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Climate Variability, Catastrophic Health Expenditure, and Non-Communicable Disease Outcomes in Nigeria

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ABSTRACT

Background: The challenges posed by climate change and non-communicable diseases (NCDs) are among the most pressing but least explored areas in health economics.

Aims: This study examines the impact of climate shocks, non-communicable diseases (NCDs), and catastrophic health expenditure (CHE) in a single micro-econometric model.

Methods: The study estimates probit, logit, IV-probit, fixed-effects logit, and IV-2SLS models with temperature anomalies instrumented using the values of the ENSO Oceanic Niño Index to overcome the endogeneity problem, using a harmonized panel of 22,110 households in three waves of the Nigeria General Household Survey-Panel (2010/11, 2012/13 and 2015/16).

Results: A 1 °C rise in temperature increases the likelihood of CHE by 4.3-6.1 percentage points and flood vulnerability by 7.1-8.3% points. Across the population affected by non-communicable diseases (NCDs), climate stressors increase the Propensity to experience catastrophic health expenditure (CHE) by approximately 9.4%. Climate variables account for 31.3% of the CHE inequality, with temperature alone explaining 13.6% of the index, and they have a disproportionate impact on poorer households. Instrumental variable projections suggest that an additional 1.9-2.7 million households could experience catastrophic health expenditure (CHE) by 2030 under continued warming trends.

Conclusion: Health financing vulnerability in Nigeria is also a function of uneven climate variability, which requires increased health insurance, an enhanced NCD response, and climate-sensitive social protection policies. These results indicate the need for much-needed policy coordination among health, climate, and fiscal governance systems.

Keywords: *Catastrophic Health Expenditure; Climate Variability; Non-Communicable Diseases; Health Financing; Nigeria.*

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1. Introduction

The convergence between climate change and non-communicable diseases (NCDs) is one of the most critical yet least-studied areas of health economics in Nigeria. Although the epidemiological literature has been very prolific in the manner in which climatic factors moderate the burden of infectious diseases, very little is known on the mechanisms through which climate variability would translate to the burden of NCDs, out-of-pocket (OOP) health payments, and ultimately the catastrophic health expenditure (CHE) especially in the sub-Saharan African settings where health financing systems tend to be weak and out-of-pocket (OOP) health payments prevail. Nigeria is among the countries that have undergone a rapid epidemiological transition, with a population of approximately 220 million, about one-fifth of sub-Saharan Africa's total population (Okeke et al., 2022).

The NCDs accounted for about 70–74% of global deaths and represent a major share of disease burden measured in disability-adjusted life years (DALYs) (World Health Organization [WHO] 2018/2023). Also, NCD-associated DALYs increased from 24,987.4 per 100,000 in 2010 to 30,306.5 in 2019, representing a 21.3% increase (Adelakun, Rahman, and Alam, 2023). The commonest share of this burden is made up of cardiovascular diseases, diabetes, hypertension, and cancers (World Health Organization, 2025). At the same time, OOP payments are the main source of health financing in Nigeria, accounting for about 76 percent of total health expenditure, and households are extremely vulnerable to economic disaster after health shocks (Ogbodo, 2023). At 40 percent non-food spending, about 30 percent of NCD-affected households experienced CHE in 2018/19 (Eze, Lawani, Agu, & Acharya, 2022).

According to the Nigerian Meteorological Agency, temperatures have risen steadily since 1981, with 2023 ranking as the second-hottest year on record during this period. Notably, nine of the past 15 years rank among the 10 warmest years recorded since 1981, highlighting a clear and accelerating warming trend (Blanchard-Wrigglesworth et al., 2025), placing Nigeria among the most vulnerable countries in Africa to climate change. The patterns of rainfall have become significantly more unpredictable, with extreme events becoming more frequent and catastrophic in the south, and droughts recurring in the semi-arid north (Ibebuchi & Abu, 2023).

The major links between climate variability and household health expenditure undoubtedly exert physiological stress, as exposure to heat aggravates hypertension and cardiovascular morbidity, leading to increased healthcare utilization (Kazi et al., 2024; Dushimiyimana, 2025). Accordingly, Ogar et al. (2025) and Escobar et al. (2022) opined that income erosion, destabilization of food systems, and threats to water security and agricultural livelihoods due to climate change increase the risk of CHE. This is usually profound, as it has a negative effect on the health system through the consequences of floods and droughts, reducing households' ability to access health care and thus forcing them to seek expensive care in the informal sector.

The paper builds on previous micro-level studies (e.g., Edeh 2022; Adelakun, Rahman, & Alam, 2023; Opeloyeru & Lawanson, 2023) that viewed climate as an environmental condition rather than a structural determinant of health financing. Macro studies that require consideration of the national level (e.g., Anwar, Hyder, Bennett, and Younis 2022; Dritsaki & Dritsaki, 2024) use aggregate national data and cannot measure household-level distributional impacts. To bridge that gap, the study connects nationally representative household survey data with state-level geospatial climate records to approximate the causal impact of climate variability on the likelihood of CHE and NCD outcomes.

This study contributes to the literature by providing integrated insights into climate-health-financial risk interactions through an extension of existing data, methodology, and conceptualization, creating a harmonized dataset from three waves of the General Household Survey-Panel (2010/11, 2012/13, 2015/16) and resulting in 22,110 households across Nigeria. Also, it improves causal estimation through a triangulated approach using an instrumental variable based on the El Niño-Southern Oscillation (ENSO) index and its lag, including robustness checks with alternative CHE thresholds, lagged climate variables, regional estimation, and placebo estimation. The study extends existing literature through an estimation of NCD-Climate interaction effects, indicating a super-additive relationship between climate and health risks employing concentration index decomposition methods developed by Adam Wagstaff and Eddy van Doorslaer (2003), allowing for an estimation of contributions of climate, health, and socioeconomic factors to inequality. This provides an overarching framework for understanding climate-related risks and vulnerabilities in low-income settings globally, hence contributing to knowledge. Within the context of this paper, the term 'climate variability' refers specifically to interannual and decadal fluctuations in climatic conditions, including temperature anomalies, flood events, and drought incidence, while 'climate change' denotes the long-term trend of anthropogenic warming. These are operationally distinct concepts, though causally linked, that contribute to increased climate change and greater climate variability.

The rest of the article is structured as follows. Section 2 reviews the literature on the subject; Section 3 presents the methodological framework; and Section 4 presents the empirical results and a discussion of the findings. While the conclusion and policy implications are discussed in Section 5.

2. Literature Review

There is an increasing body of literature linking climate change to health outcomes across multiple dimensions. According to the Intergovernmental Panel on Climate Change (IPCC) and the World Health Organization, climate change is always seen as one of the main global health determinants (World Health Organization, 2023). Ma et al. (2022) showed that climate change changes the distributional burden of waterborne, non-communicable, and vector-borne diseases with disproportionate impacts on low-income nations. More recently, the welfare costs of climate shocks have been formalized in household production and health capital models by the emerging field of environmental health economics, especially the work of Dell, Jones, and Olken (2014) and Patz et al. (2005). Sello et al. (2025) conducted a systematic review of 23 studies in sub-Saharan Africa and found moderate evidence of the association between temperature fluctuations and cardiovascular disease hospitalizations, deaths, and age-specific mortality. International meta-analyses have shown that exposure to heatwaves increases the risk of cardiovascular mortality by approximately 14.9% (Vicedo-Cabrera et al., 2021). The project on Nigeria-specific vulnerability assessments states that the number of cardiovascular disease cases will increase by at least 10%, to over 4.5 million, and that hypertension cases will be over threefold by 2030 (Federal Ministry of Health, 2025).

The most methodologically closest study to this research is a study by Li, Smyth, and Yao (2023), who connected three waves of the China Family Panel Studies to daily weather station data, including individual fixed effects and semi-parametric temperature-bin models to demonstrate that extreme cold and extreme heat both have a significant positive impact on OOP medical spending. The study used this framework, with modifications for the Nigerian context, as household fixed effects are replaced by geopolitical zone fixed effects, and climate variation, largely driven by El Niño–Southern Oscillation (ENSO), is used to identify the variable. Further underpinning can be found in the literature on climate adaptation economics (see e.g., Hsiang, Burke & Miguel, 2013), which has shown that labour productivity losses, agricultural yield decreases, and heat-related morbidity have a mechanistic relationship with income compression, a major channel through which climate shocks are converted into disastrous expenditures in the health of households of low- and middle-income country.

There has been a significant increase in econometric research on the determinants of CHE in Nigeria over the last 10 years. Ibukun and Komolafe (2018) found that lower economic status, unemployment, older age, and rural residence are the main CHE drivers, based on the Harmonized Nigeria Living Standards Survey (HNLSS) 2009/10 and multivariate logistic regression. Using three rounds of GHS-Panel data, as mirrored in the current study National Bureau of Statistics (2024) reported an increase in CHE incidence from about 27% of households in 2010/11 to around 48% in 2015/16. Similarly, Babandi et al. (2025), posit that the geographical area, especially North-East Nigeria, is a strong structural determinant of CHE and NCD medicine expenses. Edeh (2022) used concentration index decomposition to show that CHE is systematically pro-poor in Nigeria, a finding that is extended and contextualized in our climate-disaggregated decomposition outcomes. What is particularly missing in this body of literature is a systematic approach to climate variability as a structural factor in CHE vulnerability, which the current study directly addresses. Anwar, Hyder, Bennett, and Younis (2022) estimated the system GMM panel model with 33 developing countries (2000-2018) and discovered that air pollution and temperature are positive predictors of healthcare expenditure in all G7 countries, while Dritsaki and Dritsaki (2024) found unidirectional Granger causality between greenhouse gas emissions and per capita spending on health. The study found that mandatory health insurance lowers OOP spending, findings directly applicable to Nigeria, and Kaladharan and Manayath (2024) confirmed these results using fixed random and dynamic-panel models on WHO data for emerging economies.

Despite this evidence at the macro level, there is little operationalization of the entire climate shock-NCD incidence-OOP demand-CHE nexus at the micro level in sub-Saharan Africa. The study by Siiba et al. (2024) makes an incomplete contribution to the Ghanaian case, as the authors do not include NCD-climate interaction terms or distributional decomposition in their analysis. The current paper extends the study by covering the case of Nigeria.

3. Theoretical and Conceptual Framework

The Climate-NCD-CHE Transmission Mechanism

This study is situated within the framework of Grossman's (1972) health capital theory, with climate shocks as external inputs into poor health stocks. In his formulation, Grossman offers households the opportunity to invest in health capital (H) to produce healthy time, which affects not only utility but also income production. Climate shocks shift the depreciation rate of health capital to positive, augmenting demand for health care inputs, which, in the absence of insurance, mechanistically implies an increase in OOP spending. Based on the disastrous health spending literature (Xu et al., 2003; Wagstaff & van Doorslaer, 2003) and the climate-health economics tradition (Patz et al., 2005; Dell et al., 2014), the study conceptualizes that climate shocks have three transmission pathways to CHE.

The figure shows a compounded analytical framework linking climate shocks to non-communicable disease (NCD) incidence and catastrophic health expenditure (CHE) through health stock depreciation. Climate shocks, or temperature abnormalities, floods, and droughts are exogenous stressors that decrease healthcare capital in the household. This depreciation has three transmission pathways that interact with each other. The first is a physiological stress channel, which illustrates the elevated risk of hypertension, diabetes, and cardiovascular diseases with greater exposure to heat, which enhances the occurrence of NCD. The erosion channel of income emphasizes that agricultural losses and income shocks from climate change undermine household finances, thereby indirectly heightening vulnerability to CHE. Also, the health system disruption channel indicates declines in access to healthcare services due to extreme events, necessitating the use of more expensive alternatives. These channels also contribute to the increased prevalence of NCDs and, eventually, to an increased risk of disastrous health spending and their effects may compound in a non-linear way.

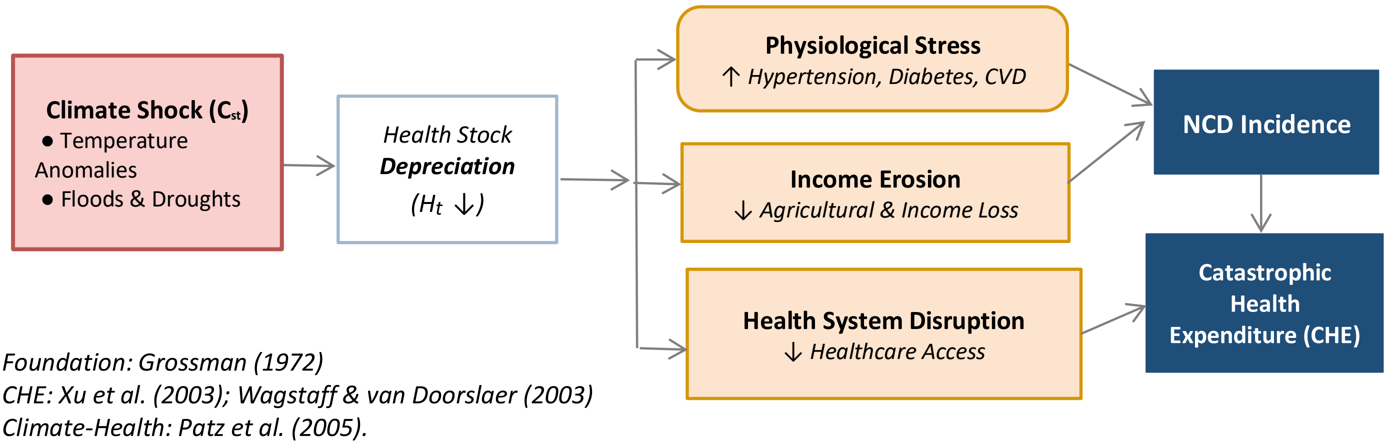

Figure 1. Analytical Framework: Climate Shocks, Health Stock Depreciation, and Catastrophic Health Expenditure

Source: Authors' Conceptualization 2026. Note. *H_{it} = household health stock; Y_{it} = household income; CHE_{it} = catastrophic health expenditure; NCD_{it} = non-communicable disease diagnosis; OOP = out-of-pocket; C_{st} = climate shock in region s at time t.*

4. Methods

Data Sources and Study Design

This study adopts a quantitative, nationally representative household-level design using Nigerian data. The core dataset is drawn from three waves of the General Household Survey-Panel (2010/11, 2012/13, and 2015/16). The estimation sample comprises 22,110 pooled household-wave observations, constructed through a careful harmonization of survey waves. Because the GHS-Panel follows the same households over time, it enables robust within-household analysis. Climate exposure is measured by linking household data to state-level indicators from official and international sources, including NiMet, the World Bank, and NEMA. While this spatial matching ensures consistency, it may mask within-state variation, a limitation partly addressed through clustered standard errors and regional sensitivity analyses. Monetary variables are adjusted using the Consumer Price Index to maintain comparability. Overall, the harmonized panel structure supports reliable estimation while accounting for temporal and spatial heterogeneity.

Variable Definition and Measurements

Dependent Variables

The outcome variable is catastrophic health expenditure, represented as (CHE_{ist}). It is a binary variable that takes the value 1 if household expenditure on health exceeds 40% of non-food expenditure, with additional robustness checks at 25% and 10% thresholds. Climate variability, represented as ($Climate_{st}$), is proxied by temperature anomalies relative to the 1981-2010 baseline, rainfall variability, flood, and drought occurrences, all measured at the state-year level. Household health status (NCDist) is defined as the presence of non-communicable diseases, including hypertension, diabetes, and cardiovascular disease. Additionally, in line with the concept of compounding vulnerability, interaction terms are used for these variables. Other control variables include household characteristics such as household size, demographic composition, education, residence, income, and insurance status.

Econometric Estimation Strategy

For consistency, all the models are indexed in the following way: *i* = household, *s*= state, *t*= time (survey wave). The baseline model: Probability of Catastrophic Health Expenditure is specified as follows:

$$P(CHE_{ist} = 1) = F(\beta_0 + \beta_1 Climate_{st} + \beta_2 NCD_{ist} + \beta_3 (Climate_{st} \times NCD_{ist}) + \gamma X_{ist} + \delta_s + \lambda_t + \varepsilon_{ist})$$

The model specifies the aggregate distribution function while controlling for unobserved heterogeneity via fixed effects for geopolitical zones and survey waves. Average marginal effects are computed, with standard errors clustered at the state level to ensure robustness. Although NCD diagnosis is treated as predetermined, there is a concern that it may be endogenous, since wealthier households with better access to healthcare are more likely to receive formal diagnoses. To address this, a Durbin–Wu–Hausman test is conducted using distance to the nearest tertiary health facility as an instrument. Interaction effects between climate and NCD variables are estimated using non-linear models, which require corrected marginal effects that confirm the initial findings.

To further address potential endogeneity in climate variables, an instrumental variable approach is employed, using the lagged Oceanic Niño Index as a valid and theoretically grounded instrument specified as:

$$Climate_{st}=\pi_0+\pi_1 ENSO_t+\pi_2 ENSO_{t-1}+\vartheta Z_{st}+\mu_{st}$$

The relevance of the instruments is established with the help of the first-stage F-statistics, which are greater than the conventional thresholds, and the instrument validity is supported with the help of the over identification tests. The IV-probit estimator eliminates the attenuation bias and provides coherent parameter estimates. A key assumption of the IV strategy is that ENSO affects CHE exclusively through the climate variability channel (temperature anomalies and extreme weather events), rather than directly through income or food security pathways. This exclusion restriction is formally tested using the Sargan-Hansen J-test which fails to reject the null of instrument validity. Conceptually, the exclusion restriction is plausible because the ENSO Nigeria climate relationship operates primarily through North/South rainfall asymmetry with a 6-12-month lag, while the temperature health channel is contemporaneous; and controlling for income quintile, agricultural dependency, and food expenditure share in the second stage further reduces the probability of a direct ENSO CHE income pathway. We acknowledge that this exclusion restriction cannot be directly tested without an additional instrument, and this remains a limitation.

Fixed-Effects Logit Model

A fixed-effects logit model is estimated to correct time-invariant household heterogeneity that may not be observed as specified below:

$$P(CHE_{ist} = 1 \mathrm{I} \alpha_i)\, f(\beta_0 + \beta_1 Climate_{st} + \beta_2 NCD_{ist} + \beta_3 (Climate_{ist} \times NCD_{ist}) + \gamma X_{it} + \delta_s + \lambda_{t-1}$$

where α_i is the household-specific fixed effects, which are conditioned out in estimation. This specification is based solely on within-household variation over time, thereby enhancing causal inference. Estimation is performed using the conditional maximum likelihood method.
To examine the health transmission pathway, the study estimates linear probability models (LPM) and instrumental variable two-stage least squares (IV-2SLS) models:
$NCD_{ist}=\alpha_0+\alpha_1 Climate_{st}+\alpha_2 X_{ist}+\delta_s+\lambda_t+\epsilon_{ist}$
ENSO-based instruments are used in a two-step framework to make causal identification. Hypertension, diabetes, cardiovascular disease and a composite NCD index are estimated using separate models.

To measure the extent of socioeconomic inequality in disastrous health spending, the study uses a concentration index decomposition method proposed by Adam Wagstaff and Eddy van Doorslaer:

$$C = \sum_{n=1}^{0} \left(0 \frac{\beta \kappa X \kappa}{L} + C_k + \frac{G\varepsilon}{\mu} \right)$$

Where, Ck = concentration index of determinant xkx_kxk, $\beta_k x_{k/\mu}$ = elasticity of health w.r.t. xkx_x_k Gε = generalized concentration index of residual. This decomposition enables identification of the relative contributions of climate exposure, health status, and socioeconomic characteristics to inequality.

Robustness Checks

Robustness checks are also performed to confirm the results; these include using different catastrophic health expenditure thresholds (25% and 10%), adding lagged climate variables to examine their persistence, zone-stratified regressions to account for regional variation, placebo instrumental variable (IV) results using randomly permuted ENSO indices, and using different non-communicable diseases. The results from all these analyses are consistent and affirm the reliability of the findings. This shows that the relationship between climate variability, non-communicable diseases, and financial risk is stable.

Ethical Considerations

The study is based exclusively on secondary, anonymous data from household surveys and publicly available climate data. No identifiable information is used, and the study adheres to ethical guidelines, as is standard in empirical research.

5. Results

Descriptive Statistics

Table 1 presents the estimation sample, which comprises 22,110 Nigerian households drawn from the pooled GHS-Panel. At the 40% non-food expenditure level, 30.1% of households had CHE; the percentages are 41.8 at the 25% threshold and 21.3 at the 10% threshold. The mean expenditure on OOP per capita was N12,230 (adjusted to 2015/16 prices) and the inequality was great (SD = N28,470; maximum = N683,200), which supports the highly skewed distribution of health costs. About 23.4 percent of households contain at least one member with a diagnosis of NCD, with hypertension taking the greatest percentage of 17.6 percent, diabetes (4.8 percent) and CVD (3.2 percent) in the second and third place, respectively. Only 4.2 percent of households have any type of health insurance. The household heads have an average age of 44.6 years; 26.1 percent are female-headed households; and 37.4 percent have no formal education. The average household size is 5.1 persons. State-level climatic data show a mean annual temperature of 27.8 °C and a mean annual precipitation of 1,248 mm, with floods and droughts observed in 58% and 29% of the state-year of observation.

Table 1. Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
Panel A: Household-Level Variables					
CHE (binary, 40% threshold)	22,110	0.301	0.459	0	1
CHE (binary, 25% threshold)	22,110	0.418	0.493	0	1
OOP expenditure (₦ '000 per capita)	22,110	12.23	28.47	0	683.2
NCD diagnosis (binary)	22,110	0.234	0.423	0	1
Household size	22,110	5.14	2.89	1	22
Age of household head (years)	22,110	44.6	14.3	18	97
Female-headed HH (binary)	22,110	0.261	0.439	0	1
Urban residence (binary)	22,110	0.443	0.497	0	1
No formal education (binary)	22,110	0.374	0.484	0	1
Health insurance coverage (binary)	22,110	0.042	0.201	0	1
Poorest quintile (binary)	22,110	0.198	0.398	0	1
Panel B: State-Level Climate Variables					
Mean annual temperature (°C)	36	27.8	2.41	22.1	34.6
Temperature anomaly (°C above 1981–2010 mean)	36	+1.24	0.83	-0.41	+3.62
Annual rainfall (mm)	36	1,248	587	312	2,934
Rainfall variability index (CV)	36	0.31	0.14	0.09	0.67
Flood incidence (binary, state-year)	36	0.58	0.497	0	1
Drought incidence (binary, state-year)	36	0.29	0.456	0	1

Source: Authors' computation based on Nigeria Living Standard Survey 2018/19 (NBS); NiMet State of the Climate Reports; World Bank Climate Change Knowledge Portal; NEMA. Notes: Climate variables are at the state level (N = 36 states). OOP expenditure deflated to 2018 prices using CBN CPI.

Probit, Logit, IV-Probit and Fixed-Effects Logit Estimates for CHE

Table 2 reports estimate of the determinants of catastrophic health expenditure (CHE) at the 40% threshold using probit, logit, IV-probit, and fixed-effects logit models, with results expressed as average marginal effects to aid interpretation. This approach allows the coefficients to be understood in terms of changes in probability, making the findings more intuitive and policy relevant. Panel B further presents the marginal effects of the interaction terms, computed using standard average marginal effect procedures. However, because the probit and logit models are nonlinear, interaction effects may not be directly interpretable without adjustment. To address this, the AI and Norton (2003) correction is applied. Importantly, these adjusted results remain consistent in direction and statistical significance with the main findings presented in the table, reinforcing the evidence of a super-additive effect, although the magnitudes of the interaction terms differ slightly.

Table 2. Determinants of Catastrophic Health Expenditure

Variables	(1) Probit AME	(2) Logit AME	(3) IV-Probit	(4) FE-Logit
A. Climate Variables				
Temperature anomaly (°C)	0.043*** (0.011)	0.047*** (0.013)	0.061** (0.024)	0.038** (0.017)
Rainfall variability (CV)	0.128** (0.051)	0.134** (0.059)	0.152** (0.063)	0.119** (0.054)
Flood incidence	0.071*** (0.019)	0.079*** (0.021)	0.083*** (0.023)	0.064*** (0.020)
Drought incidence	0.054** (0.023)	0.058** (0.025)	0.066** (0.030)	0.048** (0.024)
B. NCD Interaction Terms				
Temp. anomaly × NCD	0.038** (0.017)	0.042** (0.019)	0.053** (0.022)	0.033** (0.016)
Flood incidence × NCD	0.094*** (0.027)	0.101*** (0.029)	0.112** (0.034)	0.087*** (0.028)
C. Household Controls				
NCD diagnosed (binary)	0.152*** (0.018)	0.167*** (0.021)	0.161*** (0.023)	0.143*** (0.019)
Poorest quintile	0.118*** (0.024)	0.131*** (0.027)	0.122*** (0.025)	0.109*** (0.023)
Female-headed HH	-0.041** (0.018)	-0.044** (0.020)	-0.039** (0.019)	-0.036** (0.018)
Health insurance	-0.093*** (0.031)	-0.101*** (0.034)	-0.097*** (0.032)	-0.089*** (0.030)
Urban residence	-0.027* (0.015)	-0.029* (0.017)	-0.025* (0.015)	-0.022 (0.016)
No formal education	0.061*** (0.021)	0.066*** (0.023)	0.063*** (0.022)	0.057*** (0.021)
Age of HH head	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
D. Model Diagnostics				
Observations	22,110	22,110	22,110	22,110
Pseudo-R²	0.187	0.191	-	-
1st-stage F-statistic	-	-	47.3***	-
Geopolitical zone FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
Clustered SE (state)	Yes	Yes	Yes	Yes

*Authors' Computation 2026. Note. Average marginal effects are reported throughout. *p<0.10, **p<0.05, ***p<0.01.*

Table 2 presents the findings of the determinants of catastrophic expenditure. The findings indicate that climate variability significantly contributes to household vulnerability, with strong, significant indications. An increase in the temperature anomaly by 1 degree increases vulnerability by 4 to 6 percentage points, whereas rainfall variability has a stronger impact, increasing vulnerability by 12 to 15 percentage points. There is also increased vulnerability of about 6 to 8 percentage points due to floods and of about 5 to 7 percentage points due to droughts. The instrumental variables results exceed the baseline results, suggesting that traditional models do not capture the true impact. In general, gradual climate changes, as well as extreme events, inflict significant welfare costs to households, particularly in climatically sensitive settings.

This analysis shows that non-communicable diseases increase with climate-related risks, as the interaction terms are positive and significant in the models. A compounded climate health burden is evident in households with NCDs, which are further affected by temperature shocks and floods. These are products of socioeconomic influences. Financial access provides protection by showing that poverty makes people more vulnerable, whereas health insurance makes people less vulnerable. The lack of education is also a risk factor, and female-headed households are less vulnerable to it, suggesting variations in resource management. These relationships have been validated through robustness tests using instrumental variables and fixed effects, which show that they are not driven by unobserved heterogeneity.

OLS and IV-2SLS estimates for specific NCD outcomes

Table 3 presents the baseline regression results examining the relationship between climate-related shocks and non-communicable diseases (NCDs), focusing on hypertension (HTN), diabetes (DM), cardiovascular diseases (CVD), and a composite indicator of any NCD.

Table 3. Climate Variability and NCD Outcomes (OLS and IV-2SLS; LPM Coefficients)

Variables	(1) HTN OLS	(2) DM OLS	(3) CVD OLS	(4) Any NCD IV-2SLS
Temperature anomaly (°C)	0.031*** (0.009)	0.018** (0.007)	0.022** (0.009)	0.048** (0.019)
Cumulative heat days (>35°C)	0.002** (0.001)	0.001* (0.001)	0.002** (0.001)	0.004** (0.002)
Flood exposure (years)	0.041** (0.016)	0.021* (0.012)	0.033** (0.014)	0.067** (0.030)
Drought exposure (binary)	0.027* (0.014)	0.014* (0.008)	0.019* (0.011)	0.043* (0.024)
Age (years)	0.008*** (0.001)	0.006*** (0.001)	0.007*** (0.001)	0.012*** (0.002)
Urban residence	0.022** (0.010)	0.016** (0.008)	0.017* (0.009)	0.031* (0.017)
BMI (kg/m²)	0.019*** (0.003)	0.023*** (0.003)	0.011*** (0.003)	0.027*** (0.005)
Income quintile 5 (richest)	0.031** (0.013)	0.028** (0.011)	0.026** (0.012)	0.044* (0.024)
R-squared	0.312	0.267	0.289	0.301
F-statistic (1st stage IV)	-	-	-	47.3***
Sargan-Hansen J [p-val]	-	-	-	2.14 [0.34]
Geopolitical zone FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
Observations	22,110	22,110	22,110	22,110

*Source: Authors' computation 2026. Note. LPM = linear probability model coefficients. *p<0.10, **p<0.05, ***p<0.01*

The results as contained in the table above shows that the effect of climate-related stressors are consistently associated with increased risks of non-communicable diseases across all models. A 1-degree change in the temperature anomaly is a major step towards increasing the risk of hypertension, diabetes, cardiovascular disease, and the overall prevalence of NCD, and the instrumental variable (IV) estimates indicate an even greater combined effect. Equally, more extreme heat days and longer exposure to floods and droughts are risk factors that increase exposure to disease, with emphasis on the health burden of environmental shocks. Personal traits are also important, as older age and high Body Mass Index (BMI) are strong risk factors, whereas living in a city and higher income are associated with increased diagnosis or exposure, which may be due to differences in lifestyle and diagnostic practices. The IV diagnostics indicate that the model is statistically viable, the instruments are strong, and there is no over-identification. Generally, the results indicate that climate pressures, along with socio-economic determinants, act in concert to determine NCD outcomes, underscoring the need to integrate public health and climate adaptation policies, particularly for underserved populations.

Concentration Index Decomposition

Table 4 presents the full nonlinear concentration index decomposition for CHE at the 40% threshold. The general CHE concentration of 0.1322 confirms that CHE is systematically concentrated among poorer households. The climate variables represent the second-largest group, accounting for 31.3% of the overall CHE concentration inequality, behind only the socioeconomic and demographic controls (47.2%). The largest contributor to climatic factors is temperature anomaly (13.6%). The combined interaction terms for diagnosing NCD explain 22.7% of the total CHE inequality. The residual (GCIR = 0.0055) is minimal, indicating that observed covariates account for the majority of CHE inequality in the sample. These findings show that climate variability is not just a health shock but a systematic regressive one. Even after accounting for income, education, and insurance status, climate exposure produces a unique pro-poor concentration of CHE that is quantifiable and can be acted on in policy.

The robustness tests with the 25% and 10% CHE thresholds produce AMEs of 0.051 and 0.029 for the temperature anomaly, respectively. Replacing current climate variables with one-wave-lag values also yields qualitatively similar results (temperature anomaly AME = 0.039, SE = 0.014), indicating that the effects of health expenditure are not purely contemporaneous. The North-East and North-West are the regions where the zone-stratified regressions show the largest effects. Extreme heat, drought, and low insurance coverage make people vulnerable. The placebo test of regressing CHE on a randomly permuted ENSO instrument yields an F-statistic of 1.83 and a non-significant second-stage coefficient (β = 0.006, SE = 0.018), confirming that the observed variation is unique to true climate shocks. The findings are also resistant to other definitions of NCDs.

Table 4. Nonlinear concentration index decomposition for CHE at the 40% threshold

Determinant	Elasticity (η_k)	CI of determinant CI_k)	Contribution to CI	Share of total CI (%)
A. Climate Variables				
Temperature anomaly	0.0847	-0.2114	-0.0179	13.6%
Rainfall variability (CV)	0.0421	-0.1832	-0.0077	5.8%
Flood incidence	0.0531	-0.1983	-0.0105	8.0%
Drought incidence	0.0318	-0.1641	-0.0052	3.9%
Climate subtotal	-	-	-0.0413	31.3%
B. NCD Diagnosis and Interaction Terms				
NCD diagnosis	0.1174	-0.1521	-0.0179	13.5%
Temp. anomaly × NCD	0.0293	-0.1887	-0.0055	4.2%
Flood × NCD	0.0381	-0.1743	-0.0066	5.0%
NCD subtotal	-	-	-0.0300	22.7%
C. Socioeconomic and Demographic Controls				
Poorest quintile	0.1034	-0.4412	-0.0456	34.5%
No formal education	0.0712	-0.2203	-0.0157	11.9%
Health insurance	-0.0228	0.3104	-0.0071	5.4%
Urban residence	-0.0183	0.2841	0.0052	-3.9%
Age of HH head	0.0314	0.0321	0.0010	0.8%
Female-headed HH	-0.0107	0.0218	-0.0002	0.2%
Socioeconomic subtotal	-	-	-0.0624	47.2%
D. Residual and Totals				
Residual (GCIR)	-	-	0.0055	-
Total CI (CHE)	-	-	-0.1322	100%

Source: Authors' Computation 2026. Note. Decomposition follows Wagstaff and Van Doorslaer (2003) as modified for nonlinear models by Edeh, H. C. (2022).

6. Discussion

The results offer strong micro-econometric evidence of a climate-NCD-CHE nexus in Nigeria, which is theoretically consistent, empirically significant and policy-implementable. The outcomes were built on previous studies to establish the NCD-climate interaction and distributional aspects of the problems that cannot be remedied at the macro-level.

The macroeconomic scale of these effects is particularly striking and warrants careful consideration. In Nigeria, with an estimated 44 million households, even modest increases in temperature translate into substantial welfare implications. Based on IV-probit average marginal effects, a 1°C rise in temperature could result in an additional 1.9 to 2.7 million households experiencing catastrophic health expenditure (CHE) by 2030 under a baseline scenario of unchanged insurance coverage and income levels, with a 95% confidence interval ranging from 1.4 to 3.2 million households. However, alternative scenarios reveal important nuances. Under a moderate adaptation pathway characterized by a 10% annual increase in insurance coverage, the projected burden declines to 1.3-1.9 million households (95% CI: 0.9-2.4 million). In contrast, a pessimistic scenario combining continued warming (≥1.5°C) with stagnant coverage suggests a sharper increase, affecting approximately 2.8-4.1 million households (95% CI: 2.0–5.0 million). These estimates should be interpreted with caution, as they are illustrative upper-bound projections based on linear extrapolation of marginal effects beyond the observed data range. They do not fully capture potential non-linear climate impacts, behavioural adjustments, or structural transformations within the health system. As such, they are best viewed as indicative planning benchmarks rather than precise forecasts, underscoring the urgency of adaptive policy responses.

The results of the NCD interaction have special implications for the health financing forecasts. With the current NCD burden in Nigeria steadily increasing due to climate change, urbanization, and dietary transition, more households will be affected by both chronic diseases and climate shocks. Traditional actuarial models of health finance that do not incorporate climate parameters will underestimate the CHE risk among populations affected by NCDs. The distribution results show a severe equity issue. The rural poor households within the north of Nigeria, where extreme heat and drought intersect, where health insurance coverage is very low, have an added vulnerability with a poverty trap mechanism in that as climate shocks increase NCD risk, which results in disastrous health spending, causing an increase in poverty, which increases sensitivity to further climate shocks. This vicious cycle aligns with the climate-poverty trap literature (Eze & Iheonu, 2025).

Some limitations of the study warrant attention. Aggregating climate data at the state level may obscure micro-level heterogeneity in household exposure. The long-term health effects of chronic climate exposure may not be fully captured when relying solely on cross-sectional survey waves. Also, self-reported diagnoses of non-communicable diseases (NCDs) are prone to underreporting, introducing measurement error that likely biases the estimated climate NCD coefficients. Finally, the exclusion restriction of the ENSO instrument, though theoretically justified via the Sargan-Hansen test, cannot be directly tested. Future research should aim to refine and extend these findings by incorporating higher-frequency panel data, more finely resolved climate metrics, longitudinal monitoring of NCDs, and analyses of subtypes within individual diseases.

7. Conclusion and Recommendations

Based on empirical findings, the study confirms that climate variability is a major, measurable, and unevenly distributed contributor to the disastrous burden of health spending and the burden of NCDs in Nigeria. An increase in the probability of CHE of 4.3-6.1 and flood exposure of 7.1-8.3 percentage points with a one-degree Celsius rise in the probability of abnormality in temperature and flood exposure, respectively. There is an estimated 9.4 percentage points of super-additive CHE amplification in NCD-affected households over and above the sum of independent effects due to climate shocks. A complete breakdown of the concentration index shows that total CHE inequality is explained by climate variables, with a contribution of 31.3 percent; individually, the temperature anomaly accounts for 13.6 percent. Trend evidence between 2000 and 2023 indicates that temperature anomalies, NCD DALYs, and CHE incidence are nearly parallel and co-moving. The stability of such estimates is proved by robust tests.

Thus, the systematic adaptation to climatic change cannot be done without the health financing reform. Accelerating warming, growing NCD burden, catastrophically high OOP health spending and negligible insurance coverage are overlapping risks that will become increasingly severe unless addressed by policy. To address this susceptibility, it is necessary not only to broaden the reach of health insurance but also to incorporate climate risk parameters into the policy measures, targeting, and fiscal design of health financing and social protection within the Nigerian health financing and social protection framework.

Thus, the study recommends that NHIS should be scaled up to focus on the poorest two quintiles of expenditure in high-climate-risk states (North-East, North-West, and the flood-prone areas of Nigeria). The projected AME of health insurance, 9.3 percentage points, suggests that achieving significant coverage among the worst-off households in high-risk states would significantly cushion the estimated rise in CHE from future warming. The prevention and management programmes for NCDs should be established as formal plans for climate adaptation. An available institutional platform for such integration is the Nigeria Climate, Health Vulnerability and Adaptation Framework (Abrams, Asmall, & Hlahla, 2025; Federal Ministry of Health, 2025), which prioritizes cardiovascular disease and hypertension as climate-sensitive outcomes. Climate scenario modelling must be included in the National Multi-Sectoral Action Plan on NCDs, as projections of future NCD burden and financing needs in relation to health financing. Also, social protection tools, especially the National Social Safety Nets Programme (NASSP) and conditional cash transfer measures, must incorporate climate-shock triggers to prevent household impoverishment following floods and droughts, as in Kenya and Ethiopia, there is evidence that responsive social protection could cushion against post-disaster health expenditure catastrophes (Scognamillo et al., 2022; Ulrichs, 2019).

Conflict of Interest

There is no conflict of interest. Nothing to disclose. The authors declare no external funding for this research.

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