TSITICA WORKING PAPER NO 7

June 2023

THE IMPACTS OF CLIMATE CHANGE SHOCKS AND ASSET OWNERSHIP ON HOUSEHOLD ASSETS IN KENYA

Damiano Kulundu Manda, Martine Oleche,
Samuel Kipruto, Moses Muriithi,
Reuben Mutegi, Germano Mwabu

TSITICA WORKING PAPER NO. 7, 2023

The Impacts of Climate Change Shocks and Asset Ownership on Household Assets in Kenya

Damiano Kulundu Manda, Martine Oleche,
Samuel Kipruto, Moses Muriithi,
Reuben Mutegi, Germano Mwabu

DISCLAIMER

ACKNOWLEDGEMENTS

The Transforming Social Inequalities Through Inclusive Climate Action (TSITICA) project investigates how climate change action can be socially transformative in three contrasting African countries: Ghana, Kenya and South Africa. The research agenda addresses the nexus between climate change, sustainable livelihoods and multidimensional poverty and inequality to tackle the overall question: how can climate actions be deliberately targeted to improve livelihoods and lead to equitable benefits for the most vulnerable and poor – especially for women and youth? With the goal of inspiring climate actions that also reduce poverty and inequality, based on evidence and insights from the research, TSITICA aims to contribute the Agenda 2030 ambition of leaving no one behind.

The full project team comprises researchers from two African Research Universities Alliance (ARUA) Centres of Excellence hosted by the University of Cape Town (UCT); researchers from the centres' regional nodes at universities in Ghana and Kenya; and collaborators from four universities in the United Kingdom:

- African Centre of Excellence for Inequality Research, hosted by UCT's Southern Africa Labour and Development Research Unit, School of Economics
- ARUA Centre of Excellence in Climate and Development, hosted by UCT's African Climate and Development Institute
- ARUA-CD and ACEIR nodes convened respectively by the Institute for Environment and Sanitation Studies and the Institute of Statistical, Social and Economic Research, University of Ghana
- ARUA-CD and ACEIR nodes convened respectively by the Institute for Climate Change and Adaptation and the School of Economics, University of Nairobi
- Grantham Research Institute on the Environment and Climate Change, London School of Economics and Political Science
- Townsend Centre for International Poverty Research, University of Bristol
- International Inequalities Institute, London School of Economics and Political Science
- Tyndall Centre for Climate Change Research, University of East Anglia
- Tyndall Manchester, University of Manchester

The support of ARUA and UK Research and Innovation is gratefully acknowledged.

For more information, please contact:

Project manager: Haajirah Esau (Haajirah.Esau@uct.ac.za)

Communications: Charmaine Smith (Charmaine.Smith@uct.ac.za)

Research Coordination: Dr Britta Rennkamp (Britta.Rennkamp@uct.ac.za

Abstract

The main objective of this study is to analyse the impacts of climate change shocks and asset endowments on household welfare - proxied by per adult consumption expenditure. In addition, the study assesses whether the impacts differ between the poor and the non-poor, and the extent to which asset ownership and access to credit can help cushion against the negative effects of the shocks. To achieve the study's objective, we use household data merged with county-level data on climate change shocks to examine the impacts of the shocks on household wellbeing using control functions. The results demonstrate that climate change shocks reduce household welfare, with impacts being more pronounced for rural than for urban populations. Furthermore, poor households are much more affected by climate change shocks than the non-poor, irrespective of residence status. Generally, asset ownership and credit access help mitigate the negative welfare effects of climate shocks. There is some evidence that social protection schemes can complement the welfare cushioning roles of assets and credit in contexts of climate change.
Keywords: Climate change shocks, Asset ownership, Access to credit, Poverty, Inequality, Household welfare, Kenya

JEL Codes: C51, D13, J18, Q54

TABLE OF CONTENTS

1. Introduction

Over the period 2015-2019, Kenya achieved a broad-based growth, averaging 4.8% per year (see World Bank, 2022). Moreover, the country experienced significant reduction in poverty (which fell from 46.8% in2005/06 to 36.1% in 2015/16 (and declined further to 34.4% at the $1.90/day poverty line in 2019), undoubtedly resulting in a welfare improvement. Although the COVID-19 pandemic negatively hit the Kenyan economy disrupting international trade, transport, tourism, and urban services, the agricultural sector remained resilient, helping to limit the contraction in GDP by a small but noticeable 0.3%. There is now optimism for a better future, following the recovery of the economy in 2021 with growth projected at 5.5% in 2022. With this growth continuing into the future, poverty is expected to decline substantially. Nevertheless, at over 30%, the poverty rate in Kenya over the last decade remained is a source of concern, especially when compared with levels for other lower-middle-income countries, such as Ghana, and Ethiopia (see Fosu, 2015). Furthermore, with the current pace of poverty reduction of about 1 percentage point per year, Kenya is unlikely to eradicate poverty by 2030 as per Sustainable Development Goals (World Bank, 2022). Thus, despite the broadly positive economic outlook for the country, the elevated short-term uncertainty, including high prices for fuel, wheat, and fertilizer imports, partly due to the war in Ukraine and the uncertain weather patterns induced by climate change, the welfare of the Kenyan population seems at risk.

Climate change is associated with long-term general increase in temperatures and change in precipitation patterns. Over the past century, surface temperatures have increased, and the associated impacts on physical and biological systems are increasingly being observed and felt (Pelser and Chimukuche, 2022). Climate change brings about gradual earth changes, such as the sea level rise, and degradation in climatic zones due to increased temperatures and declines in precipitation levels (IPCC, 2022, 2021). Climate change is very likely to increase the frequency and magnitude of extreme weather events, such as droughts, floods, and storms (New Climate Economy, 2018). While there is uncertainty in the projections with regard to the exact magnitude, rate, and regional patterns of climate change, its consequences continue to change the fate of many generations and particularly that of the poor. Africa is regarded as the continent that is most vulnerable to climate change impacts, due mainly, to its low adaptive capacity and overdependence on natural resource-based livelihoods (Nyiwul, 2021; IPCC, 2022; Pelser and Chimukuche (2022); and Rahut, Aryal, and Marenya, 2021).

Climate-induced changes in Africa are likely to have dramatic effects on the livelihoods of poor rural communities in particular, as the continent struggles to eradicate extreme poverty as part of the United Nations' SDGs for 2030 (United Nations Department of Economic and Social Affairs, 2015). Most countries in Sub-Saharan Africa, Kenya included, heavily depend on a smallholder-based agriculture sector, and this dependence makes people's welfare very vulnerable to climate changes (Barrios et al. 2008). Urban dwellers in Sub-Saharan Africa, especially those living in flood prone areas in cities, suffer perennially due to flooding as a result of expansion of impermeable surfaces and global climate change shocks (Owuor and Mwiturubani, 2021; Adelekan and Asiyanbi, 2016). In Kenya, poverty has been exacerbated by the changing climate of recent decades, to such an extent that climate change is now hampering efforts to achieve sustainable development in the country (Rahut, Aryal and Marenya, 2021). However, there is inadequate research knowledge on how climate change shocks affect household welfare. This study analyses the impacts of climate change shocks on household welfare in Kenya and assesses whether the impacts differ between the poor and the non-poor. In addition, this study assesses how well household asset ownership and access to credit (liquid asset) can help cushion households' welfare against the negative effects of climate change. In analysing the impacts of climate change shocks on household welfare, we cover both rural and urban households.

On the one hand, there are observable climate-related factors that affect the wellbeing of households in multiple ways, such as via the interactions of shocks with asset levels, while on the other hand such interaction effects might be absent, and where present, unobservable. Households' assets are considered as drivers of sustainable growth and better intergenerational outcomes (Siegel 2005). Physical assets promote the economic well-being of households by generating income, creating other types of assets (e.g. livestock units), smoothing consumption during periods of uncertainty and hardship, and building resilience in the face of external shocks. Beyond such economic benefits, household asset ownership provides personal and social benefits, including improvements in education and health (see e.g., Kumaraswamy, et.al. 2020). Poor households typically are constrained by low quantity and quality of assets, as well as adverse contextual factors, such as distance from markets and low-quality public infrastructure that limit their ability to optimize off their asset portfolios. This has consequences for their long-term growth and poverty status (Dorosh et al. 2011). Thus, an assessment of the buffering role of assets in times of crisis might help one to understand the ways in which net household incomes might be affected by climate change shocks. Taking into account the role of asset ownership in a household wellbeing function, for instance, can show whether households with diversified or more assets tend to be resilient to shocks (see Kodwo-Ansah and Gardebroek, 2021; Mckay, 2009). It is known that households lacking assets to begin with risk being caught in poverty traps (Carter and Barrett, 2006), but the consumption smoothing role of assets and credit in periods of shocks is not as well documented.

Assets can moderate the effect of climate change shocks cushioning the negative effects of climate change on household welfare. However, assets are not unlimited, and when asset depletion takes place, or the magnitude of a shock cannot be buffered by the existing assets, the role of assets in helping households cope with shocks diminishes. According to McKernan, Ratcliffe and Shanks, (2012) households with limited assets are unable to borrow, even when they have access to credit, because they have insufficient collateral. This suggests that extreme poverty and asset accumulation (including access to credit), are incompatible, as one cannot be poor and still be in a position to build up wealth. Since lack of assets may continue to perpetuate poverty, governments need to devise policies that will promote asset acquisition by the poor, thus enabling such households to lift themselves out of poverty (McKay, 2009; Thorbecke and Ouyang, 2022; Mwabu, 2023).

In Africa, studies on effects of climate change on welfare include (Ahmed et al. 2011; FAO 2016a, b; Ubisi et al., 2017; Nsubuga et al. 2021; Ajaero et al. 2021), while only a few of the studies (Mulwa et al., 2016; Sherwood, 2013; Oduor and Mwiturubani, 2021) have been done in Kenya. Most climate change related studies done in Africa are country-specific, with many of them analyzing the impacts of climate change-related shocks, such as drought and flooding on rural households or agricultural sector, while very little focus exists on effects in urban areas. Based on studies done in Kenya, effects of climate change shocks are felt in rural and urban areas. Our study takes inspiration from these studies. Previous such studies in Kenya show that the effects of climate change on urban households can be negative (Oduor and Mwiturubani, 2021); or insignificant, as shown by Andersen and Verner (2010) in five Latin American countries (Bolivia, Mexico, Brazil, Peru, and Chile).Further, except for a few studies (see e.g. FAO, 2016b) most of the studies in Africa do not assess the differential impact of climate change by social groups. This is a pertinent issue, because climate-related shocks can impact household welfare both directly by reducing agricultural yields and productivity, and indirectly through, for instance, reducing farm employment and destroying household assets. The direct and indirect welfare effects of climate change are highlighted in the paper.

Kenya experiences major droughts every decade and minor ones every three to four years, a situation which has led to significant crop failures and higher food prices. At the other extreme, Kenya experiences severe riverine and flash flooding, particularly during the rainy seasons. Both shocks devastate lives, livelihoods and infrastructure (Opere 2013). This study contributes to existing literature in several ways. First, unlike previous studies which concentrate on the impacts of climate change in rural or urban areas, this study carries out similar analyses using national samples and sub-samples of rural and urban populations. Second, the study does not only look at separate welfare impacts of the climate shocks but also examines how and where shocks interact with household assets to worsen or improve livelihoods. Third, in addition to analysing the impacts of climate change shocks, our study analyses the differential impacts of climate change across social groups. Finally, our research design is such that its findings can be used to reduce poverty and inequality, and to achieve other SDG targets.

The remainder of the paper is organized as follows. Section 2 outlines an overview of climate change issues in Kenya while section 3 explains the methodology employed in the paper. Together, Sections 4 and 5 present, estimations results, the main findings and conclusions.

2. An Overview of Climate Change Issues in Kenya

The Republic of Kenya covers a total land area of 582,646 km^2 with varied formations of plains, escarpments, and hills, as well as low lands and high mountains. Kenya shares borders with Ethiopia to the north, South Sudan and Uganda to the northwest and west, Somali to the east, Tanzania to the south and has southeast coastline that borders the Indian Ocean. Approximately 85% of Kenya's land area is classified as a fragile, arid and semi-arid ecosystem, and is largely pastoral (NEMA, 2015). A majority of the population in Kenya lives in the highlands, which host significant farm lands, but they too, like the semi-arid ecosystem, are not immune to climate change shocks.

Climate change is increasingly impacting the lives of Kenyans and the environment, and has led to more frequent extreme weather events, like droughts which last longer, and irregular and unpredictable rainfall, flooding and increasing temperatures. Kenya is highly exposed to many natural hazards, the most common being floods and droughts. It is estimated that over 70% of natural disasters in Kenya are attributable to extreme climatic events (World Bank, 2021). Normally, in Kenya, major droughts occur approximately every ten years, and moderate droughts or floods break out every three to four years. Repeating patterns of floods and droughts in the country have had large, negative socio-economic impacts and high economic costs. For example, the 1998 to 2000 drought cost an estimated $2.8 billion, principally due to crops and livestock loss, as well as forest fires, damage to fisheries, reduced hydropower generation, reduced industrial production and reduced water supplies (NEMA, 2015). Droughts are often nation-wide and normally have the most severe impacts in the country's highly arid zones and remain a significant concern to Kenya's agricultural sector (Republic of Kenya, 2013a). On the other hand, floods have normally caused the greatest losses in terms of human lives and property. Vulnerability from these hazards poses major challenges for Kenya's economic stability and fiscal sustainability and have had adverse social and fiscal consequences. They also, make the already existing challenges with water security, food security and economic growth more difficult. Indeed, lower-income populations reside in more hazard prone locations.

Some of the counties that are most disaster-prone include Baringo, West Pokot, Kisumu, Laikipia, Turkana among others (see Development Initiatives Kenya, 2019). Figure1 shows a map of Kenya showing the prevalence of climate change shocks at county levels over the period 2010-2018. Datasets on climate shocks were obtained from the Geocoded Disasters (GDIS) data from the International Disasters Database (EM-DAT) which contains essential core information on the occurrence and effects of over 22,000 mass disasters in the world from the 1900s to the present day. The database is compiled from various sources, including UN agencies, non-governmental organisations, insurance companies, research institutes and press agencies. For a disaster to be entered into the EM-DAT database, at least one of the following criteria must be fulfilled: Ten (10) or more people reported killed; hundred (100) or more people reported affected; there must have been a declaration of a state of emergency; or a call for international assistance. For Kenya, there has been a total of about 412 events that meet the above criteria between 1997 and 2018. As shown in the figure, counties that experience high number of disasters are relatively in dark colours and those that experince fewer numbers are in relatively lighter colours. Counties in the northern, eastern, western and southern parts of the country experience a higher number of disasters due to drought and flooding, Many of the counties in Central Kenya and in parts of the rift valley experience fewer disasaters.

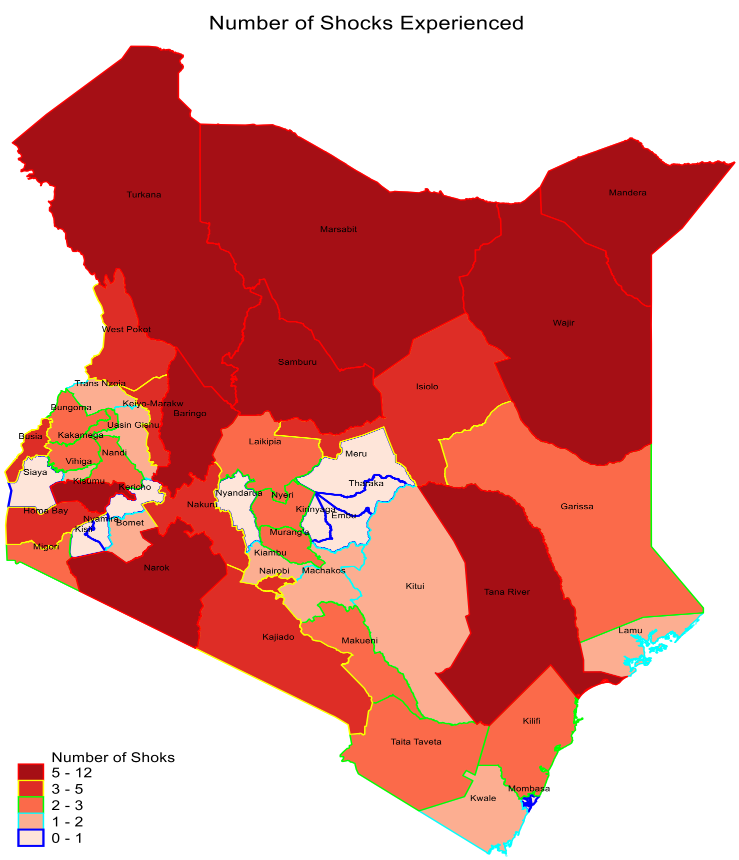


Figure 1: Map depicting county level number of climate change shocks encountered in 2010-2018

Climate change is expected to increase the risk and intensity of flood events, as well as increase average annual rainfall amounts, while also increasing drought likelihoods for many areas across Kenya. This is likely to increase the occurrence of mudslides and landslides, particularly in mountainous areas. Additionally, extreme rainfall rises may lead to soil erosion and water logging of crops is likely to reduce yields and increase food insecurity (World Bank, 2021). Furthermore, rising temperatures are also likely to increase the periods of aridity in the northwest counties of the country and reduce water storage capacities resulting in significant economic losses, damage to agricultural lands and infrastructure, as well as human casualties. Recurring disasters, particularly droughts and floods, have significantly impacted livelihoods and the country's economic development agenda. For instance, flood and drought events are becoming more frequent, with drought cycles occurring every 2–3 years instead of every 5–10 years, while severe and prolonged drought from 2008–2011 affected 3.7 million people, caused $12.1 billion in damages and losses, and cost over $1.7 billion in recovery and reconstruction (GFDRR, 2020). Additionally, deforestation, watershed degradation, land use changes, urbanisation and poor management of settlements have exacerbated the likelihood of, and negative impacts from floods and droughts, thereby contributing to water scarcity and pollution. Increasing urbanisation, particularly into flood plains and/or low-lying areas also has increased flood risk, as water drainage systems fail. Water stress may be further exacerbated as household consumption and agriculture continue to compete for limited supply (Republic of Kenya, 2013b).

In a bid to respond to climate change, from 2010 onwards, the government of Kenya developed a National Climate Change Response Strategy, NCCRS (2010), National Climate Change Action Plan, NCCAP (2013), and a National Adaptation Plan, NAP (2015). These strategies and plans jointly provided a vision for low carbon and climate-resilient development pathway. The government of Kenya also adopted the National Climate Change Framework Policy and enacted Climate Change Act (2016) to facilitate an effective response to climate change. Kenya has operationalised these policies and plans through the implementation of climate change actions in various sectoral plans, programs and projects, focusing on afforestation and reforestation, geothermal and other clean energy developments, and innovations in climate smart agriculture and drought management, amongst other endeavours.

In terms of the Nationally Determined Contribution (NDC) to reductions in pollutant emissions, the Kenyan government agreed to provide reports on NDCs every five years. The first NDC action went into effect on January 27, 2017. Based on conditional support, this NDC was designed to address both adaptation and mitigation contributions. The mitigation contribution aims to reduce greenhouse gas (CHG) emissions by 30% by 2030 compared to the business-as-usual scenario. However, the amended NDC for 2020 pledges to reducing CHG emissions by 32% by 2030 compared to the Business-as-Usual scenario of 143 Metric tons of carbon dioxide equivalence (MtC02eq). The implementation timetable for the 2020 NDC is up to 2030, with milestone objectives in 2025.Regarding Adaptation, Kenya aims at ensuring a climate resilient society. This is to be achieved through mainstreaming climate change adaptation into the Medium-Term Plans (MTPs) and County Integrated Development Plans (CIDPs) and implementing adaptation actions. Kenya is committed to enhancing its adaptation ambition by committing to bridging the implementation gaps.

3. Methodology

This section describes the conceptual and empirical models used in the analysis of the nexus between household welfare and climate change and ends with a discussion of the datasets used. The dependent, endogenous, exogenous and control variables that characterise the different models estimated are presented in some detail.

3.1 The conceptual model: narrative and diagrammatic representation

Climate change shocks can be defined as adverse events that lead to a loss of household income, a reduction in consumption and/or a loss of productive assets (Dercon et al. 2005). Given the adverse nature of the climate change shocks, the welfare loss associated with them is worth measuring (see, e.g. Dercon, 2004; Kazianga and Udry, 2006; Tol, 2009). Moreover, although it is known from these studies that household access to credit and asset ownership can help households cope with the adverse effects of climate change shocks, the mechanisms involved are unclear. The impact of climate change shocks on household welfare may be felt directly or indirectly through asset endowments. To analyse the impact of climate change shocks on welfare, we draw from the conceptual framework proposed in Skoufias et al. (2011).

According to Skoufias et al (2011) climate change shocks may impact household welfare through a variety of channels due to the fact that the impacts of climate change shocks are not homogeneous, as the shocks themselves can be different (e.g., droughts, floods, forest fires) and also, can affect households at different levels through direct or indirect pathways at different moments in time. Due to the complexities involved in modelling some of the channels, the strand of literature in this area largely focuses on agricultural and livelihoods impacts of climate change, especially as felt through losses in physical, financial, human, social and natural assets.

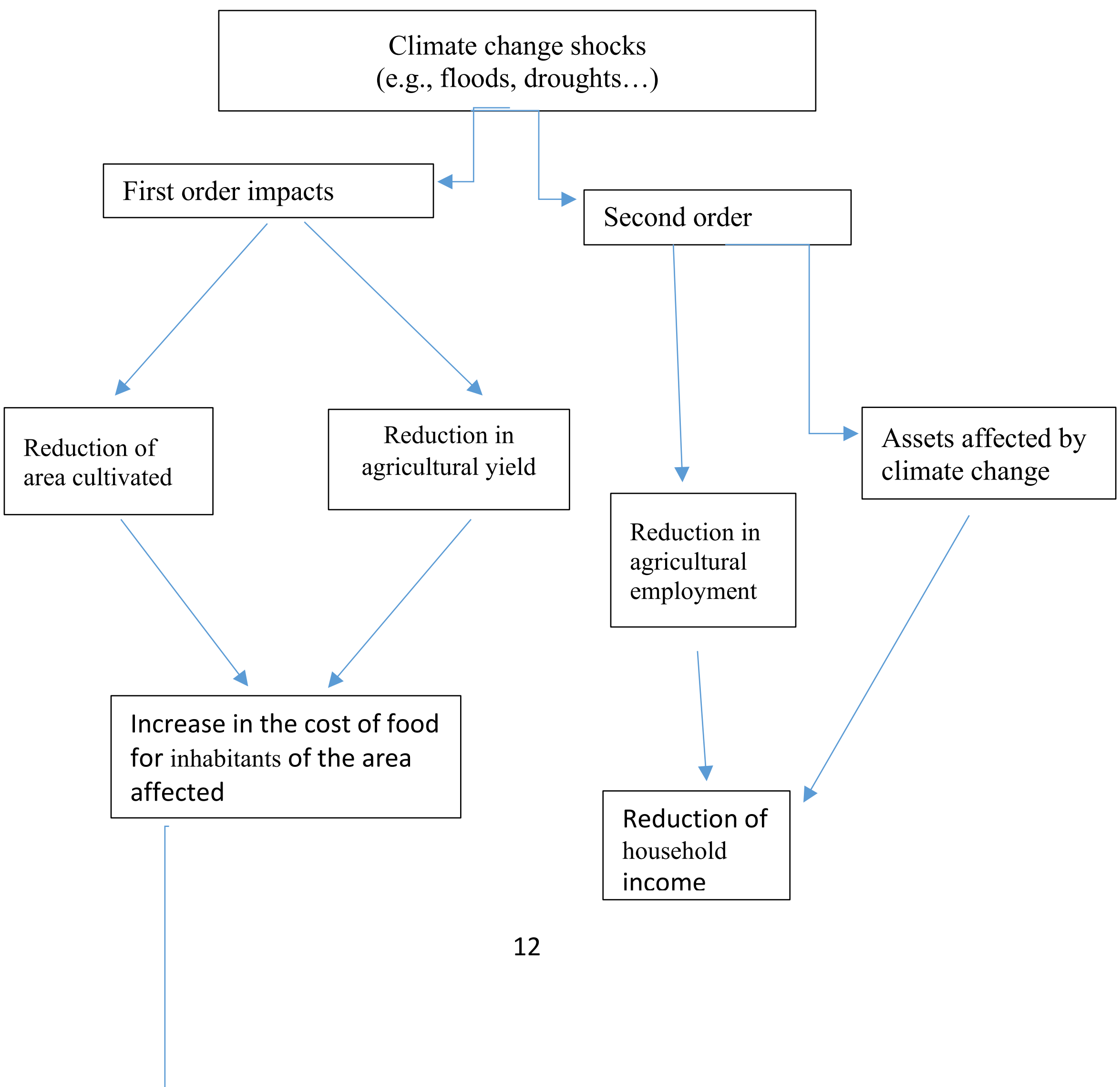
As shown in Figure 2, a particular climate change shock has different and sometimes compounding impacts on household well-being. The climate change impacts can be mitigated by accumulation of certain assets and by access to credit, among others. As shown in the figure, a climate change shock (e.g., a flood) can have first order (direct) or second order (indirect) impact. For instance, the direct impacts would be the damage of agricultural yields, and a reduction in the area cultivated that a flood damages. The compounded impacts of these direct and indirect impacts for inhabitants of the area affected implies an increase in the cost of food. The cost is induced by higher temperatures and highly variable rainfall patterns that change the hydrological cycle, ultimately affecting crop yields and total factor productivities. Moreover, if the rain is excessive, it can lead to loss of lives, and to severe damage in agricultural production and infrastructure (IPCC, 2001). When the agricultural activity is of subsistence nature, the effect on consumption is through reductions in the quantities produced, while in the case of market-oriented activity, the adverse welfare effects would typically be through quantities and prices.

These adverse effects can be observed depending on whether households are able to put in place effective ex-ante and/or ex-post coping strategies. The former protect households from income losses before they occur while the latter take effect after realisation of shocks and losses (Morduch, 1995). Ex-ante strategies, such as diversification of economic activities, allow households to smooth income and thus consumption. For example, when climate change shocks occur frequently, rural households would be expected to shift production into more climate resilient but less profitable crops (Rosenzweig and Binswanger, 1993; Dercon, 1996). On the other hand, ex-post strategies, allow households to directly smooth consumption through borrowing, saving and insurance schemes. Many of these strategies may not be pursued by small-holders in low-income countries because of incomplete or missing financial markets. However, farmers may still achieve some level of consumption smoothing by accumulating and depleting non-financial assets or using non-market mechanisms. In Ethiopia, for instance, Dercon (2004) shows that rural households are able to offset the risk of food consumption losses caused by the low level of rainfall by addressing the risk within the village, but obviously leaving the aggregate rainfall shocks that affect all villages uninsured.

Figure 2 shows that floods can have large indirect impacts, such as reducing agricultural employment in each area and damaging some of the assets owned by households. Due to this, household income would be affected in different ways. However, not all assets are affected by floods in the same way. As such, unscathed assets provide some source of income against negative impacts of the climate shock. The balance of household income versus the cost of food shapes different dimensions of wellbeing depending on pathways at work. For example, the buffering role of assets might help one to understand the ways in which climate change impacts differ across locations and households. The resilience of households relying on asset accumulation as a buffer against climate change losses has been revealed by

Kodwo-Ansah and Gardebroek (2021). Assets, thus, have been found to effectively moderate effects of climate change shocks. Due to this, it has been argued that physical, financial, and social assets play an important role in cushioning adverse effects of climate change on livelihoods (Kodwo-Ansah and Gardebroek, 2021). However, assets are not unlimited, and when asset depletion takes place, or the magnitude of a shock cannot be entirely compensated by the existing assets, their effectiveness as a coping strategy is greatly diminished.

The outcome variables in Figure 2 comprise various measures of the household economic wellbeing. If households are able to implement sufficient ex-ante and ex-post protection measures, then one would expect to see zero impact of climate shocks on per adult consumption expenditure. Statistically significant negative impacts of climate change shocks on welfare measures would be an indication of household reliance on insufficient coping mechanisms (see e.g., Musyoka, 2020). Our empirical analysis sheds light on the linkages between climatic shocks, households' welfare - their adaptation strategies and public policies that can be implemented to address climate change risks to livelihoods.



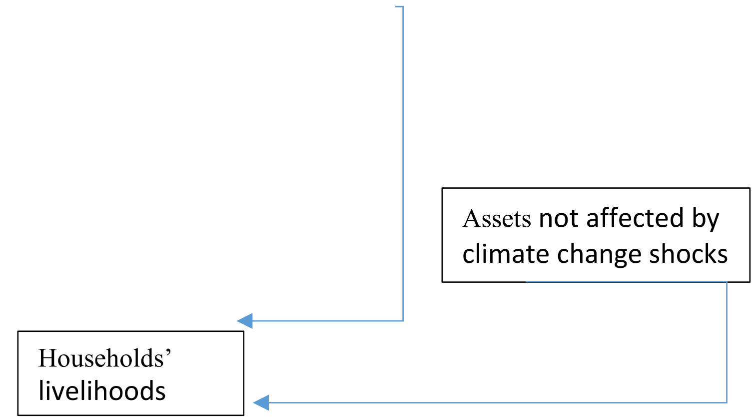


Figure 2: Multiple welfare impacts of climate change shocks

Source: Adapted from (Bimal, 1998)

3.2 Empirical Models

When estimating the impacts of climate change shocks and asset ownership on welfare, we take into account the problems of endogeneity and heterogeneity that are likely to bias the estimated impacts. First, household asset ownership and welfare are likely to be jointly determined. In this case, asset ownership is likely to be correlated with the structural error term. In addition, unobserved household preferences can interact non-linearly with the asset ownership, yielding unobservable differences in consumption across households. Other hidden variables (such as inherited traits or attitudes to risk) could similarly bias the estimates of the welfare function. We use the control function approach (Wooldridge, 2002, 2015) and (Papke and Wooldridge, 2008) to address these estimation challenges.

Equation (1) presents the first stage regression in the control function procedure.

$$\mathbf{HAI_i = \alpha + \lambda ACHAI + \gamma CCS_\tau + \Sigma \delta_k Z_{ip} + \upsilon_i} \tag{1}$$

Where, **HAI** is household asset index; **ACHAI** is cluster level average of household asset index which is used as an instrument for **HAI; CCS** is a set of climate change shocks, **Z** is a set of other control variables and $\mathbf{\upsilon_i}$ is the reduced-form error term.

The second step of the control function estimates the structural welfare equation, as in Wooldridge (2015).

$$\ln(PAECE_i) = \alpha + \phi CCS_i + \mu HAI_i + + \Sigma\beta_k Z_k + \theta_1 HAI\_res_i + \theta_2 (HAI_i{*}HAI\_res_i) + \varepsilon_i \quad (2)$$

where household welfare is proxied by per adult equivalent consumption expenditure (**PAECE**),

HAI_res_i is the reduced-form residual from equation (1), while **$HAI_i{*}HAI\_res_i$** is the interaction term constructed by interacting the reduced-form residual with the observed (actual) value for the index of the assets owned by a household (**HAI).** The reduced residual, on its own serves as a control for the unobservable variables contained in ε_i - that are potentially correlated with **HAI_i.** The control ensures that in the absence of heterogeneity the coefficient on **HAI.**is unbiased. The interaction removes any heterogeneity in household welfare function (i.e. in μ) due to unobservable factors across households. The disturbance term, ε_i, comprises random and the unobservable parts and **α, λ, γ, δ,ϕ, μ, β,** and **θ** are vectors of parameters to be estimated.

Two variants of the model are estimated: in the first variant, climate change shock is proxied by flooding/drought, as reported in the household surveys; in the second version, the climate change shock is generated using county level monthly rainfall data. The reason for estimating the two models is to see whether there is any consistency in results based on climate change shocks reported at the household- and county levels.

The models can allow one to test the hypothesis that households are able to completely mitigate the negative effects of climate change shocks. In addition, by including variables that capture asset ownership and access to credit, we are able to investigate whether their impacts are effective in reducing the negative welfare effects of climate change.

Further, we analyse effects of climatic change shocks on different household profiles such as area of residence and poverty status using quantile regression. The same analysis is extended to the national level. Quantile regression estimates are preferred because they are more robust to data outliers than the classical linear regression estimates (Blunch and Verner, 2001; Koenker and Hallock, 2001; Mwabu, 2023). The quantile regression provides a richer examination of the data, allowing one to consider the impacts of a covariate on the entire distribution of the household economic wellbeing.

We adopt the estimation strategies of Armstrong, Frome and King (1979), Buchinsky (1994), Barrodale and Roberts (1973) and Chamberlain (1994) and minimise the sum of absolute deviations of the outcome variable from an arbitrarily chosen quantile. The standard errors of the estimated quantile regression coefficients are computed by the methods of Chamberlain (1994), Koenker and Bassett (1982).

3.3 Variables

The climate change shock is proxied by flooding or drought as reported in the household surveys (in the first variant of the model), while in the second, the drought/flooding shock is approximated by generated monthly rainfall amounts computed using county level data.

The climate change shock variables (CCS) for equation (1) are as reported by respondents. It is not possible to isolate flooding from drought as both are reported as shocks in a single variable. The covariates for equation (1), include generated climate change shocks ($CRSG_{2i}$) and ($CRSG_{4i}$), which respectively, refer to standardised 2-year and 4-year generated climate change shocks, with each being included separately in regressions. Following previous research (e.g., Asmamaw et. al., 2019; Makate et al., 2022), a climate change shock is measured as the deviation from a historical average for a year before the year of the survey. Thus, the climate change shock is calculated using 2-year and 4-year average monthly rainfall deviations from a long-term average monthly rainfall, which is then divided by standard deviation of the long-run average, as follows:

$$\text{Rainfall\_shock}_{c,} = \frac{\overline{monthly\_rain}_{\ 2or4year} - \overline{mean\_rain_{(1985-2014)}}}{\sigma_{Rc}} \qquad (3)$$

Where, rainfall_shock$_{c,}$ is a standardised rainfall deviation measure for a county. This is the average monthly rainfall in the previous 2 or 4 years before the survey year (*t*). In our case, t=2015, and the long run average monthly rainfall for the county is for the period 1985-2014. The parameter, σ_{Rc}. is the standard deviation of the average monthly rainfall for this long run period. Negative deviations denote scarcity of precipitation while positive values indicate excessive precipitation. Although negative/positive values do not necessarily mean drought/flooding conditions, they are likely to have an impact on agricultural production and productivity in one way or another.

We use the above formula to generate the 2-year and 4-year rainfall shocks for each county, which are then merged with the household-level data from KIHBS for 2015/16. Two separate regression estimations are conducted, the first based on past 2-year average climate change shocks, and the second one based on a 4-years average climate change shocks, as just defined. To summarise - for robustness checks, 2 model variants are estimated with generated rainfall shocks: in the first, the welfare variable is conditioned on the preceding 2-year climate change shock, plus the controls, and in the second, it is similarly regressed on the preceding 4-year shock. It is worth noting that a control variable need not be exogenous. When it's not exogenous, its main role is to absorb unobservables in the structural error term that are correlated with the policy variable of interest, such as the HAI (Stock, 2010).

The household asset (**HAI**) is constructed from the following assets: household durables, livestock, vehicles, farm machinery, among others. The household asset ownership index is obtained using the method developed by Wittenberg and Leibbrandt (2017).

The measurements and definitions of the variables used in the analysis are summarised in Table 1. The unit of analysis in the household but climate variables driving household welfare is at the county level. The dependent variable is the natural logarithm of per adult equivalent consumption expenditure. When estimating the regression equations, we include the interaction term between climate change shocks and asset ownership index. The second order impacts of climate change may be through destruction of some of the assets from which the index is constructed. Alternatively, the shock may not destroy the assets, meaning, income and consumption expenditure would not be affected. If the effect of climate change shock on welfare is negative and the coefficient of interaction term between climate change shock and the assets index is also negative, the household ability to mitigate the negative welfare impacts of the shock is doubly reduced. If the effect of climate change shock is negative but the coefficient of interaction term between climate change shock and assets index is positive, the negative welfare impact is mitigated.

Table 1: Description of variables

Variables	**Measurements**
Dependent variable	
Per adult equivalent consumption expenditure	Natural logarithm of per adult equivalent consumption expenditure
Exogenous and endogenous variables	
Climate change shock (CCS)	Dummy variable taking a value of 1 if the household reported flooding/drought as a severe shock, 0 otherwise
Standardised rainfall shock ($CSRG_2$)	Standardised difference (SD) in average monthly rainfall for each county for 2-year periods before 2015. The SD is equal to the mean rainfall for (2013-2014) minus the rainfall mean for (1985-2014), standardized using Equation (3).
Standardised rainfall shock ($CSRG_4$)	Standardised difference in average mean monthly rainfall for each county for 4-year periods before 2015; i.e., computed as the difference between the mean for (2011-2014) and (1985-2014), as in Equation (3).

Asset ownership index (HAI) (endogenous)	Household asset ownership index (see Wittenberg and Leibbrandt, 2017).
Cluster mean of asset ownership index (ACHAI)	Cluster level average of household asset ownership index
Household access to credit (HAC)	Dummy variable taking a value of 1 for households that reported having access to credit (a proxy for an opportunity to convert assets into liquidity using them as collateral for loans); 0 otherwise
Household size (HS)	Number of individuals in each household
Male head of household (MHD)	Dummy variable taking a value of 1 for male headed households, 0 otherwise.
Age of household head (AH)	Age of head of household, years
Urban residence (URD)	Dummy variable taking a value of 1 for urban household residence, 0 otherwise
Primary education (HPE)	Dummy variables taking a value 1 for the household head with primary education level, 0 for no schooling
Secondary education (HSE)	Dummy variables taking the value of 1 for household head with secondary education level, 0 otherwise
Tertiary education (HTE)	Dummy variables taking the value of 1 for household head with tertiary education level, 0 otherwise
A member of the household has formal employment (HHFE)	Dummy variable taking the value of 1 if a household's member has formal employment, 0 otherwise

3.4 Data Sources

The Kenya Integrated Household Survey (KIHBS) 2015/2016 is the main data set used. The KIHBS 2015/16 is a population-based survey, covering the whole country. The main objectives of the survey are to provide data that can be used to compute poverty and inequality indicators. The 2015/16 KIHBS sample is drawn from NASSEP V frame used by the Kenya National Bureau of Statistics (KNBS) to conduct the national surveys. The sample size for KIHBS 2015/16 survey is 24,000 households, spread across 2,400 clusters. KIHBS 2015/16 isa nationally representative household survey collected over a period of about 12 months. The survey covers all the regions in the country both rural and urban areas. The reference periods used in the KIHBS (last week, last month, last year) are not bounded, which can lead to serious telescoping (misdating) errors. The data on food consumption used a 7-day recall period; regular non-food expenditures used a one-month recall period, while data on household durables used a one-year recall period. The weighting of the two datasets is based on the selection probabilities in each survey domain. The design weights are adjusted using the survey response to give the final weights. This is necessitated by the survey data being not self-weighting, since the sample allocation is not proportional to the size of the strata. Seasonality is not controlled for when collecting the data and this may affect measurement of household expenditure. Further, some counties especially those from North Eastern of Kenya may be under-represented in the sample. (see, KNBS, 2016).

Climate variables are derived using temperature and rainfall data extracted from the IGAD Climate Prediction and Application Centre (ICPAC) website available at: http://digilib.icpac.net/SOURCES/.UEA/.CRU/.TS3p21/.monthly/.pre/dataselection.html. The link is for Climate Research Unit at the University of East Anglia. Climatic Research Unit (CRU) TS (time-series) datasets are month-by-month variations in climate over the last century or so. The data are calculated on high-resolution (0.5x0.5 degrees) grids, which are based on an archive of monthly average daily maximum and minimum temperatures provided by more than 4000 weather stations distributed around the world allowing for variations in climate to be studied. CRU TS 3.21 variables are cloud cover, diurnal temperature range, frost day frequency, PET, precipitation, daily mean temperature, monthly average daily maximum and minimum temperature, vapour pressure and wet day frequency for the period Jan. 1901 - Dec. 2012. In addition to updating the dataset with 2012 data, the v3.21 release corrects two errors in the v3.20 dataset. This data is citable as; (DOI: 10.5285/D0E1585D-3417-485F-87AE-4FCECF10A992). We obtained monthly data on rainfall and temperature for each county for the period 1950-2019 and use it to generate the climate shock and climate variation variables.

3.5 Descriptive Statistics

The descriptive results are presented in Table 2. As shown in the table, on average per adult equivalent consumption expenditure is Kshs. 7809.96 but with large variation across households in rural and urban areas. The average per adult equivalent consumption expenditure in urban areas is about double that in rural areas. The national average household asset ownership index is 5.52. The variation in asset index between rural and urban areas is very high with the mean index for urban areas being 9.15 and 3.14 for rural areas. The average household size at the national level is 4 members but household size differs between rural and urban areas with a typical household size in rural areas being 5 and in urban areas being 3. The average age of a household head is 43 years with the average age in rural areas being higher than in urban areas. About 43.4% of the households in sample reside in urban areas.

Table 2: Descriptive Statistics at the national level

Variables	National Mean	Rural Mean	Urban mean
Per adult consumption expenditure (annual)	7809.96	5328.44	11,076.34
Asset ownership index	5.52	3.14	9.15
Household size	4.00	5.00	3.00
Age of household head	43.39	47.05	38.58

Source: own estimates based on KIHBS 2015/2016 datasets

Figure 3 shows proportion of some of characteristics of the sample data at national level and both in rural and urban areas. About 27% of the households in the sample indicated that they have access to credit (liquid asset), and this does not differ across rural and urban areas. About 67% of the households in our sample are headed by men with 72% and 63% of households in urban and rural areas headed by men, respectively. In terms of education, most household heads at the national and rural areas have primary education (45%) followed by those with secondary education (25%) and tertiary education (15%) with the remaining having no formal education. Urban areas have relatively higher proportion of household heads with secondary and tertiary education. About 44% of the households have at least one of their members in formal employment with households in the urban areas having 53% and those rural areas having 38%.

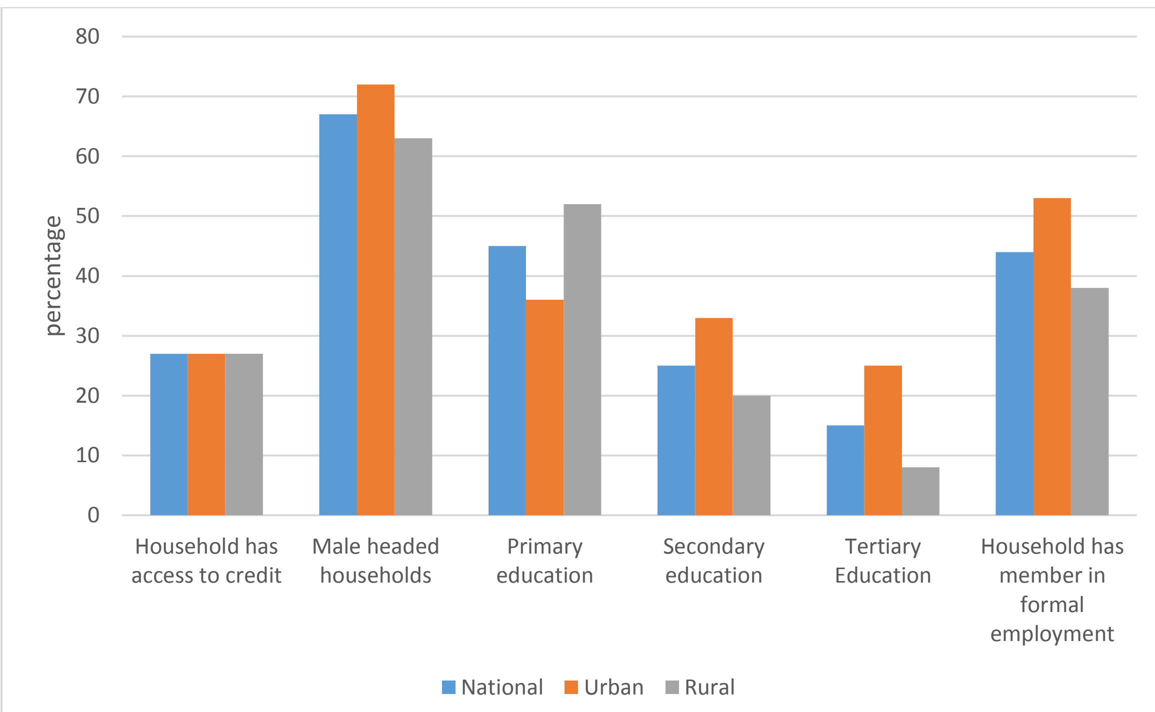


Figure 3: Proportion of selected variables for the sample data at national level and by region

Source: own estimates based on KIHBS 2015/2016 datasets

4. Estimation Results

This section presents the estimated regression results. We start by presenting and discussing control function parameters estimates, followed by quantile regressions results. Before discussing the welfare regression results, we briefly discuss results from the reduced form regressions (see some of the results in Appendix Table 2). As shown in the table, the coefficient of average cluster household asset ownership index is statistically significant at the 1 percent level. This shows that it is a strong and relevant instrument for asset ownership. Other variables with statistically significant coefficients include access to credit, family size, age of the household head, and education of the household head.

4.1 Control Function Estimates

Table 3 shows the control function results for the first variant of equation 2 based on household reported climate change shocks. As shown in Table 3, the coefficient of residuals from the reduced form regression is statistically significant in the national regression, and insignificant in the rural and urban regression sub-samples. This shows that household asset ownership is endogenous in the national welfare regression equation but not in the rural and urban sub-samples. The coefficient of the interaction term between household asset ownership and the residuals is negative and significant in all the three sub-samples. This shows that heterogeneity is addressed by the control function procedure.

Table 3: Control function estimates - welfare impact of reported climate change shocks (dependent variable: natural logarithm of per adult consumption expenditure)

Variables	National	Urban	Rural
	Coefficients	Coefficients	Coefficients
Household reported flooding/drought	-0.1354*** (0.040)	-0.0951** (0.042)	-0.1331*** (0.048)
Interaction of climate change shocks and asset ownership index	0.0196*** (0.003)	0.0120*** (0.003)	0.0241*** (0.006)
Asset ownership Index	0.0364*** (0.004)	0.0313*** (0.003)	0.0699*** (0.008)
Household has access to credit	0.0815*** (0.020)	0.0459*** (0.020)	0.0949*** (0.027)
Household size	-0.0922*** (0.004)	-0.1040*** (0.005)	-0.0846*** (0.004)
Male headed households	0.0287*** (0.011)	0.0150 (0.013)	0.0392*** (0.015)
Age of household head/10	-0.0230*** (0.005)	-0.0285*** (0.007)	-0.0247*** (0.006)
Urban household residence	0.1522*** (0.024)		
Household head has primary education	0.1858** (0.036)	0.1311*** (0.039)	0.1578*** (0.041)
Household head has secondary education	0.2977*** (0.033)	0.2503*** (0.042)	0.2279*** (0.046)
Household head has tertiary education	0.4247*** (0.045)	0.4103*** (0.0064)	0.2358*** (0.064)
Household member has formal employment	0.0077 (0.016)	0.0078 (0.018)	-0.0057 (0.019)
Household asset residuals	0.0038** (0.002)	0.0001 (0.002)	-0.0025 (0.006)
Interaction between residuals and household assets	-0.0008***	-0.0005***	-0.0018***

	(0.0001)	(0.048)	(0.0002)
Constant	8.5620*** (0.053)	8.8717*** (0.048)	8.46940*** (0.055)
R-squared	0.497	0.514	0.361
Number of observations	22,914	9,074	13,840

As shown in Table 3, the impact of drought/flooding on household welfare is negative and statistically significant in the national level and in the urban and rural areas. This shows that climate change shocks reduce household welfare (see FAO 2016 for similar findings for Tanzania). The negative impact of climate change shocks on household welfare is higher for rural areas than for urban areas. The coefficients on climate changes shocks and that for the interaction terms are jointly statistically significant in all the three regressions. The interaction terms have positive coefficients meaning that they help to cushion the households from negative impacts of climate change shocks

Also, the results show that household welfare is higher for households with higher asset ownership levels than for those with lower levels as shown by its positive and significant coefficients. This pattern is consistent at the national level and for households living in urban and rural areas. Further, having access to credit improves the welfare of the household as shown by the positive and statistically significant coefficient for this variable at the national and in rural and urban areas. However, the fact that the coefficient of climate change shocks at the national, urban and rural areas is negative and statically significant shows that household asset ownerships and access to credit both of which have positive coefficients, help to cushion household welfare from the negative effects of shocks but this buffering might not be sufficient to eliminate these adverse effects.

The results further show that regardless of whether households live in rural or urban areas, a large household size is associated with lower welfare and vice versa, as shown by the negative and statistically significant coefficient of the household size. Also, households that are headed by men experience higher welfare compared to female headed households, but this is significant at the national and rural areas regressions but not for urban regression. As expected, household welfare decreases as age of household head increases. Household welfare is positively correlated with urban residence. Relative to household headed by members with pre-primary/no education, the estimated coefficient of those heads with primary, secondary and tertiary education is positive and statistically significant at the nation level and in the rural and urban regressions. Furthermore, the coefficients increase with the level of education of the head of household, and this shows that welfare is higher for households headed by individuals with higher levels of education. In general, human capital endowment (proxied by health and education) are major determinants of household economic wellbeing, even after taking into account impacts of climate shocks. Finally, the coefficients on formal employment are positive but statistically insignificant in all regressions.

Table 4 shows results of the effect of climate change shocks using climate change shocks generated using county level monthly rainfall. Two variants are estimated, one using a 2-year and the other using 4-year standardised deviation of rainfall from the long run average. As shown in Table 4, the coefficient of residuals from the reduced form regressions are statistically insignificant in all welfare regressions estimates of the two variants. This shows that household asset ownership is not endogenous. The coefficients of the interaction term between household asset ownership and the residuals are statistically significant in all the regressions. It also shows that including the interaction term in the regression has resolved the problem of heterogeneity.

As shown in the table, coefficient estimates based on 2-year and 4-year climate change shocks are negative and statistically significant, an indication that climate change shocks reduce household welfare at national level and in rural and urban areas. The climate change shock coefficients show that whether based on 2-year or 4-year averages, the effects of climate change shock on household welfare are similar to those obtained when using respondents-reported climate change shocks (see Table 3). Thus, there is some consistency in the results on the impact of climate change shock on household welfare when using either reported or generated climate change shocks. The coefficients of the climate change shocks and interaction term between the shocks and household asset ownership are jointly statistically significant (except for the 2-year generated climate change shock for rural regression). The positive coefficient of the interaction terms is an indication that it helps cushion household welfare from the negative climate change impact.

Asset ownership index has a positive and statistically significant impact on per adult consumption expenditure. Similarly, having access to credit improves the welfare of the household as shown by the positive and statistically significant coefficient on credit access. Again, the fact that the coefficient of climate change shock on household welfare at the national, urban and rural areas is negative and statistically significant shows that household asset ownerships and access to credit (with their positive coefficients) help to cushion household welfare from the negative effects of climate change but might not eliminate these effects. The results of the other control variables are generally similar to those of the results in Table 3.

Table 4: Control function estimates: welfare impacts of generated climate change shocks:(Dependent variable: natural logarithm of per adult consumption expenditure)

	Model: 2-year generated climate change shocks	**Model: 4-year generated climate change shocks**

Variable	National	Urban	Rural	National	Urban	Rural
	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients
Rainfall shock	-0.1368*** (0.049)	-0.1477*** (0.057)	-0.0976* (0.054)	-0.1421*** (0.034)	-0.1473*** (0.032)	-0.1159*** (0.039)
Interaction-of rainfall shock with asset index	0.0112*** (0.004)	0.0099*** (0.004)	0.0100* (0.006)	0.0105*** (0.002)	0.0086*** (0.002)	0.0114*** (0.004)
Asset ownership index	0.0395*** (0.003)	0.0334*** (0.002)	0.0746*** (0.007)	0.0380*** (0.003)	0.0319*** (0.002)	0.0711*** (0.007)
Household has access to credit (liquid asset)	0.0775*** (0.019)	0.0475*** (0.019)	0.0886*** (0.027)	0.0862*** (0.018)	0.0548*** (0.019)	0.0972*** (0.025)
Household size	-0.0917*** (0.004)	-0.1029*** (0.005)	-0.0845*** (0.004)	-0.0915*** (0.004)	-0.1018*** (0.005)	-0.0848*** (0.004)
Male headed households	0.0280*** (0.010)	0.0154 (0.013)	0.0381*** (0.015)	0.0257*** (0.010)	0.0118 (0.013)	0.0367*** (0.014)
Age of household head/100?	-0.0222*** (0.005)	-0.0286*** (0.006)	-0.0239*** (0.006)	-0.0203*** (0.005)	-0.0261*** (0.006)	-0.0224*** (0.006)
Urban household residence	0.1604*** (0.023)			0.1570*** (0.022)		
Household head has primary education	0.2040*** (0.038)	0.1392*** (0.037)	0.1757*** (0.044)	0.2133*** (0.036)	0.1478*** (0.038)	0.1866*** (0.041)
Household head has secondary education	0.3177*** (0.038)	0.2576*** (0.040)	0.2501*** (0.047)	0.3274*** (0.036)	0.2670*** (0.041)	0.2644*** (0.043)
Household head has tertiary education	0.4374*** (0.041)	0.4111*** (0.042)	0.2537*** (0.062)	0.4430*** (0.037)	0.4219*** (0.044)	0.2698*** (0.054)
Household member has formal employment	-0.0119 (0.016)	0.0082 (0.018)	-0.0010 (0.019)	0.0109 (0.016)	0.0069 (0.017)	-0.0008 (0.019)
Household asset residual	0.0035 (0.002)	-0.0003 (0.002)	0.0022 (0.002)	0.0032 (0.002)	0.0002 (0.002)	-0.0019 {0.006}
Interaction between household asset index and its residuals	-0.0008*** (0.0002)	-0.0005*** (0.0001)	-0.0018*** (0.0002)	-0.0008*** (0.0002)	-0.0005*** (0.0001)	-0.0018*** (0.0002)
Constant	8.5106*** (0.060)	8.8453*** (0.044)	8.4638*** (0.069)	8.5241*** (0.056)	8.8531*** (0.043)	8.4327*** (0.061)
R-squared	0.496	0.516	0.358	0.501	0.521	0.362
Number of observations	22,914	9,074	13,840	22,914	9,074	13,840

4.2 Quantile Regression Results

The motivation for quantile regression analysis is to understand whether there are differential impacts of the climate change shocks at different points of the household wellbeing function. Only results of interest (on climate change shocks, household asset ownership index and their interaction terms) are presented in Table 5. As shown in the table, the coefficients of respondents-reported climate change shock are negative and statistically significant at the national level and for urban and rural areas at all quantiles. As in Table, the endogeneity issue is addressed in the quantile regressions.

Table 5: Selected quantile regression results (dependent variable: per adult equivalent consumption expenditure).

Selected variables	*Quantile Regressions*				
	0.1	**0.25**	**0.5**	**0.75**	**0.9**
	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients
National Regressions					
Respondents-reported drought/rainfall shock	-0.1759*** (0.018)	-0.1456*** (0.011)	-0.1321*** (0.012)	-0.1036*** (0.016)	-0.0924*** (0.016)
Interaction climate change shock and asset ownership index	0.0172*** (0.003)	0.0178*** (0.002)	0.0218*** (0.029)	0.0213*** (0.004)	0.0224*** (0.030)
Asset ownership Index	0.0331*** (0.001)	0.0364*** (0.001)	0.0371*** (0.001)	0.0392*** (0.001)	0.0370*** (0.001)
Generated 2-year rainfall shock	-0.1911*** (0.016)	-0.1451*** (0.016)	-0.1239*** (0.011)	-0.1077*** (0.013)	-0.0846*** (0.013)
Interaction- rainfall shock and asset index	0.0144*** (0.001)	0.0101*** (0.002)	0.0084*** (0.001)	0.0109*** (0.003)	0.0120*** (0.002)
Asset ownership index	0.0363*** (0.001)	0.0384*** (0.002)	0.0394*** (0.001)	0.0425*** (0.001)	0.0407*** (0.001)
Rural Regressions					
Respondents-reported drought/rainfall shock	-0.1932*** (0.020)	-0.1653*** (0.015)	-0.1261*** (0.018)	-0.0876*** (0.020)	-0.0641*** (0.018)
Interaction climate change shock and asset ownership index	0.0300*** (0.003)	0.0284*** (0.004)	0.0233*** (0.003)	0.0259*** (0.004)	0.0180*** (0.004)
Asset ownership Index	0.0632*** (0.005)	0.0693*** (0.005)	0.0753*** (0.003)	0.0718*** (0.005)	0.0694*** (0.005)
Generated 2-year rainfall shock	-0.1583*** (0.017)	-0.0960*** (0.019)	-0.0831*** (0.018)	-0.0751*** (0.022)	-0.0596*** (0.015)
Interaction- rainfall shock and asset index	0.0114*** (0.004)	0.0094** (0.004)	0.0100*** (0.003)	0.0128*** (0.004)	0.0103*** (0.003)
Asset ownership index	0.0659*** (0.006)	0.0758*** (0.003)	0.0803*** (0.003)	0.0776*** (0.003)	0.0719*** (0.004)
Urban Regression					
Respondents-reported drought/rainfall shock	-0.1243*** (0.034)	-0.0768*** (0.034)	-0.0925*** (0.029)	-0.1049*** (0.032)	-0.0779** (0.034)
Interaction climate change shock and asset ownership index	0.0082*** (0.003)	0.0006** (0.004)	0.0134*** (0.003)	0.0130*** (0.003)	0.0098** (0.027)
Asset ownership Index	0.0283** (0.001)	0.0312*** (0.001)	0.0312*** (0.001)	0.0323*** (0.001)	0.0309*** (0.002)
Generated 2-year rainfall shock	-0.1992*** (0.022)	-0.1795*** (0.028)	-0.1630*** (0.022)	-0.1199*** (0.021)	-0.0816*** (0.032)
Interaction- rainfall shock and asset index	0.0102*** (0.001)	0.0109*** (0.002)	0.0085*** (0.001)	0.0098*** (0.002)	0.0089*** (0.003)
Asset ownership index	0.0306*** (0.002)	0.0329*** (0.001)	0.0322*** (0.001)	0.0354*** (0.001)	0.0334*** (0.002)

The coefficients of the climate change shocks are higher at lower quantiles than at higher quantiles. Since the poor and the non-poor can have residuals of the same magnitude, it is not possible to tell how differently the two groups are being affected by shocks. However, the effects on mean residuals differ from those at other quantiles of the household expenditure residuals. That is, the residuals of household expenditures can be small or large irrespective of the economic status of a household. Thus, it is hard to tell from these results how the poor and rich households are affected by climate shocks. Still, if we assume that rich households are able to smooth consumption better than poor households, it is possible to conclude that the latter are more affected by climate shocks. The negative and statically significant coefficient for the rainfall shocks for urban areas quantile regression supports the finding by Owuor and Mwiturubani (2021) that the indirect impacts of floods in Nairobi's settlements especially households living in flood-prone areas suffer perennial loss of livelihoods, environmental degradation, loss of man hours in traffic jams and economic loss. The joint tests for the coefficients of the shocks and those of their interaction with household asset ownership are all statistically significant in all the regression (see Table 5). The coefficients for the interaction term are positive in all the regressions meaning that it helps to cushion rural households from the negative effect of climate change shocks. The coefficients on asset ownership remain positive and statistically significant for national, urban and rural areas at all quantiles, irrespective of the variant of regression model estimated.

Similar results are replicated by the coefficients for the 4-year climate change shocks (see Appendix Table 2 for results) where the coefficients for climate change shocks are negative and statistically significant. The interaction terms between the asset ownership and the climate shocks are generally positive and statistically significant, as seen earlier.

5. Summary and Conclusion

There is little doubt that climate change shocks are a major concern globally and Kenya is no exception as it experiences various climate and weather extremes resulting from climate change, including prolonged droughts; frost in some of the productive agricultural areas; hailstorms; extreme flooding leading to fluctuating lake levels; and drying of rivers and wetlands. These extremes can lead to large economic losses, adversely impact food security and other dimensions of household welfare. The main objective of this study is to analyse the impact of climate change shocks on household welfare and assess the effects across the poor and non-poor households. We further assess how well household asset ownership and access to credit can help cushion household welfare from the negative effects of climate change. To achieve the objective, merged household data - KIHBS 2015/2016 and county level climate change shocks data are used to analyse the impact of climate change on household welfare. We estimate the model using control functions and conditional quantile methods. The analysis is done at the national level and separately for rural and urban households to assess heterogeneous welfare effects of climate change.

The results based on households reported climate change shocks and the generated standardised climate change (deviations from long run average monthly county level rainfall) show that climate change shocks reduce the welfare of Kenyans, regardless of residence poverty status. However, household assets and access to credit cushion households from adverse effects of climate change but partially.

The results based on quantile regressions show the climate change effects vary by quantiles but it is not easy to tell how the poor and the non-poor are affected by the shocks without assumptions on consumption smoothing. Depending on what happens to the assets owned by households when climate change shocks occur it may or may not reduce the household economic wellbeing. Overall, the effect of asset ownership on household welfare remains positive for all quantiles.

Ideally, if household coping strategies are effective or provide adequate insurance against adverse effects of climate change shocks household welfare would not be affected. This means that any action taken by government to protect households would have no added value. However, if households' strategies fall short, government actions can be hugely beneficial. Examples of public policies that could be implemented include creation of a favourable environment for households to increase asset ownership; enhancement of access to credit in times of economic crisis; and establishment of non-contributory social protection programme – to be activated whenever severe shocks occur.

References

Adelekan, I. O and A.P. Asiyanbi (2016). Flood risk perception in flood-affected communities in Lagos, Nigeria, *Nat. Hazards* 80 (1) (2016) 445–469. https://doi.org/10.1007/s11069-015-1977-2.

Ahmed, S., N. Diffenbaugh, and T. Hertel. (2009). Climate volatility deepens poverty vulnerability in developing countries, *Environmental Research Letters* 4(3): 1-8.

Andersen, L. and D. Verner. (2010). Simulating the effects of climate change on poverty and inequality, Chapter 9. In: D. Verner (2010), Reducing poverty, protecting livelihoods and building assets in a changing climate: social implications of climate change for Latin America and the Caribbean. World Bank, Washington, DC.

Armstrong, R. D., Frome, E., and Kung, D. S. (1979). A revised simplex algorithm for the absolute deviation curve fitting problem. *Communications in Statistics*, BS, 175-190.

Bardhan, P. and Udry, C. (1999). *Development Microeconomics*. Oxford University Press

Barrios, S., Bertinelli, L. and E. Strobl (2003). Dry times in Africa, CREDIT Working Paper, 03/07.

Barrodale, I. and F. Roberts. (1974). Solution of an over-determined system of equations in the L1 norm [F4] (Algorithm 478). *Communications of the ACM*. 17:6, pp. 319–20.

Blunch, N H and Verner, D (2001). Revisiting the link between poverty and child labour: The Ghanaian experience. CLS Working Paper No. 01-03, Available at SSRN: https://ssrn.com/abstract=298562 or http://dx.doi.org/10.2139/ssrn298562

Buchinsky, M., (1994). Changes in the U.S. wage structure 1963 - 1987: Application of quantile regression. *Econometrica,* 62, 405-458.

Carter, M. R. and Barrett, C. B. (2006). The economics of poverty traps and persistent poverty: An asset-based approach. *Journal of Development Studies*, 42(2): 178-199.

Chamberlain, Gary. (1994). Quantile regression, censoring and the structure of wages, In: *Advances in Econometrics*, Christopher Sims, ed., New York: Elsevier, pp. 171–209.

Dercon, S. (1996). Risk, crop choice, and savings: Evidence from Tanzania. *Economic development and cultural change*, 44(3):485–514.

Dercon, S. (2004). Growth and shocks: evidence from rural Ethiopia. *Journal of Development Economics, 74*(2):309–329.

Dercon, S., J. Hoddinott and T. Woldehanna. (2005). Consumption and shocks in 15 Ethiopian Villages, 1999-2004. *Journal of African Economies*, 14: 559-585.

Dercon, S., and P. Krishnan. (1996). A consumption-based measure of poverty in Ethiopia: 1989-1994, In: M. Taddesse and B. Kebede, Poverty and economic reform in Ethiopia, Proceedings Annual Conference of the Ethiopian Economics Association.

Development Initiatives Kenya (2019). Tracking subnational government investments in disaster risk reduction in Kenya. https://reliefweb.int/sites/reliefweb.int/files/resources/Tracking-subnational-government-investments-in-disaster-risk-reduction-in-Kenya.pdf

Dorosh, Paul, Hyoung Gun Wang, Liangzhi You, and Emily Schmidt. (2011). Road Connectivity, Population, and Crop Production in Sub-Saharan Africa. Agricultural Economics 43 (1): 89–103. https://www.researchgate.net/publication/230469503_Road_connectivity_population_and_crop_production_in_ Sub-SaharanAfrica

FAO (2016a). *Welfare impacts of climate shocks: evidence from Tanzania*, by Aslihan Arslan, Federico Rome, FAO.

FAO 2016 b). *Welfare impacts of climate shocks: Evidence from Uganda* by Asfaw, S., Mortari, A. P., Arslan, A., Karfakis, P., and L., Lipper (2016)" Technical Report, DOI: 10.13140/RG.2.1.4581.7200

Fosu, A.K. (2015). Growth, inequality and poverty in Sub-Saharan Africa: Recent progress in a global context. *Oxford Development Studies*. 43:1, 44-59.

GFDRR (2020). Kenya Overview. https://www.gfdrr.org/en/kenya

Intergovernmental Panel on Climate Change [IPCC] (2021). Summary for Policymakers. In: Masson-Delmotte V et al. (eds.) Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Intergovernmental Panel on Climate Change [IPCC] (2022). Summary for Policymakers. In: Pörtner H-O et al. (eds.) Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Kazianga, H. and Udry, C. (2006). Consumption smoothing? livestock, insurance and drought in rural Burkina Faso. *Journal of Development Economics*, 79(2):413–446.

Kodwo-Andoh and Gardebroek, C.(2021). Shock interactions, coping strategy choices, and household food security.*Climate and Development*. 13, 5, p. 414-426.

Koenker, R. and Hallock, K. (2001), Quantile regression. Journal of Economic Perspectives, 15, 143-156. http://dx.doi.org/10.1257/jep.15.4.143.

Koenker, R., & Bassett, G. (1982). Robust tests for heteroskedasticity based on regression quantiles. *Econometrica*, 50, 43-61.http://dx.doi.org/10.2307/1912528.

Kumaraswamy, S K, Max M, and E Hernandez. (2020). "Assets matter to poor people: But what do we know about financing assets?" Working Paper. Washington, D.C.: CGAP.

Makate, C., Angelsen, A., Holden, S. T., andWestengen, O. T. (2022). Crops in crises: Shocks shape smallholders' diversification in rural Ethiopia. *World Development*, *159*, 106054.

McKay, A. (2009). Assets and chronic poverty: Background paper. Working Paper No. 100. Chronic Poverty Research Centre. University of Sussex, Brighton, UK.

Morduch, J. (1995). Income smoothing and consumption smoothing. *Journal of Economic Perspectives*, 9:103–103.

Musyoka P K (2020). Shocks and household welfare in Kenya. PhD Thesis,University of Nairobi.

Mwabu, G. (2023), Poverty reduction through growth, redistribution and social inclusion in times of COVID-19: Kenyan evidence on the underlying mechanisms, *Journal of African Economies,* **32,** ii69–ii80.

National Environment Management Authority (2015). Kenya- second national communication to the United National Framework Convention on Climate Change, Executive Summary. https://unfccc.int/sites/default/files/resource/Kennc2.pdf

New Climate Economy (2018). Unlocking the inclusive growth story of the 21st century: Accelerating climate action in urgent times. Global Commission on the Economy and Climate.

Nyiwul L. (2021). Climate change adaptation and inequality in Africa: Case of water, energy and food insecurity. *Journal of Cleaner Production*. 278:123393. DOI: 10.1016/j.jclepro.2020.123393.

Otegui, M. E., Nicolini, M. G., Ruiz, R. A., and Dodds, P. A. (1995). Sowing date effects on grain yield components for different maize genotypes. *Agron. J.*, pages 29–33.

Owuor M O and D. A Mwiturubani (2021). Nexus between flooding impacts and coping strategies in Nairobi's settlements,*International Journal of Disaster Risk Reduction*, Vol. 64.

Pelser, A. J. and Chimukuche, R.S. (2022). Climate change, rural livelihoods, and human well-being: experiences from Kenya. In (Ed.), Vegetation Dynamics, Changing Ecosystems and Human Responsibility [Working Title]. IntechOpen. https://doi.org/10.5772/intechopen.104965.

Rahut DB, Aryal JP, Marenya P. (2021). Understanding climate-risk coping strategies among farm households: Evidence from five countries in eastern and southern Africa. *The Science of the Total Environment*. 769:145236. DOI: 10.1016/j.scitotenv.2021.145236.

Rahut DB, Aryal JP, and Marenya P. (2021). Understanding climate-risk coping strategies among farm households: Evidence from five countries in eastern and southern Africa. *The Science of the Total Environment*. 769:145236. DOI: 10.1016/j.scitotenv.2021.145236.

Republic of Kenya (2013a). National Climate Change Action Plan, 2013–2017: Vision 2030. https://cdkn.org/wp-content/uploads/2013/03/Kenya-National-Climate-Change-Action-Plan.pdf

Republic of Kenya (2013b). Sector plan for drought risk management and ending drought emergencies, Second medium-term plan: 2013–2017. https://www.ndma.go.ke/index.php/resource-center/send/43-ending-drought-emergencies/4271-ede-mediumterm-plan-2013-2017

Siegel, Paul. (2005). Using an asset-based approach to identify drivers of sustainable rural growth and poverty reduction in Central America: A conceptual framework. Policy Research Working Paper

3475. http://documents.worldbank.org/curated/en/307691468743185566/Using-an-asset-based-approach-to-identify-drivers-of-sustainable-rural-growth-and-poverty-reduction-in-Central-America-a-conceptual-framework..

Skoufias, E., K. Vinha, and H. V. Conroy (2011). The Impacts of climate variability on welfare in Rural Mexico,Policy Research Working Paper 5555. World Bank, Washington DC.

Stock, James H, (2010). The other transformation in econometric practice robust teols for inference, *Journal of Economic Perspectives*, 24 (2):83–94.

Thorbecke, E. and Ouyang, Y. (2022). Towards a virtuous spiral between poverty reduction and growth: Comparing Sub Saharan Africa with the developing world, *World Development*, Vol. 152.

Tol, R. S. (2009). The economic effects of climate change. *The Journal of Economic Perspectives*, 23(2):29–51.

United Nations Department of Economic and Social Affairs (2015). Sustainable Development: The 17 goals. Available from: https://sdgs.un.org/goals.

Wittenburg, M. and Leibbrandt, M. (2017), Measuring inequality by asset indices: A general approach with application to South Africa. *Review of Income and Wealth*, 63(4): 706-730.

Wopereis, M., Kropff, M., Maligaya, A., and Tuong, T. (1996). Drought-stress responses of two lowland rice cultivars to soil water status. *Field Crops Research*, 46(1–3):21 – 39.

World Bank (2021). Climate Risk Country Profile: Kenya, Washington, DC.

World Bank (2022). Kenya Economic Update. Washington, DC.

APPENDICES

Appendix A:

Selected quantile regression results (Dependent variable is per adult equivalent consumption expenditure).

Selected variables	***Quantile Regressions***				
	0.1	**0.25**	**0.5**	**0.75**	**0.9**
	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients
National Level Regressions					
Generated 4-year rainfall shock	-0.1560*** (0.010)	-0.1447*** (0.006)	-0.1323*** (0.010)	-0.1311*** (0.011)	-0.1447*** (0.014)
Interaction- rainfall shock and asset index	0.0094*** (0.001)	0.0096*** (0.001)	0.0088*** (0.001)	0.0110*** (0.001)	0.0137*** (0.002)
Asset ownership index	0.0353*** (0.001)	0.0365*** (0.001)	0.0380*** (0.001)	0.0397*** (0.001)	0.0403*** (0.002)
Rural Areas Regressions					
Generated 4-year rainfall shock	-0.1355*** (0.019)	-0.1078*** (0.012)	-0.1011*** (0.011)	-0.0997*** (0.016)	-0.1132*** (0.019)
Interaction- rainfall shock and asset index	0.0106*** (0.003)	0.0119*** (0.002)	0.0112*** (0.003)	0.0117*** (0.003)	0.0128*** (0.004)
Asset ownership index	0.0628*** (0.006)	0.0714*** (0.004)	0.0762*** (0.003)	0.0732*** (0.002)	0.0691*** (0.005)
Urban Areas Regression					
Generated 4-year rainfall shock	-0.1703*** (0.021)	-0.1662*** (0.018)	-0.1544*** (0.015)	-0.1380*** (0.014)	-0.1402*** (0.026)
Interaction- rainfall shock and asset index	0.0088*** (0.001)	0.0086*** (0.001)	0.0075*** (0.001)	0.0090*** (0.002)	0.0100*** (0.002)
Asset ownership index	0.0294*** (0.002)	0.0313*** (0.001)	0.0305*** (0.001)	0.0334*** (0.001)	0.0325***(0.001)

Appendix B:

First step regression: - reduced form household asset ownership equation (Dependent variable is household asset ownership index)

Variables	National	Urban	Rural
	Coefficients	Coefficients	Coefficients
Cluster level average household asset index	0.8826*** (0.012)	0.8766*** (0.013)	0.8423*** (0.015)
Household reported flooding/drought	-0.0172 (0.066)	-0.1783 (0.189)	-0.0300 (0.061)
Household has access to credit	0.3476*** (0.093)	0.5757*** (0.148)	0.2385*** (0.094)
Household size	0.1362*** (0.020)	0.2509*** (0.044)	0.0627*** (0.011)
Male headed households	-0.0146 (0.070)	-0.0824 (0.133)	0.0505 (0.064)
Age of household head/10	0.1350*** (0.030)	0.2817*** (0.062)	0.0601*** (0.021)
Urban household residence	-0.1274** (0.051)		
Household head has primary education	0.0506 (0.093)	0.4290* (0.236)	0.1161 (0.081)
Household head has secondary education	1.4319*** (0.162)	2.4277*** (0.337)	1.1144*** (0.130)
Household head has tertiary education	6.6799*** (0.366)	8.1259*** (0.510)	5.4222*** (0.394)
Household member has formal employment	0.4567*** (0.088)	0.7756*** (0.173)	0.2390*** (0.075)
Constant	-1.8968***	-3.8690***	-0.8898***

	(0.270)	(0.544)	(0.168)
R-squared	0.647	0.631	0.458
Number of observations	22,914	9,074	13,840