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Abstract

Purpose: To investigate whether access to agricultural support and the choice of adaptive strategy influence smallholder farmers' on-farm and off-farm behavioural responses to extreme drought exposure.

Materials and Methods: Using a large nationally representative rural household-level panel dataset, the study employs a matched Correlated Random Effects (CRE) tobit model to exploit regional variations in drought exposure conditions.

Findings: Relative to the counterfactual group, the results show that beneficiaries of fertilizer-seed support and agricultural credit respond to severe drought stresses by improving crop portfolio management strategies. Further, the results also reveal that recipients of fertilizer-seed support expand croplands, seed consumption, and fertilizer utilization in response to extreme drought conditions while access to agricultural credit contributes to higher off-farm incomes and hence promotes occupational diversity in treatment farm households. Collectively, this points to the instrumental role of agricultural support in influencing the margin of adjustment in a way that strengthens the adaptive capacity of poor treatment farm households to climatic variability and change. However, for the large part, the choice of adaptive strategy appears to induce the opposite effects, with drought exposed adopters not only shifting towards more specialized cropping systems but also reducing hectarage shares, agricultural inputs, and off-farm incomes. Together, this is an indication that treatment adopters are relatively more vulnerable to future extreme moisture stress conditions, mainly cultivate improved localized staple crops, fortify agricultural investments on smaller manageable croplands, reallocate labour away from off-farm income enterprises towards own-farm activities, and are unlikely to increase seed and fertilizer uptake alongside adaptive land investments that are not suitable to localized weather conditions. The estimated results are robust to alternative estimation strategies, sample size adjustments, and alternate dataset.

Unique Contribution to Theory, Practice and Policy: Based on the results of this study, agricultural policy should be localized and targeted to be effective. Support programs, particularly fertilizer-seed support, credit access, and extension services, must be designed to reflect regional agroclimatic conditions to strengthen farmers' resilience. Specifically, policies should prioritize providing accessible finance and technical guidance to encourage climate-smart agricultural investments that are suitable to local weather patterns. By doing so, policymakers can help smallholders adopt adaptive behaviours that reduce vulnerability and enhance long-term climate resilience.

Keywords: *Drought Exposure, Crop Diversification, Cropland Adjustment, Fertilizer and Seed Uptake, Off-Farm Income, Zambia*

JEL Classifications: *Q12, Q15, Q54, J31*

1.0 INTRODUCTION

There is substantial suggestive evidence showing that the ripple adverse social and economic costs of climatic variability and change are far-reaching (Burke & Emerick, 2016; Chen & Gong, 2021; Colmer, 2021; Di Falco et al., 2012; IPCC, 2022; Ortiz-Bobea et al., 2021). Rural farm households located in developing countries are relatively more exposed to climate shocks largely because agricultural production is characterized by low land productivity and punitive weather conditions (Aragón et al., 2021; Di Falco et al., 2011). Besides this, small-scale farmers in resource-constrained settings are particularly vulnerable because they lack both the adaptive capacity and technology to respond to climate change (IPCC, 2014, 2022), and the recent devastating yield impacts of climatic hazards is a manifestation of their vulnerability to weather anomalies (Di Falco et al., 2012; Eggen et al., 2019; Gröger & Zylberberg, 2016; McCarthy et al., 2021; Parida & Chowdhury, 2021). Therefore, unless sufficient adaptation and risk-coping strategies are adopted, food insecurity will continue to be endemic especially in Southern Africa and South Asia (Asfaw et al., 2016; IPCC, 2014, 2022; Lobell et al., 2008). This imminent food security threat posed by climate variability has led to increased calls for smallholder farmers and other economic agents to boost their adaptive capacity to attenuate the extent of economic damage (Branco & Féres, 2021; Burke & Emerick, 2016; McCord et al., 2015; Piedra-Bonilla et al., 2020; Skoufias et al., 2017).

However, an exclusive focus on the yield impacts of climate variability may not show the full extent of the vulnerability of agricultural output to adverse weather anomalies (Cohn et al., 2016). Moreover, the inability of damage functions to capture behavioural responses to climate change results in biased yield loss estimates and provides an incomplete picture of rural farm households' vulnerability and/or adaptive capacity (Aragón et al., 2021; Cui, 2020a). This is largely because weather-induced agricultural production losses may stem not only from reduced agricultural yields but also triggered behavioural responses such as cropland adjustments, crop abandonment, and changes in cropping frequency and input mix (Aragón et al., 2021; Benhin, 2006; Cohn et al., 2016; Cui, 2020a; Iizumi & Ramankutty, 2015). There is empirical support to this effect, with estimates showing that approximately 70% of changes in agricultural output caused by climate change originates from changes in cropland area and cropping frequency (Cohn et al., 2016). Therefore, understanding the impacts of climatic variability on the behavioural components of agricultural production and off-farm income enterprises provides critical insights into the potential adaptive capacity of farm households.

Across developing countries, rural smallholder farmers attempt to hedge against adverse climate stressors using a variety of micro-level on-farm and off-farm responses because the pervasiveness of incomplete and/or missing insurance markets coupled with market failures makes it difficult to transfer the climate risk to third parties (Bezabih & Sarr, 2012; McCord et al., 2015; Mulwa & Visser, 2020; Piedra-Bonilla et al., 2020). Despite factors such as risk-aversion and tenure security affecting climate adaptation, the prevailing evidence largely show that smallholder farmers adopt polyculture agricultural systems to minimize climate-related crop production risks (Arslan et al., 2018; Asfaw et al., 2019; Auffhammer & Carleton, 2018; Bezabih & Sarr, 2012; Birthal & Hazrana, 2019; Huang et al., 2014; McCord et al., 2015; Mulwa & Visser, 2020; Piedra-Bonilla et al., 2020). However, other studies show that adverse weather conditions incentivize monoculture agricultural practices that perpetuate the cultivation of low-value crops (Bradshaw et al., 2004; Cohn et al., 2016; Di Falco et al., 2010; Ochieng et al., 2020; Sesmero et al., 2018). Relatedly, rural farm households either expand croplands (Aragón et al., 2021; Cho & McCarl, 2017; Cui, 2020b) or shrink acreage shares (Benhin, 2006; Cohn et al., 2016; Cui, 2020a) in response to the undesirable effects of extreme weather stressors. Additionally, while some households reduce consumption of agricultural inputs (Chen & Gong, 2021; Sesmero et al., 2018), others respond to changing climatic conditions by cultivating early maturing seed varieties and suitable localized crops, increasing fertilizer usage, and staggering planting, weeding and harvesting dates (Amare & Simane, 2017; Below et al., 2010; Benhin, 2006; Bryan et al., 2013; Di Falco et al., 2011). Besides, smallholder farmers respond to recurrent severe weather stressors by undertaking adaptive land investments such as agroforestry, crop rotation, and legume-intercropping to strengthen, among others, soil fertility and agricultural productivity (Below et al., 2010; Benhin, 2006; Bryan et al., 2013; Deressa et al., 2009; Gbetibouo et al., 2010; Karanja Ng'ang'a et al., 2016).

Further, small-scale farmers also adjust livestock management practices by adopting drought and heat tolerant livestock breeds to moderate the impacts of global warming (Below et al., 2010; Benhin, 2006; Gbetibouo et al., 2010; Mulwa & Visser, 2020). In addition, alterations to farm households' occupational diversity are not uncommon behavioural responses to climate-related risks. Specifically, extreme weather conditions contribute to labour diversification and higher off-farm incomes (Arslan et al., 2018; Asfaw et al., 2018; Branco & Féres, 2021; Skoufias et al., 2017). Although off-farm work reduces weather-induced income variability and the need to depend on savings to smooth household consumption (Kochar, 1999), the evidence also shows that weather anomalies contribute to job redundancies, lower wages, and labour reallocation towards own-farm cropping activities at the expense of other remunerative off-farm income enterprises (Banerjee, 2007; Chen & Gong, 2021; Jessoe et al., 2018; Mueller & Quisumbing, 2011; Njuki, 2021; Parida & Chowdhury, 2021; Sesmero et al., 2018). Furthermore, households with limited coping mechanisms either reallocate labour across industries or migrate to other less affected regions so that migration, through migrant remittances and additional incomes, serves as an effective shock-copping instrument against severe weather shocks (Cattaneo & Peri, 2016; Colmer, 2021; Dercon, 2002; Feng et al., 2010; Feng et al., 2012; Gray & Mueller, 2012; Gröger & Zylberberg, 2016; Jessoe et al., 2018; Marchiori et al., 2012). Additionally, government interventions that provide relief support through, among others, input subsidies and transfers, attempt to not only offset the impacts and risks of climate-related shocks but also influence behavioural responses in a way that improves farm households' adaptive capacity to climatic variability (Below et al., 2010; Berhane et al., 2014; Halsnæs & Trærup, 2009; McLeman et al., 2008; Pan, 2009).

1.1 Problem Statement

The 2015/2016 El Niño drought-induced shock severely affected large parts of Zambia. In particular, Figure 1 below shows that the 2015/2016 El Niño droughts mostly affected regions located in the southern half of Zambia. The main objective of this study is to exploit this unique natural experiment to compare on-farm and off-farm behavioural responses between treatment groups. Despite the growing evidence-base, empirical studies thus far especially from Sub-Saharan Africa (SSA) do not provide comparative insights into the effectiveness of agricultural policy in influencing on-farm and off-farm margin of adjustments to severe weather conditions. This notwithstanding, I contribute to the literature in at least two main ways:

Firstly, there is a shortage of studies exploiting regional differences in drought exposure conditions to explore whether access to agricultural support and the choice of adaptive strategy influence on-farm and off-farm behavioural responses of drought-exposed households differently vis-à-vis the counterfactual group. Current studies largely ignore localized variations in weather characteristics that affect the effectiveness of agricultural policy in influencing smallholder farmers' behavioural margin of adjustments. Therefore, by adopting a matched panel Correlated Random Effects (CRE) estimation strategy to compare behavioural responses between treatment groups, I significantly distinguish this research from previous studies. Besides, this study further differentiates itself by comparing on-farm and off-farm behavioural responses of treatment groups both before and after drought exposure to obtain autonomous adaptation insights.

Secondly, unlike previous research, I incorporate matching methods into a panel data estimation framework to generate robust and reliable causal estimates since a matched panel estimation strategy compares observationally similar treatment groups whilst controlling for unobserved heterogeneity. Moreover, I use high-resolution gridded satellite precipitation data to calculate unbiassed rainfall shock identifiers and validate the drought exposure status of treatment households.

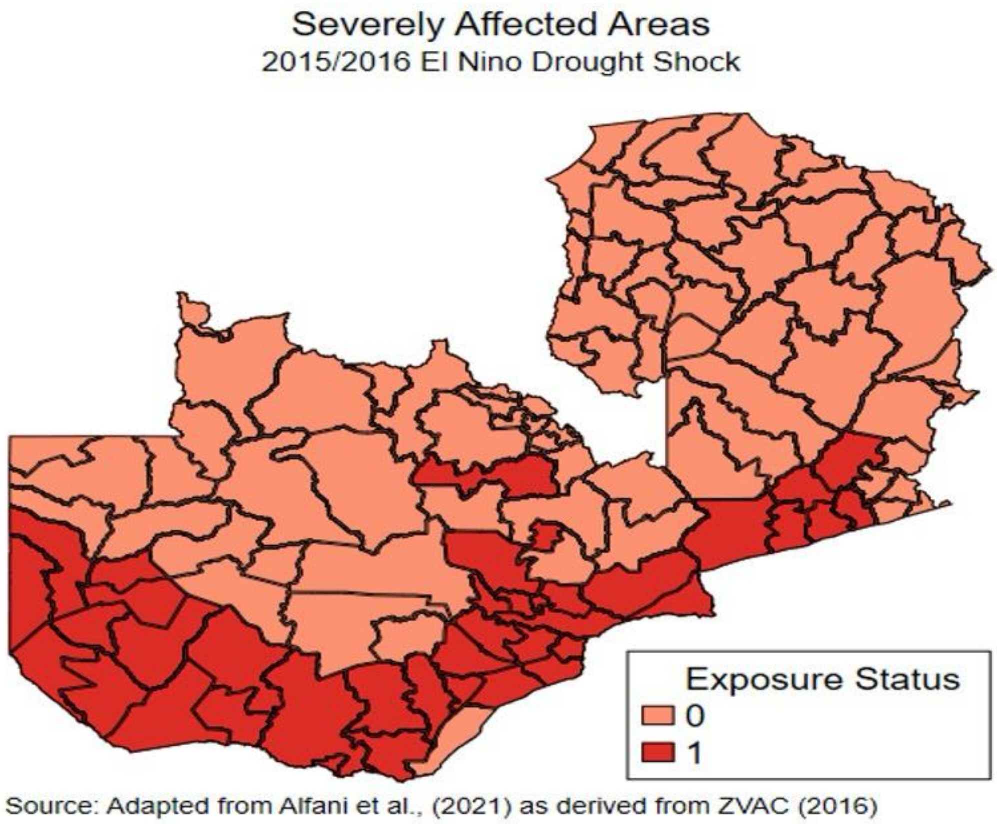

Figure 1: Severely Drought Exposed Areas

The rest of the paper is structured as follows: Section 2 presents the study's theoretical framework; Section 3 describes the data while Section 4 outlines the methodology; Section 5 reports and discusses the results and robustness checks before providing a conclusion in Section 6.

2.0 THEORETICAL FRAMEWORK

Across developing countries, incomplete markets are pervasive and largely characterize the environment in which smallholder farmers operate. The simple theoretical agricultural model derived in this section is primarily informed by the works of De Janvry et al. (1991), Benjamin (1992), and Taylor and Adelman (2003) who modelled and conceptualized the behaviour of peasant households in terms of utility and profit maximization under imperfect market conditions where the corresponding household commodities are rendered non-tradable. This entails that the presence of market failures in the goods and factor markets constrains households from responding optimally to price incentives and/or shocks, but instead pushes households to shift the burden of adjustment onto non-tradable inputs (e.g. labour) and consumption that are within the control of households (De Janvry et al., 1991). Besides, smallholder farmers' consumption and production decisions are interdependent because households are both producers and consumers of goods in settings characterized by missing and/or incomplete markets. Thus, unlike in standard consumer models where the household budget is fixed, the farm household budget in agricultural models is endogenous because household incomes are a function of profits – which are influenced by, among others, production decisions (Taylor & Adelman, 2003).

To illustrate the simple model, let's consider a representative rural farm household i producing only one commodity q_{it} at time t and deriving utility from consuming the commodity C_{it} and leisure l_{it} given by the following quasi-concave utility function $U_{it} = U(C_{it}, l_{it}: Z_{it})$, where Z_{it} is a vector of exogenous household characteristics such as household size, age, and sex that affect overall household utility. Furthermore, for illustration purposes, let's also assume that the production technology employed by the farm household i is given by the following quasi-concave production function $q_{it} = f(A_{it}, L_{it}, \overline{K}_{it}, S_{it})$, where A_{it} captures crop diversification and other related crop management strategies, L_{it} represents total farm labour supply (and any other variable input employed in production such as fertilizer) and constitutes family labour L_{it}^F and hired L_{it}^H labour given by $L_{it} = L_{it}^F + L_{it}^H$, $\overline{K}_{it}$ denotes capital that is assumed to be fixed in the short-run, and S_{it} captures agricultural support variables such as fertilizer-seed support and agricultural credit that are largely assumed to be fixed at the start of the growing season. Besides, I consider S_{it} to serve not only as a shift factor but also to broadly capture various attributes influencing the adoption of conservation agricultural techniques, soil quality, and farming skills that allow the employment of identical agricultural inputs such as labour to yield different outputs. Additionally, I also assume that the farm household i has an exogenous income and total time endowment of y and $T_{it}(Z_{it})$ respectively at its disposal, and that the household can supply L_{it}^O as off-farm labour. Therefore, the farm household divides its time between leisure (l_{it}), working on the farm (L_{it}^F), and working off-farm (L_{it}^O) as shown in the following linear expression $T_{it}(Z_{it}) = l_{it} + L_{it}^F + L_{it}^O$.

Following studies such as Jessoe et al. (2018), Behrer and Park (2017) and Aragón et al. (2021) coupled with overwhelming empirical support showing that extreme weather stressors induce unfavourable impacts on agricultural output, labour productivity, and labour supply (Burke & Emerick, 2016; Chen & Gong, 2021; Colmer, 2021; Njuki, 2021; Ortiz-Bobea et al., 2021; Schlenker & Roberts, 2009; Wang et al., 2021), I allow growing weather conditions (W) to affect agricultural production (q_{it}) through its impact on attributes of crop management strategies (A_{it}) and farm labour supply (L_{it}) as shown in the following re-specified quasi-concave production function $q_{it} = f(A_{it}(W), L_{it}(W), \overline{K}_{it}, S_{it})$, where W is the realized weather at the location of the smallholder farmer – with moderately higher values of W representing favourable growing weather conditions. Besides this, I also make the assumption that (i) agricultural labour supply and weather conditions are complements; (ii) smallholder farmers are mostly price takers; and (iii) that the cost of hiring labour is equivalent to the wage accrued from off-farm work (w) (Benjamin, 1992; De Janvry et al., 1991; Jessoe et al., 2018).

Therefore, assuming the existence of well-functioning labour markets, the farm household maximizes utility subject to the total income constraint as follows:

$$Max\ U(C_{it}, l_{it}: Z_{it}) \quad \ldots \ldots 1$$

$$s.t.\quad C_{it} = P_c f(A_{it}(W), L_{it}(W), \overline{K}_{it}, S_{it}) - wL_{it}^H(W) + wL_{it}^O(W) + y \quad \ldots \ldots 2$$

Allowing for the influence of weather conditions, the total time endowment and farm labour supply functions can be re-written as follows:

$$T_{it}(Z_{it}) = l_{it}(W) + L_{it}^{F}(W) + L_{it}^{O}(W) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \; 3$$

$$L_{it}(W) = L_{it}^{F}(W) + L_{it}^{H}(W) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . 4$$

Using equation (3) and (4) to make $L_{it}^{O}(W)$ and $L_{it}^{H}(W)$ respectively the subject of the formula as shown below in equations (5) and (6), and then substituting these expressions into equation (2) alongside the competitive market equilibrium condition $P_c = P$, where P_c is the price of the agricultural produce, we obtain the simplified expression shown below in equation (7):

$$L_{it}^{O}(W) = T_{it}(Z_{it}) - l_{it}(W) - L_{it}^{F}(W) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . . 5$$

$$L_{it}^{H}(W) = L_{it}(W) - L_{it}^{F}(W) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . . \; 6$$

$$C_{it} + wl_{it}(W) = Pf(A_{it}(W), L_{it}(W), \bar{K}_{it}, S_{it}) - wL_{it}(W) + wT_{it}(Z_{it}) + y \ldots . \ldots \ldots \; 7$$

The right hand side of equation (7) is simply the total farm household income, which is a function of farm households' profits $\pi_{it}(w, P, W, \bar{K}_{it}, S_{it}) = Pf(A_{it}(W), L_{it}(W), \bar{K}_{it}, S_{it}) - wL_{it}(W)$, the value of the total time endowment $[wT_{it}(Z_{it})]$, and farm households' cash endowment (y). By letting Y^* represent the total household income, equation (7) can be re-written as follows:

$$C_{it} + wl_{it}(W) = Y^* \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . . 8$$

Maximizing the utility function $U_{it} = U(C_{it}, l_{it}: Z_{it})$ in equation (1) subject to the total household income constraint represented in equation (8), and then solving the first order conditions yields the following household demand functions:

$$C_{it}^{*} = C(Y^*, w, W) = C(P, w, W, \bar{K}_{it}, S_{it}) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \; 9$$

$$l_{it}^{*} = l(Y^*, w, W) = l(P, w, W, \bar{K}_{it}, S_{it}) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \; 10$$

Similarly, optimizing the household profit function and solving the first order conditions results in the following input demand functions:

$$A_{it}^{*} = A(P, w, W, \bar{K}_{it}, S_{it}) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \; 11$$

$$L_{it}^{*} = L(P, w, W, \bar{K}_{it}, S_{it}) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . 12$$

Based on equations (11) and (12) above, we can observe that weather conditions (W) and agricultural support (S_{it}) directly influence on-farm behavioural margin of adjustments. Notwithstanding the overwhelming empirical support showing that adverse climatic variability harms crop production and labour market conditions – and informed by the implications of equations (5) and (6) –, I hypothesize that farm households respond to extreme weather events by laying off hired labour, devoting more family labour hours towards own-farm cropping activities, and shifting towards specialized, locally-adapted staple-crop systems to ensure food security. Additionally, equations (11) and (12) suggest that expansionary agricultural policies that enhance fertilizer-seed support, agricultural credit, and agricultural extension services can incentivize smallholder farmers located in regions predisposed to severe weather conditions to improve both crop management strategies and uptake of suitable agricultural inputs.

Formally, the first- and second-order conditions of the input demand functions support these expectations. Within the derived model, equations (13) and (14) below indicate that extreme weather reduces crop diversity and leads to labour layoffs. In contrast, equations (15) and (16) suggest that recipients of agricultural support mitigate these impacts by improving crop diversification and farm labour supply respectively in response to climate variability.

$$\frac{\partial A_{it}^{*}}{\partial W} < 0 \quad \ldots\ldots 13$$

$$\frac{\partial L_{it}^{*}}{\partial W} < 0 \quad \ldots\ldots 14$$

$$\frac{\partial^2 A_{it}^{*}}{\partial W \partial S} > 0 \quad \ldots\ldots 15$$

$$\frac{\partial^2 L_{it}^{*}}{\partial W \partial S} > 0 \quad \ldots\ldots 16$$

Therefore, on the basis of all the above derived expressions, I postulate the following testable hypotheses:

Hypothesis 1: ***Adverse drought conditions stimulate monoculture agricultural practices.*** This hypothesis is drawn directly from the first-order derivative in equation (13), which indicates that a low crop diversification value signifies a shift toward monoculture or more specialized cropping systems.

Hypothesis 2: ***Severe aridity conditions contribute to cropland expansion and increased utilization of productivity-enhancing inputs such as improved seed varieties and inorganic fertilizers***. This hypothesis builds indirectly on Hypothesis 1 by suggesting that specialization in low-value crops increases the use of inputs such as drought-resistant seeds to raise productivity. Accordingly, I propose that risk-averse smallholders – particularly in areas with imperfect labour markets and food-insecurity concerns – respond to extreme drought by expanding land use shares and boosting input application to mitigate losses in crop yields and household consumption.

Hypothesis 3: ***Extreme weather conditions such as droughts lower off-farm incomes and occupational diversity.*** This hypothesis, informed by equations (5), (6), (9), (10), and (14), is consistent with the first hypothesis. It posits that an increase in family labour supply reduces off-farm labour and income (equation 5 and 6). This income decline lowers demand for both agricultural and non-agricultural goods, reducing consumption and leisure activity (equation 9 and 10). In response, farm and non-farm sectors lay off workers, further depressing off-farm income. Concurrently, under extreme weather, net farm labour supply decreases because layoffs of hired labour exceed any rise in family labour supply (equation 14).

Hypothesis 4: ***Beneficiaries of agricultural support in drought-hit areas diversify crop portfolio management strategies, expand hectarage shares, boost agricultural inputs uptake, and earn lower off-farm incomes***. This hypothesis is derived from the second-order derivatives in equations (15) and (16), with equation (16) also indirectly relating to equations (5) and (6). Specifically, equation (15) indicates that recipients of agricultural support adopt polyculture systems in response to drought, positively influencing cropland expansion and input use. Equation (16) shows that these beneficiaries also reallocate labor from off-farm activities to their own farms, which reduces off-farm income and limits occupational diversity.

Hypothesis 5: ***The choice of adaptive strategy constrains crop diversity, cropland shares and input utilization, and further contributes to lower off-farm incomes in drought-hit regions***. This hypothesis follows indirectly from Hypothesis 4, as agricultural support – often delivered through extension services – shapes the choice of adaptive land investments. I propose that drought-affected farmers with limited resources, for whom implementing suitable land strategies across large, diverse croplands is costly and time-intensive, are likely to concentrate labour on smaller, manageable plots of low-value crops to ensure basic food security.

Consequently, this reduces the use of productivity-enhancing inputs, depresses off-farm income, and limits occupational diversity.

3.0 DATA DESCRIPTION AND ANALYSIS

3.1 Data Description

This study combines a large three-wave rural household-level dataset with geocoded satellite rainfall data to form a unique panel dataset. The nationally representative rural household-level dataset comes from the Rural Agricultural Livelihoods Survey (RALS) which is conducted every three years since 2012. RALSs collects and reports various agricultural and non-agricultural information related to, among others, cropland shares, cultivated crops and seed types, quantities of basal and top-dressing fertilizer used, and off-farm income enterprises. Thus, the uniqueness of RALS lies in its comprehensiveness and national coverage, with the 2012 RALS utilizing the 2010 national census as its sampling frame. So far, a total of 7,241 rural agricultural farm households were re-interviewed in the latest 2019 RALS. Given that the 2015/2016 El Niño weather event triggered regional variations in aridity conditions and severely affected areas mostly situated in the southern parts of Zambia, I follow Alfani et al. (2021) and adopt the same treatment definition of extreme drought exposure used in the 2016 vulnerability and needs assessment report to categorize severely affected farm households (ZVAC, 2016). This, in turn, partitions the 2015 RALS dataset into two separate groups, namely, treatment and counterfactual group households. Thereafter, I track these farm households back to the 2012 RALS and forward in the 2019 RALS to form a unique panel dataset of treated and untreated farm households. On the other hand, I obtain the geocoded satellite rainfall data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). CHIRPS collects daily precipitation data with a grid spatial resolution of 0.05° by 0.05° as far back as 1981 (Funk et al., 2015).

To combine the two respective georeferenced datasets, I use the nearest neighbour approach that links each farm household in the household-level dataset to the nearest gridded precipitation data point (Ndhlovu & Muchapondwa, 2020; Picard, 2019). Furthermore, following studies such as Larcom et al. (2019) and Alfani et al. (2021), satellite precipitation data is used to calculate rainfall shock identifiers at the location of the smallholder farmer in order to objectively establish drought exposure and validate the treatment status of farm households located in areas that were identified to be extremely affected by the 2015/2016 El Niño drought shock. This secondary validation is vital because it ensures that only households that experienced severe aridity conditions induced by the El Niño drought shock are included in the treatment sample. Therefore, to calculate objective rainfall shock identifiers over the 2015/2016 growing season – i.e., October to March, I use the following standardized deviation measure:

$$Rainfall\_Anomally_{it} = \frac{R_{it} - \bar{R}_{it}}{\sigma_{sd}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad 1$$

where R_{it} is the total 2015/2016 growing season rainfall at the location of the smallholder farmer i in the survey year of interest $t = 2015$, and $\bar{R}_{it}$ and σ_{sd} are the average and standard deviation growing season rainfall respectively at the location of the smallholder farmer i over the growing season reference period 2008/2009 - 2014/2015 preceding the 2015/2016 growing season. The treatment group is validated and defined by assigning a value of 1 to all smallholder farmers located in districts severely impacted by the El Niño drought-induced shock where the rainfall shock identifier is negative. However, households in areas that were either less affected or unaffected by the droughts are assigned a value of zero, serving as the counterfactual group.

Furthermore, note that I synonymously use the terminologies treatment vs control, treatment vs untreated, treated vs counterfactual, and exposed vs unexposed.

This study considers five behavioural responses to extreme weather stressors that are commonly hypothesized to influence farm households' adaptive capacity. These include crop diversification, cropland adjustment, seed consumption and inorganic fertilizer variations, and off-farm income enterprises. The first four responses capture productive margin of adjustments to adverse climatic conditions whereas off-farm income captures all off-farm income enterprises that serve as shock-coping instruments against extreme weather events. Due to space restrictions, the subsection below only defines and constructs the crop diversification index while the rest of the dependent variables are defined in appendix A alongside all other variables.

Crop Diversification Index

Crop diversification involves the cultivation of different crop types or consumption of different seed varieties of the same crop type during the cropping season (Bezabih & Sarr, 2012; Bradshaw et al., 2004; McCord et al., 2015; Mulwa & Visser, 2020). Although there exist several variants of indices that measure crop diversification, these indices all intuitively attempt to capture and relay information on the degree of climate risk smallholder farmers are willing to assume or show how diversified crop portfolio management strategies are with respect to the number of different cultivated crops over the growing season. Besides, irrespective of the crop diversification measure, the degree of crop diversity is inversely related to both risk and vulnerability to adverse weather conditions. Therefore, a relatively lower crop diversification increases the risks of exposure and vulnerability to random weather shocks whereas the opposite minimizes climate-related risks and strengthens farm households' adaptive capacity to extreme weather stressors.

Most previous empirical research either adopts the Simpson Index of Diversification (SID) or Herfindahl-Hirschman Index (HHI) as crop diversification measures because they both adequately provide insights into farm households' cropping frequency and intensity using information on the number of cultivated crops and corresponding hectarage shares (Auffhammer & Carleton, 2018; Birthal & Hazrana, 2019; Kankwamba et al., 2018; Mulwa & Visser, 2020; Ochieng et al., 2020; Piedra-Bonilla et al., 2020). Since the HHI is a subset of the SID, and notwithstanding that the two indices are closely related and arrive at the same conclusion on the degree of climate risk, I adopt the SID (Simpson, 1949) as a measure of crop diversity. Therefore, following studies such as Kankwamba et al. (2018), Piedra-Bonilla et al. (2020), and Ochieng et al. (2020), I exploit information on cropping frequency and associated cropland shares at the location of the smallholder farmer to construct the SID shown below:

$$SID = 1 - \sum_{j=1}^{n} N_j^2 \quad \ldots\ldots\ldots 2$$

where HHI= $\sum_{j=1}^{n} N_j^2$, $N_j = \frac{c_j}{\sum_j^n c_j}$ represents the percentage of land in hectares allocated to the j^{th} crop, and $j = 1,2,3, \ldots n$ is the number of cultivated crops. As can be seen in equation (2), the number of cultivated crops and how equally the land is apportioned across these crops determines the overall value of the SID, which ranges between 0 and 1 (Joshi et al., 2004; Kankwamba et al., 2018; Ochieng et al., 2020; Piedra-Bonilla et al., 2020). Thus, the implications of equation (2) are that the degree of crop diversity and farm specialization increase as the SID approaches 1 and 0 respectively. By extension, this implies that highly diversified farm households have HHI values closer to zero while higher values of HHI that tends towards 1 are an indication of increased farm specialization.

3.2 Descriptive Analysis

Table 1 below shows selected vital summary statistics of smallholder farmers in the overall sample and treatment groups using the 2012 RALS as the baseline sample. The average values in the overall sample suggest that farm households cultivate roughly 2.3 hectares and consume about 86 and 251 kg's of seeds and inorganic fertilizers respectively. Further, column 1 also shows a high average off-farm income, an indication that most farm households participate in off-farm income activities. Additionally, a low SID value is indicative of a more specialized cropping pattern and/or increased reliance on monoculture agricultural systems. Besides, nearly 45% of farm households belong to a cooperative society, and about 49%, 55%, and 16% accessed fertilizer-seed support, agricultural extension services, and agricultural credit respectively.

With regard to the choice of adaptive strategy, the majority of farm households (66%) rely more on crop residues. Furthermore, almost 32% of smallholder farmers adopt minimum soil disturbance and soil moisture-enhancing technologies, while around 17%, 11%, 18%, and 9% of the sample adopt crop rotation, legume-intercropping, irrigation, and animal-plant manure respectively. Moving on, panel D shows that the average age and highest level of formal education for the household head is about 45 and 6 years respectively. Moreover, most farm households are headed by males (81%), of which 82% are either in a monogamous or polygamous marriage. Additionally, on average, a typical rural household size consists of about 6 members. In terms of farm characteristics shown in panel E, smallholder farmers in the overall sample own approximately 7 farm implements and cultivate about 3 crops and 4 agricultural fields during the growing season. Besides this, farm households maintain roughly 6 livestock units.

Table 1: Summary Statistics

Variable	All	Treatment	Control
	(1)	(2)	(3)
Panel A: Outcome Variables			
Hectares Cultivated (ha)	2.30	2.51	2.20
Seed Consumption (kg)	85.56	84.57	86.09
Fertilizer Usage (kg)	250.78	256.90	247.50
Off-Farm Income (ZMW)	7,793,169	8,633,276	7,343,866
Simpson Index of Diversification	0.36	0.33	0.37
Panel B: Agricultural Support			
Membership – Agricultural Cooperative Societies (Yes=1)	0.45	0.40	0.48
Fertilizer & Seed Support (Yes=1)	0.49	0.41	0.53
Agricultural Extension Services (Yes=1)	0.55	0.57	0.54
Access to Agricultural Credit (Yes=1)	0.16	0.22	0.13
Panel C: Choice of Adaptive Strategy			
Minimum Soil Disturbance (Yes=1)	0.32	0.09	0.44
Crop Rotation (Yes=1)	0.17	0.07	0.22
Legume Intercropping (Yes=1)	0.11	0.05	0.14
Crop Residues – Soil (Yes=1)	0.66	0.69	0.65
Irrigation (Yes=1)	0.18	0.21	0.16
Animal & Plant Manure (Yes=1)	0.09	0.14	0.07
Soil Erosion Prevention Measures (Yes=1)	0.32	0.21	0.38
Panel D: Socio-demographic Characteristics			
Age (Head)	45.49	45.79	45.33
Education (Head)	6.17	6.09	6.22
Household Head (Male=1)	0.81	0.79	0.82
Marital Status (Married=1)	0.82	0.80	0.83
Household Size	5.85	5.86	5.84
Panel E: Farm Characteristics			
Number of Farm Implements	6.72	7.09	6.52
Number of Cultivated Crops	2.96	2.62	3.14
Number of Cultivated Fields	3.80	3.40	4.02
Number of Livestock Owned	6.24	9.33	4.59
Observations	**8,839**	**3,080**	**5,759**

Note: ZMW denotes the units for the Zambian currency "Kwacha"

However, partitioning the overall sample into treatment and counterfactual groups reveals striking differences between the two groups. In particular, a comparison of columns (2) and (3) show that treatment farm households cultivate more hectares than control group households. Furthermore, treated households relatively earn more from off-farm income activities than counterfactual households. However, the degree of crop diversification is relatively lower in the treatment sample. Besides this, more counterfactual group households belong to cooperative societies and benefit from fertilizer-seed support compared to treatment households. However, there are more beneficiary treated farm households of agricultural extension services and credit relative to the untreated group. Moreover, panel C shows that treatment groups exhibit different adoption rates across all adaptive strategies. Likewise, socio-demographic and farm characteristics of treatment groups are noticeably different. Altogether, these noticeable differences between treated groups may have serious implications on the effectiveness of agricultural policy in influencing behavioural responses of treatment groups to climatic variability and change.

Given that there may be justified fears that these pre-treatment compositional differences may bias the estimated results and affect the effectiveness of agricultural policy, I apply matching methods to generate a matched panel sample of treated groups that are observationally similar (Khandker et al., 2009; Rosenbaum & Rubin, 1983, 1984, 1985). More specifically, I employ both the Kernel and Nearest Neighbour (NN) matching approaches to evaluate matching quality. Due to space limitations, I only show the standard Kernel matching quality results because the Kernel matching estimator relatively produces better matching results. Table 2 below shows covariate balance tests for selected variables, and we can see that the application of matching significantly minimizes the average differences between treatment groups in the matched sample.

Additionally, figure 2 below shows baseline compositional distributional differences between treatment and untreated groups both before and after matching. Particularly, panels A and B of figure 2 both show the appeal of matching and visibly suggest that the differences between treated and counterfactual groups dissipate and become indistinguishable from zero after applying matching. Therefore, matching shrinks the compositional differences in observable pre-exposure characteristics and consequently minimize the associated potential selection bias. This, in turn, enables the study to derive reliable causal estimates and insights that can guide the development of targeted agricultural policies aimed at enhancing the adaptive capacity of treatment farm households. Although matching does not completely eliminate unobserved pre-exposure compositional differences in household characteristics between treated groups (Heckman et al., 1997; Rosenbaum & Rubin, 1985), applying panel data methods to a matched panel dataset helps to significantly eliminate or address selection bias concerns since panel data methods such as the Mundlak CRE and FE model controls for, among others, unobserved heterogeneity.

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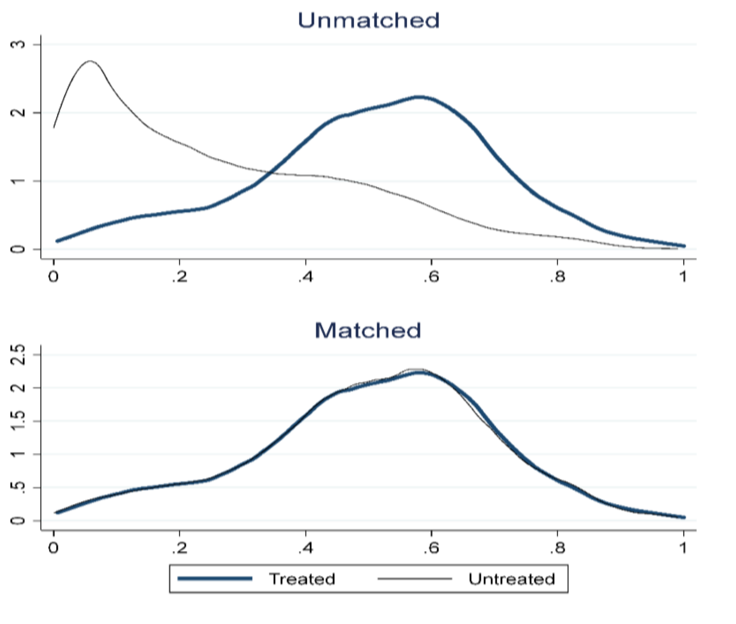
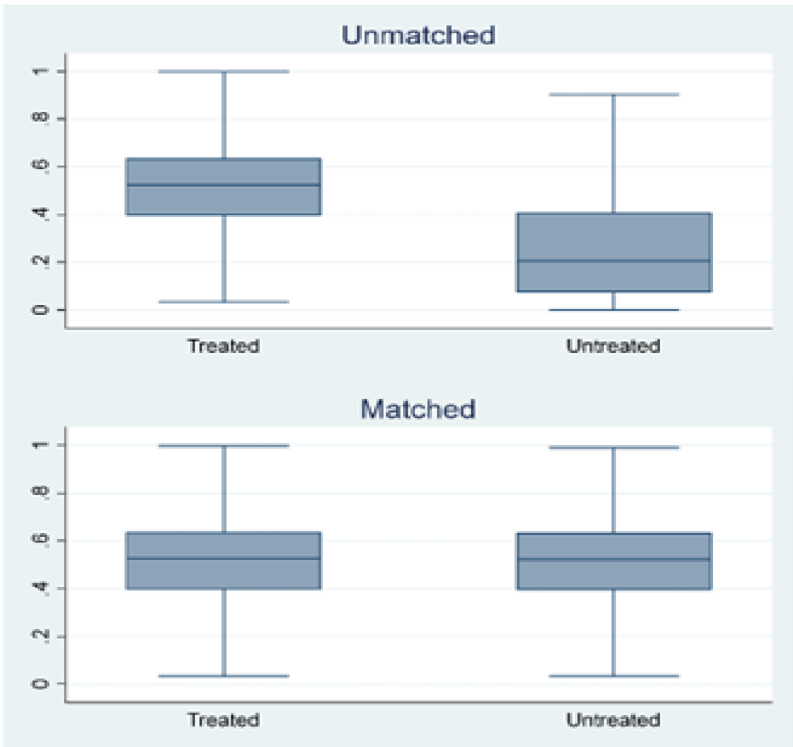
Table 2: Covariate Balance Test

	Unmatched	Mean			%Reduct	t-test	
Variable	**Matched**	**Treated**	**Control**	**%Bias**	**|Bias|**	t	p > |t|
Household Head	U	.79384	.82648	-8.3		-3.28	0.001
	M	.79384	.80474	-2.8	66.6	-0.94	0.349
Education	U	5.9519	6.0952	-3.9		-1.53	0.125
	M	5.9519	6.0103	-1.6	59.3	-0.54	0.592
Age	U	46.799	45.974	5.6		2.20	0.027
	M	46.799	46.296	3.4	39.1	1.17	0.244
Marital Status	U	.81029	.83729	-7.1		-2.79	0.005
	M	.81029	.81922	-2.3	66.9	-0.79	0.429
Farm Implements	U	7.3803	6.7482	8.3		3.10	0.002
	M	7.3803	7.5916	-2.3	66.6	-0.95	0.340
Cultivated Crops	U	2.7154	3.2302	-32.6		-12.49	0.000
	M	2.7154	2.7109	0.3	99.1	0.11	0.915
Cultivated Fields	U	3.5384	4.154	-29.9		-11.56	0.000
	M	3.5384	3.5373	0.0	99.8	0.02	0.985
Livestock Units	U	10.367	5.0901	31.4		13.30	0.000
	M	10.367	9.0162	8.0	74.4	2.37	0.018
Membership – Agricultural Cooperative	U	.43676	.50835	-14.4		-5.60	0.000
	M	.43676	.45572	-3.8	73.5	-1.31	0.189
Fertilizer & Seed Support	U	.4296	.56149	-26.6		-10.38	0.000
	M	.4296	.45729	-5.6	79.0	-1.92	0.055
Peer Influence	U	.11046	.10299	2.4		0.95	0.343
	M	.11046	.10669	1.2	49.6	0.42	0.677
Access to Credit	U	.23145	.14178	23.2		9.29	0.000
	M	.23145	.24131	-2.5	89.0	-0.80	0.424
Crop Rotation	U	.0801	.22949	-42.2		-15.58	0.000
	M	.0801	.08311	-0.9	98.0	-0.38	0.705
Intercropping	U	.04722	.14108	-32.6		-11.95	0.000
	M	.04722	.04479	0.8	97.4	0.40	0.691
Crop Residues – Soil	U	.69519	.65225	9.2		3.56	0.000
	M	.69519	.69053	1.0	89.1	0.35	0.728
Irrigation	U	.22386	.1707	13.4		5.30	0.000
	M	.22386	.20959	3.6	73.1	1.19	0.233
Animal & Plant Manure	U	.14798	.07007	25.2		10.31	0.000
	M	.14798	.13001	5.8	76.9	1.79	0.074
Bunding	U	.01265	.19092	-61.7		-21.61	0.000
	M	.01265	.06657	-18.7	69.8	-9.61	0.000
Ridging	U	.06239	.42934	-94.2		-33.91	0.000
	M	.06239	.08486	-5.8	93.9	-2.96	0.003
Hectares Cultivated	U	2.6356	2.3133	13.9		5.47	0.000
	M	2.6356	2.6909	-2.4	82.9	-0.71	0.481
Simpson Index of Diversification	U	.33741	.38408	-18.7		-7.19	0.000

	M	.33741	.33767	-0.1	99.4	-0.04	0.971



Panel A: Kernel Density Plots



Panel B: Kernel Box Plots

Figure 2: Summary Distributional Characteristics between Unmatched and Matched Samples

4.0 MATERIALS AND METHODS

This study adopts the Mundlak CRE model to assess whether agricultural support and choice of adaptive strategy influence on-farm and off-farm behavioural responses to extreme drought conditions vis-à-vis the counterfactual group. As discussed in the preceding section, I apply matching methods prior to estimating the CRE model to minimize the potential selection bias that may confound the treatment effect. The two widely used standard panel data models in applied research are FE and RE models. Despite their prominence, the two models are not devoid of weaknesses. Notably, FE estimations are unable to capture time-constant effects while RE models require the strict exogeneity assumption to hold to guarantee unbiased estimates (Wooldridge, 2015). However, the CRE model is relatively more flexible because it captures the unobserved heterogeneity that stems from time-constant omitted variables using averages of time-varying observed covariates (McCarthy et al., 2021; Mundlak, 1978; Schunck, 2013; Schunck & Perales, 2017; Wooldridge, 2019). Thus, the CRE framework not only retains time-constant effects and other desirable attributes of both FE and RE models but also explicitly accounts for any statistical dependence between time-varying observed covariates and random effects (Mundlak, 1978; Wooldridge, 2011, 2019).

Given the foregoing, I estimate the matched CRE model using the following reduced-form econometric specification to explore behavioural responses of treatment farm households relative to the control group:

$$lny_{it} = \alpha + \beta T_{it} + \varphi I_{time} + \delta D_{it} + \theta T_{it} D_{it} + \psi Z_{it} + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; 3$$

where lny_{it} represents the natural logarithm of the dependent variables of interest (crop diversity, cropland share, seed consumption, fertilizer use, and off-farm income) for household i in year t, T_{it} is a treatment dummy variable taking the value 1 for extreme drought exposure (i.e., treatment group) and zero otherwise, I_{time} is the time dummy variable capturing the period before ($I_{time} = 0$) and after ($I_{time} = 1$) drought exposure, D_{it} is a vector of dummy variables capturing access to agricultural support and the choice of adaptive strategy, Z_{it} is a set of control variables such as household characteristics, farm attributes and social/peer influence, and ε_{it} is the error term. The coefficient α is the intercept, β measures the average treatment effect of severe drought exposure relative to unexposed households, φ compares the average difference in the behavioural margin of adjustment between pre- and post-exposure periods, δ captures the average differential influence of the choice of adaptive strategy and agricultural support variables on productive and off-farm behavioural responses during average weather conditions, and the average differential coefficient of interest θ determines whether agricultural support and the choice of adaptive strategy influence behavioural responses of treatment farm households differently relative to the untreated group.

To shade further insights into the extent of autonomous adaptation, I also separately evaluate and compare on-farm and off-farm behavioural responses of treatment groups both before and after the drought shock. Therefore, I re-specify equation (3) and estimate the following estimable reduced form matched CRE model:

$$lny_{it} = \alpha + \beta_{pre} T_{it}^{pre} + \beta_{post} T_{it}^{post} + \varphi I_{time} + \delta D_{it} + \theta T_{it} D_{it} + \psi Z_{it} + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots \; 4$$

where T_{it}^{pre} is a binary variable equal to 1 and captures the treatment group prior to the drought shock whereas T_{it}^{post} is the counterpart dummy variable equal to 1 that captures treated households after the drought shock, and all the other variables are as defined previously. The coefficient β_{pre} compares behavioural margin of adjustments between treatment groups before the drought shock. Similarly, the coefficient β_{post} measures differential behavioural responses of treatment farm households relative to the counterfactual group after the drought shock.

As the case is with many other household-level datasets, the observational dataset that this study exploits also contains outliers on both extremes. Specifically, on the one hand, the dataset contains true zeros because some smallholder farmers adopt mono-cropping agricultural practices, rely more on organic than inorganic fertilizers, choose not to cultivate during the growing season, or genuinely earn zero off-farm incomes. On the other hand, there are also farm households that earn unusually high off-farm incomes and consume extremely large quantities of farming inputs. Thus, it is not uncommon for rural household-level datasets to contain outliers, and the presence of these extreme values inhibits the variables from exhibiting the normal distribution properties. Besides, since the logarithm of zero is undefined, taking the natural logarithm of genuine zero-valued observations drops the zero-values from the dataset. Therefore, despite being attractive, the log transformation eliminates zero-valued observations from the dataset and hence, deprives the study of a meaningful analysis and perspective that would potentially come from the subset of zero-valued observations that the log-transformation drops (Bellemare & Wichman, 2020).

There are several ad hoc log transformations in the applied econometrics literature that attempt to simultaneously minimize the influence of outliers and sidestep the dropping of meaningful nonpositive observations (Bellemare & Wichman, 2020; MaCurdy & Pencavel, 1986; Michalopoulos & Papaioannou, 2013; Norton, 2022). As a case in point, Michalopoulos and Papaioannou (2013) adds a small number of about 0.01 to zero-valued observations prior to executing the log transformation while MaCurdy and Pencavel (1986) adopts a similar approach that adds a value of 1 to nonnegative values. Similarly, the empirical literature also shows growing use of the inverse hyperbolic sine function (also dubbed the arcsinh transformation) to preserve zero-valued observations (Bellemare & Wichman, 2020; Burbidge et al., 1988; MacKinnon & Magee, 1990; Norton, 2022; Pence, 2006; Ravallion, 2017). Given the foregoing, it is obvious that ad hoc log transformations affect the size of effect estimates. Recent empirical support to this effect demonstrates that there are substantial differences in elasticity estimates derived from the arcsinh transformation and common ad hoc log transformations that add 1 to zero-valued observations (Bellemare & Wichman, 2020). Thus, this suggests that the choice of ad hoc log transformation can have huge direct implications on the magnitude of coefficient estimates. This notwithstanding, and given the growing use of the inverse hyperbolic sine function and its associated attractive properties (Bellemare & Wichman, 2020; Norton, 2022; Ravallion, 2017), I also apply the inverse hyperbolic sine function defined below to transform all continuous dependent and independent variables of interest in the dataset.

$$sinh^{-1}(x) = \ln\left[x + (x^2+1)^{\frac{1}{2}} \right] \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.\dots\dots\dots\dots\dots\dots\dots\dots \; 5$$

Since the inverse hyperbolic sine transformation retains zero-valued observations across all the dependent variables, the appropriate model to estimate is the CRE tobit model. More specifically, I use the bounded CRE tobit to model the association between crop diversification and drought exposure since the SID lies between zero and one. However, the rest of the estimations involving the other dependent variables – i.e., cropland share, seed uptake, fertilizer use, and off-farm income – adopts a left-censored CRE tobit model that is truncated at the lower bound of zero to evaluate respective behavioural responses to severe drought conditions vis-à-vis the counterfactual group.

5.0 FINDINGS

To compare behavioural responses between treatment groups, I conduct two sets of analysis using specifications (3) and (4) discussed in the previous section. Specifically, the first comparative assessment focuses on productive margin of adjustments while the second set compares off-farm behavioural responses of treatment units. Furthermore, to correctly interpret the coefficients on dummy variables across the estimated semilogarithmic specifications, I transform the coefficients of interest by exponentiating them and thereafter subtracting one from the outcome. This method of transforming coefficients is consistent with the approach taken and/or guidance provided by Halvorsen and Palmquist (1980), Kennedy (1981), and Bellemare and Wichman (2020). As such, the estimates discussed in the text will be slightly different from those reported in the results tables. Additionally, note that each table reports the estimated results derived from both specifications (3) and (4) (hereafter labelled model 1 and 2 respectively). Later on, I conduct several robustness tests to check the sensitivity of the main CRE results to alternative estimation approaches, sample size restrictions, and alternate dataset.

5.1 On-Farm Margin of Adjustments

5.1.1 Crop Diversification

Table 3 below reports the results derived from the bounded CRE tobit specification that associates crop diversification with extreme drought exposure, agricultural support, and choice of adaptive strategy. Columns (1) and (2) both show that drought exposure significantly reduces the degree of crop diversification among treatment farm households. Specifically, the drought shock coefficient in the naïve specification (1) is negative and highly statistically significant, suggesting that drought exposure lowers the degree of crop diversification in drought-hit areas by roughly 9% relative to the unexposed group. Similarly, this coefficient remains negative and statistically significant in the preferred conditional specification (2) although the absolute size of the coefficient reduces to about 2.1%. A relatively lower level of crop diversity is indicative of increased farm specialization and vulnerability to climate-related risks. As such, I interpret this to be evidence that poor farm households respond to drought exposure by shifting towards more specialized cropping practices and cultivating suitable low-value crops to guarantee food security. Although this observation is at variance with studies showing that farm households improve crop diversification strategies to cope with extreme weather stressors (Asfaw et al., 2018; Bezabih & Sarr, 2012; McCord et al., 2015; Mulwa & Visser, 2020; Piedra-Bonilla et al., 2020), the results are broadly consistent with other previous studies that establish a negative association between crop diversification and adverse climatic conditions (Bradshaw et al., 2004; Cohn et al., 2016; Di Falco et al., 2010; Ndhlovu & Muchapondwa, 2020; Ochieng et al., 2020).

In addition, the naïve specification (3) shows that the coefficients on the pre- and post-treatment variables are negative and highly statistically significant. While these coefficients retain the direction of impact in the preferred conditional specification (4), the post-treatment coefficient losses statistical significance. Moving on, column (2) shows that the time dummy coefficient is positive and highly statistically significant, suggesting that overall crop diversity improves by about 2.3% after the drought shock. Likewise, this coefficient remains positive in specification (4) but becomes statistically insignificant. Furthermore, under average weather conditions, specifications (2) and (4) both show that access to fertilizer-seed support induce discernible adverse effects. This dissuading crop diversification effect is not surprising given that Zambia's past agricultural policy has largely been biased towards supporting the cultivation of maize at the expense of other crops. Therefore, this finding points to the inherent structural bias of the fertilizer-seed support programme towards the cultivation of localized staple crops. Further to this, noticeable positive impacts of agricultural credit can be seen in both specifications (2) and (4). This finding supports the widely held premise that improved access to credit can allow smallholder farmers to boost crop diversification strategies. With regard to the impacts of adaptive strategies, columns (2) and (4) both show that most adaptive land investments appear to largely strengthen the degree of crop diversity during regular weather conditions.

However, under extreme drought conditions, the estimated coefficients on the interaction terms across specifications (2) and (4) show contrasting and, in some cases, limited impacts. Specifically, restricting the analysis to statistically significant interaction coefficients, the results in column (2) suggest that treatment beneficiaries of fertilizer-seed support and agricultural credit improve crop diversification strategies by about 3.3% and 7.3% respectively relative to the counterfactual group. Comparable estimates can also be observed in specification (4). Thus, I take this to be empirical support that treatment beneficiaries of fertilizer-seed support and agricultural credit respond to drought conditions by improving crop portfolio management strategies. As such, strengthening government support towards fertilizer and seed acquisition, and eliminating agricultural credit bottlenecks can be effective conduits through which crop diversification can be improved in areas experiencing severe moisture stress conditions. Additionally, specification (2) shows that treated adopters of adaptive strategies largely reduce the degree of crop diversification compared to the control group. Similarly, the results shown in specification (4) provides comparable noticeable negative interaction effects. Although these findings mostly contradict the impacts of adaptive strategies on crop diversification previously observed under average weather conditions, I however take these results to be empirical support that treated adopters largely reduce their crop diversity or adopt mono-cropping agricultural practices in response to extreme drought exposure to guarantee food security. Therefore, localized drought conditions appear to incentivize rural smallholder farmers to embrace adaptive land strategies that complement monoculture agricultural systems. Besides, since climate-smart practices are expensive to implement and sustain, I take this to be suggestive evidence that costly adaptive land investments dissuade poor treated adopters from diversifying their crop portfolio management strategies.

Table 3: Productive Margin of Adjustment - Crop Diversification

Dependent Variable: ln (Simpson Index of Diversification - SID)	Model 1		Model 2	
	(1)	(2)	(3)	(4)
Drought Shock (1=Yes)	-0.0861***	-0.0204*		
	(0.00553)	(0.0108)		
Pre-Treatment			-0.102***	-0.0319***
			(0.00629)	(0.0118)
Post-Treatment			-0.0603***	-0.00325
			(0.00733)	(0.0130)
Time Dummy		0.0230***		0.0117
		(0.00705)		(0.00854)
Agricultural Support				
Fertilizer-Seed Support (1=Yes)		-0.0240***		-0.0244***
		(0.00785)		(0.00785)
Agricultural Extension (1=Yes)		0.00806		0.00843
		(0.00636)		(0.00636)
Agricultural Credit (1=Yes)		0.0969***		0.0962***
		(0.00768)		(0.00768)
Choice of Adaptive Strategy				
Minimum Soil Disturbance (1=Yes)		0.0868***		0.0859***
		(0.00595)		(0.00596)
Crop Rotation (1=Yes)		0.118***		0.118***
		(0.00624)		(0.00624)
Crop Residues – Soil (1=Yes)		0.0350***		0.0333***
		(0.00586)		(0.00590)
Legume Intercropping (1=Yes)		0.0308***		0.0312***
		(0.00799)		(0.00798)
Agroforestry (1=Yes)		0.0420***		0.0485***
		(0.00825)		(0.00869)
Irrigation (1=Yes)		0.0121		0.0131*
		(0.00755)		(0.00756)
Animal Plant Manure (1=Yes)		0.00377		0.00341
		(0.0108)		(0.0108)
Soil Erosion Prevention Practices (1=Yes)		0.0261***		0.0267***
		(0.00580)		(0.00581)
Extreme Drought Conditions – Interaction Terms				
Shock × Fertilizer-Seed Support		0.0323**		0.0329**
		(0.0128)		(0.0128)
Shock × Agricultural Extension		0.00750		0.00625
		(0.0105)		(0.0105)
Shock × Agricultural Credit		0.0700***		0.0716***
		(0.0117)		(0.0118)
Shock × Minimum Soil Disturbance		-0.0509***		-0.0479***
		(0.0104)		(0.0105)
Shock × Crop Rotation		-0.0200*		-0.0165
		(0.0110)		(0.0111)
Shock × Legume Intercropping		-0.0317*		-0.0337**
		(0.0171)		(0.0171)
Shock × Crop Residues – Soil		-0.0349***		-0.0289***
		(0.00974)		(0.0101)
Shock × Agroforestry		-0.0262**		-0.0421***
		(0.0119)		(0.0137)
Shock × Irrigation		0.00137		0.000583
		(0.0119)		(0.0119)
Shock × Animal Plant Manure		0.00154		0.00211
		(0.0146)		(0.0146)
Shock × Soil Erosion Prevention		0.00419		0.00253

Measures				
		(0.0102)		(0.0102)
Constant	0.361***	0.171***	0.360***	0.164***
	(0.00305)	(0.0502)	(0.00306)	(0.0502)
Demographic Household Characteristics	No	Yes	No	Yes
Household Wealth	No	Yes	No	Yes
Farm Characteristics	No	Yes	No	Yes
Membership – Farmer Support Groups	No	Yes	No	Yes
Peer Influence	No	Yes	No	Yes
Observations	21800	21800	21800	21800

Standard errors in parentheses

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

5.1.2 Cropland Adjustment

Table 4 below reports empirical estimates showing farm households' cropland response to extreme drought exposure and how agricultural support and the choice of adaptive strategy affects cropland adjustments under regular and extreme weather conditions. The unconditional specification (1) shows a positive and highly statistically significant drought exposure impact. This coefficient retains the direction of impact and statistical significance in the preferred specification (2), suggesting that extreme drought exposure results in cropland expansion of about 11.6% among treated households relative to the untreated group. Notwithstanding the inducement effect of severe drought stresses on farm specialization observed in the preceding subsection, I interpret this result to be empirical support that smallholder farmers respond to extreme drought exposure conditions by expanding hectarage shares of localized low-value staple crops to minimize the risks of yield losses. This observation speaks to previous empirical findings (Aragón et al., 2021; Cho & McCarl, 2017; Cohn et al., 2016; Cui, 2020b; Iizumi & Ramankutty, 2015), and thus, cropland expansion appears to be one response strategy used by risk-averse farmers to mitigate drought-induced crop production risks.

Next, columns (3) and (4) both show that treatment households relatively cultivate large portions of land both pre- and post-drought exposure. Particularly, unlike in the unconditional specification (3), the preferred conditional specification (4) shows that treatment smallholder farmers cultivate more land both before and after drought exposure of about 14.5% and 7.4% respectively relative to the untreated group. However, since the post-drought exposure cropland expansion of treatment households is relatively lower than that of the analogous pre-treatment period, I hypothesize that exposure to severe drought conditions incentivize farm households to reduce the rate of cropland expansion. Further, columns (2) and (4) both show that the time dummy coefficients are positive and highly statistically significant. This suggests that overall hectarage shares increased in the range 11.1% - 13.9% among smallholder farmers after the drought shock.

With regard to the impacts of agricultural support on cropland share under average weather conditions, specification (2) reveals that beneficiaries of agricultural extension services and credit considerably expand croplands by approximately 4.2% and 18.4% respectively. Similarly, comparable results can also be seen in specification (4) with respect to the effect size, statistical significance, and direction of impact. Besides this, specification (2) also shows that the adoption of adaptive land investments such as crop rotation and agroforestry contributes to cropland expansion of roughly 6.4% and 3.6% respectively. However, adopters of intercropping, irrigation, and soil erosion prevention measures downsize their land use shares by about 5.5%, 4.8%, and 2.4% respectively. Similar findings are reported in specification (4) where the results remain largely unchanged with respect to the coefficient sign, effect size, and statistical significance.

However, under extreme drought stresses, columns (2) and (4) both show that agricultural support and choice of adaptive strategy influence cropland adjustment decisions of treatment households differently relative to the counterfactual group. Restricting the discussion to discernible interaction effects, specification (2) reveals that treated beneficiaries of fertilizer-seed support and agricultural credit respond to extreme drought exposure conditions by expanding and downsizing croplands by approximately 5.9% and 11.2% respectively relative to the control group. The latter results are in sharp contrast to the results previously observed under average weather conditions. Therefore, I speculate that access to agricultural credit allows poor treated farm households to either strengthen adaptive land investments on smaller manageable croplands or diversify away from field crops to other on-farm activities such as livestock farming that are relatively less susceptible to aridity conditions. Similarly, specification (4) also reports comparable results on the impacts of agricultural support on cropland responses of treatment households. Additionally, specification (2) shows that treated adopters of minimum soil disturbance, crop rotation, and agroforestry reduce their cropland shares by about 4%, 9%, and 4.9% respectively compared to counterfactual group households. Similarly, specification (4) also reports equivalent results that largely retain statistical significance in addition to showing that adopters of legume-intercropping respond to water stress conditions by expanding hectarage shares by roughly 5.7% relative to non-adopters in control areas. Overall, I interpret these results to be suggestive evidence that adaptive land strategies that are costly to implement and maintain largely discourage cropland expansion in drought-hit regions.

Table 4: Productive Margin of Adjustment - Cropland Adjustment

Dependent Variable: ln (Hectares Cultivated)	**Model 1**		**Model 2**	
	(1)	**(2)**	**(3)**	**(4)**
Drought Shock (1=Yes)	0.0560***	0.110***		
	(0.0140)	(0.0204)		
Pre-Treatment			0.0865***	0.135***
			(0.0160)	(0.0224)
Post-Treatment			0.00707	0.0715***
			(0.0187)	(0.0248)
Time Dummy		0.105***		0.130***
		(0.0135)		(0.0163)
Agricultural Support				
Fertilizer-Seed Support (1=Yes)		0.0159		0.0169
		(0.0149)		(0.0149)
Agricultural Extension (1=Yes)		0.0407***		0.0399***
		(0.0121)		(0.0121)
Agricultural Credit (1=Yes)		0.169***		0.170***
		(0.0148)		(0.0148)
Choice of Adaptive Strategy				
Minimum Soil Disturbance (1=Yes)		-0.00563		-0.00356
		(0.0114)		(0.0114)
Crop Rotation (1=Yes)		0.0620***		0.0631***
		(0.0120)		(0.0120)
Crop Residues – Soil (1=Yes)		0.0117		0.0153
		(0.0112)		(0.0112)
Legume Intercropping (1=Yes)		- 0.0534***		- 0.0542***
		(0.0154)		(0.0154)
Agroforestry (1=Yes)		0.0350**		0.0206
		(0.0158)		(0.0166)
Irrigation (1=Yes)		- 0.0466***		- 0.0482***
		(0.0148)		(0.0148)
Animal Plant Manure (1=Yes)		0.0129		0.0136
		(0.0205)		(0.0205)
Soil Erosion Prevention Practices (1=Yes)		-0.0237**		-0.0251**
		(0.0111)		(0.0111)
Extreme Drought Conditions – Interaction Terms				
Shock × Fertilizer-Seed Support		0.0572**		0.0560**
		(0.0243)		(0.0243)
Shock × Agricultural Extension		-0.0186		-0.0158
		(0.0199)		(0.0199)
Shock × Agricultural Credit		-0.106***		-0.109***
		(0.0225)		(0.0225)
Shock × Minimum Soil Disturbance		-0.0396**		-0.0462**
		(0.0198)		(0.0200)
Shock × Crop Rotation		- 0.0871***		- 0.0949***
		(0.0209)		(0.0211)
Shock × Legume Intercropping		0.0516		0.0558*
		(0.0324)		(0.0325)
Shock × Crop Residues – Soil		0.0160		0.00299
		(0.0185)		(0.0191)
Shock × Agroforestry		-0.0482**		-0.0131
		(0.0226)		(0.0260)
Shock × Irrigation		0.00936		0.0112
		(0.0226)		(0.0226)
Shock × Animal Plant Manure		-0.0338		-0.0350

		(0.0279)		(0.0279)
Shock × Soil Erosion Prevention Measures		0.00219		0.00593
		(0.0194)		(0.0194)
Constant	1.307***	-0.731***	1.304***	-0.729***
	(0.00750)	(0.0965)	(0.00752)	(0.0965)
Demographic Household Characteristics	No	Yes	No	Yes
Household Wealth	No	Yes	No	Yes
Farm Characteristics	No	Yes	No	Yes
Membership – Farmer Support Groups	No	Yes	No	Yes
Peer Influence	No	Yes	No	Yes
Observations	21800	21800	21800	21800

Standard errors in parentheses

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

5.1.3 Seed Uptake

The results in table 5 below show farm households' seed consumption response to severe drought stresses, and how agricultural support and choice of adaptive strategy influence seed uptake of treatment farm households relative to the control group. To begin with, the drought exposure coefficient in the unconditional specification (1) is positive and highly statistically significant. Conditioning on demographic household characteristics, wealth, farm attributes, membership to farmer support groups, and peer influence, the drought shock coefficient in the preferred specification (2) remains positive and highly statistically significant. This, therefore, suggests that drought-exposed farm households relatively consume approximately 81.1% more seed varieties than their counterparts in the counterfactual group. This observation is in line with previous studies that find a positive correlation between extreme weather stressors and input utilization (Benhin, 2006; Bryan et al., 2013; Call et al., 2019). Thus, I take this to be empirical support that treatment farm households respond to extreme aridity stresses by increasing their uptake of drought-resistant seed varieties to improve crop yields and climate resilience.

Moving on, the naïve specification (3) shows that the coefficients on the pre- and post-treatment variables are positive and highly statistically significant. Similarly, the preferred specification (4) equally shows discernible pre- and post-treatment coefficients that are relatively larger than those observed in the naïve specification (3). This suggests that treated households, on average, consume more quantities of seed varieties than control group households both before and after the drought shock. However, the post-treatment coefficient is relatively lower than that of the counterpart pre-treatment coefficient. Therefore, I take this to be indicative evidence that drought-exposed farm households are reluctant to increase their seed uptake to pre-drought consumption levels. Nevertheless, taken as a whole, I find supportive evidence showing that risk-averse treatment farm households generally consume larger quantities of improved drought-resistant seed varieties to strengthen their adaptive capacity and food security. Furthermore, specifications (2) and (4) both show that the coefficients on the time dummy variable are positive and highly statistically significant. This suggests that there was an overall increase in seed uptake of roughly between 11.1% and 26.4% after the drought shock. Thus, I hypothesize that farm households generally boost consumption of drought-resistant seeds post-drought shock to lower climate-related crop production risks and losses.

With regard to the impacts of agricultural support on seed consumption under average weather conditions, specification (2) reveals that the coefficient on fertilizer-seed support is negative and significant, suggesting that beneficiaries of government fertilizer-seed support lower their seed uptake levels by roughly 21.9%. Although this observation is surprising and counterintuitive, it does however suggest that risk-averse beneficiaries adopt a staggered planting approach and hence withhold some of the seed supplies received and/or postpone the acquisition of additional seed stocks. Further, column (2) also shows that beneficiaries of agricultural extension services and credit increase their seed uptake by about 17.5% and 5.6% respectively. Parallel results in terms of the magnitude and direction of impact can be seen in specification (4) where the estimates largely retain statistical significance. Additionally, with respect to the influence of adaptive strategies, column (2) shows that adopters of minimum soil disturbance, crop rotation, and irrigation relatively consume larger seed quantities of approximately 27.9%, 7.9%, and 11.7% respectively compared to non-adopters. However, the estimated results in specification (2) also reveal that adopters of legume-intercropping reduce seed uptake by about 8.6% during average weather conditions. Comparable results can be observed in specification (4) where the coefficient estimates largely retain statistical significance.

However, contradictory impacts can be seen under extreme drought conditions, with specifications (2) and (4) both showing that agricultural support and choice of adaptive strategy influence seed uptake responses of treatment households differently relative to the unexposed group. Specifically, zeroing on the statistically significant interaction coefficients, column (2) results show that treated beneficiaries of fertilizer-seed support consume about 41.6% more seed varieties than untreated households. Thus, recipients of fertilizer-seed support respond to extreme drought shocks by increasing their seed uptake. However, column (2) results also reveals that agricultural credit beneficiaries in treated areas reduce seed uptake by roughly 21.3% relative to the untreated group. Although surprising, I interpret this result to be evidence that agricultural finance recipients in treatment regions diversify away from cropping activities to other on-farm enterprises. Note that the corresponding estimated results in column (4) mirror that of specification (2) with respect to the coefficient sign and statistical significance. In addition, the preferred specifications (2) and (4) both show several noticeable interaction terms between drought shock and adaptive strategies. Particularly, column (2) shows that treatment adopters of minimum soil disturbance, crop rotation, legume- intercropping, and irrigation reduce seed uptake levels by approximately 35.3%, 13.9%, 23.4%, and 15.3% respectively relative to the counterfactual group. However, column (2) also reveals that the adoption of crop residues and soil erosion prevention practices in treatment districts contribute to higher seed utilization of roughly 16.5% and 8.7% respectively compared to the untreated group. Equivalent results can also be seen in specification (4) where the interaction coefficients of interest largely retain the direction of impact and statistical significance. Collectively, I take the above results to be indicative evidence that risk-averse smallholder farmers in drought-hit regions are unlikely to increase their seed uptake alongside costly adaptive land investments that are not suitable to localized aridity conditions.

Table 5: Productive Margin of Adjustment - Seed Consumption

Dependent Variable: ln (Seed Quantity-kg)	Model 1		Model 2	
	(1)	(2)	(3)	(4)
Drought Shock (1=Yes)	0.293***	0.637***		
	(0.0291)	(0.0429)		
Pre-Treatment			0.345***	0.765***
			(0.0332)	(0.0471)
Post-Treatment			0.209***	0.441***
			(0.0387)	(0.0520)
Time Dummy		0.105***		0.234***
		(0.0284)		(0.0344)
Agricultural Support				
Fertilizer-Seed Support (1=Yes)		-0.198***		-0.193***
		(0.0314)		(0.0313)
Agricultural Extension (1=Yes)		0.161***		0.156***
		(0.0255)		(0.0255)
Agricultural Credit (1=Yes)		0.0542*		0.0619**
		(0.0311)		(0.0311)
Choice of Adaptive Strategy				
Minimum Soil Disturbance (1=Yes)		0.246***		0.256***
		(0.0240)		(0.0240)
Crop Rotation (1=Yes)		0.0761***		0.0818***
		(0.0254)		(0.0254)
Crop Residues – Soil (1=Yes)		0.0121		0.0306
		(0.0236)		(0.0237)
Legume Intercropping (1=Yes)		-0.0821**		-0.0862***
		(0.0325)		(0.0324)
Agroforestry (1=Yes)		0.0329		-0.0401
		(0.0332)		(0.0350)
Irrigation (1=Yes)		0.111***		0.103***
		(0.0312)		(0.0312)
Animal Plant Manure (1=Yes)		0.0399		0.0434
		(0.0433)		(0.0432)
Soil Erosion Prevention Practices (1=Yes)		-0.0101		-0.0173
		(0.0234)		(0.0234)
Extreme Drought Conditions – Interaction Terms				
Shock × Fertilizer-Seed Support		0.348***		0.341***
		(0.0512)		(0.0512)
Shock × Agricultural Extension		-0.0307		-0.0166
		(0.0420)		(0.0420)
Shock × Agricultural Credit		-0.193***		-0.211***
		(0.0474)		(0.0474)
Shock × Minimum Soil Disturbance		-0.302***		-0.336***
		(0.0418)		(0.0420)
Shock × Crop Rotation		-0.130***		-0.170***
		(0.0442)		(0.0445)
Shock × Legume Intercropping		-0.210***		-0.189***
		(0.0684)		(0.0684)
Shock × Crop Residues – Soil		0.153***		0.0866**
		(0.0390)		(0.0402)
Shock × Agroforestry		-0.00378		0.175***
		(0.0478)		(0.0548)
Shock × Irrigation		-0.142***		-0.133***
		(0.0477)		(0.0477)
Shock × Animal Plant Manure		-0.0576		-0.0638
		(0.0588)		(0.0587)
Shock × Soil Erosion Prevention Measures		0.0835**		0.102**
		(0.0409)		(0.0409)

Constant	4.327***	0.928***	4.320***	0.923***
	(0.0155)	(0.208)	(0.0155)	(0.208)
Demographic Household Characteristics	No	Yes	No	Yes
Household Wealth	No	Yes	No	Yes
Farm Characteristics	No	Yes	No	Yes
Membership – Farmer Support Groups	No	Yes	No	Yes
Peer Influence	No	Yes	No	Yes
Observations	21800	21800	21800	21800

Standard errors in parentheses

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

5.1.4 Fertilizer Consumption

Table 6 below reports regression estimates showing the correlation between fertilizer uptake and extreme drought exposure, and how agricultural support and choice of adaptive strategy affects fertilizer use under average and severe weather conditions. The unconditional specification (1) shows a positive and highly statistically significant coefficient on the drought exposure variable. Conditioning on other relevant covariates in the preferred specification (2), the absolute size of the coefficient on the drought exposure variable reduces and loses statistical significance although the estimate retains the coefficient sign.

Further, the naïve specification (3) shows that the coefficient on the pre-treatment variable is positive and highly statistically significant. Similarly, a noticeable positive analogous coefficient can also be seen in the preferred specification (4). This suggests that treated farm households mostly consume larger quantities of inorganic fertilizers relative to control group households prior to experiencing severe aridity conditions. Besides this, the unconditional specification (3) also shows that the coefficient on the post-treatment variable is positive but not statistically significant. However, the corresponding coefficient on the post-treatment variable in the preferred specification (4) is negative and highly statistically significant. Interestingly, this is an indication that treatment smallholder farmers relatively consume lower fertilizer quantities than counterfactual group households after the drought shock. Moreover, comparing fertilizer usage of treated households between the two periods, the preferred conditional specification (4) shows that the post-drought exposure fertilizer uptake levels of treatment households are significantly lower than that of the analogous pre-treatment period. Overall, this observation does speak to selected previous empirical studies such as Sesmero et al. (2018) and Chen and Gong (2021). Thus, relative to the unexposed group, I take this to be suggestive evidence that poor treated farm households increasingly rely more on organic fertilizers such as crop residues post-drought exposure, and hence respond to severe drought conditions by reducing their inorganic fertilizer use.

The time dummy coefficients in specifications (2) and (4) are both positive and highly statistically significant. This suggests that overall uptake of inorganic fertilizers was significantly higher post-drought exposure among rural smallholder farmers. With respect to the impacts of agricultural support and choice of adaptive strategy on fertilizer use under average weather conditions, the preferred specification (2) reveals that the coefficients on fertilizer-seed support, agricultural extension services, and agricultural credit are positive and highly statistically significant. Similar results in terms of the direction of impact, coefficients size, and statistical significance can be seen in column (4). Taken together, it can be inferred that beneficiaries of agricultural support relatively consume greater quantities of inorganic fertilizers during regular weather conditions. Additionally, specifications (2) and (4) both show discernible positive coefficients on minimum soil disturbance, crop rotation, crop residues, and irrigation, suggesting that adopters relatively consume larger quantities of inorganic fertilizers during average weather conditions. However, specifications (2) and (4) also reveal that the coefficients on legume-intercropping are negative and highly statistically significant. Therefore, I take this to be empirical support that the adoption of legume-intercropping stimulates retrogressive effects on inorganic fertilizer uptake during normal weather conditions. This observation is not surprising and makes intuitive sense since legume-intercropping improves and/or maintains nitrogen levels beneath the soil. Hence, I conjecture that the benefits of legume-intercropping such as improvements in soil structure, quality and porosity alongside nitrogen fixation attributes reduces the attractiveness of inorganic fertilizers and subsequently renders the uptake of chemical fertilizers redundant.

Last but not least, focusing on the statistically significant interaction coefficients, specifications (2) and (4) both show that the coefficient on the interaction term between drought exposure and fertilizer-seed support is positive and highly statistically significant. This suggests that treatment beneficiaries of fertilizer-seed support consume larger quantities of inorganic fertilizer relative to the counterfactual group. However, unlike the results observed under average weather conditions, columns (2) and (4) both show that access to agricultural extension services and credit stimulate undesirable effects on fertilizer uptake among treated households compared to the counterfactual group. Therefore, this observation suggests that treatment beneficiaries of agricultural extension services and credit respond to severe aridity conditions by reducing their application of inorganic fertilizers. Although this observation is counterintuitive, there are several plausible explanations for this observed reducing effect. For example, there is a high likelihood that treatment beneficiaries of agricultural credit and agricultural extension services with appropriate agricultural information abandon unsuitable crops, diversify away from cropping activities towards livestock farming, or increase reliance on compost fertilization such as animal-plant manure.

Further, specification (2) estimates suggest that treatment adopters of minimum soil disturbance and legume-intercropping respond to extreme drought conditions by reducing inorganic fertilizer application relative to the control group. Thus, I attribute the reduction in inorganic fertilizer use to the nitrogen fixation benefits, among others, of legume-intercropping. However, specification (2) results also show that drought-exposed adopters of crop residues, animal-plant manure, and soil moisture-enhancing measures consume greater amounts of chemical fertilizer compared to the counterfactual group. Therefore, I take this observation to be suggestive evidence of complementarity between organic and inorganic fertilizer use in areas prone to extreme water stress conditions among adopters of soil moisture-enhancing technologies. Equivalent estimates can also be observed in the analogous preferred specification (4) where the absolute magnitudes of the coefficient estimates are slightly larger but remain mostly intact in terms of statistical significance and direction of impact.

Table 6: Productive Margin of Adjustment - Fertilizer Utilization

Dependent Variable: ln (Fertilizer Usage -kg)	Model 1		Model 2	
	(1)	(2)	(3)	(4)
Drought Shock (1=Yes)	0.511***	0.0400		
	(0.0951)	(0.147)		
Pre-Treatment			0.724***	0.604***
			(0.108)	(0.160)
Post-Treatment			0.145	-0.805***
			(0.126)	(0.176)
Time Dummy		1.190***		1.735***
		(0.0935)		(0.113)
Agricultural Support				
Fertilizer-Seed Support (1=Yes)		2.716***		2.737***
		(0.102)		(0.101)
Agricultural Extension (1=Yes)		0.266***		0.248***
		(0.0820)		(0.0818)
Agricultural Credit (1=Yes)		0.288***		0.320***
		(0.0999)		(0.0997)
Choice of Adaptive Strategy				
Minimum Soil Disturbance (1=Yes)		0.786***		0.832***
		(0.0787)		(0.0787)
Crop Rotation (1=Yes)		0.377***		0.401***
		(0.0819)		(0.0817)
Crop Residues – Soil (1=Yes)		0.100		0.179**
		(0.0768)		(0.0772)
Legume Intercropping (1=Yes)		-0.521***		-0.540***
		(0.107)		(0.107)
Agroforestry (1=Yes)		-0.0378		-0.343***
		(0.108)		(0.113)
Irrigation (1=Yes)		0.564***		0.530***
		(0.100)		(0.100)
Animal Plant Manure (1=Yes)		-0.0535		-0.0374
		(0.139)		(0.139)
Soil Erosion Prevention Practices (1=Yes)		0.0384		0.00840
		(0.0761)		(0.0759)
Extreme Drought Conditions – Interaction Terms				
Shock × Fertilizer-Seed Support		1.484***		1.455***
		(0.167)		(0.167)
Shock × Agricultural Extension		-0.323**		-0.256*
		(0.138)		(0.138)
Shock × Agricultural Credit		-0.754***		-0.820***
		(0.155)		(0.155)
Shock × Minimum Soil Disturbance		-0.831***		-0.981***
		(0.138)		(0.139)
Shock × Crop Rotation		0.0793		-0.0881
		(0.144)		(0.145)
Shock × Legume Intercropping		-0.638***		-0.574**
		(0.232)		(0.232)
Shock × Crop Residues – Soil		0.590***		0.300**
		(0.129)		(0.133)
Shock × Agroforestry		-0.229		0.548***
		(0.156)		(0.180)
Shock × Irrigation		-0.117		-0.0761
		(0.156)		(0.156)
Shock × Animal Plant Manure		0.490**		0.462**
		(0.191)		(0.191)
Shock × Soil Erosion Prevention Measures		0.252*		0.338**
		(0.135)		(0.135)

Constant	3.753***	-6.013***	3.697***	-6.007***
	(0.0515)	(0.681)	(0.0514)	(0.681)
Demographic Household Characteristics	No	Yes	No	Yes
Household Wealth	No	Yes	No	Yes
Farm Characteristics	No	Yes	No	Yes
Membership – Farmer Support Groups	No	Yes	No	Yes
Peer Influence	No	Yes	No	Yes
Observations	21800	21800	21800	21800

Standard errors in parentheses

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

5.2 Off-Farm Income Adjustment

This subsection first considers the average treatment impact of extreme drought exposure on the off-farm income margin of adjustment. Thereafter, I examine the average differential impact of access to agricultural support and choice of adaptive strategy on the off-farm income behavioural response under average and extreme weather events. Column (1) of table 7 below shows a negative and highly statistically significant coefficient on the drought shock variable. However, conditioning on other relevant covariates, the preferred specification (2) reveals that the drought exposure coefficient loses statistical significance despite retaining the direction of impact. Further, the naïve specification (3) shows that the pre- and post-treatment coefficients are both negative and highly statistically significant. Likewise, the corresponding effect estimates in the preferred specification (4) retains the coefficient sign but becomes statistically insignificant.

Additionally, specifications (2) and (4) both show noticeable positive time dummy coefficients, suggesting that households relatively earn higher off-farm incomes after the drought shock. This is indicative evidence that smallholder farmers generally participate more in off-farm income enterprises following the drought shock. Besides, under average weather conditions, specifications (2) and (4) both show that recipients of fertilizer-seed support and agricultural extension services relatively earn higher off-farm incomes while access to agricultural credit contributes to lower off-farm incomes in beneficiary farm households. The latter observation makes intuitive sense because beneficiaries of agricultural credit reallocate labour hours towards own-farm cropping activities. Furthermore, specifications (2) and (4) both show that the adoption of minimum soil disturbance and crop rotation contributes to lower off-farm incomes while adopters of crop residues, legume-intercropping, and soil moisture-enhancing measures experience the opposite impacts during average weather conditions. Thus, the choice of adaptive land investment appears to influence the amount of time smallholder farmers devote towards off-farm income enterprises.

However, under extreme drought conditions, the impacts of agricultural support and adaptive strategies largely contrast that observed under regular weather conditions. Specifically, restricting the analysis to visible interaction coefficients, columns (2) and (4) both show that the coefficient on the interaction term between drought shock and agricultural credit is positive and highly statistically significant. This suggests that treatment beneficiaries of agricultural credit earn higher off-farm incomes relative to counterfactual households. Although this observation is counterintuitive, I theorize that treatment beneficiaries of agricultural credit boost their occupational diversity through income diversification to supplement agricultural loans, support agricultural investments, and minimize the variability of overall household incomes and consumption. Thus, I take this to be empirical support that access to agricultural credit improves occupational diversity and off-farm labour hours in treatment farm households.

Further, the interaction coefficient on the drought shock-crop rotation interaction term is positive and highly statistically significant in both columns (2) and (4). This suggests that treatment adopters of crop rotation relatively earn higher off-farm incomes than counterfactual households. This result is not surprising, and I hypothesize that treatment adopters of crop rotation strengthen their occupational diversity to earn additional incomes so that they can successfully sustain crop rotation cycles over a long period to significantly improve land productivity. Hence, I take this to be suggestive evidence that treated adopters of crop rotation respond to severe drought stresses by devoting more labour hours towards off-farm income enterprises. However, the results in columns (2) and (4) both show that treatment adopters of legume-intercropping, crop residues, and soil moisture-enhancing technologies accrue lower off-farm incomes than the control group. This, therefore, is indicative evidence that treatment adopters of suitable climate-smart agricultural practices reallocate labour away from off-farm income initiatives towards own-farm cropping activities. As a result, this lowers off-farm incomes and, to a large extent, associated occupational diversity.

Table 7: Off-Farm Margin of Adjustment - Off-Farm Income

Dependent Variable: ln (Off-Farm Income)	**Model 1**		**Model 2**	
	(1)	**(2)**	**(3)**	**(4)**
Drought Shock (1=Yes)	-0.676***	-0.106		
	(0.134)	(0.272)		
Pre-Treatment			-0.721***	-0.0252
			(0.153)	(0.299)
Post-Treatment			-0.599***	-0.226
			(0.178)	(0.329)
Time Dummy		0.600***		0.680***
		(0.180)		(0.219)
Agricultural Support				
Fertilizer-Seed Support (1=Yes)		0.788***		0.792***
		(0.199)		(0.199)
Agricultural Extension (1=Yes)		1.383***		1.381***
		(0.162)		(0.162)
Agricultural Credit (1=Yes)		-0.747***		-0.742***
		(0.198)		(0.198)
Choice of Adaptive Strategy				
Minimum Soil Disturbance (1=Yes)		-0.396***		-0.389**
		(0.153)		(0.153)
Crop Rotation (1=Yes)		-1.905***		-1.902***
		(0.162)		(0.162)
Crop Residues – Soil (1=Yes)		0.986***		0.998***
		(0.150)		(0.151)
Legume Intercropping (1=Yes)		0.601***		0.598***
		(0.206)		(0.206)
Agroforestry (1=Yes)		-0.185		-0.230
		(0.211)		(0.222)
Irrigation (1=Yes)		-0.234		-0.239
		(0.199)		(0.199)
Animal Plant Manure (1=Yes)		-0.204		-0.202
		(0.276)		(0.276)
Soil Erosion Prevention Practices (1=Yes)		0.687***		0.683***
		(0.149)		(0.149)
Extreme Drought Conditions – Interaction Terms				
Shock × Fertilizer-Seed Support		-0.493		-0.498
		(0.325)		(0.325)
Shock × Agricultural Extension		-0.357		-0.347
		(0.267)		(0.268)
Shock × Agricultural Credit		1.029***		1.019***

		(0.302)		(0.303)
Shock × Minimum Soil Disturbance		-0.320		-0.342
		(0.266)		(0.268)
Shock × Crop Rotation		0.672**		0.647**
		(0.282)		(0.284)
Shock × Legume Intercropping		-1.910***		-1.896***
		(0.437)		(0.437)
Shock × Crop Residues – Soil		-1.140***		-1.182***
		(0.248)		(0.256)
Shock × Agroforestry		-0.0422		0.0684
		(0.304)		(0.349)
Shock × Irrigation		0.000284		0.00593
		(0.304)		(0.304)
Shock × Animal Plant Manure		0.583		0.579
		(0.374)		(0.374)
Shock × Soil Erosion Prevention Measures		-1.010***		-0.998***
		(0.260)		(0.261)
Constant	7.376***	9.638***	7.402***	9.602***
	(0.0700)	(1.250)	(0.0702)	(1.251)
Demographic Household Characteristics	No	Yes	No	Yes
Household Wealth	No	Yes	No	Yes
Farm Characteristics	No	Yes	No	Yes
Membership – Farmer Support Groups	No	Yes	No	Yes
Peer Influence	No	Yes	No	Yes
Observations	21800	21800	21800	21800

Standard errors in parentheses

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

5.3 Robustness Checks

One of the major concerns that may be tabled against the results presented in the previous sections is that the CRE model does not completely control for all the unobserved heterogeneity that stems from unobserved time-invariant household-level factors. Furthermore, there may be fears that the observable correlations between the outcomes and covariates of interest are driven by village-level factors and other regional, national, or environmental-level characteristics. As such, the Fixed Effects (FE) estimation method can be considered to be a suitable alternative estimation strategy that can circumvent and allay a lot of such concerns because of its ability to significantly account for, among other advantages, unobserved heterogeneity. Besides this, it also imperative to check whether the main CRE tobit results that exploits the panel structure of the dataset are robust to other estimation approaches such as the pooled Ordinary Least Squares (OLS), Random Effects (RE), and pooled CRE tobit.

Thus, I explore the sensitivity of the results presented in the main analysis section by; (i) re-estimating the main CRE results using alternative estimation frameworks; (ii) conducting a subsample re-analysis of the main CRE results using alternative estimation strategies; and (iii) using the El Niño Impact Assessment Survey (ENIAS) data to construct a unique alternate panel dataset and thereafter applying alternative estimation techniques to replicate the main CRE results. Due to space constraints, note that the results I reproduce and present in the ensuing subsections are derived from model 1 – i.e., equation (3). Further to this, I report only the replicated results obtained from the FE estimation technique while the re-estimated results from other estimation approaches are shown in appendix B. Besides, note that I cluster the standard errors at the unit of analysis (i.e., household-level) across all the reproduced specifications.

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5.3.1 Robustness to Alternative Estimation Strategies

In this section, I re-estimate the main CRE tobit results using the FE estimation approach to completely control for all unobserved time-constant omitted variables that may potentially affect the correlation between the dependent and independent variables of interest. The replicated FE results displayed in table 8 below show that the impacts of agricultural support and adaptive strategies on treatment farm households' behavioural responses are mostly consistent with the main CRE results because the direction of impact and statistical significance remain largely unchanged across the re-estimated specifications. Similarly, the replicated results derived from the RE, pooled OLS, and pooled CRE tobit estimation strategies show that behavioural responses of treatment smallholder farmers remain largely intact. However, what is strikingly noticeable and interesting is that replicating the main CRE results using the RE and pooled OLS models both duplicates the FE estimates. This observation is consistent with the theoretical proposition that applying the pooled OLS and RE models to the CRE equation reproduces the FE estimator (Wooldridge, 2019; Yang, 2022). Thus, I only show the replicated pooled CRE tobit results in table B.1 in the appendix. By extension, subsequent sensitivity checks also re-estimates the main results using the FE and pooled CRE tobit estimation methods. Overall, there is strong evidence showing that the main CRE tobit results are robust to alternative estimation strategies, and thus, the key insights and conclusions derived from the main analysis remain largely unaffected.

Table 8: Robustness to Alternative Estimation Method – Fixed Effects (FE)

	Model 1	Model 1	Model 1	Model 1	Model 1
	Crop Diversification	Cropland Adjustment	Seed Uptake	Fertilizer Utilization	Off-Farm Income
Drought Shock (1=Yes)	-0.0192**	0.104***	0.592***	0.140	-0.113
	(0.00886)	(0.0197)	(0.0428)	(0.0926)	(0.209)
Time Dummy	0.0183***	0.118***	0.118***	0.838***	0.0976
	(0.00562)	(0.0136)	(0.0275)	(0.0612)	(0.135)
Agricultural Support					
Fertilizer-Seed Support (1=Yes)	-0.0144**	0.0184	-0.168***	2.015***	0.798***
	(0.00649)	(0.0148)	(0.0353)	(0.0774)	(0.162)
Agricultural Extension (1=Yes)	0.00749	0.0430***	0.158***	0.204***	1.351***
	(0.00501)	(0.0122)	(0.0244)	(0.0536)	(0.130)
Agricultural Credit (1=Yes)	0.0854***	0.172***	0.0547**	0.193***	-0.661**
	(0.00557)	(0.0145)	(0.0276)	(0.0658)	(0.156)
Choice of Adaptive Strategy					
Minimum Soil Disturbance (1=Yes)	0.0686***	-0.0127	0.223***	0.492***	-0.493**
	(0.00485)	(0.0113)	(0.0247)	(0.0516)	(0.123)
Crop Rotation (1=Yes)	0.0994***	0.0714***	0.0847***	0.319***	-1.711**
	(0.00482)	(0.0121)	(0.0240)	(0.0535)	(0.130)
Crop Residues – Soil (1=Yes)	0.0269***	0.00723	0.00644	0.0469	0.856***
	(0.00475)	(0.0110)	(0.0240)	(0.0500)	(0.119)
Legume Intercropping (1=Yes)	0.0256***	-0.0480***	-0.0845**	-0.325***	0.474***
	(0.00655)	(0.0148)	(0.0327)	(0.0681)	(0.159)
Agroforestry (1=Yes)	0.0335***	0.0270*	0.0240	-0.0529	-0.169
	(0.00644)	(0.0152)	(0.0313)	(0.0706)	(0.152)
Irrigation (1=Yes)	0.0113*	-0.0420***	0.109***	0.384***	-0.146
	(0.00592)	(0.0148)	(0.0295)	(0.0664)	(0.157)
Animal Plant Manure (1=Yes)	0.000726	0.0109	0.0335	-0.0280	-0.239
	(0.00842)	(0.0221)	(0.0394)	(0.0922)	(0.222)
Soil Erosion Prevention Practices (1=Yes)	0.0204***	-0.0248**	-0.00729	0.0196	0.513***
	(0.00464)	(0.0108)	(0.0235)	(0.0494)	(0.118)

Extreme Drought Conditions – Interaction Terms					
Shock × Fertilizer-Seed Support	0.0184*	0.0583**	0.321***	1.060***	-0.427*
	(0.0101)	(0.0238)	(0.0482)	(0.124)	(0.257)
Shock × Agricultural Extension	0.00504	-0.0239	-0.0320	-0.285***	-0.327
	(0.00816)	(0.0198)	(0.0375)	(0.0897)	(0.213)
Shock × Agricultural Credit	0.0583***	-0.105***	-0.183***	-0.636***	0.919***
	(0.00852)	(0.0212)	(0.0383)	(0.0997)	(0.236)
Shock × Minimum Soil Disturbance	-0.0406***	-0.0362*	-0.284***	-0.501***	-0.374*
	(0.00805)	(0.0192)	(0.0367)	(0.0892)	(0.199)
Shock × Crop Rotation	-0.0232***	-0.0870***	-0.123***	0.0211	0.440**
	(0.00828)	(0.0203)	(0.0368)	(0.0963)	(0.215)
Shock × Legume Intercropping	-0.0234	0.0482	-0.200***	-0.362**	-1.607**
	(0.0145)	(0.0335)	(0.0615)	(0.151)	(0.330)
Shock × Crop Residues – Soil	-0.0292***	0.00892	0.145***	0.379***	-0.932**
	(0.00762)	(0.0184)	(0.0363)	(0.0849)	(0.191)
Shock × Agroforestry	-0.0200**	-0.0512**	-0.00326	-0.195*	-0.110
	(0.00915)	(0.0220)	(0.0404)	(0.103)	(0.222)
Shock × Irrigation	0.00207	0.0109	-0.135***	-0.126	-0.00788
	(0.00933)	(0.0226)	(0.0429)	(0.105)	(0.235)
Shock × Animal Plant Manure	0.00354	-0.0307	-0.0497	0.281**	0.527*
	(0.0113)	(0.0293)	(0.0519)	(0.126)	(0.292)
Shock × Soil Erosion Prevention Measures	0.00264	-0.000106	0.0753**	0.173**	-0.778**
	(0.00790)	(0.0192)	(0.0367)	(0.0879)	(0.201)
Constant	0.120***	-0.718***	0.515***	-0.295	8.449***
	(0.0321)	(0.0715)	(0.152)	(0.339)	(0.817)
Demographic Household Characteristics	Yes	Yes	Yes	Yes	Yes
Household Wealth	Yes	Yes	Yes	Yes	Yes
Farm Characteristics	Yes	Yes	Yes	Yes	Yes
Membership – Farmer Support Groups	Yes	Yes	Yes	Yes	Yes
Peer Influence	Yes	Yes	Yes	Yes	Yes
Observations	21800	21800	21800	21800	21800

Cluster-robust standard errors in parentheses

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

5.3.2 Robustness to Sample Size Adjustments: Subsample Analysis

Further, I also conduct a subsample re-analysis of the main CRE tobit results using the FE and pooled CRE tobit estimation strategies. Specifically, I derive a subsample by dropping all the observations from the 2012 RALS so that the resulting subsample panel dataset consists of the most recent two waves on either side of the drought shock (i.e., conducted just before and after the drought). As can be seen in table 9 below, the replicated FE results remain largely unchanged with respect to the sign and statistical significance of the main variables of interest, although the absolute magnitude of some coefficients are either slightly or considerably different from those observed in the main analysis section. Similarly, the pooled CRE tobit results (shown in the appendix – i.e., table B.2) remain largely intact. Overall, the main CRE tobit estimates are largely consistent and robust to both sample size restrictions/changes and alternative estimation strategies.

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Table 9: Robustness to Sample Size Adjustments (Subsample Analysis) and Alternative Estimation Method - FE

	Model 1	Model 1	Model 1	Model 1	Model 1
	Crop Diversification	Cropland Adjustment	Seed Uptake	Fertilizer Utilization	Off-Farm Income
Drought Shock (1=Yes)	-0.0310***	0.0527**	0.348***	0.140	-0.0624
	(0.0118)	(0.0260)	(0.0540)	(0.122)	(0.204)
Time Dummy	0.0439***	0.123***	0.189***	0.619***	1.912***
	(0.00734)	(0.0175)	(0.0349)	(0.0785)	(0.138)
Agricultural Support					
Fertilizer-Seed Support (1=Yes)	0.0337***	0.0660***	0.222***	2.550***	-0.116
	(0.00888)	(0.0217)	(0.0414)	(0.101)	(0.166)
Agricultural Extension (1=Yes)	-0.0122*	0.0143	0.0600*	0.123*	0.138
	(0.00708)	(0.0171)	(0.0327)	(0.0741)	(0.133)
Agricultural Credit (1=Yes)	0.0711***	0.140***	0.0514	0.225***	-0.345**
	(0.00734)	(0.0183)	(0.0358)	(0.0859)	(0.150)
Choice of Adaptive Strategy					
Minimum Soil Disturbance (1=Yes)	0.0735***	-0.0296*	0.258***	0.399***	0.181
	(0.00665)	(0.0157)	(0.0330)	(0.0701)	(0.122)
Crop Rotation (1=Yes)	0.102***	0.0857***	0.134***	0.262***	-0.214
	(0.00675)	(0.0163)	(0.0326)	(0.0728)	(0.134)
Crop Residues – Soil (1=Yes)	0.0225***	0.0246	-0.0176	0.113*	0.371***
	(0.00640)	(0.0152)	(0.0312)	(0.0669)	(0.119)
Legume Intercropping (1=Yes)	-0.0251***	-0.0865***	-0.214**	-0.143	0.359**
	(0.00859)	(0.0207)	(0.0404)	(0.0897)	(0.158)
Agroforestry (1=Yes)	0.0331***	0.0612***	0.0459	0.0956	-0.157
	(0.00756)	(0.0179)	(0.0359)	(0.0829)	(0.142)
Irrigation (1=Yes)	-0.00101	-0.0562***	0.142***	0.489***	-0.238
	(0.00780)	(0.0193)	(0.0383)	(0.0856)	(0.150)
Animal Plant Manure (1=Yes)	-0.00342	0.0292	0.0494	-0.251**	-0.0350
	(0.0110)	(0.0283)	(0.0507)	(0.117)	(0.221)
Soil Erosion Prevention Practices (1=Yes)	0.0373***	0.00278	-0.0105	0.0790	0.215*
	(0.00619)	(0.0145)	(0.0302)	(0.0655)	(0.117)
Extreme Drought Conditions – Interaction Terms					
Shock × Fertilizer-Seed Support	-0.0199	-0.0131	-0.0756	0.406**	-0.0157
	(0.0135)	(0.0324)	(0.0617)	(0.165)	(0.257)
Shock × Agricultural Extension	0.00740	0.0125	0.0397	-0.206*	0.133
	(0.0112)	(0.0270)	(0.0504)	(0.123)	(0.209)
Shock × Agricultural Credit	0.0691***	-0.0855***	-0.183**	-0.589***	0.401*
	(0.0113)	(0.0281)	(0.0509)	(0.135)	(0.235)
Shock × Minimum Soil Disturbance	-0.0427***	-0.0263	-0.217**	-0.421***	0.213
	(0.0103)	(0.0247)	(0.0472)	(0.114)	(0.194)
Shock × Crop Rotation	-0.0159	-0.0673***	-0.0446	0.0928	0.340
	(0.0108)	(0.0255)	(0.0484)	(0.122)	(0.211)
Shock × Legume Intercropping	0.0204	0.0560	-0.0569	-0.444**	-0.835**
	(0.0179)	(0.0408)	(0.0734)	(0.183)	(0.319)
Shock × Crop Residues – Soil	-0.0369***	-0.00892	0.203***	0.250**	-0.217
	(0.0102)	(0.0244)	(0.0468)	(0.113)	(0.193)
Shock × Agroforestry	0.00395	-0.0575**	0.00964	-0.236*	0.0775
	(0.0114)	(0.0267)	(0.0504)	(0.127)	(0.212)
Shock × Irrigation	0.00750	0.0434	-0.169**	-0.393***	-0.102
	(0.0123)	(0.0300)	(0.0559)	(0.137)	(0.231)
Shock × Animal Plant Manure	0.000412	-0.0568	-0.0213	0.518***	-0.0167
	(0.0147)	(0.0373)	(0.0669)	(0.160)	(0.287)
Shock × Soil Erosion Prevention	-0.0234**	-0.0124	0.125***	0.204*	-0.323

Measures					
	(0.0105)	(0.0252)	(0.0486)	(0.119)	(0.198)
Constant	0.125***	-0.550***	0.777***	0.479	6.160***
	(0.0439)	(0.0990)	(0.201)	(0.463)	(0.815)
Demographic Household Characteristics	Yes	Yes	Yes	Yes	Yes
Household Wealth	Yes	Yes	Yes	Yes	Yes
Farm Characteristics	Yes	Yes	Yes	Yes	Yes
Membership – Farmer Support Groups	Yes	Yes	Yes	Yes	Yes
Peer Influence	Yes	Yes	Yes	Yes	Yes
Observations	15175	15175	15175	15175	15175

Cluster-robust standard errors in parentheses

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

5.3.3 Robustness to Alternate Dataset

Other than the above robustness checks, I also explore the sensitivity of the main CRE tobit results to alternative subsample panel dataset. Particularly, I utilize the 2016 El Niño Impact Assessment Survey (ENIAS) data to construct a unique panel dataset and subsequently replicate the main CRE tobit results using both the FE and pooled CRE tobit estimation approaches. The 2016 ENIAS was implemented as a subset of the 2015 RALS by the Indaba Agricultural Policy Research Institute (IAPRI) to primarily assess the impacts of extreme aridity conditions on rural household welfare. However, the survey also collected other relevant data on productive and off-farm behavioural responses that I exploit to check the sensitivity of the main results. Thus, similar to the approach taken in studies such as Alfani et al. (2021) and McCarthy et al. (2021), I track smallholder farmers captured in the 2016 ENIAS backwards to the 2015 and 2012 RALS. Thereafter, I also trace these ENIAS farm households forward in the latest 2019 RALS to form a unique long panel subsample dataset comprising four waves (i.e., 2012, 2015, 2016, and 2019) and at least 5,200 observations.

Table 10 below reports selected results of four behavioural responses to extreme drought exposure, and we can see that the replicated FE results closely align with the main CRE tobit results in terms of both the direction of impact and statistical significance of the estimated regression coefficients. Similarly, the estimated pooled CRE tobit results (shown in table B.3 in the appendix) are also largely consistent with the main CRE results with respect to the sign and statistical significance of the estimates, although the effect sizes are relatively slightly different for some coefficients. Overall, the replicated results remain largely intact and hence, the core CRE tobit estimates are simultaneously robust to different estimation methods, alternative subsample dataset, and sample size adjustments.

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Table 10: Robustness to Alternate Dataset, Sample Size Restrictions, and Alternative Estimation Method - FE

	Model 1 Crop Diversification	Model 1 Cropland Adjustment	Model 1 Seed Uptake	Model 1 Off-Farm Income
Drought Shock (1=Yes)	-0.0188**	0.106***	0.619***	-0.247
	(0.00831)	(0.0186)	(0.0398)	(0.200)
Time Dummy	0.0118**	0.113***	0.104***	-0.0691
	(0.00531)	(0.0129)	(0.0261)	(0.130)
Agricultural Support				
Fertilizer-Seed Support (1=Yes)	-0.0226***	0.00391	-0.271***	0.822***
	(0.00589)	(0.0137)	(0.0328)	(0.152)
Agricultural Extension (1=Yes)	0.0127***	0.0501***	0.177***	1.395***
	(0.00468)	(0.0114)	(0.0229)	(0.123)
Agricultural Credit (1=Yes)	0.0849***	0.171***	0.0601**	-0.684***
	(0.00535)	(0.0137)	(0.0260)	(0.151)
Choice of Adaptive Strategy				
Minimum Soil Disturbance (1=Yes)	0.0702***	-0.00855	0.223***	-0.614***
	(0.00451)	(0.0105)	(0.0229)	(0.117)
Crop Rotation (1=Yes)	0.0978***	0.0699***	0.0718***	-1.801***
	(0.00451)	(0.0113)	(0.0223)	(0.124)
Crop Residues – Soil (1=Yes)	0.0295***	0.00255	0.0216	0.884***
	(0.00442)	(0.0102)	(0.0224)	(0.113)
Legume Intercropping (1=Yes)	0.0300***	-0.0415***	-0.0489	0.391**
	(0.00615)	(0.0139)	(0.0306)	(0.154)
Agroforestry (1=Yes)	0.0380***	0.0222	0.0159	-0.224
	(0.00619)	(0.0147)	(0.0303)	(0.148)
Irrigation (1=Yes)	0.00630	-0.0407***	0.0947***	-0.216
	(0.00557)	(0.0139)	(0.0280)	(0.151)
Animal Plant Manure (1=Yes)	-0.000587	0.0112	0.0368	-0.216
	(0.00795)	(0.0209)	(0.0372)	(0.218)
Soil Erosion Prevention Practices (1=Yes)	0.0261***	-0.0212**	0.0101	0.421***
	(0.00433)	(0.0101)	(0.0221)	(0.113)
Extreme Drought Conditions – Interaction Terms				
Shock × Fertilizer-Seed Support	0.0157*	0.0736***	0.376***	-0.382
	(0.00933)	(0.0223)	(0.0453)	(0.245)
Shock × Agricultural Extension	0.00244	-0.0336*	-0.0709**	-0.409**
	(0.00771)	(0.0185)	(0.0352)	(0.203)
Shock × Agricultural Credit	0.0558***	-0.0981***	-0.169***	0.955***
	(0.00810)	(0.0201)	(0.0362)	(0.230)
Shock × Minimum Soil Disturbance	-0.0393***	-0.0452**	-0.294***	-0.478**
	(0.00763)	(0.0181)	(0.0346)	(0.193)
Shock × Crop Rotation	-0.0198**	-0.0861***	-0.115***	0.476**
	(0.00787)	(0.0193)	(0.0347)	(0.209)
Shock × Legume Intercropping	-0.0218	0.0350	-0.225***	-1.560***
	(0.0139)	(0.0318)	(0.0582)	(0.321)
Shock × Crop Residues – Soil	-0.0309***	0.0107	0.117***	-0.948***
	(0.00717)	(0.0173)	(0.0339)	(0.184)
Shock × Agroforestry	-0.0231***	-0.0449**	0.0237	-0.0298
	(0.00875)	(0.0212)	(0.0388)	(0.216)
Shock × Irrigation	0.0104	0.00585	-0.133***	0.0606
	(0.00880)	(0.0213)	(0.0405)	(0.227)
Shock × Animal Plant Manure	0.00447	-0.0270	-0.0539	0.551*
	(0.0108)	(0.0278)	(0.0494)	(0.285)
Shock × Soil Erosion Prevention Measures	-0.000606	-0.00525	0.0492	-0.829***

	(0.00751)	(0.0180)	(0.0345)	(0.194)
Constant	0.105***	-0.773***	0.467***	10.57***
	(0.0296)	(0.0659)	(0.140)	(0.770)
Demographic Household Characteristics	Yes	Yes	Yes	Yes
Household Wealth	Yes	Yes	Yes	Yes
Farm Characteristics	Yes	Yes	Yes	Yes
Membership – Farmer Support Groups	Yes	Yes	Yes	Yes
Peer Influence	Yes	Yes	Yes	Yes
Observations	5243	5243	5243	5243

Cluster-robust standard errors in parentheses

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

5.4 Study Implications

This study highlights key policy implications for building climate resilience. Firstly, there is need for policymakers to facilitate the rapid distribution of improved seed technologies, input subsidies, and irrigation facilities in regions prone to extreme weather conditions. Secondly, the governments world-over should consider investing substantially in early warning systems for natural disasters to minimise the negative welfare effects. Thirdly, policymakers should lead in disseminating climate information, enhancing agricultural extension services, and promoting climate technologies to reduce undesirable welfare impacts of climatic variability. Last but not least, promoting farm diversification, exempting critical farm implements like irrigation equipment from taxes, improving access to agricultural finance, offering tax incentives to households adopting climate-resilient practices, and discouraging land degradation are critical to strengthening long-term adaptive capacity.

6.0 CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

This study conducts a comparative assessment that explores whether access to agricultural support and choice of adaptive strategy influence on-farm and off-farm behavioural responses of drought-exposed households differently vis-à-vis the counterfactual group using a relevant SSA context. A matched CRE model is used to exploit regional variations in drought exposure conditions and generate reliable causal estimates. Compared to counterfactual group households, the results show, for the most part, that access to agricultural support plays an instrumental role in strengthening treated smallholder farmers' adaptive capacity. Particularly, the findings show that treated beneficiaries of agricultural support mostly respond to precipitation shortfalls by adopting polyculture agricultural systems, expanding croplands and agricultural input uptake, and earning higher off-farm incomes. Contrariwise, the choice of adaptive strategy appears to largely stimulate contrasting impacts, with results showing that adopters tilt crop production towards reduced crop diversity and/or monoculture agricultural systems, reduce hectarage shares and agricultural input consumption, and earn lower off-farm incomes in response to severe water stress conditions. Taken together, this suggests that drought-exposed adopters are relatively more susceptible to climate-related risks over the medium to long-term period.

Additionally, I also obtain further insights into the extent of autonomous adaptation by conducting a disaggregated analysis that compares behavioural responses of treated farm households relative to control group households both before and after the drought shock. For example, relative to the pre-exposure period, the estimated results show strong empirical support that drought-exposed smallholder farmers lower their consumption of inorganic fertilizers post-drought exposure. Moreover, the results also show that although treatment farm households expand croplands and boost their seed uptake after the drought shock, the increase is relatively lower than that of the corresponding pre-treatment period. Collectively, this is suggestive evidence that extreme drought exposure stimulates a dissuading effect that discourages treatment smallholder farmers from expanding their croplands and seed consumption to pre-drought exposure levels.

The results of this study present a first attempt at highlighting the importance of agricultural policy in influencing behavioural responses of drought-hit farm households. Without agricultural support, the regression estimates suggest that smallholder farmers' short-term responses to severe drought conditions amplifies their vulnerability to future climate-related risks.

6.2 Recommendation

Overall, the estimated regression results provide at least two critical implications: Firstly, variations in agroclimatic conditions significantly impact the effectiveness of agricultural policy components (such as fertilizer-seed support, agricultural credit, and extension services) in shaping the extent and nature of smallholder farmers' behavioural responses to extreme weather conditions. Secondly, access to agricultural support and the choice of adaptive strategy can influence the behavioural response strategies of treatment farm households in a way that strengthens their climate resilience. Besides this, the availability of agricultural finance and agricultural extension services can allow farm households in regions predisposed to severe drought stressors to not only adjust crop management strategies but also invest in climate-smart agricultural technologies that are suitable to localized weather characteristics. Therefore, given the varied impacts of agricultural support, the results of this study are of paramount importance in growing the evidence-base that can be useful in localizing agricultural support, policies, and identifying appropriate conservation farming techniques that positively influence smallholder farmers' behavioural responses to unfavourable weather anomalies. This, in turn, will improve the overall adaptive capacity of rural agricultural communities to climatic variability and change.

Declaration of Competing Interest

The author declares NO potential conflict of interest, financial or otherwise, that could have influenced the study results.

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Appendix A: Description of Variables

Table A.1: Description of Variables

Variable Name	Variable Description	Measurement Unit
Dependent Variables		
Crop diversification	The cultivation of different crop types or consumption of different seed varieties of the same crop type during the cropping season.	Simpson Index of Diversification (SID) - ranges between 0 and 1.
Cropland share	The total cropping or cultivated area (in hectares) at the location of the smallholder farmer – used as a proxy for land use.	Hectares (ha)
Seed uptake	The total quantity of seed varieties (in kg) consumed during the growing season at the location of the smallholder farmer.	Kilograms (kg)
Fertilizer utilization	The total quantity (in kg) of basal and top-dressing chemical fertilizer used during the growing season at the location of the smallholder farmer.	Kilograms (kg)
Off-farm income	The total wage/income paid in cash or in-kind accruing to labour supplied either formally or informally to the agriculture and non-agriculture sectors – note that included in this definition are remittances in the form of pensions that are disbursed to farm households.	ZMW (K) – i.e., denotes Zambia's currency "Kwacha".
Independent Variables		
Age	The age of the household head.	Years
Gender	Sex of the household head.	Dummy: 1=male and 0=female
Education	The highest level of formal education for the household head.	Years
Marital status	Marital status of the household head.	Dummy: 1=married and 0=otherwise
Household size	The number of persons in the household.	Number of household members
Farmer support groups	Membership to farmer support groups such as agricultural cooperative societies, savings and loan groups, and women's groups.	Dummy: 1=yes and 0=no
Peer influence	The smallholder farmer received advice from fellow farmers, friends, or relatives.	Dummy: 1=yes and 0=no
Farm characteristics	This captures different farm implements and other related farm attributes that influence productive behavioural responses.	Number of farm implements.
Household wealth	The total value of household assets – used as a proxy for household wealth.	ZMW (K) – i.e., denotes Zambia's currency "Kwacha".
Agricultural support	The smallholder farmer accessed fertilizer-seed support, agricultural extension services, and/or agricultural credit.	Dummy: 1=yes and 0=no
Adaptive land strategy	The smallholder farmer adopts adaptive land investments such as crop rotation, minimum tillage, intercropping, ridging, agroforestry, irrigation, and soil erosion prevention measures.	Dummy: 1=yes and 0=no

Appendix B: Additional Robustness Results

Table B.1: Robustness to Alternative Estimation Method - Pooled Correlated Random Effects (CRE)

	Model 1	Model 1	Model 1	Model 1	Model 1
	Crop Diversification	Cropland Adjustment	Seed Utilization	Fertilizer Use	Off-Farm Income
Drought Shock (1=Yes)	-0.0204*	0.110***	0.637***	0.0399	-0.106
	(0.0117)	(0.0204)	(0.0461)	(0.163)	(0.266)
Time Dummy	0.0230***	0.105***	0.105***	1.190***	0.600***
	(0.00705)	(0.0138)	(0.0289)	(0.0943)	(0.175)
Agricultural Support					
Fertilizer-Seed Support (1=Yes)	-0.0240***	0.0159	-0.199***	2.716***	0.788***
	(0.00826)	(0.0151)	(0.0377)	(0.112)	(0.206)
Agricultural Extension (1=Yes)	0.00806	0.0407***	0.161***	0.266***	1.383***
	(0.00617)	(0.0124)	(0.0254)	(0.0777)	(0.165)
Agricultural Credit (1=Yes)	0.0969***	0.169***	0.0541*	0.288***	-0.747**
	(0.00671)	(0.0146)	(0.0285)	(0.0947)	(0.200)
Choice of Adaptive Strategy					
Minimum Soil Disturbance (1=Yes)	0.0868***	-0.00561	0.246***	0.786***	-0.396**
	(0.00607)	(0.0114)	(0.0258)	(0.0788)	(0.156)
Crop Rotation (1=Yes)	0.118***	0.0620***	0.0761***	0.377***	-1.905**
	(0.00582)	(0.0122)	(0.0248)	(0.0782)	(0.167)
Crop Residues – Soil (1=Yes)	0.0350***	0.0117	0.0122	0.1000	0.986***
	(0.00590)	(0.0111)	(0.0250)	(0.0758)	(0.151)
Legume Intercropping (1=Yes)	0.0308***	-0.0534***	-0.0821**	-0.521**	0.601***
	(0.00797)	(0.0149)	(0.0338)	(0.107)	(0.202)
Agroforestry (1=Yes)	0.0420***	0.0349**	0.0329	-0.0374	-0.185
	(0.00788)	(0.0154)	(0.0325)	(0.104)	(0.196)
Irrigation (1=Yes)	0.0121*	-0.0465***	0.111***	0.564***	-0.234
	(0.00724)	(0.0150)	(0.0307)	(0.0965)	(0.200)
Animal Plant Manure (1=Yes)	0.00376	0.0129	0.0398	-0.0529	-0.204
	(0.0102)	(0.0222)	(0.0405)	(0.133)	(0.283)
Soil Erosion Prevention Practices (1=Yes)	0.0260***	-0.0237**	-0.0101	0.0388	0.687***
	(0.00574)	(0.0109)	(0.0245)	(0.0741)	(0.150)
Extreme Drought Conditions – Interaction Terms					
Shock × Fertilizer-Seed Support	0.0323**	0.0573**	0.348***	1.484***	-0.493
	(0.0127)	(0.0243)	(0.0511)	(0.185)	(0.328)
Shock × Agricultural Extension	0.00747	-0.0186	-0.0306	-0.323**	-0.357
	(0.0102)	(0.0200)	(0.0391)	(0.138)	(0.271)
Shock × Agricultural Credit	0.0700***	-0.106***	-0.193***	-0.753**	1.029***
	(0.0103)	(0.0215)	(0.0399)	(0.151)	(0.304)
Shock × Minimum Soil Disturbance	-0.0509***	-0.0396**	-0.302***	-0.831***	-0.320
	(0.00998)	(0.0194)	(0.0382)	(0.141)	(0.255)
Shock × Crop Rotation	-0.0201**	-0.0870***	-0.130***	0.0804	0.672**
	(0.0101)	(0.0204)	(0.0380)	(0.146)	(0.278)
Shock × Legume Intercropping	-0.0317*	0.0515	-0.210***	-0.640**	-1.910**
	(0.0182)	(0.0337)	(0.0636)	(0.254)	(0.432)
Shock × Crop Residues – Soil	-0.0349***	0.0160	0.153***	0.590***	-1.140***
	(0.00957)	(0.0187)	(0.0380)	(0.135)	(0.245)
Shock × Agroforestry	-0.0262**	-0.0482**	-0.00379	-0.230	-0.0422
	(0.0113)	(0.0222)	(0.0418)	(0.156)	(0.287)
Shock × Irrigation	0.00137	0.00934	-0.143***	-0.117	0.000284

	(0.0116)	(0.0229)	(0.0446)	(0.160)	(0.301)
Shock × Animal Plant Manure	0.00154	-0.0338	-0.0576	0.489***	0.583
	(0.0139)	(0.0295)	(0.0536)	(0.189)	(0.373)
Shock × Soil Erosion Prevention Measures	0.00421	0.00222	0.0836**	0.251*	-1.010**
	(0.00982)	(0.0193)	(0.0382)	(0.136)	(0.257)
Constant	0.173***	-0.731***	0.916***	-6.014**	9.638***
	(0.0520)	(0.0952)	(0.212)	(0.686)	(1.249)
Demographic Household Characteristics	Yes	Yes	Yes	Yes	Yes
Household Wealth	Yes	Yes	Yes	Yes	Yes
Farm Characteristics	Yes	Yes	Yes	Yes	Yes
Membership – Farmer Support Groups	Yes	Yes	Yes	Yes	Yes
Peer Influence	Yes	Yes	Yes	Yes	Yes
Observations	21800	21800	21800	21800	21800

Standard errors in parentheses

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

Table B.2: Robustness to Sample Size Adjustments (Subsample Analysis) and Alternative Estimation Method – Pooled CRE

	Model 1	**Model 1**	**Model 1**	**Model 1**	**Model 1**
	Crop Diversification	**Cropland Adjustment**	**Seed Use**	**Fertilizer Utilization**	**Off-Farm Income**
Drought Shock (1=Yes)	-0.0375***	0.0681***	0.449***	-0.127	-0.227
	(0.0136)	(0.0244)	(0.0532)	(0.183)	(0.225)
Time Dummy	0.0525***	0.112***	0.186***	1.016***	2.093***
	(0.00841)	(0.0166)	(0.0346)	(0.109)	(0.158)
Agricultural Support					
Fertilizer-Seed Support (1=Yes)	0.0401***	0.0701***	0.257***	3.281***	0.0473
	(0.00932)	(0.0187)	(0.0377)	(0.126)	(0.180)
Agricultural Extension (1=Yes)	-0.0135*	0.0314**	0.0656**	0.128	0.204
	(0.00744)	(0.0153)	(0.0307)	(0.0904)	(0.147)
Agricultural Credit (1=Yes)	0.0755***	0.135***	0.0630*	0.448***	-0.286*
	(0.00759)	(0.0168)	(0.0330)	(0.108)	(0.170)
Choice of Adaptive Strategy					
Minimum Soil Disturbance (1=Yes)	0.102***	-0.0229*	0.255***	0.618***	0.147
	(0.00724)	(0.0139)	(0.0312)	(0.0914)	(0.134)
Crop Rotation (1=Yes)	0.119***	0.0656***	0.149***	0.398***	-0.418**
	(0.00705)	(0.0148)	(0.0305)	(0.0925)	(0.146)
Crop Residues – Soil (1=Yes)	0.0318***	0.0301**	-0.0368	0.148*	0.474***
	(0.00679)	(0.0133)	(0.0291)	(0.0864)	(0.130)
Legume Intercropping (1=Yes)	-0.0178*	-0.0800***	-0.205***	-0.327***	0.258
	(0.00922)	(0.0182)	(0.0379)	(0.119)	(0.173)
Agroforestry (1=Yes)	0.0355***	0.0521***	0.0547	0.0754	-0.210
	(0.00861)	(0.0172)	(0.0358)	(0.114)	(0.168)
Irrigation (1=Yes)	-0.00523	-0.0593***	0.146***	0.610***	-0.210
	(0.00840)	(0.0177)	(0.0358)	(0.108)	(0.167)
Animal Plant Manure (1=Yes)	-0.00436	0.0247	0.0647	-0.447***	0.0362
	(0.0117)	(0.0257)	(0.0463)	(0.150)	(0.245)
Soil Erosion Prevention Practices (1=Yes)	0.0402***	-0.0111	-0.0346	0.0535	0.346***
	(0.00661)	(0.0130)	(0.0284)	(0.0850)	(0.128)
Extreme Drought Conditions – Interaction Terms					

Shock × Fertilizer-Seed Support	-0.0172	-0.0153	-0.0952*	0.587***	-0.00935
	(0.0144)	(0.0291)	(0.0558)	(0.213)	(0.280)
Shock × Agricultural Extension	0.00166	-0.00838	0.0142	-0.245	0.145
	(0.0120)	(0.0242)	(0.0462)	(0.158)	(0.231)
Shock × Agricultural Credit	0.0763***	-0.0844***	- 0.169***	-0.593***	0.365
	(0.0118)	(0.0251)	(0.0464)	(0.175)	(0.259)
Shock × Minimum Soil Disturbance	-0.0593***	-0.0196	-0.212**	-0.531***	0.354
	(0.0114)	(0.0228)	(0.0447)	(0.159)	(0.217)
Shock × Crop Rotation	-0.00985	-0.0498**	-0.0806*	0.253	0.504**
	(0.0117)	(0.0237)	(0.0450)	(0.165)	(0.237)
Shock × Legume Intercropping	0.00217	0.0705*	-0.0474	-0.571**	-0.895**
	(0.0207)	(0.0386)	(0.0718)	(0.274)	(0.372)
Shock × Crop Residues – Soil	-0.0382***	-0.0202	0.164***	0.290*	-0.251
	(0.0112)	(0.0221)	(0.0443)	(0.152)	(0.212)
Shock × Agroforestry	0.00745	-0.0384	0.0163	-0.194	0.191
	(0.0128)	(0.0253)	(0.0482)	(0.176)	(0.248)
Shock × Irrigation	0.0124	0.0242	- 0.186***	-0.326*	-0.228
	(0.0134)	(0.0271)	(0.0519)	(0.181)	(0.257)
Shock × Animal Plant Manure	0.00924	-0.0706**	-0.101	0.799***	0.0179
	(0.0158)	(0.0341)	(0.0615)	(0.212)	(0.321)
Shock × Soil Erosion Prevention Measures	-0.0237**	0.00270	0.144***	0.417***	-0.482**
	(0.0114)	(0.0230)	(0.0445)	(0.158)	(0.218)
Constant	0.224***	-0.761***	0.688***	-4.224***	4.020***
	(0.0610)	(0.116)	(0.253)	(0.799)	(1.094)
Demographic Household Characteristics	Yes	Yes	Yes	Yes	Yes
Household Wealth	Yes	Yes	Yes	Yes	Yes
Farm Characteristics	Yes	Yes	Yes	Yes	Yes
Membership – Farmer Support Groups	Yes	Yes	Yes	Yes	Yes
Peer Influence	Yes	Yes	Yes	Yes	Yes
Observations	15175	15175	15175	15175	15175

Standard errors in parentheses

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

Table B.3: Robustness to Alternate Dataset, Sample Size Restrictions, and Alternative Estimation Method – Pooled CRE

	Model 1	Model 1	Model 1	Model 1
	Crop Diversification	Cropland Adjustment	Seed Use	Off-Farm Income
Drought Shock (1=Yes)	-0.0162	0.123***	0.656***	-0.345
	(0.0110)	(0.0192)	(0.0425)	(0.253)
Time Dummy	0.0257***	0.0736***	-0.0116	0.532***
	(0.00663)	(0.0130)	(0.0270)	(0.167)
Agricultural Support				
Fertilizer-Seed Support (1=Yes)	-0.0356***	-0.00523	-0.313**	0.801***
	(0.00755)	(0.0139)	(0.0349)	(0.192)
Agricultural Extension (1=Yes)	0.0138**	0.0562***	0.199***	1.404***
	(0.00578)	(0.0115)	(0.0237)	(0.156)
Agricultural Credit (1=Yes)	0.0992***	0.170***	0.0481*	-0.744***
	(0.00641)	(0.0137)	(0.0264)	(0.191)
Choice of Adaptive Strategy				
Minimum Soil Disturbance (1=Yes)	0.0894***	-0.00578	0.229***	-0.511***
	(0.00564)	(0.0106)	(0.0236)	(0.147)
Crop Rotation (1=Yes)	0.117***	0.0547***	0.0529**	-1.940***
	(0.00541)	(0.0113)	(0.0229)	(0.157)
Crop Residues – Soil (1=Yes)	0.0416***	0.00332	0.0125	1.047***
	(0.00551)	(0.0103)	(0.0231)	(0.143)
Legume Intercropping (1=Yes)	0.0378***	-0.0457***	-0.0469	0.560***
	(0.00752)	(0.0139)	(0.0315)	(0.195)
Agroforestry (1=Yes)	0.0434***	0.0461***	0.0797**	-0.287
	(0.00754)	(0.0148)	(0.0312)	(0.190)
Irrigation (1=Yes)	0.00278	-0.0455***	0.105***	-0.293
	(0.00682)	(0.0139)	(0.0288)	(0.190)
Animal Plant Manure (1=Yes)	0.0000800	0.0112	0.0474	-0.0695
	(0.00964)	(0.0207)	(0.0373)	(0.276)
Soil Erosion Prevention Practices (1=Yes)	0.0338***	-0.0224**	0.0160	0.572***
	(0.00536)	(0.0101)	(0.0228)	(0.142)
Extreme Drought Conditions – Interaction Terms				
Shock × Fertilizer-Seed Support	0.0288**	0.0728***	0.408***	-0.463
	(0.0119)	(0.0228)	(0.0479)	(0.310)
Shock × Agricultural Extension	-0.000553	-0.0334*	-0.0615*	-0.406
	(0.00968)	(0.0187)	(0.0365)	(0.259)
Shock × Agricultural Credit	0.0671***	-0.100***	-0.177**	1.078***
	(0.00975)	(0.0201)	(0.0372)	(0.294)
Shock × Minimum Soil Disturbance	-0.0455***	-0.0502***	-0.309**	-0.429*
	(0.00943)	(0.0182)	(0.0358)	(0.244)
Shock × Crop Rotation	-0.0115	-0.0868***	-0.157**	0.654**
	(0.00952)	(0.0193)	(0.0357)	(0.265)
Shock × Legume Intercropping	-0.0334*	0.0397	-0.216**	-1.820***
	(0.0173)	(0.0317)	(0.0597)	(0.417)
Shock × Crop Residues – Soil	-0.0352***	0.0202	0.114***	-1.169***
	(0.00906)	(0.0174)	(0.0353)	(0.234)
Shock × Agroforestry	-0.0316***	-0.0442**	0.0237	0.124
	(0.0108)	(0.0213)	(0.0401)	(0.279)
Shock × Irrigation	0.0122	0.000960	-0.136**	0.0501
	(0.0109)	(0.0215)	(0.0417)	(0.288)
Shock × Animal Plant Manure	0.00268	-0.0274	-0.0411	0.454
	(0.0132)	(0.0277)	(0.0503)	(0.361)
Shock × Soil Erosion Prevention Measures	-0.00176	-0.00246	0.0549	-1.003***

	(0.00932)	(0.0180)	(0.0357)	(0.246)
Constant	0.106**	-0.688***	0.669***	8.445***
	(0.0519)	(0.0929)	(0.204)	(1.296)
Demographic Household Characteristics	Yes	Yes	Yes	Yes
Household Wealth	Yes	Yes	Yes	Yes
Farm Characteristics	Yes	Yes	Yes	Yes
Membership – Farmer Support Groups	Yes	Yes	Yes	Yes
Peer Influence	Yes	Yes	Yes	Yes
Observations	5243	5243	5243	5243

Standard errors in parentheses

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

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