022. www.mecs.org.uk
59. Shrestha N. Detecting multicollinearity in regression analysis. Am J Appl Math Stat. 2020;8(2):39–42. https://doi.org/10.12691/ajams-8-2-1.
60. Hair J, Anderson R, Babin B, Black W. Multivariate data analysis.pdf, vol. 7. Australia : Cengage. 2010. p. 758.
61. Mishra P, Pandey CM, Singh U, Gupta A, Sahu C, Keshri A. Descriptive statistics and normality tests for statistical data. Ann Card Anaesth. 2019;22(1):67–72. https://doi.org/10.4103/aca.ACA_157_18.
62. Allison PD. Using panel data to estimate the effects of events. Sociol Methods Res. 1994;23(2):174–99. https://doi.org/10.1177/0049124194023002002.
63. Hardy M, Bryman A. The handbook of data analyses; 2009.
64. Hausman JA. Soecification test in econometrics. Econometrica. 1978;46(6):1251–71.
65. Le Gallo J, Sénégas MA. On the proper computation of the Hausman test statistic in standard linear panel data models: some clarifications and new results. Econometrics. 2023. https://doi.org/10.3390/econometrics11040025.
66. Genoni ME. Health shocks and consumption smoothing: evidence from Indonesia. Econ Dev Cult Change. 2012;60(3):475–506. https://doi.org/10.1086/664019.

67. Amondo EI, Nshakira-Rukundo E, Mirzabaev A. The effect of extreme weather events on child nutrition and health. Food Secur. 2023;15(3):571–96. https://doi.org/10.1007/s12571-023-01354-8.
68. Nchofoung TN. Oil price shocks and energy transition in Africa. Energy Policy. 2024;184: 113855. https://doi.org/10.1016/j.enpol.2023.113855.
69. Oriangi G, et al. Household resilience to climate change hazards in Uganda. Int J Clim Chang Strateg Manag. 2020;12(1):59–73. https://doi.org/10.1108/IJCCSM-10-2018-0069.
70. Arthur JL, Owusu E, Arthur SD. Strategies for coping with energy security challenges in SMEs in Ghana. Discov Environ. 2023. https://doi.org/10.1007/s44274-023-00019-9.
71. Lama PD, et al. Scrutinizing the relationship between adaptation and resilience: Longitudinal comparative case studies across shocks in two Nepalese villages. Int J Disaster Risk Reduct. 2017;23:193–203. https://doi.org/10.1016/j.ijdrr.2017.04.010.

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