Shouldering the Weight of Climate Change: Intra-household Resource Allocation after Rainfall Shocks*

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PRELIMINARY VERSION

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Abstract

This paper investigates the effect of rainfall shocks on the allocation of household consumption among children, women, and men in Malawi. The identification relies on the spatial-temporal variation in the occurrence of rainfall shocks in four agricultural growing seasons between 2010 and 2019. I estimate a collective model of household to retrieve individual resource shares and their determinants. Results show that a drought in the growing season is likely to induce the redistribution of household resources from women and children towards men. Welfare analyses based on the comparison of individual consumption and poverty rates show that women tend to bear the burden of the shock within the household. The negative effect of a drought on women's resource shares is more pronounced in areas where men are more actively involved in income-generating and off-farm activities than women after a drought. This suggests that the drought-induced redistribution of resources within household is likely motivated by 'life-boat ethics', that is, nourishing the members with higher marginal productivity and potential to bring cash income to the household.

Keywords: Climate shock, rainfall, collective model, intra-household inequality, individual poverty, life-boat ethics, cultural norms.
JEL codes: D13, I15, J16, Q15, Q54, Z13

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1 Introduction

Extreme weather events have become more frequent due to the accelerating pace of climate change. Poorer countries are particularly vulnerable to climate shocks, as they heavily depend on agricultural resources and lack necessary means to cope with these extreme events (Georgieva et al., 2022).[1] A large body of literature shows that climate shocks, such as drought and floods, tend to damage or completely destroy crops and other productive assets of households in low-income countries, which further result in substantial losses of income and consumption (Morduch, 1995, Townsend, 1995, Kazianga and Udry, 2006, Maccini and Yang, 2009, Skoufias and Vinha, 2013, Janzen and Carter, 2019).

While household-level welfare impacts of climate shocks are well-documented, little is known about who bears the burden of these shocks within the household.[2] Unequal welfare impacts within the household can be driven by various factors. For instance, if individuals make labor supply adjustments in response to climate-induced negative income shocks by increasing the number of hours worked or switching to off-farm employment (Branco and Féres, 2021, Agamile et al., 2021, Afridi et al., 2022), their consumption needs may also change accordingly and reflect on the intra-household distribution of consumption. Another possible mechanism may operate through the impact of climate shocks on the distribution of bargaining power within household. For example, if only husband's income or productive assets are negatively affected by extreme weather events, his contribution to household income diminishes, so as his say on intra-household decisions related to the allocation of food or other household resources (Duflo and Udry, 2004, Dubois and Ligon, 2011, Quisumbing et al., 2018).

This paper aims to understand whether exposure to climate shocks alters the allocation of consumption among household members. A direct assessment of this question is usually constrained by the scarcity of consumption data at the individual level. Related studies exploit individual nutrition or anthropometric data to investigate intra-household response to rainfall shocks (Dercon and Krishnan, 2000, Hoddinott and Kinsey, 2000, Hoddinott, 2006). Nevertheless, the recent extensions of collective household models offer the tractable way of recovering the share of household resources accruing to each household member and its

[1]For instance, in the period between 1998 and 2017 low-income countries lost 1.8% of their GDP due to climate-related disasters, while high-income countries lost about 0.4% of their GDP (CRED and UNISDR, 2018).

[2]Most of existing literature on the effects of climate-related disasters on individual well-being focus on health or educational outcomes. For instance, when affected by drought, women tend to lose more body weight compared to men (Hoddinott and Kinsey, 2000, Hoddinott, 2006) possibly due to a relatively larger reduction in meal intake among women (Serna, 2011). Among children, those who are born at the time of a natural disaster become less advantaged, in terms of health and educational outcomes, compared to their siblings who are born in normal times (Hoddinott and Kinsey, 2001, Alderman et al., 2006, Maccini and Yang, 2009, Currie and Vogl, 2012, Groppo and Kraehnert, 2016, 2017, Dinkelman, 2017, Lo Bue, 2019).

determinants using household-level consumption data (Bargain and Donni, 2012, Browning et al., 2013, Dunbar et al., 2013, Bargain, Donni and Hentati, 2022). These models have been applied to assess, for example, the role of cultural norms (Calvi and Keskar, 2021, Aminjonov et al., 2022) in intra-household resource sharing, the impact of positive income shocks (Tommasi, 2019, Sokullu and Valente, 2022) or negative labor market shocks (Bargain and Martinoty, 2019) on individual resource shares. In this paper, I suggest another application of this approach to test whether exposure to a rainfall shock affects the way resources are distributed among household members, and how it ultimately reflects on consumption and poverty at the individual level.

In this paper, I investigate rainfall shocks in Malawi between 2010 and 2019. Malawi is one of the poorest countries in the world, with around around 70% of population living below the poverty line of $2.5 per day (2017 PPP) (World Bank, 2023b). Most of the population live in rural areas and depend on subsistence farming, in particular, rain-fed crops such as maize, for their livelihoods. This certainly raises vulnerability to frequent natural disasters such as floods and droughts, which result in crop failures, increased food insecurity and poverty.[3] Implications of these extreme climate events in Malawi have been investigated in various contexts, often in relation with household welfare, agriculture, migration, gender or child outcomes (Fisher et al., 2010, Stevens and Madani, 2016, McCarthy et al., 2016, Asfaw and Maggio, 2018, McCarthy et al., 2018, Becerra-Valbuena and Millock, 2021, McCarthy et al., 2021, Caruso et al., 2022, Dessy et al., 2023), but not in terms of intra-household effects. Hence, the present study seeks to extend this previous research by examining intra-household effects of rainfall shocks in Malawi.

I start with the estimation of a collective household model to retrieve the share of household consumption allocated to men, women and children, following the methodological framework suggested in Bargain and Donni (2012) and Dunbar et al. (2013). I pool four waves of household consumption data for Malawi and combine it with geocoded rainfall data from Vicente-Serrano et al. (2010) to determine which households are exposed to drought or excess rainfall during agricultural growing (or rainy) seasons of 2009/10, 2012/13, 2015/16 and 2018/19. In the estimation model, the indicators of drought and excess rainfall with spatial-temporal variation is originally introduced as distribution factors in resource share functions, along with fixed effect terms to control for spatial and time differences among households. The identification relies on the fact that rainfall shocks occur randomly, in terms of space and time, and are plausibly exogenous after controlling for geographical and time differences.

I find that after a drought in the growing season, women tend to receive smaller share of

[3]For instance, droughts tend to increase poverty by 1.3 percentage points, rising to 17 percentage points if drought is extreme (i.e. 1-in-25 year drought) (World Bank, 2023a).

household resources, in comparison to the scenario with no rainfall shock. The magnitude is, on average, around 11-12 percent decrease in per-woman resource shares. Children's resource shares are also found to decrease following a drought in the rainy season, with the magnitude equivalent to 8 percent of average per-child shares. Taken together, post-disaster reductions in resource shares of women and children imply the redistribution of household resources towards men. This pattern of re-allocation makes men's individual consumption and poverty relatively more incompressible when households are hit by a drought, while exacerbating its negative income effect for women and children. Excess rainfalls (e.g. flood) in the growing season do not seem to alter women's shares significantly, but are found to increase children's resource shares. A complementary analysis involving the estimation of rainfall shock effects on time-use allocation within the household and a set of heterogeneity analyses with respect to the gender gap in employment suggest that the redistribution of resources in favor of men after droughts is likely driven by 'life-boat ethics' (Pitt et al., 1990): a larger share of resources directed to men who have higher marginal productivity and capacity to bring home income from off-farm activities in comparison to women who still have limited access to off-farm opportunities in many parts of Sub-Saharan Africa (Palacios-Lopez et al., 2017). An alternative potential mechanism could be, as noted above, a change in the distribution of bargaining power within household after droughts. I do not find any statistically significant effect of drought on the indicators of women's control over household resources. Yet, I find a relatively stronger effect of drought on the resource shares of women living in areas where subsistence crop and maize farming are more prevalent, i.e. where women are usually more involved in agricultural work and are more likely to lose, to a certain extent, their bargaining power when drought damages their crop.

To my knowledge, this is the first study to quantify the impact of extreme climate events on resource allocation among men, women and children within the household and their *individual* consumption, complementing previous studies that focus on intra-household distribution of nutrition after climate shocks (Dercon and Krishnan, 2000, Hoddinott and Kinsey, 2000, Hoddinott, 2006). From policy perspective, this contributes to identifying and targeting the most vulnerable or 'newly' poor individuals, rather than households, by taking into account both inter-household and intra-household effects of natural disasters (Skoufias, 2003). In addition, the analysis on potential underlying mechanisms highlights the importance of labor market reforms that would provide women a better access to off-farm employment opportunities, which as the findings of this paper show, is crucial for women's welfare especially in times of economic distress due to climate events.

The rest of the paper is structured as follows. Section 2 presents the empirical approach, the identification strategy, the data. Section 3 presents estimation results and discusses potential mechanisms. Section 4 provides concluding remarks.

2 Empirical Approach

2.1 Identification of Resource Allocation Process

Collective Models and Sharing Rule. The methodology applied in this paper builds on the broad literature of collective household models. The core idea in these models is that households make decisions through the bargaining process (Chiappori, 1988, Bourguignon and Browning, 1991). Originally, collective models assume that households decisions are efficient - the assumption that allows decentralization of household decision-making process. The outcome of this process is a sharing rule, that is, the way household resources are distributed among its members. After household resources are allocated, each individual makes his/her own decisions based on available resources and preferences (Chiappori, 1992). Recent methodological extensions have suggested ways to identify sharing rule using household-level consumption data both for childless couples (Lewbel and Pendakur, 2008, Browning et al., 2013) and for couples with children (Bargain and Donni, 2012, Bargain, Donni and Hentati, 2022, Dunbar et al., 2013). Identification in these methods requires additional assumptions and extra information related to preferences (e.g. preference stability, using data on singles). In this paper, I employ similar approach with the assumption that total household expenditure is shared among its members based on some rule, but without imposing the efficiency assumption that is often regarded in the collective model literature as the common way to justify decentralization of decision-making, and yet, not the only one that can explain intra-household allocation process.[4]

Sharing Rule. I start by assuming that the allocation of household resources is determined by *a sharing rule*. Denote x the log of total private expenditure and $\eta_{i,s}(z^r)$ the share of total private expenditure $\exp(x)$ accruing to each individual of type $i = f, m, c$, i.e. women, men and children, in a household of composition s. Household composition is characterized by the numbers of individuals in each of the three groups denoted by s_f, s_m and s_c respectively and stacked in vector $s = (s_f, s_m, s_c)$. Under the sharing rule, each household member of type i in a family of composition s receives, in log terms, $x_{i,s} = x + \ln \eta_{i,s}$ as her own private resources. Note that in a complex household, for example with several adult women and men, this approach allows identifying only the total resource share of each group $s_i \times \eta_{i,s}(z^r)$,

[4]Efficiency is often questioned in the context of poor countries (see Baland and Ziparo 2018). Although empirical rejections relates to production decisions (e.g. Udry 1996) rather than consumption, efficiency is more defensible in the case of frequently decisions with less of a strategic content, such as daily consumption (see Baland and Ziparo 2017). Also note that using the data from Bangladesh, Lewbel and Pendakur (2019) show that the departure from efficiency leads to relatively small variation of resource sharing estimations.

and not the resource shares among the persons of each type. Hence, $\eta_{i,s}$ represents a per-person resource share of individual type i.[5] Resource shares depend on a set of determinants in vector z^r, which include (i) household demographic characteristics (e.g. the number and average age of men, women and children, the proportion of boys among children); (ii) indicators of exposure to rainfall shocks (in binary or continuous form); and (iii) grid fixed effects (one grid corresponds a spatial area of approximately 50 km^2 at which rainfall is measured) to account grid-level differences among households, and survey wave fixed effects to account for general time-related factors.[6]

Structural Engel Curves at Individual and Household Level. Following Bargain and Donni (2012) and Dunbar et al. (2013), I adopt a semi-parametric identification based on the assumption of Piglog indirect utility function (Deaton and Muellbauer, 1980). This approach yields individual Engel curves that are linear in the logarithm of individual resources. Namely, for a good k consumed by any person of type i, the *individual budget share* is written as:

$$w_{i,s}^{k} = \alpha_{i,s}(z^p) + \beta_{i,s}(z^p) \cdot x_{i,s}(z^r), \tag{1}$$

with z^p preference shifters and z^r sharing rule determinants . The identification requires the presence of exclusive goods, that is, goods consumed only by specific type of individuals. Denote these goods k_c, k_f, k_m for children, women, and men respectively. For example, if k_f corresponds to female clothing, a woman living in a household composition of s spends $w_{f,s}^{k_f}$ share of her resources $\exp(x_{i,s})$ on clothing. As a function of (log) individual expenditure, the equation (1) defines individual Engel curves. With the structure placed on individual demand, household Engel curves can also be retrieved. Multiplying individual Engel curve $w_{i,s}^{k_i}$ by resource share $\eta_{i,s} = \exp(x_{i,s})/\exp(x_s)$ and the number of persons of type i would show the level of spending on good k_i as a fraction of total household expenditure (i.e. family budget share): $W_s^{k_i} = s_i \cdot \eta_{i,s} \cdot w_{i,s}^{k_i}$. Given that family budget shares are usually observed in standard expenditure surveys, I can write a system of household budget shares for exclusive goods of women, men and children:

$$\begin{aligned} W_s^{k_c} &= s_c \cdot \eta_{c,s}(z^r) \cdot (\alpha_{c,s}(z^p) + \beta_{c,s}(z^p) \cdot (x + \ln \eta_{c,s}(z^r))) \\ W_s^{k_f} &= s_f \cdot \eta_{f,s}(z^r) \cdot (\alpha_{f,s}(z^p) + \beta_{f,s}(z^p) \cdot (x + \ln \eta_{f,s}(z^r))) \\ W_s^{k_m} &= s_m \cdot \eta_{m,s}(z^r) \cdot (\alpha_{m,s}(z^p) + \beta_{m,s}(z^p) \cdot (x + \ln \eta_{m,s}(z^r))). \end{aligned} \tag{2}$$

[5]To estimate the resource shares of, for example, young women vs. old women among the $i = f$, the model would need expenditure data on exclusive goods related each subgroup (i.e. expenditure on young women's clothing vs. old women's clothing). While this is a data limitation, one can control in the sharing rule for specific variables such as age of women (as done in Calvi (2020)) to investigate gender bias in sharing rule (cf. Bargain et al. (2014) or Dunbar et al. (2013)).

[6]They also depend on prices but time variation in market prices is captured by survey wave fixed effects

Restrictions and Identification of Resource Shares. The identification strategy here aims at retrieving the key elements in the above system from the reduced-form estimation of family budget shares on log household expenditure. First, as resource shares add up to one, one of the resource shares can be rewritten as a complement to the rest. For instance, if I choose men's resource share as 'residual', I can rewrite it as: $s_m\eta_{m,s} = 1 - s_c\eta_{c,s} - s_f\eta_{f,s}$. Consequently, the derivatives of the system in the equation (2) with respect to log household expenditure are:

$$\begin{aligned} \partial W_s^{k_c}/\partial x &= s_c \cdot \eta_{c,s}(z^r) \cdot \beta_{c,s}(z^p) \\ \partial W_s^{k_f}/\partial x &= s_f \cdot \eta_{f,s}(z^r) \cdot \beta_{m,s}(z^p) \\ \partial W_s^{k_m}/\partial x &= s_m \cdot (1 - s_c \cdot \eta_{c,s}(z^r) - s_f \cdot \eta_{f,s}(z^r)) \cdot \beta_{m,s}(z^p) \end{aligned} \tag{3}$$

for each s out of total S household compositions. The left-hand derivatives are observed and the system has $3S$ equations and $5S$ unknowns $(\eta_{c,s}, \eta_{f,s}, \beta_{c,s}, \beta_{f,s} and \beta_{m,s}$ for each $s)$. For the identification of resource shares, one needs to put additional restriction on preference term β. I employ the Similarity Across People (SAP) assumption as suggested by Dunbar et al. (2013). This assumption implies that the shape of individual Engel curves for exclusive goods is similar across individual types, which formally yields : $\beta_{c,s} = \beta_{f,s} = \beta_{m,s} = \beta_s$ for each $s > 0$. Thus, it provides an exact identification with $3S$ unknowns $((\eta_{c,s}, \eta_{f,s}, \beta_s$ for each $s)$ and $3S$ equations.[7]

2.2 Specification and Estimation Method

Specification. As specified in the equations (1) and (2), the semi-parametric approach based on Piglog preferences provides the log-linear specification of household Engel curves. To estimate the model, I add error terms $\epsilon_{i,s}$ to each household Engel curve in the demand system in (2) and impose the SAP restriction as follows:

$$\begin{aligned} W_s^{k_c} &= s_c \cdot \eta_{c,s}(z^r) \cdot (\alpha_{c,s}(z^p) + \beta_s(z^p)(x + \ln \eta_{c,s}(z^r))) + \epsilon_{c,s} \\ W_s^{k_f} &= s_f \cdot \eta_{f,s}(z^r) \cdot (\alpha_{f,s}(z^p) + \beta_s(z^p)(x + \ln \eta_{f,s}(z^r))) + \epsilon_{f,s} \\ W_s^{k_m} &= s_m \cdot \eta_{m,s}(z^r) \cdot (\alpha_{m,s}(z^p) + \beta_s(z^p)(x + \ln \eta_{m,s}(z^r))) + \epsilon_{m,s} \end{aligned} \tag{4}$$

with

$$s_m \cdot \eta_{m,s}(z^r) = 1 - s_c \cdot \eta_{c,s}(z^r) - s_f \cdot \eta_{f,s}(z^r)$$

Engel curve parameters $\alpha(z^p)$ and $\beta(z^p)$ vary linearly with a set of preference shifters z^p. These variables include household composition indicators (s_f, s_m, s_c) and urban dummy.

[7] In a series of tests using directly observed resource shares, Bargain, Lacroix and Tiberti (2022) tend not to reject SAP.

Similarly, resource shares $\eta_{f,s}(z^r)$ also take a linear form with a set z^r variables that include: (i) variables in z^p; (ii) other household demographic factors, including average age of children, men, and women, and the proportion of boys; (iii) variables measuring rainfall shocks; and (iv) vectors of grid and survey wave fixed effects to account for differences across grids and time.[8]

The estimation of the system in (4) is computationally demanding, especially, in the presence of fixed effects and multiplicative terms that generate interactions between variables in z^p and z^r. For instance, with five regressors in z^p (including constant term) and 60 variables in z^r (including grid fixed effects for 47 grids and survey wave fixed effects for four waves, with one group dropped as a reference category in each dimension), the multiplicative term $\eta_{i,s} \cdot \beta_s$ would generate 300 parameters to be estimated in each Engel curve. To ease the burden on estimation process, I introduce a simplification in the estimation, using one of the features of the SAP assumption. Let the Engel curve for total clothing in household be given by $W_s = \sum_i W_s^{k_i}$. Then, given the SAP and that the resource shares add up to one, the derivative of this total Engel curve with respect to log expenditure is:

$$\begin{aligned} \partial W_s/\partial x &= \sum_i \partial W_s^{k_i}/\partial x \\ &= \sum_i s_i \cdot \eta_{i,s}(z^r) \cdot \beta_s(z^p) \\ &= \beta_s(z^p) \sum_i s_i \cdot \eta_{i,s}(z^r) \\ &= \beta_s(z^p) \end{aligned} \tag{5}$$

This implies that preference term $\beta_s(z^p)$ can simply be obtained by estimating the Engel curve for total clothing:

$$W_s = \alpha_s(z^p) + \beta_s(z^p)x + \epsilon_s \tag{6}$$

with $\alpha_s(z_p)$ as an approximation for the rest of terms arising from $\sum_i W_i^{k_i}$ based on the system (4). Thus, one can simplify the estimation process and identification of resource shares either by pre-estimating $\beta_s(z^p)$ and then 'plugging' into the demand system in (4). Alternatively, given that resource shares add up to one, I can replace one of three Engel curves in the system (4) with the one for total clothing (W_s). For example, if I replace Engel curve for men's exclusive good by total Engel curve (as I take men's resource shares

[8]Alternatively, one could specify resource share functions in logistic form that would ensure that resource shares are bounded in $[0, 1]$ (e.g in Bargain and Donni 2012, Bargain et al. 2014, Bargain and Martinoty 2019). Yet, in the presence of moderately high-dimensional fixed effects, this would add additional non-linearity in the model, making it computationally hard to estimate the parameters of interest. Results with linear function show that the fraction of resource shares outside $[0, 1]$ is negligible.

as 'residual'), the system transforms into:

$$\begin{aligned} W_s^{k_c} &= s_c \cdot \eta_{c,s}(z^r) \cdot (\alpha_{c,s}(z^p) + \beta_s(z^p)(x + \ln \eta_{c,s}(z^r))) + \epsilon_{c,s} \\ W_s^{k_f} &= s_f \cdot \eta_{f,s}(z^r) \cdot (\alpha_{f,s}(z^p) + \beta_s(z^p)(x + \ln \eta_{f,s}(z^r))) + \epsilon_{f,s} \\ W_s &= \alpha_s(z^p) + \beta_s(z^p)x + \epsilon_s \end{aligned} \tag{7}$$

Intuitively, the third equation in this model would 'feed' the other two with the estimates for $\beta_s(z^p)$ which accommodates the identification of resource shares $\eta_{i,s}(z^r)$.[9] Similar approach is also suggested by Lechene et al. (2022) but only as a pre-test of the model identification (i.e. testing if $\beta_s(z^p) = 0$).

Effect of Rainfall Shocks on Resource Sharing. To estimate the effect of rainfall shocks on individual resource shares, this analysis exploits spatial and temporal variation in the level of rainfall, combined with repeated cross-sectional survey data. The measure of rainfall shocks used here records the degree of rainfall for a grid cell, equivalent to geographical area of approximately 50 km^2, during *the growing period of maize* - the most prevalent rainfed crop in Malawi. This generally corresponds to the period from mid-November to mid-April.[10] Recall that the fieldwork in each wave of the survey started around April and lasted about 12 months. Such timing of survey fieldwork allows exploring whether households re-distribute resources internally *after* rainfall shocks in the growing season. To do so, I combine, for each wave the survey, indicators of rainfall shocks that reflect the level of rainfall in the growing period *preceding* the start of the survey fieldwork in that wave. For example, for all households of the wave 2010/11 (i.e. interviewed starting April 2010), rainfall shock variables would indicate the level of rainfall in the period November 2009-April 2010. Denoting $D_{g,t}$ as an indicator of drought, and $ER_{g,t}$ excess rainfall (e.g. floods) in grid g and in the growing season preceding survey wave t, I can write the resource share equation as:

$$\eta_{i,s}(z^r) = \sigma z^d + \delta^D D_{g,t} + \delta^{ER} ER_{g,t} + \phi_g + \lambda_t \tag{8}$$

with $z^r = \{z^d, D_{g,t}, ER_{g,t}, \phi_g, \lambda_t\}$, z^d a vector of demographic variables (including preference shifters z^p), ϕ_g and λ_t grid and survey wave fixed effects respectively. Grid fixed effects ϕ_g control for time-invariant differences across geographic areas, and survey wave fixed effects λ_t capture general time-related disparities across survey waves. The identification of rainfall shocks' effect on individual resource shares is based on the assumption

[9] Note that as soon as $\beta_s(z^p)$ is retrieved using total Engel curve (6) and $\beta_s(z^p) \neq 0$, resource shares can also be retrieved by estimating Engel curves for each individual type i one by one, without combining them into a system of equations.

[10] There are minor differences in the growing period across agro-climatic zones, but on average, they fall into the period from November to April. For further details about agricultural periods, please check FAO Crop Calendar https://cropcalendar.apps.fao.org.

that rainfall shocks, as with any natural disaster, occur in a random way in terms of timing and geographical location. After eliminating overall differences across grids and time using fixed effect terms, δ^D and δ^{ER} estimates the average effects of rainfall shocks on resource shares of individual type i. Notably, as the data collection lasted 12 months, one may obviously expect that the effect δ may vary by timing of interview within each wave (e.g. it might be smaller for those who were interviewed at the end of fieldwork, and vice versa). This will be investigated further in robustness checks.

Estimation Procedure and Endogeneity. As the error terms of the model are likely to be correlated across equations, each system is estimated using Non-Linear Seemingly Unrelated Regressions (as, for instance, in Calvi and Keskar 2021, Bargain, Lacroix and Tiberti 2022, or Aminjonov et al. 2022). To correct for the likely correlation between the error terms in each budget-share function and the log total expenditure, each budget share equation is augmented with the Wu-Hausman residuals (see Banks et al. 1997, Blundell and Robin 1999). I obtain these residuals from reduced-form estimations of x on all exogenous variables used in the model plus some instruments such as a quadratic form of the log household income.

2.3 Data Sources, Main Variables and Sample Selection

Malawi Integrated Household Survey. In this study, I mobilize a household survey data that pools four waves of Malawi Integrated Household Survey (IHS) conducted in 2010/11, 2013, 2016/17 and 2019/20. These survey series are a part of the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) project that aims at improving the quality of agricultural data in Sub-Saharan Africa and ultimately contributing to research on the link between agriculture and poverty reduction in the region. All waves of Malawi IHS record detailed information on household consumption and socio-demographic characteristics. I use total as well categorized expenditure variables provided by the World Bank, which aggregate household spending on food and non-food products. Most importantly, the survey collects data on clothing expenditure separately for children, women and men. Another essential feature of this data is that it has information on (approximate) geographic location of households[11], which allows combining household survey data spatially with geocoded rainfall information.

Expenditure Data on Exclusive Goods. As discussed above, the identification of resource shares requires spending data on private assignable goods. I use clothing as an exclusive household expenditure. Clothing has become a common choice of assignable good in the literature of collective models (e.g. in Browning et al. 1994, Bourguignon et al. 2009, and the applications in Dunbar et al. 2013, Bargain and Donni 2012, Bargain et al. 2014,

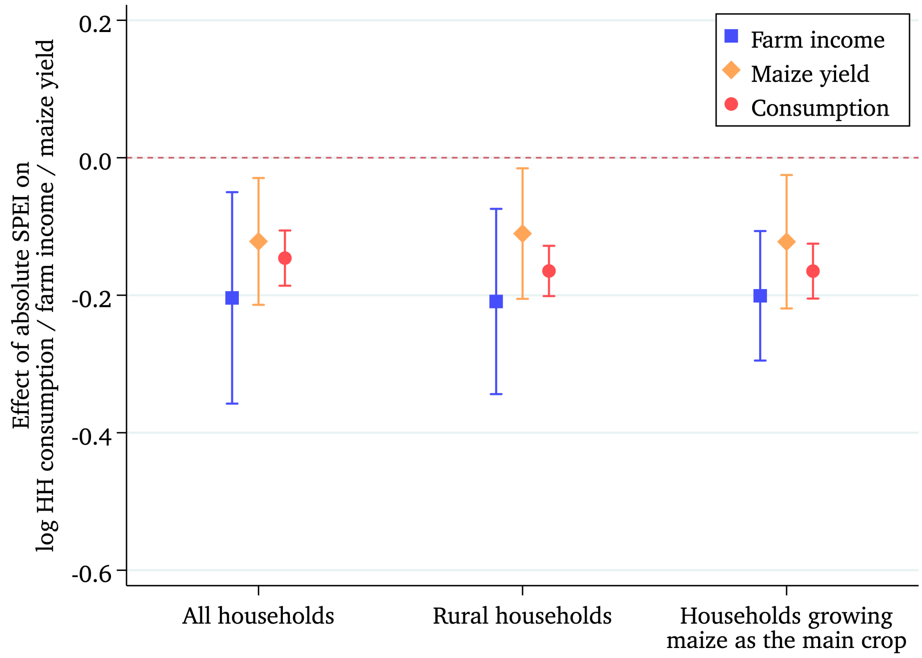
[11]Note that GPS data is provided at the level of community where households live.

Bargain, Lacroix and Tiberti 2022, Aminjonov et al. 2022) as standard household surveys usually distinguish children's, women's and men's clothing expenses.

Sample Selection. The main objective of this paper is to investigate whether climate shocks affect intra-household allocation of resources and provide insight on the implications for individual poverty as broadly as possible. Considering this nature of the analysis, I impose a following set of restrictions. First, I restrict my sample to households composed of at least one man, one woman, and one child to capture, if any, gendered as well as adult-child nature of resource allocation. Second, I focus on families with up to four men/women and eight children, which represent around 99% of all households. Note that most of earlier studies investigated resource sharing in nuclear households (Bargain and Donni, 2012, Dunbar et al., 2013, Bargain et al., 2014, 2018). However, the recent applications of this approach (Calvi and Keskar, 2021, Brown et al., 2021, Bargain, Lacroix and Tiberti, 2022, Aminjonov et al., 2022, Calvi et al., 2023) focus more on complex households, especially in the context of developing countries where families tend to live in large extended households. Third, I discard households where any adult is older than 65 to ensure that only economically active adults are part of the analysis. Moreover, since I use repeated cross-sectional survey data, not panel, I keep only grids for which there is at least one observation per wave so that the sample of grid cells observed in each wave is the same. Households for whom basic information on consumption and demographics is missing, and for whom rainfall information cannot obtained (due to missing GPS data) are also excluded. Also, I trim the top one percent of clothing budget shares and total household consumption to minimize measurement error and ensure a smoother estimation. The final pooled sample comprises 21,147 households.

Measuring Rainfall Shocks. One of the challenging tasks in this study is to choose the measure of rainfall that would detect well anomalies affecting agriculture, given that there is no consensus in the literature which rainfall indicator should be used (Hao et al., 2017). Following Björkman-Nyqvist (2013), Harari and Ferrara (2018), McCarthy et al. (2018), Marchetta et al. (2019), Dessy et al. (2023), I use the Standardized Precipitation Evapotranspiration Index (SPEI) from the Global SPEI database by Vicente-Serrano et al. (2010) to detect rainfall anomalies. This is a multiscalar index that shows how the level precipitation moves, in terms of standard deviation, with respect to its historical average for a selected area. For instance, a SPEI value of -1 implies that the level of rainfall is 1 standard deviation below than historical average for the given area. An important advantage of this index is that it takes into account, unlike other standard rainfall or drought measures, potential evapotranspiration (movement of water from earth's surface into the atmosphere via evaporation and transpiration). Another key criteria for the rainfall index in the context of this study, it should be well correlated with yield from rain-fed crops such as maize, agricultural income or household consumption. I verify this by estimating the effect of absolute variations in SPEI on maize yield, farm income and total household consumption. Results illustrated in Figure 1 show that the SPEI index correlates well with household agricultural and welfare indicators. For instance, a one standard deviation change in rainfall is associated with about 20% reduction in farm income, around 12% reduction in maize yield, and 17% reduction in household consumption in the sample of all households.

Figure 1: Effect of rainfall deviations on maize yield, farm income and household consumption



Source: Author's estimations using Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019 and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* The figure illustrates point estimates for the effect of absolute value of SPEI on log of maize yield, farm income, and per-capita annual consumption. Capped lines indicate 95% confidence interval. All regressions control for household demographic characteristics (the number of children, women and men, the average age of children, women and men, the proportion of boys), urban dummy, grid fixed effects, and survey wave fixed effects. Standard errors clustered at the grid level.

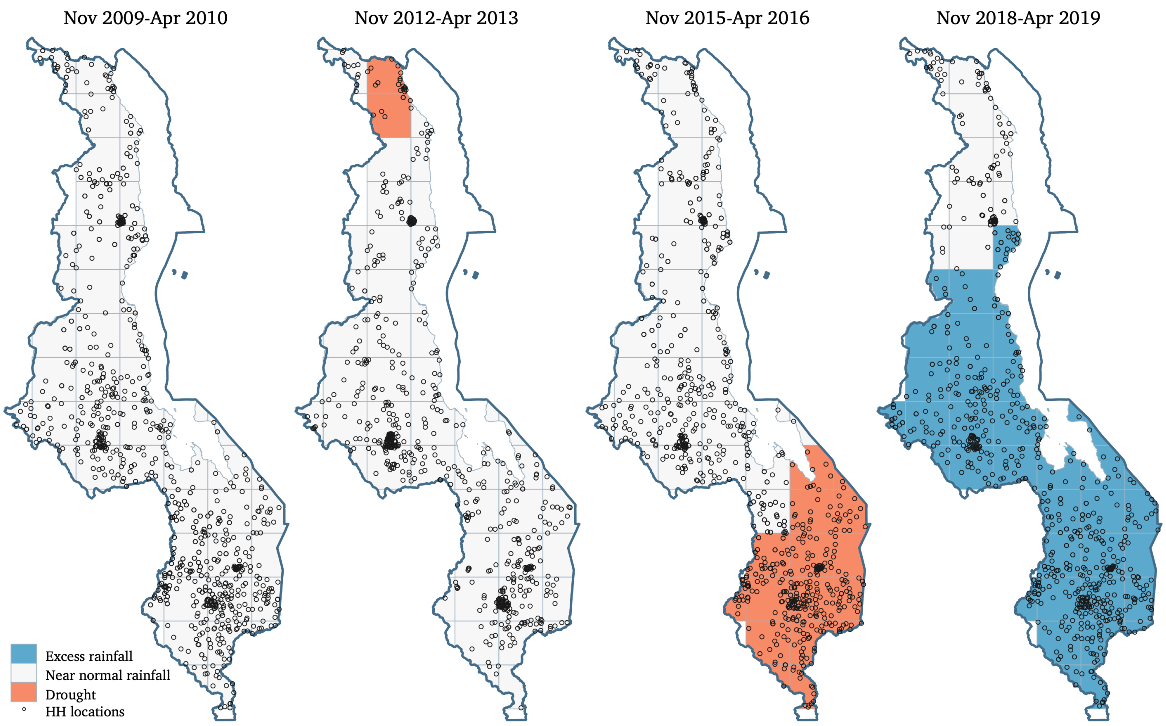
The SPEI index is measured at the level of a grid cell with a spatial resolution of 0.5 degrees in latitude and longitude, which corresponds approximately to an area of 50 km^2.[12] As I focus on the rainfall level during the growing period of maize in Malawi, I use the 6-month SPEI measured for the period from November to April and combine it spatially with the household survey data using the information on geographic location of households' residence. To simplify interpretation in the analysis, I use a dichotomized version of the SPEI index in the baseline. I define the occurrence of drought, in binary form, if SPEI is equal to or smaller than -1, in other words, if rainfall level is one standard deviations below the historical average for the given geographical area. This corresponds to around

[12]For further information on SPEI, see Vicente-Serrano et al. (2010) or https://spei.csic.es/home.html

30% reduction from its normal level. Similarly, one standard deviation above the historical average (i.e. SPEI>=1) is defined as an excess rainfall. Note that there is no general consensus on the choice of threshold. Researchers often use one or two standard deviations from the historic average to define rainfall anomaly (Rose, 2001, Marchetta et al., 2019, Caruso et al., 2022, Dessy et al., 2023). As a sensitivity check against the choice of cutoff, I estimate the model using semi-continuous or continuous forms of the SPEI index.

Figure 2 illustrates the spatial variation of SPEI across grids during growing seasons of 2009/10, 2012/13, 2015/2016 and 2018/2019 in Malawi. In 2009/10, there were no rainfall shocks as per the definition above. Droughts (SPEI<=-1) were recorded in growing seasons of 2012/13 and 2015/16, while there were excess rainfalls in the 2018/19 growing season in most parts of Malawi. Note that first wave of Malawi IHS data (2010/11) is included in the analysis, despite no rainfall shocks, to account for grid-level differences in the absence of rainfall anomalies, and also to increase the number of observations, which certainly would improve convergence in non-linear estimations and the identification of resource shares.

Figure 2: Grid-level SPEI for the period November-April (growing season) in Malawi.



Source: Malawi IHS 2010, 2013, 2016 and 2019 and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010).

2.4 Descriptive Statistics

Table A.1 documents mean and standard deviation of the variables used in the estimation of resource sharing model for each wave of Malawi IHS data. Across all waves, an average household is composed of one man, one woman and three children. Annual household expenditure is also similar across all waves, except the survey wave of 2013 which was conducted on a much smaller sample as a part of Malawi Integrated Panel Household Survey. Average budget shares of women's, men's and children's clothing are also similar across waves. Note that the infrequency of clothing purchases is not necessarily an issue for the estimation (Dunbar et al., 2013).[13] As seen in Figure 2, droughts were recorded in the growing seasons prior the survey waves of 2013 and 2016, and excess rainfall in 2019 wave. Table A.2 further compares the characteristics of households by exposure to rainfall shocks. On average, all three groups of households are similar, except noticeable differences in the cultural variables. Majority of drought-affected households are from matrilineal or matrilocal communities. Note that these cultural difference would be captured, to certain extent, by grid fixed effects in the estimation. However, it poses a limitation in potential heterogeneity analysis across cultural groups by reducing the necessary statistical power in terms of cultural variation within drought-affected households.

3 Results

3.1 Baseline Estimations

Predicted Resource Shares. I start with presenting the estimated resource shares in Table 1. Column (1) reports per-person resource shares estimated for a household with average characteristics (corresponds to a household with one man, one woman, and three children). Column (2) reports mean of resource shares estimated for each household in the sample, using the full distribution of household characteristics. Both set of estimates show that men tend to consume the largest share of resources in the household, with an average of 34% of the household budget, while women receive around 80-85% of men's resource shares. Children consume, on average, 13-14% of household resources. This pattern of resource allocation is in line with similar studies for Malawi (Dunbar et al., 2013, Penglase, 2021, Lechene et al., 2022, Aminjonov et al., 2022), as well as for other African countries (e.g. Bargain et al. 2014, Bargain et al. 2018). The last two rows at the bottom report 'validation' statistics for the estimated resource shares. As I use simple linear resource sharing function, predicted (sum of) resource shares may go outside $[0, 1]$. Reassuringly

[13] Additionally, I check whether exposure to a rainfall shock affects the frequency of clothing expenses. Results in Table A.3 show that it generally does not have a significant effect on the probability of zero clothing expenses.

the share of such cases are close to zero. Another important test for the model applicability is to check whether households have flat Engel curves for clothing, which may prevent the identification of resource shares. For all households in the sample, the estimated values of the slopes β of clothing Engel curves are statistically significantly different from zero. Table A.4 in the Appendix reports the estimated coefficients of all the covariates included in women's and children's resource share equations.

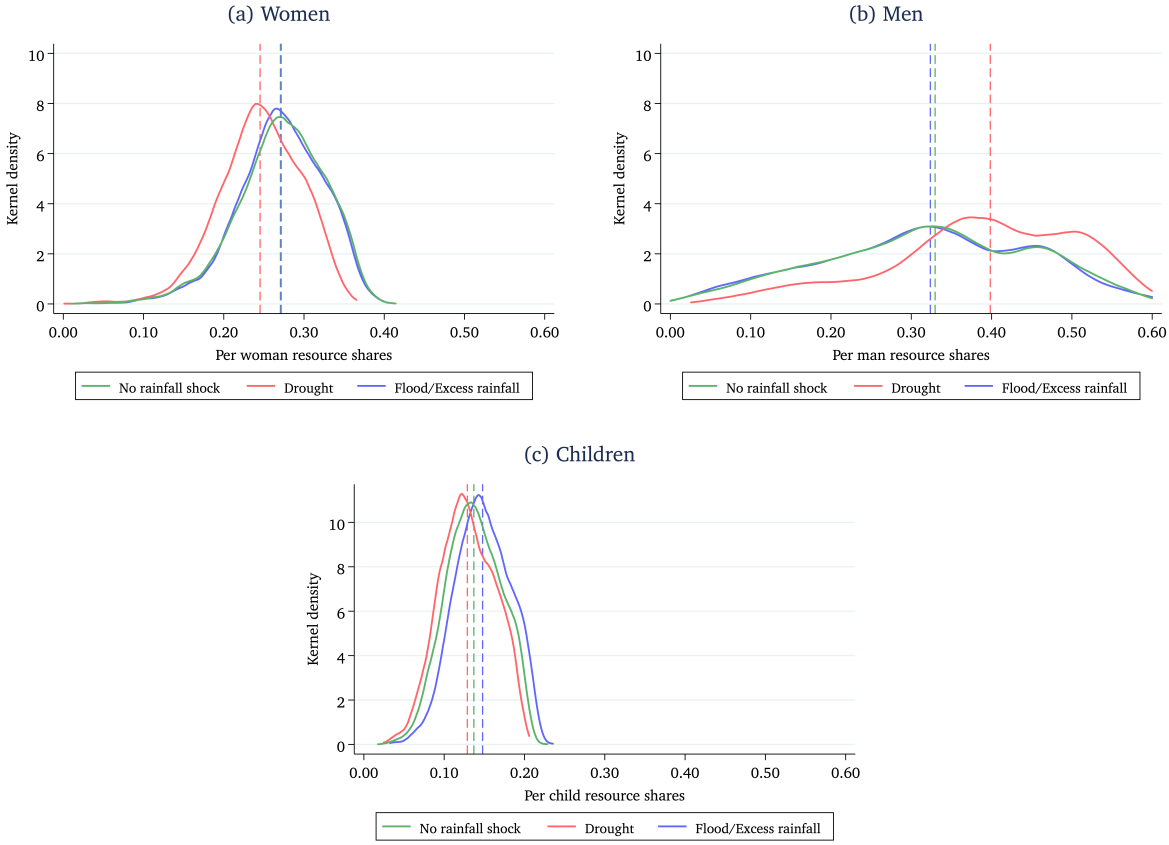
Table 1: Estimated resource shares

	Estimated at average HH characteristics	Estimated over all HH characteristics
	(1)	(2)
Children	0.125	0.138
	(0.015)	(0.035)
Women	0.291	0.268
	(0.030)	(0.055)
Men	0.335	0.337
	(0.039)	(0.138)
Observations	-	21147
% of resource shares outside [0,1]	-	0.005
% of non-zero beta	-	1.000

Source: Author's estimations using Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019 and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* The table reports per-person resource shares. Column (1) reports resource shares estimated at median household characteristics, fixing to a grid cell that intersects districts of Dowa, Kasungu, Lilongwe, Mchinji and to the survey wave 2010. Column (2) reports average resource shares estimated for all households. Standard errors in parentheses in column (1), and standard deviations in column (2).

Effect of Rainfall Shocks on Resource Shares. As reported in Table A.4 in the Appendix, the exposure to a drought, defined as the level of rainfall at least one standard deviation below the historic average in the agricultural growing season, is associated with a lower proportion of household resources accruing to women. Relative to average shares reported in Table 1, the effect approximately corresponds to 11-12 percent decrease in per-woman resource shares. The negative effect of drought is also found for children's resource shares, but with a smaller magnitude: 8 percent reduction compared to average per-child resource shares reported in Table 1. Taken together, these two effects of drought imply a redistribution of resources in favor of men. Figure 3 illustrates this shift in intra-household resource allocation, mainly from women to men, by comparing the Kernel density of resource shares by exposure to drought (red lines) and no rainfall shock (green lines). Excess rainfall, on the other hand, has no significant effect on women's resource shares, while it has a strong positive effect on children's resource shares. Yet, Figure 3 depicts that this increase in per-child resource shares induced by excess rainfall (blue lines) alters resource shares of adults only marginally, as compared to no shock scenario (green lines).

Figure 3: Distribution of estimated resource shares by exposure to rainfall shocks.

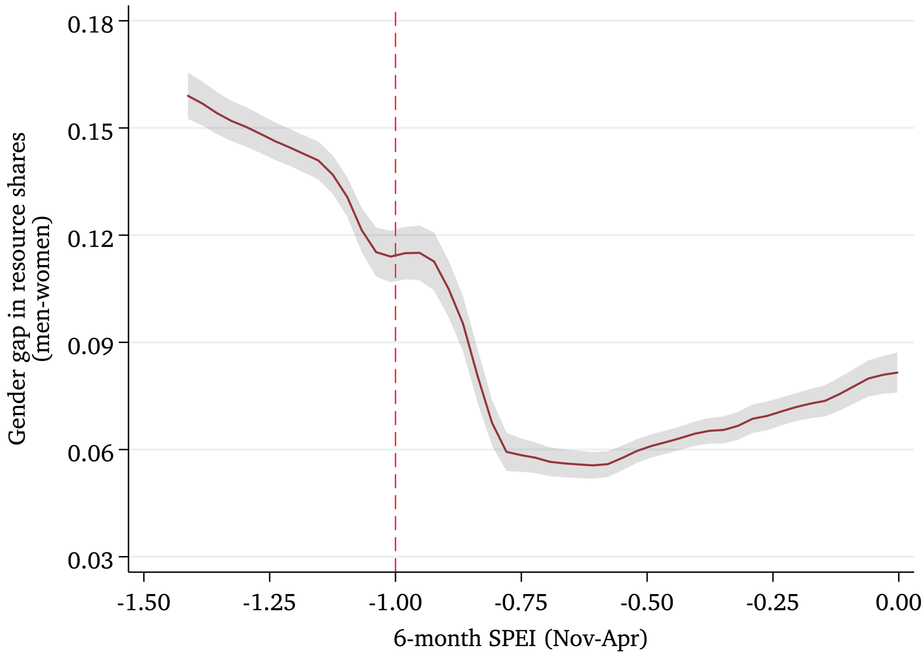


Source: Author's estimations using Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019 and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* The figure illustrates Kernel density of predicted per-person resource shares for children, women and men. Vertical lines represent median resource shares for households by exposure to rainfall shocks.

3.2 Robustness Checks.

Intensity of Rainfall Shocks. In the baseline results, I have used the binary indicator of rainfall shock to make interpretation simpler. To explore full variation in rainfall deviations (as well to check the sensitivity of results to the choice of cutoff), I estimate the same model but using the SPEI index in (i) the semi-continuous and (ii) continuous form. For drought, the semi-continuous rainfall measure takes the value of zero if SPEI is between 0 and -1 (near-normal level of rainfall), and the absolute value of SPEI if smaller or equal to -1. Similarly, for excess rainfall, it takes the value of zero if SPEI is between 0 and 1 (near-normal level of rainfall), and actual value of SPEI if larger or equal to 1. These measures of rainfall shocks capture initial effects at the threshold (-1 and 1 for drought and excess rainfall respectively) and additional effects due to variations in rainfall above the threshold. Alternatively, the continuous measure of rainfall shock exploits the full variation in the SPEI index, i.e. taking absolute value of negative SPEI for drought, and original values of positive SPEI for excess rainfall. Estimated coefficients for both measures of rainfall shock are reported in columns (2) and (3) of Table A.5. In both cases, results are in line with the baseline estimates reported in column (1) of Table A.5. The strong negative effects of semi-continuous and continuous drought on women's and children's resource shares also imply that gender gap within household is going to be wider when the drought intensity gets stronger. To check this, Figure 4 plots the difference between per-man and per-woman resource shares by negative values of the SPEI index based on the estimation results from column (3) of Table A.5. Reading the graph from left to right, the intra-household gender gap in resource sharing stay relatively stable until around the SPEI value of -0.75, but exhibits a sharp upward trend as the lack of rainfall gets stronger.

Figure 4: Gender gap in resource shares and drought intensity



Source: Author's estimations using Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019 and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* The figure plots the results of a local polynomial regression of gender gap in (per-person) resource shares on the 6-month SPEI index for the growing season in Malawi (Nov-Apr), with 95% confidence intervals. Vertical dashed line shows the cutoff used to define drought in the baseline estimations.

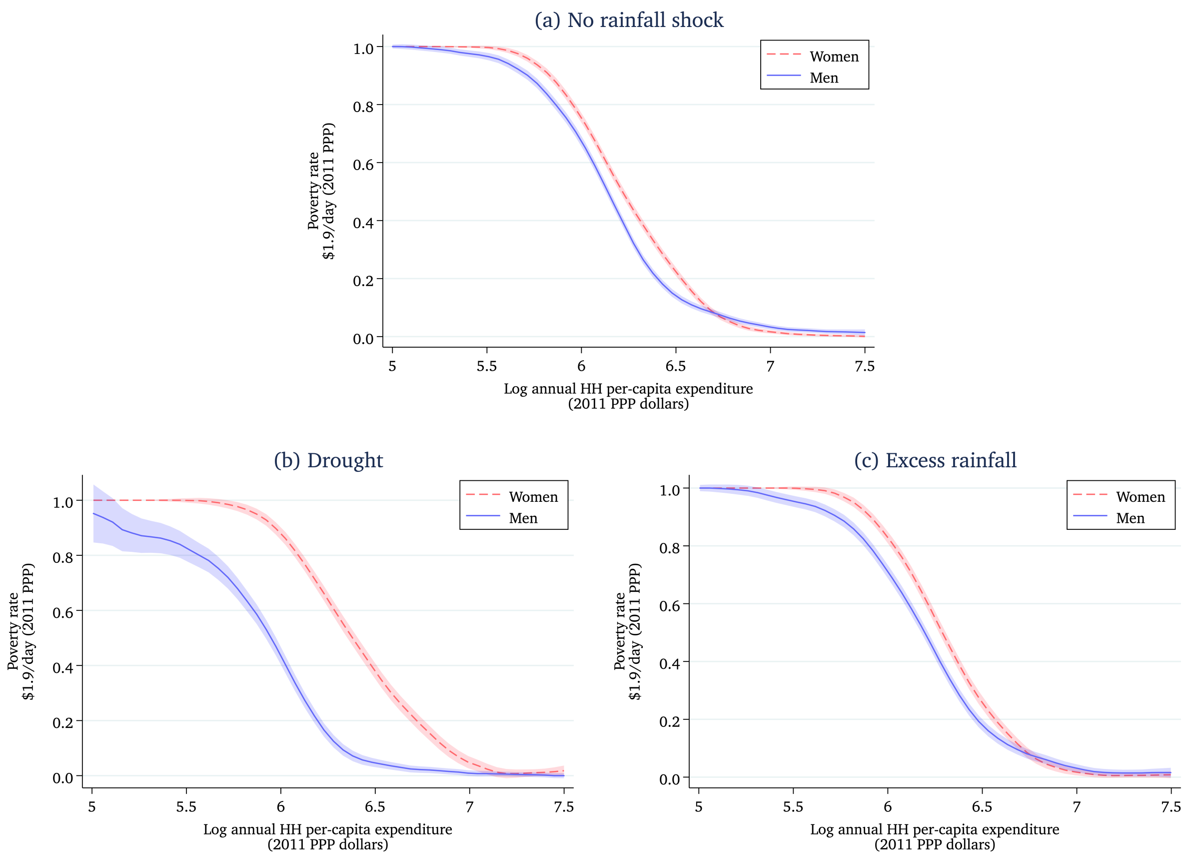
Timing of Survey Fieldwork and Agricultural Zones. The last pair of sensitivity checks is related to the timing of survey data collection and different agro-ecological zones in Malawi. As noted before, the data collection all waves of Malawi IHS starts in April and continuous for around 12 months (except 2013 wave, which lasted until December of the same year). The rainfall information is retrieved for the period November-April preceding the start of the data collection. Thus, the effect of rainfall shocks on resource sharing might also depend on the timing of survey interview (e.g. the effect may start to fade away if the household data is collected at later periods of fieldwork). However, given that the identification of resource shares is based on clothing expenditure, which are relatively less frequent, estimating heterogeneous effects of rainfall shock by timing of survey interviews may not be feasible. An alternative is simply to check the robustness of main estimates by controlling for the time of survey interview. I use the information on agricultural season (planting, growing, harvesting) at the time of interview. Results reported in columns (4) of Table A.5 shows that the effect of rainfall shock on women's resource shares only slightly decreases in magnitude. For children, the coefficient estimates remain similar to the baseline. Moreover, there are four agro-ecological zones in Malawi ((i) tropic-warm/semiarid, (ii) tropic-warm/subhumid, (iii) tropic-cool/semiarid, and (iv) tropic-cool/subhumid) differences across which may also distort the effect of rainfall shocks on resource shares. Estimates in column (5) of Table A.5, show that the baseline effects hold even when controlling for differences among agro-ecological zones.

3.3 Implications for Individual Welfare

The estimated individual resource shares presented above allows calculating consumption (by applying resource shares to total household consumption) and poverty rates for children, women, and men. Table A.6 reports the level of per-person daily consumption (in 2011 PPP dollars) and poverty rates for each demographic cell and per-adult equivalent. Column (1) shows average individual consumption and poverty rates for all households, column (2) reports figures for household not affected by a rainfall shock, column (3) and (4) for thoese affected by a drought or excess rainfall respectively. Poverty status of individuals are identified by comparing individual daily consumption in 2011 dollars to the poverty line of 1.9 dollars (2011 PPP) per day, which is commonly used poverty threshold for low-income countries. Overall, the structure of resource shares from Table 1 reflects into the indicators of individual welfare: men generally tend to consume more than women, while children's consumption is much lower than adults', which is also mirrored in individual poverty rates. Comparing individual consumption and poverty rates by exposure to rainfall shocks shows that women and children living in areas affected by drought tend to lose substantially more than men. For instance, when affected by drought, women's and children's consumption falls by around 22 and 18 percent, whereas men's consumption tends to increase slightly. The income effect of drought corresponds to around a 10 percent reduction in consumption, as observed with the trend of per-adult equivalent consumption. Hence, the redistribution of resources from women and children to men seen above (cf. Figure 3) tend to completely offset the negative income effect of drought for men, but at a significant cost for children and, particularly, women. As for excess rainfall, its income effect of a 16 percent reduction is distributed relatively more equally among household members compared to drought effects. Nevertheless, the positive effect of excess rainfall on per-child resource shares (cf. Table A.4) tends to attenuate slightly the negative income effect for children, whose individual consumption drops, on average, by 12 percent due to excess rainfall.

This pattern of welfare effects induced by rainfall shocks is also represented with individual poverty rates reported at the bottom part of Table A.6. To complement these results, Figure 5 looks further at the implications of rainfall shocks on gender gap in poverty at different levels of household living standards. In line with previous findings, drought tends to widen the gender gap in poverty almost at all levels of household welfare, while excess rainfall does not seem to affect the gender gap in poverty as compared to the no-shock scenario.

Figure 5: Gender gap in poverty by rainfall shock



Source: Author's estimations using Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019 and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* The figure plots the results of a local polynomial regression of individual poverty of men and women on log annual household per-capita consumption by exposure to rainfall shocks, with 95% confidence intervals.

3.4 Potential Mechanisms

Life-boat Ethics. The results in previous sections have documented that droughts are likely to induce the redistribution of household resources mainly from women to men, widening the gender inequality in intra-household resource allocation. This can be driven by many factors. One of possible explanations is the distribution of household consumption based on needs: more productive household members are likely to consume a larger share of household resources, which is generally referred in the literature as 'life-boat ethics' (Pitt et al., 1990, Estudillo et al., 2001, Dubois and Ligon, 2011, Coates et al., 2018). This can be even more intensified in times of an economic distress, for instance, due to climate shocks. In other words, households may start to channel more resources (e.g. food) towards family members with relatively higher marginal productivity and, more importantly, a greater chance of bringing home income from off-farm work in times of a drought that heavily disrupts farm activities (Dercon and Krishnan, 2000).

An initial step to test this hypothesis is to check whether the effect of rainfall shocks, in particular drought, on resource shares varies by the level of household welfare. It is likely that the redistribution of resources towards more productive family members might be especially common among households with limited budget. To check this, I estimate the heterogeneity effects of rainfall shocks on resource shares by differentiating grid cells with 'high' mean per-capita expenditure (above median) versus 'low' mean per-capita expenditure (below median)[14]. Note that to classify grid cells into these two groups, I use the data from Malawi IHS 2010 as the "baseline" when there was no rainfall shock. Results reported in column (1) of Table 2 show that the effect of drought on women's resource shares is slightly larger among households living in 'poorer' grids compared to those from 'richer' grids. But the negative effect of drought on per-child resource shares is almost completely driven by households from 'poorer' grids. These results provide, at least, weak evidence that the decrease in women's and children's resource shares due to drought is slightly more pronounced among households with relatively lower living standards.

Another exercise to explore the 'life-boat ethics' mechanism is to check whether drought affects the distribution of productive activities and time use within household. To do so, I use the data from time-use section of Malawi IHS data that records how much hours each individual spends in a week on various productive and non-productive activities. First, I calculate total hours spent by adult male and females on productive, in other words 'income-generating' activities and non-productive (non-income generating) activities. The former is the sum of hours spent on wage employment, agricultural activities, non-agricultural business, and ganyu labor, while the latter combines hours spent on unpaid labor and household chores. Additionally, I construct two more aggregate variables that show hours spent on farm activities (own farm and ganyu labor) and off-farm activities (wage employment and non-agricultural business). For each for these four time-use aggregates, I use three outcome variables: (i) average hours spent by women within the household, (ii) difference

[14] While I do not use panel data, the heterogeneity analysis can still be done using the aggregated variables, e.g. by calculating mean household expenditure at the grid level, at which rainfall is measured.

Table 2: Heterogenous effects of rainfall shocks on women's resource shares

	Expenditure	Subsistence crop farming	Maize farming	Crop diversification	Hybrid/OPV maize as main crop	Matrilineality	Matrilocality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Effects on per-woman resource shares							
Drought × Low	-0.033**	-0.030**	-0.031**	-0.047**	-0.035**	-0.040	-0.039
	(0.014)	(0.014)	(0.014)	(0.022)	(0.015)	(0.033)	(0.031)
Drought × High	-0.028*	-0.040**	-0.039**	-0.028**	-0.030	-0.032**	-0.031**
	(0.016)	(0.017)	(0.017)	(0.014)	(0.024)	(0.013)	(0.014)
Excess rainfall × Low	0.021	0.004	0.002	0.014	0.002	0.027**	0.015
	(0.014)	(0.009)	(0.010)	(0.010)	(0.024)	(0.012)	(0.016)
Excess rainfall × High	0.007	0.024**	0.026**	0.007	0.018	0.005	0.009
	(0.011)	(0.012)	(0.012)	(0.010)	(0.026)	(0.010)	(0.015)
Effects on per-child resource shares							
Drought × Low	-0.016**	-0.008	-0.008	-0.011	-0.010	-0.018	-0.016
	(0.006)	(0.008)	(0.008)	(0.014)	(0.007)	(0.012)	(0.012)
Drought × High	-0.004	-0.019**	-0.019**	-0.013*	-0.020	-0.010	-0.011
	(0.009)	(0.009)	(0.009)	(0.007)	(0.013)	(0.007)	(0.007)
Excess rainfall × Low	0.019***	0.011**	0.012***	0.018***	0.012***	0.017***	0.015***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.003)	(0.006)	(0.005)
Excess rainfall × High	0.011***	0.018***	0.017***	0.010***	0.014***	0.013***	0.013***
	(0.003)	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Observations	21147	21147	21147	21147	21147	21147	21147
Mean per-woman resource shares	0.268	0.271	0.273	0.270	0.267	0.273	0.270
Mean drought	0.133	0.133	0.133	0.133	0.133	0.133	0.133
Mean excess rainfall	0.234	0.234	0.234	0.234	0.234	0.234	0.234

Source: Author's estimations using pooled data from Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019, and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* The table reports group coefficients for grid cells with *low* or *high* level of variables specified on columns. Grid cells are classified as 'low' (high) if grid-level average value of heterogeneity variables from IHS 2010 is below (above) its median. Drought indicates if SPEI value for agricultural growing season (Nov-Apr) is below or equal to -1 and excess rainfall indicates if SPEI value is above or equal to 1. Sample includes households with children, women and men. All regressions control for household demographic characteristics (the number of children, women and men, the average age of children, women and men, the proportion of boys), urban dummy, household income, grid fixed effects, and survey wave fixed effects. Standard errors clustered at the grid level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

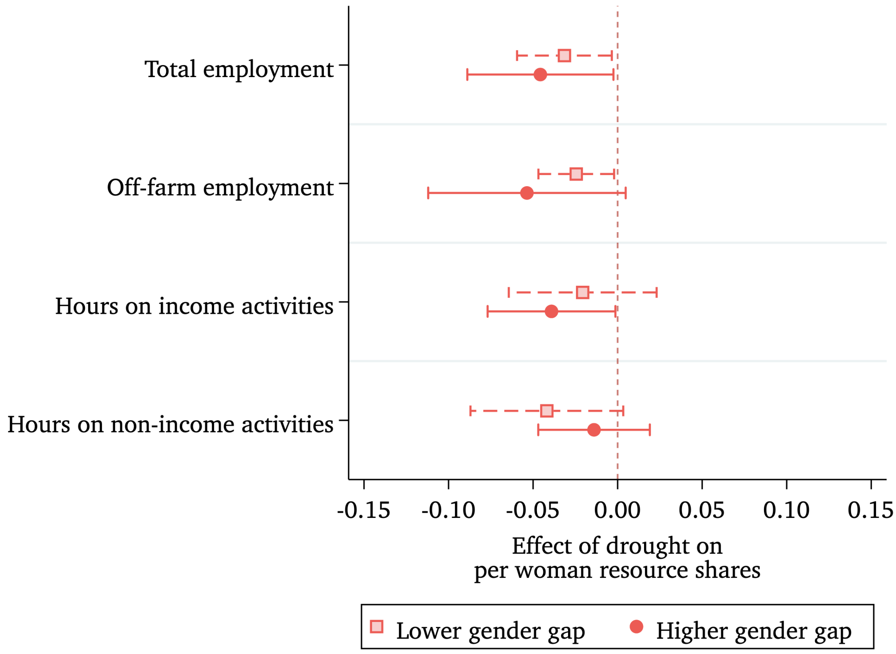
between average hours spent by men and women to capture gender gap in hours within the household, and (iii) share of women's total hours devoted to each of the above-listed group of activities. Table A.7 documents the estimation results for the effect of rainfall shocks on these indicators. Consider first the effects on hours spent for income-generating activities in columns (1)-(3). The results show that rainfall shocks do not have a significant impact neither on women's hours nor gender gap in hours spent for productive activities. However, women tends to devote less of their time on such activities after a drought in the growing season. This might be because women seems to spend significantly more time on non-productive activities such as household chores after a drought (both in absolute hours and a devoted share of their time), resulting also in a larger gap between men's and women's hours (columns (4)-(6)). Accordingly, they also seem to allocate less of their time also on farm activities (column (9)). For off-farm activities, women's hours do not seem to change significantly, but the gender gap seems to get larger following a drought, which signals about an increase in men's hours spent for such work. Overall, these results also suggest that women might be economically less active after a drought in the growing season, while men seem to shift more towards off-farm activities. Additionally, I find that the effects documented here are more pronounced among households with lower level of livings standards, as reported in Table A.8. This may further corroborate that the mechanism of 'life-boat ethics' might especially hold among poorer households.

In the final test for the 'life-boat ethics' hypothesis, I compare the effect of rainfall shock on women's resources in grids cells with higher and lower gender gap in employment indicators. To do this, I first calculate the gap between grid-level employment indicators of men and women for each survey wave. Remark that if the 'life-boat ethics' hypothesis holds, then I would expect the grid-level gender gap to be higher in periods of drought, in comparison to the level in no-shock periods. Thus, I use the values of grid-level employment indicators from the wave of 2010 as a reference point for each grid cell. In this way, I determine whether in the survey waves following 2010 the gender gap in employment indicators was 'higher' or 'lower' compared to the values from the 2010 wave, i.e. the level of gender gap in periods with no rainfall shock. Accordingly, the negative effect of drought on women's shares should be larger if the gender gap in employment has increased in drought-affected grids compared to the reference period. Estimation results for the heterogeneity effects of droughts are depicted in Figure 6[15]. Square markers show the estimated effect of drought on per-woman resource shares for grid cells where the gender gap stayed the same or was 'lower' than its reference no-shock level, and circle markers show the effect for grids where the gender gap increased. As expected, for grid-level total employment rate, off-farm employment rate, and average hours spent on productive activities, the effect of drought is slightly larger among grid cells where the gender gap was 'higher' than its 2010 level. For

[15]Figure A.1 in the Appendix illustrate results for excess rainfall.

hours spent on non-productive activities, the opposite should hold as the lower gender gap means that women are spending more time on these activities compared to men. Although differences in the effects between two groups are not statistically significant (as 95% confidence intervals overlap in all cases), it still provides suggestive evidence supporting the 'life-boat ethics' mechanism.

Figure 6: Heterogeneous effects of drought on women's shares: Gender gap in labor market activities



Source: Author's estimations using Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019 and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* The figure illustrates point estimates for the effect of drought on women's shares for grid cells with lower or higher gender gap in employment indicators listed on the Y-axis. Capped lines reflect 95% confidence interval. Drought indicates if SPEI value for agricultural growing season (Nov-Apr) is below or equal to -1. For survey waves 2013, 2016, and 2019, the level of gender gap in each cell is compared to its own gender gap level in 2010 to define whether the gender gap has decreased or stayed the same ('lower') or increased ('higher') compared the period with no rainfall shock. Total employment rate is the share of adults males/females involved in any sort of income-generating activity in a grid cell. Off-farm employment includes wage employment and non-agricultural business. Hours on income activities include hours spent for wage employment, agricultural business, non-agricultural business, and ganyu labor. Non-income hours include hours spent on household chores and unpaid labor. All regressions control for household demographic characteristics (the number of children, women and men, the average age of children, women and men, the proportion of boys), urban dummy, household income, grid fixed effects, and survey wave fixed effects. Standard errors clustered at the grid level.

Change in Intra-household Bargaining Power. In Malawi, women perform more than 50% of the agricultural work and tend to contribute less to cash-crop income than to subsistence crops (Palacios-Lopez et al., 2017). When drought disrupts farm activities, especially related to rain-fed subsistence crops such as maize, women's relative bargaining power within household may decline as their ability to contribute to household income is reduced. At the same time, the relative importance of cash income is likely to increase. Given that women often face constrained access to off-farm employment opportunities (Doss and Raney, 2011), men's higher marginal productivity and potential to bring home cash income, in particular, from off-farm activities, can improve their relative bargaining power within household, which in turn may provide them a better access to household resources (Hoddinott and Haddad, 1995). Several studies have demonstrated this mechanism by investigating gendered impacts of shocks on assets (Doss, 2001, Duflo and Udry, 2004, Quisumbing et al., 2018). To test whether exposure to drought impairs women's bargaining power within household, I utilize the data from Malawi IHS on who controls/make decisions regarding various household resources and earnings. Before estimating the effects of rainfall shocks on these indicators of bargaining power, I first check how they correlate with the estimated resource shares to verify whether they are indeed a good indicator of bargaining power. Table A.9 reports average women's shares by whether they have control over or makes decisions regarding household resources, and the results of t-tests on the equality of mean resource shares between two groups. Reassuringly, women who have control over any household productive resources or incomes tend to receive larger share of household consumption compared to those who do not have control. Yet, I do not find any significant effects of rainfall shocks on most of these indicators of women's bargaining power, as depicted in Figure A.2.

As noted before, women in Malawi are engaged more in the production of subsistence crop such as maize, which also makes their productive assets as well as their bargaining power within household vulnerable to droughts. Hence, women from households mainly involved in subsistence farming may be more likely to lose larger share of their resources after droughts in the rainy season. I suggest testing this by comparing the effects of drought in grid cells with a relatively larger versus smaller share of households producing subsistence crops or maize. Estimation results reported in columns (2) and (3) of Table 2 show that drought has a stronger negative effect on women's and children's resource shares in grid cells where more households are engaged in subsistence or maize farming. This points to the likelihood that drought-induced redistribution of household resources from women to men might be also driven by the re-allocation of decision-making power within household.

Alternative Mechanisms. Among other possible coping mechanism, labor migration is often discussed in the related literature. Yet, in low-income settings such as Malawi, this may be less likely due to high initial costs of migration that may put households in the position of higher vulnerability to future income shocks, if, for example, households have to sell their assets to cover these costs (Lewin et al., 2012, Jovanovic et al., 2019). Another strategy that households in poor countries use to reduce the burden on household budget in times of income shock is to marry off daughters (Becerra-Valbuena and Millock, 2021). As both strategies may affect intra-household consumption decisions, I suggest a simple check of whether exposure to rainfall shocks induce any substantial changes in household composition. Additionally, I exploit information from the survey section on the migration of children and check if rainfall shocks increase child migration (in the same year as as the start of the fieldwork for Malawi IHS) both at extensive and intensive margin. Results in Table A.10 show that rainfall shocks do not significantly affect the patterns of child migration (columns (1) and (2)) or household composition (columns (3)-(5)).

3.5 Role of Risk-Management Practices and Cultural Norms

Crop Diversification and Adoption of Climate-Resilient Crops. Crop diversification is plays a crucial role in protecting smallholder farmers against the impacts of extreme climatic events such as droughts or floods (Pangapanga et al., 2012, Mango et al., 2018, Acevedo et al., 2020). Cultivating a variety of crops reduces farmers' vulnerability to the specific risks associated with a single crop. In the face of a drought, for instance, certain crops may prove more resistant or adaptable, ensuring at least some level of yield. Beyond mitigating the immediate effects of extreme weather events, crop diversification can also provide alternative income streams for farmers, a better quality and diversity of diet, and nutritional security in the face of climate-related uncertainties (Mango et al., 2018). For the current study, this may imply that the extent of drought-induced redistribution of household resources from women to men may be smaller among households farming a more diverse set of crops. I try to test this again using grid-level heterogeneity analysis that compares the effect of drought on resource shares in grid cells where the average number of crop types cultivated by households is above ('high') or below ('low') average. In addition, I also check, using similar approach, the adoption of improved maize varieties such as hybrid or open pollinated variety (OPV) that are considered to be more high-yielding, early maturing or more drought-resistant as compared to traditional varieties (Katengeza et al., 2019). Results are reported in columns (4) and (5) of Table 2. As expected, the negative effect of drought on women's resource shares is more pronounced for grid areas where households diversify their crops less and hence are more vulnerable to climate shocks. A similar pattern is observed also with the adoption of hybrid or OPV varieties of maize as the main crop (i.e. cultivated in the largest part of households' agricultural land). That is, in grid cells where more households adopt hybrid or OPV maize as their main crop, women tend to relatively less of their consumption shares due to droughts, compared to women from areas where hybrid or OPV maize is less adopted as the main crop. These findings in turn highlight the importance of ex-ante agricultural risk-management strategies, such as the adoption of climate-resilient crops, increasing crop diversity, or sustainable land management practices (McCarthy et al., 2021), which would provide protection against increasing extreme climate events detrimental for livelihoods of rural households.

Cultural Norms. Lastly, I discuss whether cultural practices favoring women's roles mitigate the negative effect of droughts on women's resource shares. In the absence of rainfall shocks, traditional norms, especially those that are strongly associated with gender inequality, are suggested to have impact on the share of household resources controlled by women (Giuliano, 2020, Calvi and Keskar, 2021, Aminjonov et al., 2022). At the same time, existing evidence shows that cultural norms are also likely to alter the impact of policy interventions (La Ferrara and Milazzo, 2017, Bargain, Loper and Ziparo, 2022, Ashraf et al., 2020) as well as climate shocks (Asfaw and Maggio, 2018, Corno et al., 2020, Caruso et al., 2022). In Malawi, the prevalence of contrasted traditions, such as matrilineality versus patrilineality or matrilocality versus patrilocality, provides a rare setting to investigate the role of traditions in household decision-making. For instance, Aminjonov et al. (2022) show that in Ghana and Malawi, women in patrilocal households tend to receive lower share of resources compared to those living in matrilocal households. Here I suggest a simple test of how households practicing different traditions respond to rainfall shocks in terms of resource allocation within household. I use community-level information from Malawi IHS on cultural practices with respect to tracing lineage and post-marriage locality. I focus on matrilineality, the practice of tracing descent through mother's family line, and matrilocality, the practice of living with or near wife's family after marriage. Following the previous heterogeneity analyses, I calculate the grid-level share of matrilineal and matrilocal households and classify grid cells as 'high' ('low') matrilineality or matrilocality if the share of matrilineal/matrilocal households is above median level across grid cells. Remark that I use the grid classification from IHS 2010 wave as the baseline level (i.e. no shock period). Columns (6) and (7) of Table 2 document the estimation results. I find that the negative effect of drought on women's resource shares are smaller for grid cells with higher rates of matrilineality or matrilocality, possibly due to pre-existing stronger intra-household bargaining power of women living in these areas. However, the coefficient estimates for 'low' matrilocal and matrilineal grid-cells are not precise. This is simply due to the fact that rainfall anomalies mostly hit central and southern parts of Malawi (see Figure 2), where matrilineal or matrilocal communities are also concentrated (Berge et al., 2014). Thus, heterogeneity analysis that I propose here is only suggestive. But these results may at least shed a 'dim' light on the mitigating role of cultural norms for women after exposure to a drought.

4 Conclusion

Welfare impacts of natural disasters are often evaluated at the household level, without taking into account intra-household interactions. However, families may respond to a climate shock internally by adjusting, for instance, consumption decisions. This of course has implications on how each individual within household perceive the negative effect of a climate shock. Evidence on intra-household response to extreme weather events is very rare, and focus more on nutrition-based outcomes (e.g. Dercon and Krishnan 2000). Using recent methodological frameworks in collective household models, this study investigates the effect of climate shocks on intra-household allocation of resources and its implications for individual welfare.

In this paper, I mobilize four waves of household survey data for Malawi and combine with geocoded rainfall data to explore geographic-time variation in rainfall and to assess the implications of rainfall shocks on resource sharing within the household. Results show that an exposure to droughts during agricultural growing season is likely to decrease the share of resources accruing to women and children, which in turn exacerbates the negative income effect of them. The redistribution of household resources from mostly from women to men after the shock makes men's consumption less sensitive to droughts. I provide a suggestive evidence that this intra-household shift of resources towards men is possibly driven by relative advantages of men in marginal productivity and access to off-farm employment opportunities, which households may utilize to cope with effects of a climate hazard. Ex-ante risk management strategies such as crop diversification and adopting climate-resistant crop varieties are found to help mitigate, to a certain degree, the adverse effect of droughts on women's resource shares as these techniques may provide protection against crop failures due to climate variations. Finally, exploiting cultural heterogeneity in Malawi, I provide a weak evidence on the mitigating role of cultural norms, which favor women's roles within the household, for the intra-household impacts of droughts on women. But as noted above, this exercise is constrained by limitations in terms of power and cultural variation within affected households.

The findings of this paper entail important policy implications, particularly in terms of targeting. Even in the absence of shocks, targeting solely based on household-level poverty assessment may overlook poor individuals living in non-poor households (Haddad and Kanbur, 1990, Alderman et al., 1994, Brown et al., 2019). Similarly, policies that ignore intra-household effects of climate shocks may not effectively reach individuals who become 'newly' poor (Skoufias, 2003), for example, due to post-disaster re-allocation of resources within household, as demonstrated in the present study. Therefore, policy interventions aimed at improving disaster resilience, should be designed to target vulnerable *individuals* who are at greater risk of welfare losses during extreme climate events. Moreover, introducing labor market reforms that aim at eliminating gender discrimination in off-farm employment opportunities can further improve the resilience of women's welfare to climate-induced negative income shocks. At the same time, agricultural interventions that promote the adoption of more climate-resistant crop varieties as well as the diversification of crops among smallholder farmers would help to attenuate their vulnerability to climate variability, which would in turn reduce the adverse welfare impacts of extreme weather shocks on their family members as well.

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Appendix

Additional tables

Table A.1: Summary statistics by Malawi IHS waves

	Malawi IHS wave			
	2010	2013	2016	2019
	(1)	(2)	(3)	(4)
Number of children	2.895	2.909	2.675	2.619
	(1.501)	(1.531)	(1.390)	(1.385)
Number of man	1.196	1.318	1.183	1.221
	(0.497)	(0.642)	(0.479)	(0.527)
Number of women	1.134	1.254	1.142	1.170
	(0.415)	(0.560)	(0.423)	(0.448)
Average age of children	6.402	6.622	6.914	6.995
	(3.655)	(3.768)	(3.839)	(3.844)
Average age of women	30.974	31.061	31.919	31.943
	(9.085)	(8.844)	(9.161)	(9.270)
Average age of men	34.434	33.845	34.937	34.515
	(9.541)	(9.242)	(9.783)	(9.749)
Proportion of boys	0.491	0.494	0.498	0.499
	(0.344)	(0.347)	(0.357)	(0.359)
Urban (=1)	0.189	0.273	0.191	0.195
	(0.392)	(0.446)	(0.393)	(0.396)
Matrilineal community (=1)	0.575	0.660	0.503	0.505
	(0.494)	(0.474)	(0.500)	(0.500)
Matrilocal community (=1)	0.494	0.504	0.671	0.720
	(0.500)	(0.500)	(0.470)	(0.449)
Annual HH expenditure (ths. dollars, 2011 PPP)	3.618	6.681	3.839	3.594
	(4.181)	(7.427)	(3.483)	(2.825)
Private goods budget share	0.782	0.761	0.754	0.713
	(0.103)	(0.110)	(0.095)	(0.113)
Children's clothing budget share	0.014	0.016	0.014	0.015
	(0.020)	(0.020)	(0.019)	(0.020)
Women's clothing budget share	0.011	0.014	0.010	0.010
	(0.017)	(0.017)	(0.015)	(0.016)
Men's clothing budget share	0.007	0.009	0.006	0.006
	(0.016)	(0.016)	(0.013)	(0.012)
Zero children's clothing expenses (=1)	0.468	0.353	0.449	0.418
	(0.499)	(0.478)	(0.497)	(0.493)
Zero women's clothing expenses (=1)	0.549	0.402	0.533	0.517
	(0.498)	(0.490)	(0.499)	(0.500)
Zero men's clothing expenses (=1)	0.725	0.621	0.743	0.656
	(0.446)	(0.485)	(0.437)	(0.475)
6-month SPEI for growing season (Nov-Apr)	-0.409	-0.456	-0.631	1.796
	(0.221)	(0.273)	(0.567)	(0.715)
Drought (=1)	0.000	0.041	0.427	0.000
	(0.000)	(0.199)	(0.495)	(0.000)
Excess rainfall (=1)	0.000	0.000	0.000	0.856
	(0.000)	(0.000)	(0.000)	(0.351)
Observations	6726	2272	6376	5773

Source: Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019, and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* Clothing expenditure includes spending on clothing and footwear items. Drought indicates if SPEI value for agricultural growing season (Nov-Apr) is below or equal to -1 and excess rainfall indicates if SPEI value is above or equal to 1. Mean values of each subsample. Standard deviations in parentheses.

Table A.2: Summary statistics by rainfall shock

	No rainfall shock	Drought	Excess rainfall
	(1)	(2)	(3)
Number of children	2.815	2.687	2.630
	(1.472)	(1.408)	(1.384)
Number of man	1.218	1.174	1.218
	(0.528)	(0.474)	(0.516)
Number of women	1.164	1.135	1.161
	(0.457)	(0.410)	(0.434)
Average age of children	6.631	6.845	6.984
	(3.780)	(3.764)	(3.790)
Average age of women	31.283	31.837	32.036
	(9.032)	(9.375)	(9.289)
Average age of men	34.560	34.684	34.424
	(9.541)	(9.923)	(9.762)
Proportion of boys	0.493	0.507	0.498
	(0.349)	(0.359)	(0.357)
Urban (=1)	0.214	0.173	0.178
	(0.410)	(0.379)	(0.383)
Matrilineal community (=1)	0.479	0.783	0.588
	(0.500)	(0.412)	(0.492)
Matrilocal community (=1)	0.502	0.796	0.799
	(0.500)	(0.403)	(0.401)
Annual HH expenditure (ths. dollars, 2011 PPP)	4.279	3.684	3.454
	(4.828)	(3.476)	(2.691)
Private goods budget share	0.769	0.756	0.706
	(0.102)	(0.099)	(0.112)
Children's clothing budget share	0.015	0.012	0.015
	(0.020)	(0.018)	(0.020)
Women's clothing budget share	0.011	0.009	0.010
	(0.017)	(0.014)	(0.016)
Men's clothing budget share	0.007	0.005	0.005
	(0.016)	(0.013)	(0.011)
Zero children's clothing expenses (=1)	0.432	0.487	0.420
	(0.495)	(0.500)	(0.494)
Zero women's clothing expenses (=1)	0.512	0.555	0.520
	(0.500)	(0.497)	(0.500)
Zero men's clothing expenses (=1)	0.704	0.757	0.661
	(0.457)	(0.429)	(0.473)
Observations	13390	2814	4943

Source: Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019, and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* Clothing expenditure includes spending on clothing and footwear items. No rainfall shock indicates if SPEI value for agricultural growing season (Nov-Apr) is between -0.99 and 0.99, drought indicates if SPEI value is below or equal to -1 and excess rainfall indicates if SPEI value is above or equal to 1. Mean values of each subsample. Standard deviations in parentheses.

Table A.3: Effect of rainfall shocks on the infrequency of clothing purchases

	Zero clothing expenses (=1)	Zero children's clothing expenses (=1)	Zero women's clothing expenses (=1)	Zero men's clothing expenses (=1)
	(1)	(2)	(3)	(4)
Drought	0.042	0.052*	0.032	0.003
	(0.028)	(0.026)	(0.029)	(0.023)
Excess rainfall	-0.044	-0.047	0.016	0.016
	(0.027)	(0.034)	(0.024)	(0.023)
R-squared	0.058	0.051	0.045	0.051
Observations	21147	21147	21147	21147
Mean of outcome variable	0.324	0.436	0.520	0.701

Source: Author's estimations using pooled data from Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019, and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* Drought indicates if SPEI value for agricultural growing season (Nov-Apr) is below or equal to -1 and excess rainfall indicates if SPEI value is above or equal to 1. All regressions control for household demographic characteristics (the number of children, women and men, the average age of children, women and men, the proportion of boys), urban dummy, log of household income, grid fixed effects, and survey wave fixed effects. Standard errors clustered at the grid level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A.4: Estimated coefficients in resource share equations

	Per-woman resource shares	Per-child resource shares
	(1)	(2)
Drought	-0.032**	-0.011*
	(0.013)	(0.007)
Excess rainfall	0.011	0.013***
	(0.016)	(0.003)
Number of children	-0.008	-0.016***
	(0.008)	(0.003)
Number of women	-0.060***	-0.002
	(0.018)	(0.005)
Number of men	0.003	0.009
	(0.028)	(0.006)
Mean age of children	-0.036***	-0.035***
	(0.010)	(0.007)
Mean age of women	-0.015**	-0.002
	(0.006)	(0.002)
Mean age of men	-0.007**	-0.005***
	(0.003)	(0.001)
Proportion of boys	0.008	0.005
	(0.011)	(0.003)
Urban (=1)	-0.059**	0.008
	(0.029)	(0.009)
Observations	21147	

Source: Author's estimations using pooled data from Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019, and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* Drought indicates if SPEI value for agricultural growing season (Nov-Apr) is below or equal to -1 and excess rainfall indicates if SPEI value is above or equal to 1. Sample includes households with children, women and men. Age variables are divided by 10 to smooth estimation process. All regressions additionally include grid fixed effects, and survey wave fixed effects. Standard errors clustered at the grid level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A.5: Effects of rainfall shocks on resource shares: Sensitivity checks

	Baseline	Semi-continuous rainfall shock	Continuous rainfall shock	Interview timing FE	Agro-ecological zone FE
	(1)	(2)	(3)	(4)	(5)
Effects on per-woman resource shares					
Drought	-0.032**	-0.027**	-0.018***	-0.029**	-0.031**
	(0.013)	(0.011)	(0.007)	(0.012)	(0.012)
Excess rainfall	0.011	0.006	0.010	0.009	0.011
	(0.016)	(0.006)	(0.010)	(0.011)	(0.020)
Effects on per-child resource shares					
Drought	-0.011*	-0.010*	-0.012***	-0.011*	-0.011*
	(0.007)	(0.006)	(0.004)	(0.006)	(0.006)
Excess rainfall	0.013***	0.006***	0.007***	0.014***	0.014***
	(0.003)	(0.002)	(0.002)	(0.005)	(0.003)
Observations	21147	21147	21147	21147	21147
Mean per-woman resource shares	0.268	0.268	0.268	0.234	0.270
Mean per-child resource shares	0.138	0.139	0.137	0.131	0.140
Mean drought	0.133	0.163	0.163	0.133	0.133
Mean excess rainfall	0.234	0.476	0.476	0.234	0.234

Source: Author's estimations using pooled data from Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019, and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* Drought indicates if SPEI value for agricultural growing season (Nov-Apr) is below or equal to -1 and excess rainfall indicates if SPEI value is above or equal to 1. Sample includes households with children, women and men. All regressions control for household demographic characteristics (the number of children, women and men, the average age of children, women and men, the proportion of boys, urban dummy), grid fixed effects, and survey wave fixed effects. Semi-continuous measure of rainfall shock takes value of zero if SPEI value is between -0.99 and 0.99 (near normal level of rainfall), and continuous negative values if equal to or below -1 for drought, and positive values if equal to or above 1 for excess rainfall. Continuous measure of rainfall shock takes all negative values of SPEI for drought and positive values for excess rainfall. Column (4) additionally controls for interview timing fixed effects to capture differences related to whether household survey interview was conducted during (i) growing season for which SPEI is measured (Nov-Apr), (ii) harvesting season (May-June), (iii) period until next planting season (Jul-Oct), and (iv) next planting/growing season (Nov-Apr of the following season). Column (5) additionally controls for agro-ecological zone fixed effects to capture differences related to whether households live in (i) tropic-warm semiarid climatic zone, (ii) tropic-warm subhumid zone, (iii) tropic-cool semiarid zone, and (iv) tropic-cool subhumid zone. Standard errors clustered at the grid level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A.6: Individual consumption and poverty rates

	All households	No rainfall shock	Drought	Excess rainfall
	(1)	(2)	(3)	(4)
Daily individual consumption, 2011 PPP dollars:				
Children	1.499	1.581	1.300	1.390
	(1.688)	(1.886)	(1.420)	(1.166)
Women	2.742	2.948	2.309	2.432
	(2.466)	(2.794)	(1.770)	(1.667)
Men	3.491	3.628	3.839	2.919
	(3.805)	(4.209)	(3.441)	(2.603)
Per adult eq.	2.788	2.937	2.629	2.475
	(2.709)	(3.033)	(2.220)	(1.869)
Poverty rates:				
Children	0.534	0.513	0.610	0.549
	(0.499)	(0.500)	(0.488)	(0.498)
Women	0.417	0.382	0.501	0.464
	(0.493)	(0.486)	(0.500)	(0.499)
Men	0.342	0.341	0.239	0.406
	(0.474)	(0.474)	(0.426)	(0.491)
Per adult eq.	0.430	0.411	0.442	0.476
	(0.495)	(0.492)	(0.497)	(0.499)
Observations	21147	13390	2814	4943

Source: Author's estimations using pooled data from Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019. *Notes:* Individual-level consumption is obtained by multiplying estimated resource shares by total household daily expenditure (2011 PPP dollars). Poverty rate is based on the poverty line of 1.9 dollars (2011 PPP) per day for adults, and 0.6*1.9 dollars per day for children. Per-adult equivalent values are obtained using 0.6 weight for children.

Table A.7: Effect of rainfall shocks on time-use within household

	Income-generating activities			Non-income generating activities			Farm activities			Off-farm activities		
	Hours by women	Gender gap in hours	Share of women's time devoted	Hours by women	Gender gap in hours	Share of women's time devoted	Hours by women	Gender gap in hours	Share of women's time devoted	Hours by women	Gender gap in hours	Share of women's time devoted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Drought	-1.024	0.621	-0.056**	1.879***	-1.802***	0.067**	-0.701	-0.541	-0.044**	-0.324	1.162*	-0.013
	(0.772)	(0.666)	(0.021)	(0.317)	(0.354)	(0.027)	(0.702)	(0.375)	(0.021)	(0.359)	(0.671)	(0.008)
Excess rainfall	-0.602	0.021	-0.027	0.710*	-0.660	0.016	-0.327	-0.457	-0.013	-0.275	0.477	-0.014
	(0.873)	(1.084)	(0.018)	(0.387)	(0.396)	(0.028)	(0.685)	(0.684)	(0.016)	(0.477)	(0.826)	(0.014)
R-squared	0.032	0.109	0.041	0.083	0.076	0.043	0.101	0.026	0.132	0.106	0.091	0.126
Observations	21147	21147	21147	21147	21147	21147	21147	21147	21147	21147	21147	21147
Mean of outcome variable	13.159	9.754	0.449	7.316	-6.467	0.469	9.348	2.477	0.347	3.811	7.277	0.102

Source: Author's estimations using pooled data from Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019, and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* Outcome variables are (i) per-woman hours, (ii) gender gap (men-women) in per person hours, (iii) share of women's total hours devoted to listed activities. Income-generating activities include agricultural business, non-agricultural business, wage employment, and ganyu labor. Non-income generating activities include unpaid labor and household chores. Farm activities include agricultural business and ganyu labor. Off-farm activities include non-agricultural business and wage employment. log of annual household per-capita expenditure (total or food) in 2011 PPP dollars. Drought indicates if SPEI value for agricultural growing season (Nov-Apr) is below or equal to -1 and excess rainfall indicates if SPEI value is above or equal to 1. All regressions control for household demographic characteristics (the number of children, women and men, the average age of children, women and men, the proportion of boys), urban dummy, log of household income, grid fixed effects, and survey wave fixed effects. Standard errors clustered at the grid level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A.8: Effect of rainfall shocks on activity hours - heterogeneity by welfare level

	Income-generating activities			Non-income generating activities			Farm activities			Off-farm activities		
	Hours by women	Gender gap in hours	Share of women's time devoted	Hours by women	Gender gap in hours	Share of women's time devoted	Hours by women	Gender gap in hours	Share of women's time devoted	Hours by women	Gender gap in hours	Share of women's time devoted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Drought × Low expenditure	-1.468*	0.941	-0.081***	2.136***	-2.232***	0.102***	-0.987	-0.279	-0.065***	-0.480	1.220	-0.016**
	(0.874)	(0.921)	(0.024)	(0.488)	(0.496)	(0.027)	(0.774)	(0.361)	(0.022)	(0.349)	(0.921)	(0.007)
Drought × High expenditure	-0.215	0.341	-0.021	1.504***	-1.248***	0.026	-0.288	-0.814	-0.016	0.073	1.154	-0.005
	(0.712)	(0.691)	(0.026)	(0.233)	(0.255)	(0.041)	(0.826)	(0.564)	(0.030)	(0.396)	(0.699)	(0.010)
Excess rainfall × Low expenditure	-0.090	0.385	-0.022	0.640	-0.719	0.027	-0.263	-0.265	-0.015	0.173	0.650	-0.007
	(1.109)	(1.128)	(0.019)	(0.568)	(0.557)	(0.030)	(0.934)	(0.700)	(0.016)	(0.457)	(0.918)	(0.014)
Excess rainfall × High expenditure	-0.820	-0.186	-0.027	0.725	-0.595	0.007	-0.336	-0.573	-0.011	-0.485	0.387	-0.017
	(0.957)	(1.178)	(0.020)	(0.454)	(0.454)	(0.030)	(0.792)	(0.741)	(0.019)	(0.528)	(0.918)	(0.015)
R-squared	0.032	0.109	0.042	0.083	0.076	0.044	0.101	0.026	0.132	0.106	0.091	0.126
Observations	21147	21147	21147	21147	21147	21147	21147	21147	21147	21147	21147	21147
Mean of outcome variable	13.159	9.754	0.449	7.316	-6.467	0.469	9.348	2.477	0.347	3.811	7.277	0.102

Source: Author's estimations using pooled data from Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019, and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* Outcome variables are (i) per-woman hours, (ii) gender gap (men-women) in per person hours, (iii) share of women's total hours devoted to listed activities. Income-generating activities include agricultural business, non-agricultural business, wage employment, and ganyu labor. Non-income generating activities include unpaid labor and household chores. Farm activities include agricultural business and ganyu labor. Off-farm activities include non-agricultural business and wage employment. log of annual household per-capita expenditure (total or food) in 2011 PPP dollars. Drought indicates if SPEI value for agricultural growing season (Nov-Apr) is below or equal to -1 and excess rainfall indicates if SPEI value is above or equal to 1. Group coefficients for grid cells with *low* or *high* level of average per-capita household expenditure. Grid cells are classified to have low (high) level of expenditure if grid-level average value of per-capita household expenditure from IHS 2010 is below (above) its median. All regressions control for household demographic characteristics (the number of children, women and men, the average age of children, women and men, the proportion of boys), urban dummy, log of household income, grid fixed effects, and survey wave fixed effects. Standard errors clustered at the grid level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A.9: Comparison of women's resource shares by control over household resources

	No	Yes	Diff.	Proportion of Yes	Observations
	(1)	(2)	(3)	(4)	(5)
Control over:					
Plot(s) during rainy season	0.256	0.264	-0.008***	0.545	19367
Plot(s) during dry season	0.255	0.267	-0.012***	0.296	2912
Livestock	0.227	0.265	-0.038***	0.696	11080
Crop revenue during rainy season	0.240	0.268	-0.028***	0.692	7497
Crop revenue during dry season	0.239	0.266	-0.026***	0.664	1395
Revenue from tree sales	0.226	0.258	-0.032***	0.690	1202
Revenue from livestock products (milk, eggs)	0.225	0.268	-0.043***	0.661	755
Profits from non-agricultural business	0.246	0.250	-0.004*	0.437	8113
Other incomes (transfers etc.)	0.224	0.263	-0.038***	0.705	10377
Social safety nets received	0.222	0.260	-0.038***	0.737	5243
Gifts given out	0.230	0.258	-0.028***	0.660	10579
Loan-related decisions	0.248	0.255	-0.007***	0.471	5927
Earnings from wage employment	0.212	0.240	-0.027***	0.543	4350
Earnings from ganyu labor	0.234	0.264	-0.030***	0.756	10244

Source: Author's estimations using pooled data from Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019, and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* The table reports mean resource shares for women by whether they control or make decisions regarding listed household resources. Difference between resource shares and its significance is based on a t-test on equality of means across two groups. * p<0.1, ** p<0.05, *** p<0.01.

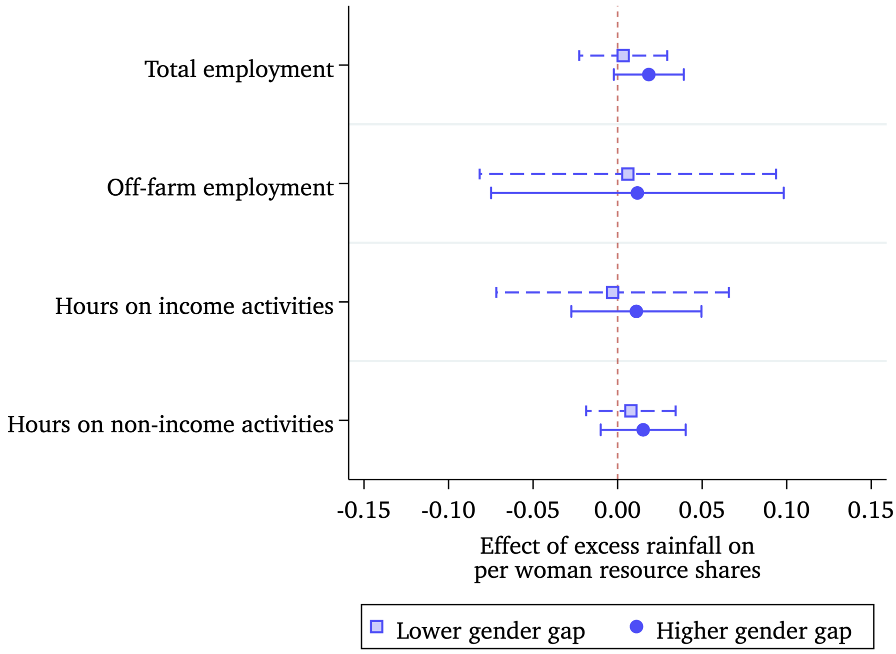
Table A.10: Effect of rainfall shocks on migration and household composition

	Any migrated child (=1)	Number of migrated children	Number of children	Number of women	Number of man
	(1)	(2)	(3)	(4)	(5)
Drought	0.002	0.002	0.076	0.017	0.016
	(0.007)	(0.008)	(0.049)	(0.014)	(0.017)
Excess rainfall	-0.000	-0.004	0.073	-0.022	0.001
	(0.010)	(0.014)	(0.051)	(0.017)	(0.018)
R-squared	0.056	0.052	0.144	0.087	0.220
Observations	21147	21147	21147	21147	21147
Mean of outcome variable	0.039	0.045	2.755	1.159	1.212

Source: Author's estimations using pooled data from Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019, and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* Drought indicates if SPEI value for agricultural growing season (Nov-Apr) is below or equal to -1 and excess rainfall indicates if SPEI value is above or equal to 1. All regressions control for household demographic characteristics (the number of children, women and men, the average age of children, women and men, the proportion of boys), urban dummy, log of household income, grid fixed effects, and survey wave fixed effects. Standard errors clustered at the grid level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

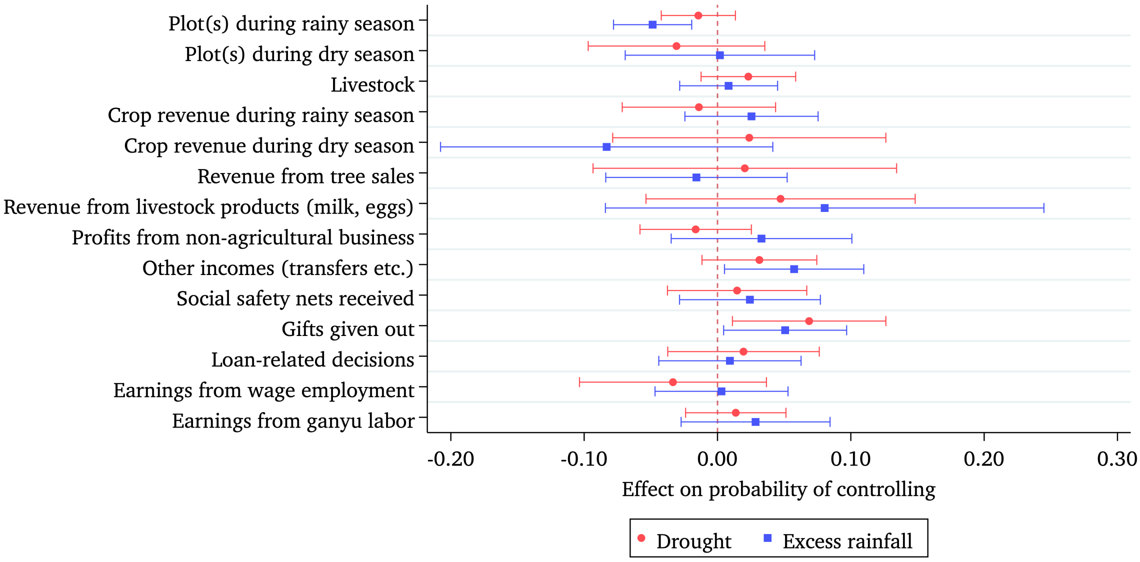
Additional figures

Figure A.1: Heterogeneous effects of excess rainfall on women's shares: Gender gap in labor market activities



Source: Author's estimations using Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019 and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* The figure illustrates point estimates for the effect of excess rainfall on women's shares for grid cells with lower or higher gender gap in employment indicators listed on the Y-axis. Capped lines reflect 95% confidence interval. Excess rainfall indicates if SPEI value is above or equal to 1. For survey waves 2013, 2016, and 2019, the level of gender gap in each cell is compared to its own gender gap level in 2010 to define whether the gender gap has decreased or stayed the same ('lower') or increased ('higher') compared the period with no rainfall shock. Total employment rate is the share of adults males/females involved in any sort of income-generating activity in a grid cell. Off-farm employment includes wage employment and non-agricultural business. Hours on income activities include hours spent for wage employment, agricultural business, non-agricultural business, and ganyu labor. Non-income hours include hours spent on household chores and unpaid labor. All regressions control for household demographic characteristics (the number of children, women and men, the average age of children, women and men, the proportion of boys), urban dummy, household income, grid fixed effects, and survey wave fixed effects. Standard errors clustered at the grid level.

Figure A.2: Effect of rainfall shocks on women's bargaining power



Source: Author's estimations using Malawi Integrated Household Survey (IHS) 2010, 2013, 2016 and 2019 and SPEI data from the Global SPEI database (Vicente-Serrano et al., 2010). *Notes:* The figure illustrates point estimates for the effect of drought and excess rainfall on women's probability of having control over listed household productive resources or incomes. Capped lines reflect 90% confidence interval. Sample of women aged 18-65. Outcome variables are binary indicators taking value of one if a woman has control over listed household resources, and zero if she does not. All regressions control for age, age squared, years of education, marital status, household-level covariates, grid and survey wave fixed effects. Standard errors clustered at the grid level.