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Wading out the storm: Exploring the effect of flooding on energy poverty amidst disaster management strategies in Dar es Salaam

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ABSTRACT

Although flooding is well-thought-out as one of the deadliest natural disasters, there is scarce evidence on how such an environmental shock affect energy poverty prevelence in a developing country context amidst the implementation of disaster risk management strategies. Using the Disaster Poverty Household Survey in Tanzania's capital Dar es Salaam, we examine the effect of flooding on multidimensional energy poverty while estimating the moderation effects of non-structural ex-ante risk management strategies. After employing a myriad of robust methods, we observe that flooding increases energy poverty prevalence by about 32 %. The mediation analysis shows that income reduction serves as a pathway through which flooding affects energy poverty. Furthermore, estimates from the interaction analysis reveal how effective fiscal non-structural ex-ante risk management methods are in reducing the incidence of energy poverty among flood victims. However, the defense strategies were noted to be inefficient. These results provide policymakers with the necessary tools to create policies that address energy-related needs in areas affected by natural disasters, especially in developing countries.

1. Introduction

Extreme weather events or natural disasters are increasing in frequency and intensity, thereby threatening lives and livelihoods worldwide. These disasters that displace three to ten times more people than conflicts are estimated to have increased sevenfold since the 1970s based on available data from World Meteorological Organization (Canton, 2021). The recent severe but infrequent occurrences, such as the floods in Pakistan and Malawi in 2022, the flood in Northwestern Europe in July 2021, the destruction caused by Hurricane Iota in 2020, and the 2017 flooding of Houston, have prompted us to reevaluate our approach to managing flood risk (de Bruijn et al., 2022). It is not surprising that the most recent Intergovernmental Panel on Climate Change Report ties this increase in extreme weather events to climatic change (IPCC, 2022) and advocates for studies on the implications and detection of these extreme weather events. Although the damages caused by natural disasters are complex, current studies have been focused on their socioeconomic implications (Berlemann and Wenzel, 2018; Brown et al., 2018; Lee and Chen, 2020). However, its impacts on energy-related variables, such as energy poverty, have been scarcely researched (Lee et al., 2021; Paudel, 2022). This energy poverty-natural disaster relationship is of particular concern to energy economists because not only does income, energy prices, and efficiency explain energy poverty, but adverse shocks such as natural disasters can further widen the energy poverty gap, especially when they pose a threat to the resilience in renewable energy usage (Iskin et al., 2012; Lee et al., 2021). With the Sustainable Development Goal 7′s (SDG-7) aim of ensuring access to clean and affordable energy services, a better understanding of the changes in clean energy adoption or consumption in the face of disasters will aid in an informed policy prescription.

Nevertheless, the results of the few studies that have examined this energy poverty-natural disaster nexus have been inconsistent. Using data from 123 countries, Lee et al. (2021), for instance, observed natural disasters such as wildfires, pandemics, and floods to improve energy

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efficiency as they reduced energy consumption. Conversely, Paudel (2022) found tornados in the US to render households energy deprived using a micro-dataset. These inconsistencies can be explained by the fact that the level of economic development, geographical location, or type of natural disaster explains energy poverty differently. Hence, to shed more light on the effect of natural disasters on energy poverty, it is appropriate to consider a specific disaster for a society with varied geography, especially at the micro-level in a developing economy setting where natural disasters and energy poverty are very prevalent (Ulucak et al., 2021). Again, these prior studies neglected how risk management and coping decisions interact with disasters to affect energy poverty outcomes. Thus, strategies for reducing or mitigating risk before (ex-ante) the realization of shocks were unaccounted for in the previous literature. Some scholars, however, view these risk management and coping decisions as ineffective since natural disasters are rare and unforeseen (Aldrich, 2012; Mitra et al., 2017). Others argue otherwise; thus, they view disasters as multifaceted shocks requiring a package of solutions capable of simultaneously addressing their complexities. Hence, empirically testing the efficacies of these strategies, as Sawada and Takasaki (2017) urges, will provide some insights for policy, especially on the mechanisms for strengthening resilience and adaptive capacity in climate change-related planning and management in marginalized communities.

Based on these pointers, this study examines a natural disaster's effect on energy poverty in a developing economy while considering the roles of ex-ante risk management methods play in shaping this association. Thus, using the Disaster Poverty Household Survey (DPHS) in Tanzania's capital Dar Es Salaam, we examine the effect of flooding on multidimensional energy poverty while estimating the moderation effects of defense and fiscal ex-ante risk management strategies. Employing robust methods, we observe that flooding increases energy poverty prevalence. We further find income reduction to mediate the relationship between the flood-energy poverty nexus. Estimates from the moderation analysis showed that while the non-structural ex-ante defense schemes were ineffective, flood victims who adopted fiscal strategies experienced a reduction in energy poverty.

In conclusion, this paper contributes significantly to the existing literature in several ways. Firstly, it expands our understanding of the determinants of energy poverty by considering the influence of natural disasters, a factor often overlooked in previous studies. While recent literature has explored various characteristics such as prosocial behaviors (Lin and Okyere, 2021a), non-farm income (Lin and Zhao, 2021), and social identity (Dogan et al., 2021; Lin and Okyere, 2022b; Okyere and Lin, 2023) to explain energy poverty, the impact of environmental disruptions on energy poverty within households in developing countries remains under-researched. This paper addresses this gap by examining the effects of flooding on energy poverty among households in Dar es Salaam, thereby contributing to ongoing debates on decarbonization, socio-economic inequality, and energy transition. Furthermore, this study adds to the existing body of research on individuals' responses to environmental shocks (Paudel, 2022). It explicitly considers the risk management strategies employed by flood victims to mitigate their vulnerability to energy poverty. By doing so, it enhances our understanding of how households cope with and adapt to adverse circumstances. Lastly, this study contributes to the limited literature that utilizes micro-data sets to investigate specific disasters in developing economies. By utilizing the Disaster Poverty Household Survey (DPHS) in Dar es Salaam to analyze the impact of flooding on energy poverty, this research sheds light on the welfare consequences experienced by emerging economies, which bear the brunt of extreme weather events due to climate change despite their minimal contribution to global emissions (Ulucak et al., 2021). The findings of this study serve as a valuable reference for empirical research and informed policy recommendations, as they provide insights into the consequences of environmental disruptions on the welfare of developing economies.

The paper is structured as follows: The following section (Section 2) presents the reason for considering Tanzania, followed by Section 3 on the conceptual framework. The penultimate section (Section 4) contains the methodology, while Sections 5 and 6 offers the results and conclusion, respectively.

2. Why Dar es Salaam

The daily life of the over 6 million inhabitants of Dar es Salaam, the capital of Tanzania, is regularly affected by severe flooding. With rising sea levels, climate change, and rapid population growth, the city's risk of flooding is expected to increase. Kebede and Nicholls (2012) assert that over 210,000 people could be exposed to a 100-year coastal flood event together with asset damages worth about US$10 billion by 2070. In April 2018, large parts of Dar es Salaam were affected by severe flooding, which caused the loss of lives, widespread damages, and disruption. The flood is estimated to have affected between 900,000 and 1.7 million of the city's population and cost US$228 million in damages, representing 4 % of the city's GDP (Erman et al., 2019). The affected population lost about 23 % of their annual income. However, these statistics are argued not to reflect the entire consequences of the disaster and hence, have pushed academia in collaboration with policymakers to identify the hidden consequences of these disasters. With Dar es Salaam projected to become a megacity (with a population of over 10 million) by 2030 (TURP, 2015), the existence of this flood risk, therefore, poses a critical challenge for the city and its achievement of sustainable growth (World Bank, 2017; Picarelli et al., 2017).

To remedy this risk, the World Bank, in collaboration with the UK Department for International Development, and the Tanzanian Government, embarked on a project to boost resilience to climate-related disasters in the city before the April 2018 floods. This program, dubbed "Tanzania Urban Resilience Program (TURP)," aims to construct new infrastructure to lower flood exposure, strengthen emergency response coordination, and develop community-level flood response and risk reduction plans. Although the program has initiated numerous flood defense mechanisms, the lack of data has impeded the accurate assessment of these strategies. With the current literature indicating that far more people are affected by floods, alongside, Sawada and Takasaki's (2017) argument of the limited evidence on how disasters interact with risk management and coping decisions to impact welfare, it will therefore be of great policy and academic significance to evaluate the impact of flooding on a welfare variable such as energy poverty alongside the moderating effect of ex-ante management methods using Dar es Salaam as a study area.

3. Literature review

3.1. The relationship between flooding and energy poverty

Taking after, Smith and Ward (1998), flood losses can be direct and indirect. The physical contact of floodwater with properties defines the direct losses (Frankenberg et al., 2011; Kellenberg and Mobarak, 2011). Thus, floodwater directly damages assets or properties and worsens the affected homes' welfare outcomes. In such situations, households are usually left to rely on unaffected assets due to the damage caused by the floodwater (Horwich, 2000). These affected assets usually comprise end-user appliances such as electric stoves, refrigerators, and televisions. With the inaccessibility to end-use devices noted to define energy poverty (Adusah-Poku and Takeuchi, 2019; Crentsil et al., 2019; Nussbaumer et al., 2012), floodwater damage to these assets renders the household energy deprived. More so, households turn to unclean energy services for their basic needs in the event of these damages caused by the flood. In Somalia, for example, fuelwood usage was observed to have increased among households months after flooding (Thulstrup et al., 2020). In addition, damages from flooding can broadly affect society through infrastructure damages that affect individual families. Thus, flooding can damage energy infrastructure, limiting people's access to energy markets and services (Bank and Nations, 2010). The 2005 Katrina, for example, leftover 2 million homes and businesses without electric power as it destroyed substations, shuttered power plants, and tore down power lines (Robertson and Schwartz, 2015). The 2013 typhoon Yolanda in the Philippines also cut electricity supplies to nearly 12 million people. A similar story can be told about the 2018 flooding in Dar es Salaam (Erman et al., 2019). These supply-side effects of flooding restrict energy access and increase energy prices as it pushes households to rely on inefficient and less costly energy forms for their household needs. Based on these pointers, we hypothesize that households that experience flooding will be energy poor than their unaffected counterparts.

H1. : Flooding positively affects energy poverty.

The indirect effect of flooding on energy poverty usually occurs through the reduction in income and expenditure. The notion here is that flooding causes income shocks leading to a decline in the consumption of clean energy services, increasing energy poverty. Focusing on the Makoko settlement in Nigeria, Lawanson et al. (2022) showed that flooding reduced the economic power of residents. Mtapuri et al. (2018) found that flooding rendered households in Zimbabwe's Tsholotsho district of Matabeleland North province poor through reduced household income. Desmet et al. (2018) estimate showed that real global GDP would be reduced by 0.19 % on average due to permanent flooding. About 46 % of the world's assets are estimated to be lost by 2100 due to flooding (Kirezci et al., 2020). The reduction in household income or expenditure directly increases energy poverty. This is founded on the Energy Ladder theory which is rooted in the concept of rational choice. This theory states that as households' income increases, they tend to move from using less efficient energy sources like traditional biomass to cleaner options like electricity and solar (Armah et al., 2015). Hence, the reduced household income resulting from the flooding renders them energy-poor. Using Ghana's demographic and health survey, Crentsil et al. (2019) found that lowering household income significantly increases energy poverty. Similarly, the energy poverty prevalence of Sri Lankans was observed to grow due to a decline in their income. Therefore, we hypothesize that the income of individuals who experience flooding will be lowered, reducing their clean energy adoption and making them energy poor.

H2. : Flooding will reduce the income of affected households such that their energy poverty will increase.

3.2. The role of disaster risk management strategies on the flooding-energy poverty nexus

Economists usually examine how households diversify their economic activities to enhance their risk management capacity to augment their income before natural disasters occur (Barrett et al., 2001; Tesfaye and Tirivayi, 2020). These strategies are referred to as ex-ante risk management strategies and are usually heralded under the prospect theory. By this theory, households are deemed more sensitive to future losses and hence assign higher premiums to natural disasters such as floods as they are motivated to take precautionary actions (Schmidt and Zank, 2008). According to UNDRR, these preventive strategies are classified into structural and non-structural measures and define the former as any physical construction or technology that lowers or averts possible effects of natural hazards while the application of knowledge and practice to reduce disaster risks and impacts without any physical structure characterizes the latter (UNDRR, 2022). Traditionally, studies on flood risk management have mainly focused on these structural strategies (Surminski and Oramas-Dorta, 2014), and hence our study considers other soft measures in the form of non-structural schemes.

These cost-effective measures serve as financial cushions against flood damages and do not necessarily reduce flood risk (Alderman and Paxon, 1994; de Janvry and Sadoulet, 2016, Heltberg et al., 2015; Sawada, 2007). Although the "no one size fits all" criterion exists, these strategies are categorized into flood defense and fiscal mechanisms (Brody et al., 2010). The flood defense non-structural ex-ante management involves education and awareness creation, evacuation and relocation, flood proofing, sandbag usage, forecasting, and flood warnings (Brody et al., 2010; Petry, 2002). Interestingly, these defense mechanisms have been noted to be ineffective, especially in developing economies. Evacuation and relocation, for example, have been observed to erode social capital within and between social groups, lowering resilience (Aldrich, 2012; Mitra et al., 2017). Taking Accra-Ghana as a research object Amoako (2016) reported that successive initiatives by local authorities to relocate informal settlements within the city only increased the population of individuals living in slums prone to flooding. Additionally, flood-proofing technologies usually cannot minimize the damages that come with high-velocity flowing floods (FEMA, 2007). Similarly, using sandbags as a defense mechanism has been noted to be ineffective in the gullies of Kinshasa (Lutete Landu et al., 2020). With these schemes observed to be ineffective, they are therefore doubtful to reduce or avert the damages that come with flooding and, in effect, have no propensity to reduce energy poverty prevalence. Consequently, we hypothesize that; flood defense non-structural ex-ante management strategies would have an insignificant impact on energy poverty.

H3. : Flood defense non-structural ex-ante management instruments adopted by flood victims would have no significant effect on energy poverty.

Conversely, the fiscal strategies consist of self and mutual insurance, savings, grants, remittances, credit, and referendums that allocate funding for flood mitigation (Anita, 2013). Cafiero et al., (2007) states that these instruments are fundamentally redistributive as recovery cost is spread across the entire population through a public budget. These schemes are argued to be efficient in reducing the adverse welfare effects of disasters (Alderman and Paxon, 1994; de Janvry and Sadoulet, 2016, chap. 22; Heltberg et al., 2015; Sawada, 2007). A study based on data from the Three Gorges Reservoir area of China showed that remittances and savings significantly reduced the effect of floods on peasant households. Furthermore, capital from social or mutual insurance schemes cushioned households from flood risk in Malawi and Tanzania (Abid et al., 2020; Panman et al., 2022). In effect, they present a better cushion amidst natural disasters such as flooding as they smoothen the energy consumption of households. Thus, in the face of flooding, credit-market transactions can be applied to smoothen the energy consumption of affected families by reallocating future resources for present consumption (Sawada, 2013; Sawada and Shimizutani, 2011; Sawada et al., 2011). When borrowing is constrained, households can draw on their savings or liquidate their accumulated financial assets to even out their energy access in the face of flooding (Carter et al., 2007; Kazianga and Udry, 2006). Again, the welfare of households is usually unaffected by such disasters as their idiosyncratic shocks are absorbed by all other members in their network as postulated by the whole consumption risk-sharing hypothesis (Ligon, 2008; Townsend, 1994). Hence, fiscal instruments such as private cash, in-kind transfers, or remittances (Fafchamps, 1992; Halliday, 2006, 2012; Yang, 2008) can help cushion the energy consumption of households, thereby reducing their energy poverty prevalence. We, therefore, hypothesize that fiscal ex-ante risk management instruments adopted by flood victims will significantly reduce their susceptibility to energy poverty.

H4. : Fiscal ex-ante flood management instruments adopted by flood victims significantly reduce energy poverty.

3.3. Analytical framework

Based on the aforementioned hypotheses, we present an analytical framework (Fig. 1) that examines the relationship between floods and energy poverty. Founded on the idea that floodwater directly damages

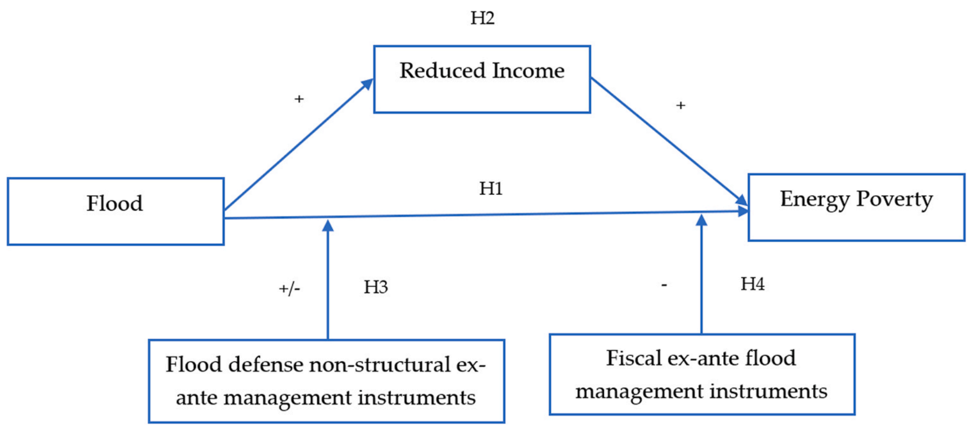

Fig. 1. Analytical framework for the flood-energy poverty nexus.

assets or properties and worsens the affected homes' welfare outcomes, hypothesis 1 (H1) presents a positive association between flooding and energy poverty. Additionally, the framework suggests that flooding is positively correlated with reduced income, further exacerbating energy poverty, as stated in Hypothesis 2 (H2). This is rooted in the notion that flooding induces income shocks, leading to a decline in the consumption of clean energy services and consequently increasing energy poverty. Once again, it is suggested that the flood defense strategies implemented by flood victims would not significantly affect energy poverty, as indicated in Hypothesis 3 (H3). Finally, it is hypothesized that fiscal flood management strategies, when implemented, would reduce the prevalence of energy poverty among flood victims, as presented in Hypothesis 4 (H4).

4. Methods

4.1. Data

Our study relied on the Disaster Poverty Household Survey (DPHS) collected by UDA Consulting under World Bank supervision in Dar es Salaam in 2018. This project was a collaborative effort between the Tanzanian Urban Resilience Program (TURP), the Poverty Global Practice and Urban, Disaster Risk Management, Resilience and Land Global Practice (GPURL), and the Global Facility for Disaster Reduction and Recovery (GFDRR). The survey aimed to collect data to enable the analysis of the association relationship between disaster risk and urban poverty. Using a Probability Proportion Size (PPS) method, a sample size based on 105 enumeration areas (EA) was selected. DPHS captured detailed information on demographic characteristics, education attainment, labor participation, asset ownership, access to services, remittances, flood preventive flooding measures, perception of risk, community engagement, and others. After processing the data, we used an entire sample of 1008 households to analyze the flood-energy poverty nexus.

4.2. Measurement of key variables

4.2.1. Energy poverty

The research used the Multidimensional Energy Poverty Index (MEPI) developed by Nussbaumer et al. (2012) to measure energy poverty. This index has been used in developing countries and concentrates on the household as its unit of analysis (Adusah-Poku and Takeuchi, 2019; Lin and Okyere, 2021b, 2021a; Ssennono et al., 2021). The measurement system utilized in this study comprises five dimensions, including lighting, cooking, household appliances, entertainment/education, and communication, with a total of six indicators. The lighting dimension consists of two indicators: access to electricity and power outages. On the other hand, the remaining dimensions are represented by a single indicator each, as presented in Table 1.

The methodology employed in this study utilizes a deprivation cut-off to identify households experiencing deprivation. To begin, we assessed whether each household is deprived of each of the indicators of the MEPI. In the lighting dimension, for instance, a household is considered energy poor if they are unconnected to the national grid and have no means of utilizing solar technologies for lighting purposes. For certain indicators, the cut-off criteria were determined based on the extent of damage caused by the floods, as indicated in the deprivation cutoff column of Table 1, rather than solely considering the presence of modern energy services. The decision to incorporate the level of destruction caused by the floods as a cut-off criterion, in addition to energy service presence, was made because the data was collected after the floods. This approach is necessary to comprehensively capture the impact of floods by considering the energy-related damages inflicted on households. Therefore, in the cooking dimension, a household was classified as energy poor if they resorted to using biomass fuel for cooking as a consequence of the floods. These indicators are subsequently weighted and summed to generate a deprivation score for each household. Given their relative importance, we prioritized the lighting and cooking dimensions by assigning them greater weights compared to other factors. It is important to note that the weights allocated to these dimensions add up to a total of 1 ($\sum_{i=1}^{6} w_i = 1$). Mathematically, the energy deprivation score (EP) based on the MEPI framework is computed as:

Table 1
Dimension, indicators, and weights for multidimensional energy poverty.

Dimension	Indicator	Deprivation Cut-off	Weight
Lighting	Electricity Access	Household has no electricity access	0.205
	Power outages	Experienced power outages during floods	0.205
Cooking	Biomass cooking fuel	Household uses biomass energy for cooking due to the floods	0.20
Services provided by means of;			
Household appliances	Household appliance ownership	Does not own a refrigerator because the appliance got damaged during the flood	0.13
Entertainment/ Education	Entertainment appliance ownership	Does not own a radio or TV because the appliance got damaged during the flood	0.13
Communication	Telecommunication	Does not own a mobile phone because the appliance got damaged during the flood	0.13

$$EP_i = w_1 d_1 + w_1 d_2 + . + w_6 d_6 \quad (1)$$

Where $d_i = 1$ if a household is deprived in dimension i and 0, otherwise. $w_i$represents the weight attached to the dimension i.

4.2.2. Independent, mediation, and moderation variables

Flooding is considered our main variable of interest in this study. We measured flooding based on the respondent's experience with the April 2018 floods. As per the DPHS, a household is categorized as a flood risk if water had entered their rooms due to the flooding or heavy downpour that took place in April 2018. The questionnaire was structured so that respondents answered yes or no to the following question "*During or immediately after the flood in April 2018, did any water enter your household?"* Those in affirmative were coded 1 and 0 otherwise. We again considered household income reduction after the flooding as the mediating variable. In the DPHS, household heads were asked whether or not their income after the April 2018 flood was reduced. Respondents who answered yes were coded 1 and 0 otherwise.

We adopted the Alkire and Foster (2011) methodology for the moderation variables to construct the flood defense and fiscal non-structural ex-ante management strategies. Explicitly, we used the following flood prevention questions from the Disaster Poverty Household Survey to construct the flood defense index. "*Before the raining season (flooding season), did you or a member of your household (1) Clean house surroundings to prevent the garbage from going down the drains when the rain starts; (2) Cleaned nearby drainage canals/gutters to prevent clogging of drains; (3) Participate in flood prevention activities organized at the neighborhood level; (4) Put together an emergency kit of essential items to be able to leave quickly in case of a flood; (5) Dig a ditch around the house for the water to deviate; (6) Build a wall around the house or the drains to protect against flood water, and (7) Put sandbags and flood bulkheads in and around the house."* All indicators are captured as binary variables (No = 0; Yes = 1) to reflect resilience. We assigned an equal weight (1/7) to all seven indicators and employed Eq. (1) formulation to produce the index. For the fiscal non-structural strategies, we relied on a Multidimensional Financial Inclusion framework developed by Essel-Gaisey and Chiang (2022a) to compute the index. The framework comprised of the following strategies that make up the fiscal management schemes; (1) ownership of insurance package; (2) ownership of bank, savings, or mobile money account; (3) loan or credit accessibility; (4) recipient of financial remittance via a bank or mobile money wallet; (5) membership of a mutual aid group; and (6) beneficiary of in-cash transfers or grants. Similarly, we set these indicators as binary variables and assigned an equal weight of 1/6, following Eq. (1) to derive the index.

4.2.3. Covariates

Previous research has indicated that a variety of demographic and socio-economic factors, including gender, age, level of education, income, marital status, and household location, may have an impact on energy poverty (Churchill et al., 2021; Lin and Okyere, 2020, 2021a, 2022a). Therefore, this study measured and took the above variables as control variables. Specifically, female is a dummy coded as "1" = female and "0" = male; age is the self-reported age of the household head; education is the years of schooling; household expenditure is the reported total household expenditure on food and non-food items; marital status is self-reported and is coded as "0" = unmarried and "1" = married; and district is the household location where "1" = Kinondoni, "2" =Ilala and "3"= Temeke. (Table 2).

4.3. Estimation strategy

Our primary model for energy poverty is a linear function of flooding alongside a vector of other explanatory variables and district dummies, as specified in Eq. (2):

Table 2
Summary statistics.

Variables	Description	Mean	Standard deviation
EP	Energy deprivation score	0.410	0.218
Flood	Equals 1 if the household experienced the April 2018 floods	0.171	0.377
Female	Equals 1 if the household head is female	0.407	0.491
Age	Age of household head	40.179	12.847
Household Size	Household Size	3.811	1.725
Educ	Years of Education	9.564	3.981
Marital Status	Equals 1 if the household head is married	2.194	1.685
Ln (Household Expenditure)	Log of household expenditure	14.630	0.138
Employed	Equals 1 if the household head is employed	0.796	0.402
District	District of residence	1.836	0.677

$$EP_i = \beta_0 + \beta_1 flood_i + \sum_k \xi_k X_{k,i} + \eta_c + \varepsilon_i \quad (2)$$

where, EP_i represents household i energy deprivation score; $flood_i$is a dummy variable that denotes whether household i experienced flooding or not;Xcaptures the individual and household characteristics of household head; η_c signifies the location level fixed effect; the error term, coefficients of the regressors and intercept are denoted by ε_i,β_1, $\xi_k$and β_0, respectively. We adopted the Ordinary Least Squares (OLS) method in estimating Eq. (2).

Our estimates using OLS will likely be biased and inconsistent due to the problem of variable omission; hence, making causal inferences may be erroneous. We employed the instrumental variable (IV) technique to resolve this endogeneity issue emanating from omission bias. When applying this method, an instrument is required in a first-stage regression where flooding is determined by the instrument and other control variables as presented in Eq. (2):

$$flood_i = \pi + \vartheta H_i + \mu_i \quad (3)$$

Where, $H_i = [Z_i, X_i]$is a vector of the instrument Z_i and explanatory variables X_i; $\pi$and ϑdenotes the estimated parameters while μ_i represents the random error term. The instrument, however, needs to meet the exclusion restriction. Thus, Z_i should correlate with $flood_i$ but have no relationship with EP_i. We used flood risk as our instrument. This variable was developed based on the Ramani Huria community flood map categorization, where households are classified into "no risk," "low to medium risk," and "high risk" based on the topography of the land they reside on and the frequency of flooding they experience (The World Bank, 2022). The variable is a good candidate for an instrument since the household's location within a particular zone might significantly affect its risk of experiencing flooding. On the other hand, it is not expected to directly influence energy poverty, especially when using modern energy services such as LPG and electricity is not dependent on the topography or nature of the land within which a household is located. Stock et al. (2002) proposed the F-statistic test to validate the instrument.

We again adopted an alternative identification strategy known as the Lewbel (2012) two-stage least squares (2SLS) approach. This technique tackles endogeneity problems by internally generating instruments based on the heteroscedasticity present in the error terms. The Lewbel technique is frequently employed by researchers when valid external instruments are not available or in conjunction with reliable external instruments (Essel-Gaisey et al., 2023; Essel-Gaisey and Chiang, 2022b; Lin and Okyere, 2021c, 2022b; Okyere and Lin, 2023). The utilization of the Lewbel technique allows us to effectively and reliably address the endogeneity concerns emanating from omission bias in our research. In the following sections, we offer comprehensive insights into the Lewbel technique and its implementation in our study for a more detailed understanding.

$$Y_1 = X'\beta + Y_2\gamma + \varepsilon_1, Y_2 = X'\alpha + \varepsilon_2 \tag{4}$$

Where Y_1 signifies energy poverty; Y_2represents the endogenous regressor, flood; X' denotes the vector of regressors; while the error terms are denoted by ε_1 and ε_2. This technique employs an identification strategy that relies on the information present in the heteroscedasticity of ε_2, thereby addressing endogeneity problems even in the absence of external instruments. The technique assumes $E(XX')$ to be non-singular, hence$E(X\varepsilon_1) = E(X\varepsilon_2) = 0, Cov(V, \varepsilon_1, \varepsilon_2) = 0$, and $Cov(\varepsilon_2^2) \neq 0$, where V equals X, a subset of the elements of X. Following this, the instruments are estimated as $(V - \bar{V})\hat{\varepsilon}_2$, where $\bar{V}$ represents the mean of V. The key assumption underlying this technique is that there should be no correlation between the regressors and heteroscedastic errors. This is tested using Cragg-Donald weak identification Wald test.

This study further employs the kinky least-squares (KLS) regression to enhance the robustness of our estimates, particularly when exclusion restrictions in instrumental variable (IV) techniques is noted not to be feasible (Kripfganz and Kiviet, 2021). The KLS approach leverages prior knowledge regarding the relationship between the flood variable and the error term, based on the researcher's understanding of omitted variables or unaccounted economic mechanisms. In the KLS approach, a range of plausible values for the correlation between the flood and the error term, known as the "kink," is specified. By focusing on economically reasonable segments of the parameter space for the correlation coefficient, the KLS estimator facilitates endogeneity-robust inference without relying on instrumental variables. Within the defined kink range, the KLS estimator calculates coefficient estimates and confidence intervals for the regression model. Notably, the confidence bands derived from the KLS estimator provide more informative results compared to IV estimations, particularly in cases where the instruments are weak, as corroborated by other studies (Churchill and Smyth, 2022; Essel-Gaisey et al., 2023). Furthermore, the KLS approach allows for a sensitivity analysis of the exclusion restrictions employed in IV estimation. For a more detailed understanding of the technique, please refer to Kripfganz and Kiviet (2021) and Kiviet (2020).

In the end, to control for the potential bias caused by observable and unobservable characteristics, we employed the propensity score match method in our study (Churchill et al., 2021; Lin and Okyere, 2021a). In line with previous research, to ensure the robustness of our findings, we utilized a variety of matching algorithms including regression adjustment, nearest-neighbor, augmented inverse-probability weighting, and the propensity score matching technique.

5. Results and discussion

5.1. Preliminary analysis

Table 3 presents the baseline analysis of the association between flooding and energy poverty. Columns 1, 2, and 3 present results for flooding only, flooding with the household factors and flooding with both the household and location characteristics, respectively. The F-statistics demonstrates that the variables jointly account for energy poverty. Again, the mean variance inflation factor (VIF) of less than 10 reveals that our estimated models are devoid of multicollinearity. Although the results from all the columns show that flooding positively correlates with energy poverty, we use the model in column 3 following the likelihood ratio test. Households affected by the April 2018 floods have about 5.7 % energy poverty prevalence than their counterparts who did not experience such disasters, at a 1 % significance level. This result is consistent with our first hypothesis; however, due to the issue of endogeneity likely to emanate from variable omission and simultaneity, we conduct a series of robustness tests in the following section to confirm this discovery.

Table 3
Estimates for the flood-energy poverty.

Variables	Column 1 EP	Column 2 EP	Column 3 EP
Flood (Yes)	0.080***	0.058***	0.057***
	(0.019)	(0.018)	(0.018)
Female		-0.020	-0.019
		(0.014)	(0.014)
Age		-0.001**	-0.001**
		(0.001)	(0.001)
Household Size		-0.007	-0.007*
		(0.004)	(0.004)
Education		-0.024***	-0.023***
		(0.002)	(0.002)
Married (Yes)		0.004	0.005
		(0.004)	(0.004)
Log (Household expenditure)		-0.134***	-0.134***
		(0.043)	(0.043)
Employed (Yes)		-0.016	-0.015
		(0.017)	(0.017)
District (Temeke)			
Kinondoni			-0.015
			(0.019)
Ilala			-0.031*
			(0.018)
Constant	0.399***	2.675***	2.698***
	(0.007)	(0.633)	(0.632)
Mean VIF	1.00	1.14	1.34
Observations	1053	1008	1008
F-Statistics	17.24***	32.86***	26.47***
R-squared	0.019	0.218	0.221

Notes: Robust standard errors in parentheses; * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

5.2. Robustness analysis

Table 4 presents the results on the effect of flood on energy poverty using variant robust techniques. In Panels A, B, and C of Table 4, we show the results using the IV, Lewbel, and Kinky Least Squares regression, respectively. The Cragg-Donald Wald F-statistics in Panel A greater than 10 indicates that our instrument does not weakly correlate with flood at the 10 % significance level (Stock et al., 2002). Consistent with our expectations, the results from the first stage regression reveal that residing in flood risk zones increases the household's chances of

Table 4
The impact of flood on energy poverty using the IV, Lewbel, and Kinky Least Squares regression.

	Coef.	Standard error
Panel A- IV with an external instrument		
Flood (Yes)	0.327**	0.161
Control variables included	Yes	
Cragg-Donald Wald F-statistics	15.166	
Observations	1008	
First Stage		
Flood Risk Zone (yes)	0.068***	0.020
Panel B – Lewbel 2SLS with external and internal instruments		
Flood (Yes)	0.143*	0.081
Control variables included	Yes	
Cragg-Donald Wald F-statistics	6.067	
Observation	1008	
Panel C – Kinky regression		
Flood (Yes)	0.357***	0.019
Control variables included	Yes	Yes
Postulated endogeneity of flood	-0.5	
Observation	1008	

Note: * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

experiencing flooding. Although the IV results in Panel A of Table 4 are consistent with the preliminary estimates, we observe that endogeneity rendered the baseline estimates biased downward. At a 5 % significant level, households that experienced the April floods have an energy poverty prevalence of 32.7 % higher than their counterparts. Similarly, the Lewbel results in Panel B of Table 3 present similar findings. This technique combined internal (based on the heteroskedasticity of the error) and external instruments (Flood Risk Zone) to calculate the effect of flooding on energy poverty. The results from the Panel show that households who encountered the April 2018 floods have an energy poverty prevalence of 14.3 % more than those who did not experience the disaster, at a 10 % significant level. Consistently, the results from the kinky regression also validate the estimates from the IV and Lewbel techniques. Given that the baseline estimates are biased downward, we expect the association between flood and the error to be negative; hence, we assign a range of − 0.5 and 0 for the postulated endogeneity for the KLS regression following Churchill and Smyth (2022). The point estimates in Panel C of Table 4 reveal that the effect of flood on energy poverty is positive and significant over the postulated range.

As a complimentary analysis of the preliminary, IV, Lewbel, and KLS estimates, we present results for the flood-energy poverty nexus using propensity score matching (see Table 5) to verify whether the positive relationship will continue to exist when observables are controlled. The nearest-neighbor matching results show that flooding is associated with a 6.5 % increase in energy poverty at a 1 % significance level. The estimates align with the variant matching algorithms (regression adjustment matching and augmented IPW). The results from the PSM technique buttress the positive correlation established per the OLS, IV, Lewbel, and KLS regression and further validate that our estimates are robust.

5.3. Further robustness and sensitivity analysis

As a further robustness check, we employed different estimations methods in calculating the flood-energy poverty relationship. Since our dependent variable involves bounded ratios, employing linear estimates such as the OLS is likely to predict values outside the bounds (Lin and Okyere, 2021a, 2021b, 2022a). Hence, we employed the fractional regression technique to estimate the association between flood and energy deprivation, as shown in Table 6. We again dropped the extreme values of the energy deprivation score (i.e., 0 and 1) and estimated Eq. (2) with the Beta regression (Algamal and Abonazel, 2022). The study finally employed the Poisson regression since our dependent variable has zero counts (Murakami and Matsui, 2022). The results in Table 6 using these estimation techniques affirms the baseline results. Thus, using the Fractional, Beta, and Poisson regression, the energy poverty prevalence of households that experienced the April 2018 flood is about 15.2 %, 14.8 %, and 13.3 % higher than those with no such experience at a 1 % significance level, respectively. This further provides evidence that flooding exacerbates energy poverty prevalence regardless of the econometric technique used.

To evaluate the consistency in our estimates, we conducted additional sensitivity analyses that included different cut-offs and weights of energy poverty, and an alternative energy poverty measure. Following Lin and Okyere (2021a, 2021b, 2022), we classified a household as energy poor if their deprivation score was at least greater or equal to a cut-off (we used 0.4 and 0.6 as the cut-offs). Columns 1 and 2 of Table 7 show that the flooding in April 2018 positively rendered household energy deprived regardless of the cut-offs. This suggests that the correlation between flooding and energy poverty is positive and consistent across the alternative cut-offs for energy deprivation. We further assigned equal weights of 0.2 to the dimensions of our energy poverty framework and subsequently estimated the flood-energy poverty nexus. As shown in Column 3 of Table 7, the findings suggest that the estimate agrees with the estimates obtained from the OLS method, and confirms that our conclusions are robust to the different weighting used for the multidimensional energy poverty index. Finally, we replaced our dependent variable with another variable that captures energy poverty. Finally, we test the robustness of our results by estimating the effect of flooding on the indicators of the MEPI. The results in Table 8 shows that flooding increases electricity inaccessibility, power outages, and the inability of households to own television and mobile phone due to property damage from the floods. The effect is more profound on the ownership of end-usage appliances.

Table 5
Propensity score matching estimates for the effect of flooding on energy poverty.

Matching Technique	ATT	Robust Standard Error
Nearest-neighbor matching	0.065***	0.021
Regression adjustment matching	0.059***	0.018
Augmented IPW	0.059***	0.018
Observation	1008	

* ** p < 0.01, * * p < 0.05, * p < 0.1.

Table 6
Estimates for the Flood-Energy poverty nexus using other regression techniques.

	Energy Poverty		
Variables	Fractional	Beta	Poisson
Flood (Yes)	0.152***	0.148***	0.133***
	(0.046)	(0.061)	(0.039)
Control variables included	Yes	Yes	Yes
Diagnostics			
Wald statistic	227.90***	147.18***	226.93***
Observation	1008	924	1008

Note: Standard errors in parentheses; * ** p < 0.01, * * p < 0.05, * p < 0.1.

5.4. Mediation analysis

This section discusses the main channel through which flooding might affect energy poverty. Following Koomson and Danquah (2021) and Lin and Okyere (2021a, 2022), we explore the mediating role of household income. The two-step approach is presented in the following equations;

$$M_i = \omega_0 + \omega_1 flood_i + \sum_k \xi_k X_{k,i} + \eta_c + \varepsilon_i \tag{4}$$

$$EP_i = \upsilon_0 + \upsilon_1 flood_i + \upsilon_2 M_i + \sum_k \xi_k X_{k,i} + \eta_c + \varepsilon_i \tag{5}$$

Where M_i represent the mediating variables. The basis for judging M_i as a mediator is as follows: First, the coefficient of $flood_i$ should be statistically significant in Eq. 4. Second, the inclusion of M_i in Eq. 5 should render the coefficient of $flood_i$ in Eq. 5 statistically insignificant. This indicates a complete mediating effect (Gan et al., 2020). However, in a situation where υ_1 is significant, M_i can be called a mediator if υ_1 is lesser than β_1 in Eq. 2. This indicates a partial mediating effect. We adopted the Sobel test to validate the mechanism analysis further.

The results in Column 1 of Table 9 reveal that flooding significantly

Table 7
Estimates for different cut-offs and measures of Energy Poverty.

Variables	Column 1 0.4 Cut-off	Column 2 0.6 Cut-off	Column 3 Equal Weight
Flood (Yes)	0.291***	0.438**	0.055***
	(0.110)	(0.125)	(0.017)
Control variables included	Yes	Yes	Yes
Diagnostics			
Wald statistic	114.46***	60.73***	28.97***
Observation	1008	1008	1008

Note: Standard errors in parentheses; * ** p < 0.01, * * p < 0.05, * p < 0.1.

Table 8
Estimates for indicators of Energy Poverty.

Variables	Electricity Access (No)	Power Outages (Yes)	Cooking fuel (Biomass)	Television (No)	Refrigerator (No)	Mobile Phone (No)
Flood (Yes)	0.242*	0.210**	0.130	0.463***	0.125	0.333**
	(0.135)	(0.115)	(0.133)	(0.123)	(0.118)	(0.139)
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes
Diagnostics						
Wald statistic	89.87***	21.71***	113.53***	74.49***	151.25***	16.28*
Observation	1008	1008	1008	1008	1008	1008

Note: Standard errors in parentheses; * **p < 0.01, * * p < 0.05, * p < 0.1.

Table 9
Mediation analysis.

	Column 1 Reduced income (Yes)	Column 2 EP
Flood (Yes)	0.147***	0.047***
	(0.022)	(0.016)
Reduced income (Yes)		0.075***
		(0.023)
Control variables included	Yes	Yes
Diagnostics		
RIT		0.192
Sobel test (z-value)		0.011***
Observation	1008	1008

Note: Robust standard errors in parentheses; * ** p < 0.01, * * p < 0.05, * p < 0.1.

correlates positively with a reduction in households' income. Thus, at a 1 % significance level, the likelihood of income reduction for households affected by the 2018 floods is estimated to be 14.7 %. Consistent with the literature, the results in Column 2 of Table 9 show that households that got their income reduced after the April 2018 floods experienced about 7.5 % increase in their energy poverty prevalence. More so, including household income as an additional variable in Column 2 of Table 9 diminished the magnitude of floods compared with the flood coefficient in Table 3. This, therefore, shows a partial mediation effect. The Sobel test further validates the reduction in household income as a channel through which flooding affects energy poverty and accounts for about 19.2 % of the total effect, as reported by the RIT. This finding validates our second hypothesis that flooding reduces the income of affected households so that their energy poverty will increase.

5.5. Moderation analysis

Next, we examine whether flood defense and fiscal non-structural ex-ante risk management methods are moderators such that they weaken the effects of flooding on energy poverty. This is mathematically shown in the following Equation;

$$EP_i = \kappa_0 + \kappa_1 flood_i + \kappa_2 flood_i * FRM_i + \kappa_3 FRM_i + \sum_k \xi_k X_{k,i} + \eta_c + \varepsilon_i \tag{4}$$

where FRM_i is the moderating variable that measures whether the household implements a non-structural flood risk management strategy or not; $flood_i * FRM_i$ represents the household that implemented the non-structural flood risk management strategy and experienced the April 2018 flooding. In this section, we concentrate on the effect of the interaction between the risk strategy and flood ($flood_i * FRM_i$) on energy poverty, as presented in Table 10. In Column 1 of Table 10, the results show that the non-structural defense ex-ante risk management strategies initiated by households who experienced the April 2018 floods are ineffective in reducing the prevalence of energy poverty, which confirms our third hypothesis. Conversely, the fiscal non-structural ex-ante risk management strategies minimize energy poverty for flood victims. Thus, flood-affected households who implemented the fiscal strategies experienced a 14.5 % reduction in their energy deprivation at a 5 % significance level, as presented in Column 2 of Table 10. This finding is consistent with hypothesis 4, which states that fiscal non-structural ex-ante management instruments adopted by flood victims significantly reduce energy poverty. Interacting both disaster management schemes with flood, as presented in Column 3 of Table 10, has no significant effect on energy poverty.

Table 10
Moderation analysis.

Variables	Column 1 EP	Column 2 EP	Column 3 EP
Flood	0.053**	0.076***	0.052
	(0.025)	(0.023)	(0.018)
Flood defense strategies	0.035		0.059***
	(0.031)		(0.030)
Flood * Flood defense strategies	0.002		
	(0.069)		
Fiscal strategies		-0.350***	-0.366***
		(0.031)	(0.030)
Flood * Fiscal strategies		-0.145**	
		(0.071)	
Flood * Flood defense strategies* Fiscal strategies			-0.184
			(0.132)
Control variables included	Yes	Yes	Yes
Diagnostics			
Observations	1008	1008	1008
Pseudo R2	0.193	0.331	0.331

* ** p < 0.01, * * p < 0.05, * p < 0.1; Standard errors in parentheses.

5.6. Discussion

Our study explored policy-relevant questions on the effect of flooding on energy poverty and the role disaster risk management strategies play in moderating this effect while accounting for the channels through which this effect occurs. Due to the limitation of studies on this issue, mainly from a developing economies perspective, our study used Tanzania's capital, Dar Es Salaam, as a study object by employing the Disaster Poverty Household Survey (DPHS) collected by UDA Consulting under the World Bank supervision in 2018.

Using the multidimensional energy poverty framework by Nussbaumer et al. (2012) as our energy poverty construct, we observe that households who experienced the April 2018 flooding have a higher prevalence of energy poverty. This result is consistent after a series of robust and sensitivity tests and confirms our first hypothesis (H1) in Section 3 which indicates a positive correlation between flooding and energy poverty. This is explained by the fact that power lines are usually affected during heavy downpours, so households end up experiencing power outages or are disconnected from the grid, which increases their energy poverty prevalence. During the April 2018 floods in Dar es Salaam, aside from the fact that over 2000 homes were directly affected and had to live in tents with no electricity connections, power outages in the city doubled (Rentschler et al., 2021). Its again explained by the fact that floodwater directly damages household assets or properties such as end-use appliances (e.g., Horwich, 2000), as found in Table 7, and therefore limits their modern energy usage. Thus, even though our results showed that households were more likely to be unconnected to the grid or experience power outages, the effect of not owning end-use appliances such as television and mobile after experiencing the floods in April 2018 was relatively high. In Dar es Salaam, the households displaced by the April 2018 floods were recorded to have lost about 77 % of their assets, including appliances such as television, radio, and mobile phones, among others, to the disaster (Erman et al., 2019; IFRC, 2019). Our finding that flooding directly leads to energy poverty matches the research of Paudel (2022), who noticed that tornadoes had the same effect on households in the US. In terms of methodology, our study is comparable to that of Paudel (2022), although there are some variations in context. For instance, the economic context of the US is characterized by relatively higher incomes and adequate modern energy access, unlike in Tanzania. Interestingly, our finding contradicts the works of Lee et al. (2021), who found natural disasters to reduce energy poverty as they lowered energy consumption. This difference could be based on the fact that our article takes advantage of a micro-dataset across households and hence can unravel the effect of flooding with a microscopic lens, unlike Lee et al. (2021), who relied on aggregate data at the national level. Again, while Lee et al. (2021) explored energy intensities at the macro-level, our study concentrated on household energy outcomes that directly measure energy poverty.

More so, the reduction in household income that comes with natural disasters explains how flooding indirectly increases energy poverty, as shown in the mechanism analysis in Table 9. Thus, flooding causes negative income shocks leading to a decline in the consumption of clean energy services, thereby increasing energy poverty. This finding aligns with our second hypothesis (H2) which shows that reduced income mediates the flood-energy poverty nexus. This is mainly explained by the fact that floods limit people from working as it confines them to their homes due to the asset damage and inability to access transport services to their workplaces. The work days lost owing to floods reduce income. During the April 2018 floods in Dar es Salaam, men and women stayed home for about 15.5 and 17 days, respectively, on average, to deal with the impact of the floods, which reduced their annual income by 23 % (Erman et al., 2019). With this reduction in income coupled with the destruction of end-use appliances, power outages, and grid disconnection, the likelihood of households accessing modern energy services is shuttered, heightening their chances of being energy-deprived. This validates the Energy Ladder theory (Armah et al., 2015) and other studies that found that the lack of income increases energy poverty (Crentsil et al., 2019; Lin and Okyere, 2022a).

The findings from the moderation analysis revealed that the non-structural ex-ante flood defense measures were ineffective in reducing the effect of flooding on energy poverty. The result is consistent with our third hypothesis (H3) and aligns with the policy debate on the effectiveness of flood defense ex-ante actions taken by households (Amoako, 2016). With the lack of governmental support, families affected by floods usually implement less elaborate flood preventive measures (Sakijege et al., 2012). In Dar es Salaam, about 86 % of the affected households were noted to have implemented less effective preventive measures, such as the removal of garbage from the surroundings of their homes and nearby drainage systems and the usage of sandbags (Erman et al., 2019). Although these strategies can lower flood peaks, they cannot avert flood damages (Freni and Liuzzo, 2019) and hence makes them ineffective in reducing energy poverty. The weaknesses in the supervision of these flood control plans on the part of social planners could further explain their ineffectiveness. The 2021 flooding audit report on Tanzania, for instance, revealed that even though these non-structural ex-ante flood defense measures were considered in planning schemes, numerous supervision weaknesses that emanated from the lack of capital existed during their implementation and rendered them ineffective (Kumburu, 2022). In contrast, our estimates showed that the fiscal non-structural ex-ante measures significantly reduced the energy poverty prevalence of flood-affected households. This aligns with our fourth hypothesis (H4). This is based on the fact that these instruments present a better cushion that smoothen the energy consumption of households in the aftermath of flooding (Gash and Odell, 2013). In Dar es Salaam, for instance, many households who belonged to saving groups or mutual schemes were noted to have taken out loans for non-income-generating activities such as the purchase of end-use appliances after the April 2018 floods (Panman et al., 2022).

6. Conclusions

Although natural disasters such as flooding are known to be deadly, studies on its implication in the energy literature are limited, especially in developing countries where disaster risk management strategies are currently instituted. This study estimates the effect of flood on energy poverty among households in a developing economy while accounting for the moderating role of non-structural ex-ante risk management schemes. Using the Disaster Poverty Household Survey in Tanzania's capital Dar Es Salaam and a series of robust techniques, we observed flooding to increase energy poverty prevalence by about 35 %. The mediation analysis also shows that income reduction is a pathway through which flooding affects energy poverty. While the fiscal ex-ante risk management methods adopted by flood victims were noted to be effective in reducing their energy poverty prevalence, the defense schemes employed by these victims were ineffective.

These findings offer several policy implications for politicians, government, academia, and international donor organizations. To promote comprehensive disaster management in Tanzania, it is imperative for policymakers and aid agencies to reinforce fiscal non-structural ex-ante risk management strategies. This entails prioritizing financial inclusion mechanisms that facilitate accessibility to formal credit and insurance schemes through microfinance products and innovative index-type insurance. Recognizing the need for structural advancements, it is crucial to place explicit emphasis on this issue throughout all phases of disaster management. This prioritization holds significant significance due to the prevailing financial exclusion experienced by a substantial proportion of Tanzanians, approximately one-quarter of the population. Furthermore, even among individuals with access to financial services, the utilization of digital payments, savings, and borrowing remains limited, necessitating improvement. To realize substantial advancements in financial inclusion, it is recommended that banks adopt a strategic approach by augmenting their delivery channels. Leveraging the existing mobile telecommunication network as a supportive infrastructure, rather than engaging in direct competition with mobile network operators, can effectively expand their reach and services to the unbanked population. The integration of mobile telecommunication networks into the financial ecosystem presents immense potential for extending accessibility to a wide range of financial products and services, thus paving the way for a more inclusive financial landscape in the country. Second, although natural disasters' implications on energy poverty are direct and predictable, they sometimes go through indirect channels to affect energy poverty. We, therefore, urge academics, policymakers, and aid agencies to consider these mechanisms to aid policy prescription.

This paper offers valuable analysis and discussion, but there are still some limitations. The study was unable to consider the household's information prior to the floods because of data unavailability. Therefore, we suggest that future studies take this into account when such data becomes available. Once again, it should be noted that the sampled households are located in unfavorable circumstances, rendering them more vulnerable to natural disasters. We acknowledge that if a nationally representative sample is utilized, the relationship between the variables is expected to be less pronounced. Although it is not possible to overlook the role of other mediators, our available data enabled us to examine the impact of reduced income. As a result, we encourage future studies to explore additional channels of influence as new datasets become accessible.

CRediT authorship contribution statement

Michael Adu Okyere: Conceptualization, Methodology, Writing – original draft, Formal analysis. **Felix Essel-Gaisey:** Conceptualization, Methodology, Data curation, Writing – original draft, Formal analysis. **Fawzia Muhammed Zuka:** Formal analysis, Methodology, Data curation Writing – original draft, Formal analysis. **Aaron Kobina Christian:** Methodology, Data curation Writing – original draft, Formal analysis. **Isaac Kwamena Nunoo:** Methodology, Data curation, Writing - original draft, Formal analysis.

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.

Data availability

Data will be made available on request.

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