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Coping or collapsing?

How climate shocks fuel a poverty–deforestation feedback loop

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Coping or collapsing? How climate shocks fuels a poverty–deforestation feedback loop

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Abstract

Climate shocks increasingly threaten rural livelihoods across Sub-Saharan Africa (SSA), where farmers depend heavily on rainfed agriculture and have limited access to insurance or social protection. This paper investigates how droughts shape household production decisions and the resulting impacts on tree-cover loss in Zambia. Combining panel data on smallholder households with high-resolution rainfall anomalies and satellite-based measures of tree-cover loss, I estimate the causal effect of rainfall shocks on both agricultural yields and charcoal production. My findings show that drought exposure reduces crop yields and increases the likelihood that households engage in charcoal production, particularly among poorer farmers located closer to markets. While charcoal production provides a short-term coping mechanism, it diverts labour from agricultural preparation, deepening vulnerability and reinforcing a cycle of declining productivity and environmental degradation. At the landscape level, these production shifts translate into higher tree-cover loss. The results highlight a self-reinforcing dynamic in which climate shocks erode both household assets and natural capital, highlighting the need for policies that promote climate-resilient livelihoods and forest conservation.

Keywords: sub-Saharan Africa, rainfall shocks, charcoal production, deforestation, poverty.

JEL Classification: Q12,Q23,Q54,O13

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1. Introduction

Tree-cover loss in sub-Saharan Africa (SSA) has accelerated in recent decades, with profound implications for climate regulation, biodiversity, and rural livelihoods (Semazzi and Song, 2001; Houghton et al., 2000). Among its leading drivers is charcoal production, which remains the dominant cooking fuel for urban populations and a critical source of income for rural households (Ordóñez et al., 2025; Mulenga et al., 2019; Chidumayo et al., 2002). While charcoal production provides short-term relief during periods of economic stress, its expansion has become deeply entangled with cycles of poverty and environmental degradation (Zulu and Richardson, 2013; Khundi et al., 2011).

Although prior research has examined the links between agriculture, tree-cover loss, and energy use, much less is known about how climate shocks influence these dynamics. Existing studies are typically single-season or focus narrowly on agricultural yields, making it difficult to identify causal pathways between droughts, household production decisions, and forest outcomes (Mulenga et al., 2017; Chibwana et al., 2013). This paper addresses this gap by combining a four-year nationally representative household panel from Zambia with high-resolution rainfall and satellite-based forest-cover data to estimate how droughts shape household production decisions and their resulting impact on tree-cover loss.

I hypothesize that rainfall shocks trigger a cycle of vulnerability in which reduced yields push households into charcoal production as a coping strategy. Charcoal provides an immediate income source but diverts labor from land preparation, reducing future yields and reinforcing dependence on forest extraction. Over time, this process can lock households into a self-reinforcing poverty and tree-cover loss trap, where climate shocks and environmental degradation perpetuate each other.

This paper provides one of the first causal links between charcoal production, deforestation, and poverty. Using a four-year nationally representative household panel from Zambia merged with high-resolution satellite data, I estimate the effects of rainfall shocks defined relative to each household's 30-year local climatology on household behavior and forest outcomes. I reveal how weather shocks trigger short-term coping responses and longer-term feedbacks that trap households in charcoal dependence, deepening environmental degradation and poverty. Unlike earlier region-specific cross-sectional studies (Zulu and Richardson, 2013; Khundi et al., 2011), my approach

offers broader and more robust insights, including heterogeneity by wealth, landholding, and market access.

My results show that rainfall shocks have large and persistent effects on both household livelihoods and forest outcomes. Drought exposure reduces maize yields by roughly 32%. These income losses push households into charcoal production: participation rises by about 3 to 4 percentage points on average from a 20% baseline, with stronger effects among poorer and more market-accessible households. Among those already engaged in production, severe shocks increase charcoal output by approximately 1,100 kilograms, concentrated in the post-harvest and pre-planting months. This reallocation of labor contributes to forest loss: charcoal production is associated with a 28% increase in local tree cover loss in simple models and around 8 to 10% when household fixed effects are included. The effects are long-lasting, as households remain 7 percentage points more likely to produce charcoal one year after severe shocks, with tree cover loss and asset declines evident for at least two years.

Welfare impacts move in the same direction. Rainfall shocks make households poorer and tighten food budgets: asset wealth falls by 0.04 SD, food consumption scores decline by about 5%, and the share of spending devoted to food rises by roughly 7%. The results point to a self-reinforcing cycle: when rainfall shocks reduce farm income, households turn to charcoal as a coping strategy, which in turn accelerates tree cover loss and deepens vulnerability. The stability of charcoal prices across years indicates that this dynamic is driven by supply-side income shocks rather than demand growth. By tracing this full cycle from rainfall shocks to poverty and forest loss, this study provides new causal evidence on how climate variability can entrench poverty and environmental degradation. The findings emphasize the need for policies that prevent this cycle and support more sustainable, climate-resilient rural livelihoods in Zambia.

2. Background

2.1. Charcoal dynamics

Sub-Saharan Africa is losing forests at some of the fastest rates in the world, and charcoal production is one of the key drivers behind this trend (Hadunka and Baylis, 2022). For many smallholder farming communities, charcoal is both an energy source and a safety net when farming

fails (Hadunka and Baylis, 2022; Yalew, 2015; Semazzi and Song, 2001). Its role expands during hard times, especially after droughts or floods that reduce harvests, when households turn to charcoal to replace lost farm income (Mulenga et al., 2019; Chidumayo et al., 2002; Mulenga et al., 2017).

Producing charcoal is labor-intensive. It requires cutting trees and carbonizing the wood, usually in simple earth-mound kilns (Chidumayo and Gumbo, 2013). These methods are highly inefficient and often waste large amounts of biomass, accelerating forest loss. Production usually peaks right after harvest, when farmers might otherwise be preparing fields for the next season. This shift in labor not only increases deforestation but can also undermine future harvests, leaving households even more dependent on charcoal. Over time, this cycle of declining farm productivity, rising charcoal reliance, and accelerating deforestation threatens to lock households into poverty while worsening environmental damage (Mulenga et al., 2017; Hadunka and Baylis, 2022).

Although there is growing discussion of climate-resilient farming and clean energy transitions, I still know little about how a single shock, such as a drought or pest, can set off a chain of deforestation that lasts for years (Hadunka and Baylis, 2022). This study aims to close that gap by tracing the links between climate shocks, household decisions, and deforestation. In doing so, it provides evidence for policies that could break the cycle, including cash transfers, access to sustainable energy, and alternative income opportunities that protect forests while supporting rural livelihoods.

Charcoal production involves cutting trees close to their roots, resulting in the complete destruction of the trees and contributing directly to deforestation. In **??** the author stands beside a pile of freshly felled trees prepared for charcoal production. Notice how the trees have been cut; these stumps are unlikely to regenerate, and even if regrowth occurs, it would take many years for the area to return to a fully developed forest.

Figure 1: Trees cut for charcoal

Source: Authors'.

2.2. Rainfall shocks in Zambia

Zambia provides a clear case of how climate and livelihoods are deeply intertwined. Rainfall variability is rising, with both droughts and floods disrupting smallholder farming. These shocks reduce yields, cut into incomes, and threaten food security (Gizaw and Gan, 2017; Ault et al., 2016). For households with no formal insurance or reliable access to credit, charcoal production becomes a fallback option. It helps cover immediate needs, but at the cost of clearing forests and undermining long-term land productivity.

This coping response is understandable but risky. Forest extraction can worsen environmental degradation, deepening poverty and leaving households even more exposed to future shocks. Yet, despite the importance of these dynamics, little is known about how one rainfall shock can trigger cascading effects on deforestation and poverty across multiple seasons.

This study takes on that challenge. By modeling the links between rainfall shocks, household responses, and deforestation, I show how short-term coping through charcoal can reinforce a cycle of poverty and environmental decline. At the same time, the results point to policy solutions:

programs that build rural resilience through cash transfers, clean energy options, and diversified livelihoods could reduce reliance on charcoal while protecting vulnerable households.

2.3. Charcoal and poverty

Charcoal production may ease short-term hardship, but it can also deepen poverty in the long run. The reasons are threefold. First, it diverts labor away from farming during critical periods in the agricultural calendar, often leading to smaller harvests the following season (Arnold et al., 2006). Second, the returns from charcoal are modest and often declining, especially once the costs of environmental degradation are considered (Zulu and Richardson, 2010; Hadunka and Baylis, 2022). Third, charcoal income is unstable: prices can be volatile and sales vary seasonally, making it a risky livelihood that rarely offers upward mobility.

Together, these factors can trap households in what we call the poverty–deforestation cycle. A rainfall shock reduces farm income, prompting households to produce charcoal. This in turn reduces forest cover and agricultural productivity, which makes future rainfall shocks even more damaging. Over time, households can become stuck in a low-income equilibrium, turning to charcoal repeatedly despite its diminishing returns and environmental costs (Barrett et al., 2016).

To capture this dynamic, I measure poverty using an asset-based wealth index constructed from housing, durable goods, and livestock. I also link charcoal production to self-reported food insecurity and household spending patterns, providing a multidimensional view of how reliance on charcoal affects both livelihoods and well-being.

3. Theoretical Model: Charcoal, poverty, and rainfall change

I model how rainfall shocks shape household production decisions and forest outcomes in a setting where livelihoods depend heavily on rainfed agriculture and nearby forest resources. When rainfall fails in period t, crop yields decline and agricultural income falls. Because most households have limited access to formal credit or insurance, they respond by reallocating labor toward activities that generate cash quickly, such as charcoal production. While charcoal provides short-term liquidity, it also accelerates forest loss and diverts labor away from agricultural preparation, potentially reinforcing future vulnerability.

To formalize these ideas, let:

(i) S_t — rainfall shock in period t (negative for drought),

(ii) Y_t — agricultural income,

(iii) L_t — labor allocated to charcoal production,

(iv) C_t — charcoal output,

(v) D_t — tree-cover loss,

(vi) F_t — forest stock, and

(vii) P_t — household poverty.

Agricultural income depends on seasonal rainfall:

$$Y_t = f(S_t), \qquad f_S > 0. \tag{1}$$

A negative deviation from the local rainfall norm ($S_t < 0$) reduces yields and liquidity, increasing the incentive to shift labor into charcoal production:

$$L_t = g(Y_t, F_t), \qquad g_Y < 0, ; g_F > 0. \tag{2}$$

Labor supply to charcoal rises when farm income falls and when forest availability lowers extraction costs.

Charcoal output depends on labor and the remaining forest stock:

$$C_t = h(L_t, F_t), \qquad h_L > 0, ; h_F > 0. \tag{3}$$

Charcoal production contributes directly to deforestation, while cropland expansion may also add to forest loss:

$$D_t = \delta_c C_t + \delta_a \Delta H_t + \varepsilon_t, \qquad \delta_c, \delta_a > 0. \tag{4}$$

Forest stock evolves as natural regeneration minus extraction:

$$F_{t+1} = F_t + R(F_t) - D_t, \qquad R_F > 0. \tag{5}$$

Finally, household well-being is shaped by reduced agricultural income and increased reliance on charcoal:

$$P_t = \phi_c C_t - \phi_y Y_t + \omega_t, \qquad \phi_c, \phi_y > 0. \tag{6}$$

This structure captures a self-reinforcing poverty–deforestation cycle. A rainfall shock lowers agricultural income, which increases charcoal production. Higher charcoal extraction accelerates forest loss, reduces future forest availability, and deepens household vulnerability. These dynamics align with the empirical patterns documented in the following sections, where rainfall shocks induce immediate shifts in labor allocation and generate persistent effects on both livelihoods and local forest conditions.

4. Empirical Strategy

I estimate the causal effects of rainfall shocks on household behavior, deforestation, and poverty using a difference-in-differences (DiD) approach. The analysis draws on a four-year household panel (2016–2019) linked to high-resolution data on rainfall anomalies and deforestation. The strategy compares changes in outcomes for households exposed to rainfall shocks ("treated") with those unexposed ("controls") before and after the shock, while accounting for time-invariant and aggregate factors through household and year fixed effects.

My main specification is:

$$Y_{it} = \beta \, \text{Shock}_{it} + \mathbf{X}'_{it}\gamma + \alpha_i + \tau_t + \varepsilon_{it}, \tag{7}$$

where Y_{it} denotes the outcome of interest for household i in year t (e.g., maize yield, charcoal participation, deforestation, or welfare). Shock_{it} equals one if the household experienced a rainfall shock (drought or flood) during the growing season and zero otherwise. $\mathbf{X}_{it}$ includes time-varying controls such as cultivated area, assets, and temperature, while α_i and τ_t capture household and year fixed effects. The coefficient β measures the average treatment effect on treated households (ATT). Standard errors are clustered at the camp level.

4.1. Identification and Validity

The difference-in-differences design assumes that, in the absence of a rainfall shock, treated and control households would have followed similar trends in their outcomes over time. To examine this assumption, I estimate an event-study model of the form

$$Y_{it} = \sum_{k \neq -1} \beta_k D_{i,t+k} + \alpha_i + \tau_t + \varepsilon_{it}, \tag{8}$$

where the coefficients β_k capture how outcomes evolve k years before and after the first rainfall shock. If the estimated coefficients for the pre-shock years ($k < 0$) are close to zero and statistically insignificant, this suggests that treated and control households were on similar paths before the shock, which supports the parallel-trends assumption.

Rainfall shocks can be considered plausibly exogenous because they are highly localized, difficult to anticipate, and unrelated to household behavior. Their spatial and temporal randomness reduces the risk that exposure is correlated with unobserved factors affecting household outcomes. To further minimize potential confounding, I include controls for key baseline characteristics such as landholding size, household wealth, and market proximity, and confirm that treated and control households were balanced along these dimensions before the shock. Measures of deforestation are obtained from satellite-based data (Hansen et al., 2013), which are independent of survey responses and reduce concerns about reporting bias.

These checks reinforce the credibility of my identification strategy and support a causal interpretation of the estimated effects of rainfall shocks on agricultural production, charcoal use, forest loss, and household welfare.

Table 1: Event-Study: Testing the parallel trends assumption

	(1) Maize Yields	(2) Charcoal Participation
Pre-shock periods (Placebo)		
1 year before shock ($t-1$)	-0.008	0.003
	(0.021)	(0.007)
Post-shock periods		
Year of shock (t)	-0.193***	0.029**
	(0.055)	(0.013)
1 year after ($t+1$)	-0.255***	0.036**
	(0.063)	(0.015)
Fixed Effects		
Household FE	✓	✓
Year FE	✓	✓
Observations	2,761	2,512
R-squared	0.25	0.17

Robust standard errors clustered at district level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Econometric Framework

To empirically evaluate the dynamic relationship between rainfall shocks, charcoal production, deforestation, and poverty, I estimate a set of linked equations. These models aim to capture both the short-term coping response and the long-run poverty–deforestation trap.

To account for possible spatial correlation among farmers exposed to the same local drought, I estimated two-way fixed effects models that include detailed location and year fixed effects, along with location-specific linear trends.

5.1. Rainfall shocks and charcoal production

I estimate the impact of drought on household participation in charcoal production using a difference-in-differences (DiD) framework for panel data. This approach compares changes in charcoal production between households exposed to drought and those not exposed before and after the shock,

while accounting for both time-invariant household characteristics and common time shocks.

Let $y_{it} \in \{0, 1\}$ indicate whether household i engaged in charcoal production in year t, and let Drought_{it} equal one if household i experienced a drought shock during the agricultural season corresponding to year t. The main DiD model is:

$$y_{it} = \beta \, \text{Drought}_{it} + \mathbf{X}'_{it}\boldsymbol{\gamma} + \alpha_i + \tau_t + \varepsilon_{it}, \tag{9}$$

where $\mathbf{X}_{it}$ represents a vector of time-varying controls (such as temperature, farm size, and household assets), α_i are household fixed effects that control for unobserved, time-invariant heterogeneity, τ_t are year fixed effects that absorb aggregate time shocks, and ε_{it} is an idiosyncratic error term. The coefficient of interest, β, measures the average treatment effect of drought exposure on the probability that a household produces charcoal. Standard errors are clustered at the camp level to allow for correlation within local markets and rainfall zones.

As a robustness check, I also estimate a nonlinear difference-in-differences specification using a correlated random-effects (CRE) probit model following Wooldridge (2010) and Wooldridge (2019). This model accounts for unobserved heterogeneity by parameterizing household-specific effects as functions of time-averaged regressors (the Mundlak adjustment), which allows consistent estimation of average partial effects (APEs) in nonlinear panels:

$$\Pr(y_{it} = 1 \mid \text{Drought}_{it}, \mathbf{X}_{it}, \bar{\mathbf{X}}_i, \overline{\text{Drought}}_i) = \Phi\Big(\beta \, \text{Drought}_{it} + \mathbf{X}'_{it}\boldsymbol{\gamma} + \bar{\mathbf{X}}'_i\boldsymbol{\delta} + \vartheta \, \overline{\text{Drought}}_i + c_i + \tau_t\Big), \tag{10}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, c_i is the unobserved household effect, $\bar{\mathbf{X}}_i$ and $\overline{\text{Drought}}_i$ denote household-specific means of the time-varying covariates and drought exposure, respectively. The coefficient β captures the difference-in-differences effect of drought on the probability of engaging in charcoal production, holding all other factors constant.

For completeness, the underlying latent index representation of Equation (10) is:

$$\text{Charcoal}_{it}^{*} = \beta\,\text{Drought}_{it} + \mathbf{X}_{it}'\boldsymbol{\gamma} + \bar{\mathbf{X}}_{i}'\boldsymbol{\delta} + \vartheta\,\overline{\text{Drought}}_{i} + c_i + \tau_t + \varepsilon_{it}, \tag{11}$$

$$\text{Charcoal}_{it} = \begin{cases} 1 & \text{if Charcoal}_{it}^{*} > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{12}$$

To explore the intensive margin in survey rounds where charcoal quantities are reported (and include zeros), I estimate a fixed-effects Tobit model:

$$Q_{it}^{*} = \beta_q\,\text{Drought}_{it} + \mathbf{X}_{it}'\boldsymbol{\theta} + \alpha_i + \tau_t + \upsilon_{it}, \tag{13}$$

$$Q_{it} = \max\{0,\, Q_{it}^{*}\}, \tag{14}$$

where Q_{it} is the observed charcoal quantity and Q_{it}^{*} is its latent counterpart. The parameter β_q reflects the DiD effect of drought on charcoal production intensity among households at risk of engaging in this coping activity.

Across all specifications, I interpret the coefficient β as the average difference-in-differences effect of drought exposure, capturing how the likelihood or intensity of charcoal production changes for treated households after a shock relative to their own pre-shock outcomes and to control households that were not exposed.

5.2. Charcoal production and deforestation

I examine how household charcoal production affects nearby forest loss using a difference-in-differences model with two-way fixed effects:

$$Deforestation_{jt} = \theta, Charcoal_{jt} + \mathbf{Z}jt'\boldsymbol{\lambda} + \mu_j + \tau_t + ujt \tag{15}$$

Here, $Deforestation_{jt}$ is the measured forest loss within a 5 km buffer j at time t, and $Charcoal_{jt}$ is the share of households producing charcoal in that buffer and year. The vector $\mathbf{Z}_{jt}$ includes time-varying controls such as rainfall, temperature, and population density. Spatial fixed effects (μ_j) control for unobserved, time-invariant location characteristics, while year fixed

effects (τ_t) capture national trends and common shocks. The coefficient θ represents the average difference-in-differences effect of increased charcoal activity on deforestation, comparing changes in forest loss before and after growth in charcoal production between treated and control areas.

5.3. Charcoal production and poverty outcomes

To examine whether charcoal production mitigates or deepens poverty, I estimate a difference-in-differences model that compares changes in household welfare before and after engagement in charcoal production, relative to households that did not engage in charcoal activities. The model is specified as:

$$Poverty_{it} = \eta, Charcoal_{it} + \mathbf{X}it'\boldsymbol{\kappa} + \alpha_i + \delta_t + \xi it \tag{16}$$

$Poverty_{it}$ represents a continuous index of household well-being for household i in year t, measured using an asset-based wealth index constructed from principal components analysis (PCA) of durable goods, housing characteristics, and livestock holdings. $Charcoal_{it}$ is a treatment indicator equal to one if a household engages in charcoal production during year t, and $\mathbf{X}_{it}$ includes time-varying controls such as education, household size, and landholding. Household fixed effects (α_i) account for unobserved, time-invariant heterogeneity, while year fixed effects (δ_t) capture common shocks affecting all households.

The coefficient η measures the average difference-in-differences effect of charcoal participation on household welfare, capturing how poverty changes for households that begin producing charcoal relative to non-producers over time.

In additional specifications, I use alternative welfare indicators as dependent variables, including:

1. Food consumption score,
2. Share of income spent on food, and
3. Coping strategies adopted during shocks.

5.4. Dynamic feedback mechanism

To examine whether the effects of drought and charcoal production persist over time, I extend the difference-in-differences framework to a dynamic specification that includes lagged shocks and past charcoal activity:

$$Charcoal_{it} = \sum_{k=0}^{K} \delta_k Shock_{i,t-k} + \sum_{k=1}^{K} \phi_k Charcoal_{i,t-k} + \mathbf{X}it'\boldsymbol{\psi} + \alpha_i + \delta_t + \nu it \tag{17}$$

In this model, $Charcoal_{it}$ indicates whether household i engages in charcoal production in year t, and $Shock_{i,t-k}$ represents current and lagged drought exposure up to K years prior. The household fixed effects (α_i) control for unobserved, time-invariant differences, while year fixed effects (δ_t) capture aggregate trends and common shocks.

This dynamic difference-in-differences approach allows us to trace how the impact of a rainfall shock evolves over time, specifically whether an initial production shock leads to prolonged engagement in charcoal production, thereby sustaining deforestation and deepening poverty. I further examine heterogeneity by household wealth and credit access to assess whether poorer households are more likely to remain caught in this poverty–deforestation trap.

6. Identification assumptions

My identification strategy builds on the idea that deviations from long-run local rainfall patterns provide plausibly exogenous variation in household exposure to climate shocks. I measure these shocks as standardized anomalies relative to a 30-year historical baseline at each household's location. This holds shocks in the household's own climatology, stripping out persistent spatial differences and capturing truly unexpected weather events. Because droughts and floods are highly localized and difficult to predict, they are unlikely to be driven by household characteristics or past land-use decisions, which supports their validity as exogenous shocks.

I also assess whether households adjust in anticipation of shocks by testing for pre-trend deforestation. The absence of such anticipatory responses lends credibility to the parallel trends assumption. To address unobserved heterogeneity, I include household fixed effects to absorb time-invariant factors such as proximity to forests, while year fixed effects control for broader economic

or policy shifts. I further assume that shocks remain geographically contained.

Finally, my deforestation outcomes are derived from high-resolution satellite data, which are independent of household reporting and provide reliable measures of forest loss. I supplement these design features with robustness checks that use alternative shock definitions, exclude extreme outliers, and adjust standard errors for spatial autocorrelation. These steps strengthen the credibility of my identification framework and support a causal interpretation of the results.

7. Data

I use a four–year household panel survey, conducted in Zambia between 2016 and 2019. Each round took place in June–July, corresponding to the 2015/16 through 2018/19 agricultural seasons. The sample includes about 1,200 smallholder households across 12 districts, selected through a multi–stage, stratified design. Within each district, We randomly chose agricultural camps. An agricultural camp is the local administrative units that organize farmers for extension services (Alamu et al., 2018). Camps bring together cooperatives of neighboring farmers who typically coordinate on input access, bargaining, and service delivery; while cooperatives differ in size and structure, members within a given cooperative generally share similar timing and access to inputs and extension support (Bijman and Wijers, 2019; Blekking et al., 2021). From these camps, we then drew a random sample of households.

The survey provides detailed information on demographics, socioeconomic status, income sources, crop production, and natural–resource use (forests).

To measure environmental exposure, I link households by their GPS locations to high–resolution (30 m) annual tree–cover loss data from the University of Maryland's Global Forest Change dataset, constructing local forest–loss rates around each household for every year (Hansen et al., 2013). Rainfall exposure is captured using gridded precipitation data from CHIRPS, which I use to build season–specific indices of rainfall variability [1]. To account for heat stress, I also merge in temperature data from MODIS products, allowing me to examine rainfall anomalies alongside temperature–driven water stress (Funk et al., 2015).

[1] To minimize potential attenuation bias from measurement error, I aggregate rainfall data to the seasonal level and normalize anomalies relative to each household's 30-year local climatology, which reduces random noise in grid-level rainfall estimates.

7.1. Measuring rainfall shocks

I measure rainfall shocks using household-specific deviations from the long-run rainfall climatology at each location. Following the World Meteorological Organization's definition of a 30-year climate "normal," [2] I compute mean seasonal rainfall and its standard deviation for each household's location using the 30-year historical record (Harris et al., 2014). This household-specific normalization removes persistent spatial differences in rainfall levels and aligns directly with the difference-in-differences design by allowing identification of rainfall deviations relative to each household's own long-run environment.

Seasonal rainfall for each household–year is obtained from the CHIRPS dataset (Funk et al., 2015), which blends satellite estimates with station observations.[3] For each household h in year t, I compute the standardized anomaly:

$$z_{ht} = \frac{\text{rain}_{ht} - \overline{\text{rain}}_{h,30}}{\sigma_{h,30}},$$

where $\overline{\text{rain}}_{h,30}$ and $\sigma_{h,30}$ denote the long-run mean and standard deviation of seasonal rainfall at that location (Dell et al., 2014). This transformation does not impose normality on rainfall; rather, it measures how unusual a given season is relative to the household's historical baseline.[4]

A drought is defined as $z_{ht} \leq -1$, corresponding to rainfall at least one standard deviation below the long-run mean, and a flood as $z_{ht} \geq 1$. These thresholds are commonly used in agronomic studies and predict yield reductions in rainfed systems (Carleton and Hsiang, 2016; Dell et al., 2014).

This household-normalized approach ensures that rainfall shocks capture exogenous, location-specific deviations from long-run conditions, which is precisely the type of variation that motivates the difference-in-differences identification strategy used throughout the analysis.

With these rainfall anomalies in hand, the empirical strategy estimates the impact of climatic shocks on charcoal production, forest loss, and household welfare using a consistent difference-in-

[2] The World Meteorological Organization defines a climatological "normal" as a 30-year period composed of three consecutive ten-year intervals. This baseline is widely used for assessing anomalies relative to local climate conditions (World Meteorological Organization, 2017).

[3] While rainfall measurement error is possible where gauges are sparse, aggregating to seasonal totals and standardizing relative to each household's own climatology reduces noise and captures meaningful anomalies in rainfall conditions.

[4] Because rainfall is often right-skewed, assuming normality may be inappropriate. Standardizing relative to each household's own 30-year record avoids distributional assumptions and focuses on deviations from local norms (Carleton and Hsiang, 2016).

differences (DiD) framework. The identifying assumption is that, in the absence of a rainfall shock, households experiencing negative anomalies would have followed similar trends as those that did not. Household fixed effects absorb all time-invariant characteristics such as forest proximity and market access, while year fixed effects capture aggregate shocks.

8. Descriptive statistics

This section presents descriptive evidence linking rainfall shocks, charcoal production, and deforestation among smallholder households in Zambia. My data span the 2015/16 to 2018/19 agricultural seasons and come from a nationally representative household panel survey (HICPS), combined with satellite-based measures of forest loss and weather data.

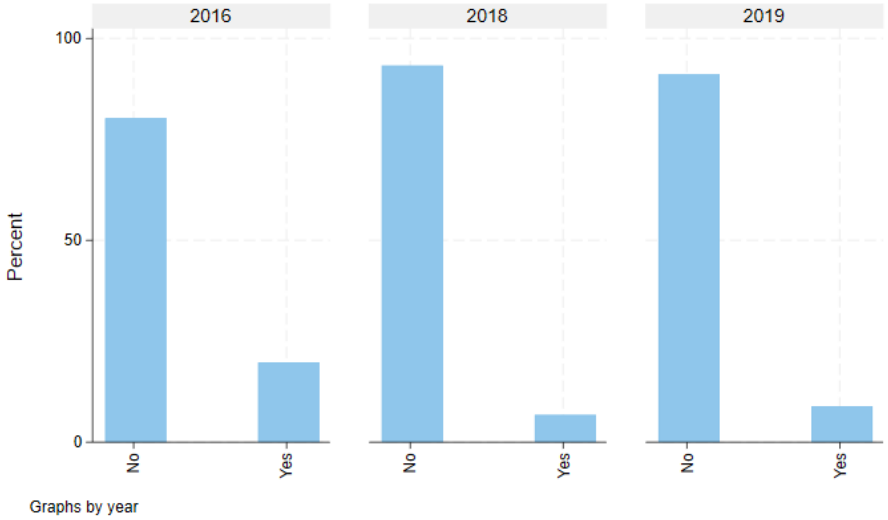

Figure 2: Proportion of Households Producing Charcoal

Source: HICPS survey.

Figure 2 shows that the proportion of households producing charcoal for commercial purposes peaked in 2016, coinciding with the aftermath of a severe drought that forced households to seek alternative income sources. In subsequent years, commercial charcoal production declined somewhat (2018–2019), but remained above pre-shock levels, suggesting that drought-induced entry into charcoal markets had persistent effects. This pattern underscores how rainfall shocks can trigger a shift toward reliance on forest resources, reinforcing the vulnerability of rural livelihoods and the importance of sustainable and rainfall-resilient livelihood alternatives.

8.1. Rainfall shocks and charcoal production

As Figure 3 demonstrates, deforestation trends prior to the 2015 drought were relatively flat and statistically indistinguishable between treated and control districts, providing support for the parallel trends assumption. Estimates from 2012 through 2014 fluctuate around zero with wide

confidence intervals, suggesting no systematic differences in deforestation before the shock.

Following the onset of the drought in 2015 (indicated by the vertical dashed line), however, the estimates shift upward and become consistently positive, particularly in 2016 and 2017. This break in trend indicates that the increase in deforestation is driven by the rainfall shock rather than by pre-existing differences between treatment and control groups. The timing aligns with the agricultural calendar: poor harvests reduce household income after July, and the reliance on charcoal production as a coping strategy intensifies in the lean season, making the deforestation effects visible in the year after the drought.

Thus, the figure provides strong visual evidence that the parallel trends assumption holds prior to the shock, and that the observed post-2015 divergence is plausibly attributable to the drought.

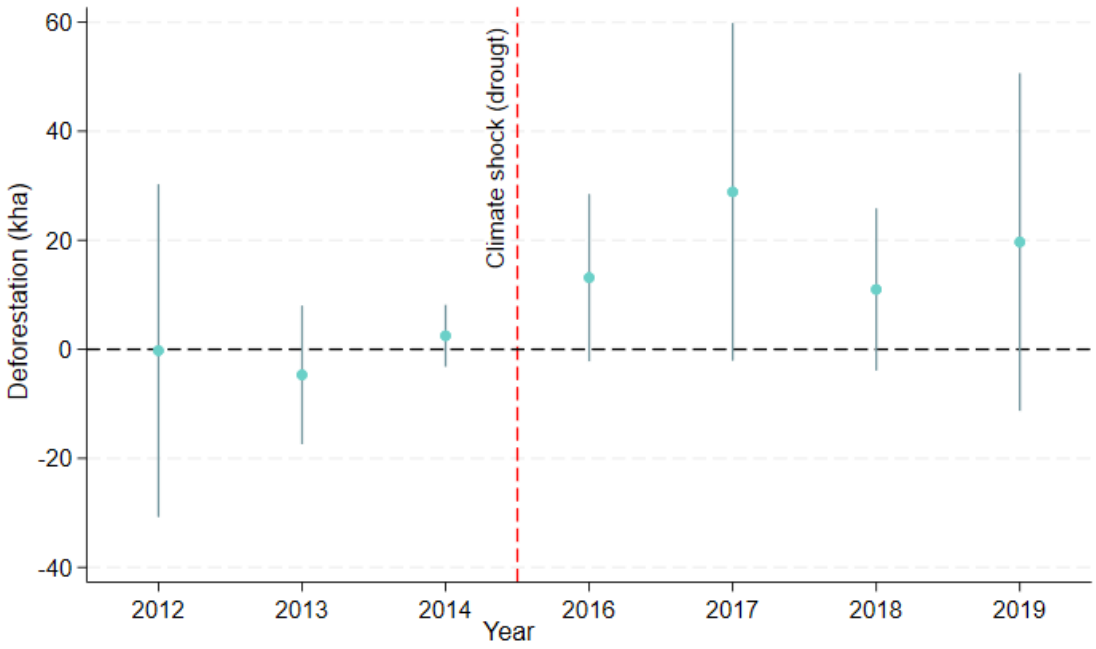

Figure 3: The figure illustrates that deforestation rates in Zambia rose in the years following the 2015 drought, with a noticeable increase in 2016 and 2017. The increase appears after the drought, rather than during it, reflecting the structure of the agricultural season.

8.2. Rainfall shocks and maize yields

Figure 4 shows, maize yields in treated and control districts followed similar, relatively stable trajectories before the 2015 drought, providing strong support for the parallel-trends assumption. Between 2011 and 2014, yield estimates remain positive and statistically indistinguishable from one another, indicating no systematic pre-shock differences across districts.

The pattern changes sharply following the onset of the 2015 drought, marked by the vertical dashed line. Beginning that year, yield coefficients drop and remain below zero throughout the subsequent period, with the largest declines observed after 2017. This downward shift signals a significant and persistent negative impact of the drought on maize productivity.

In general, the figure provides clear visual evidence that yields were stable prior to the rainfall shock and declined substantially afterward, with no immediate recovery. These results suggest that drought-induced yield losses were both severe and long-lasting, consistent with limited adaptive capacity or slower post-shock recovery among affected farmers.

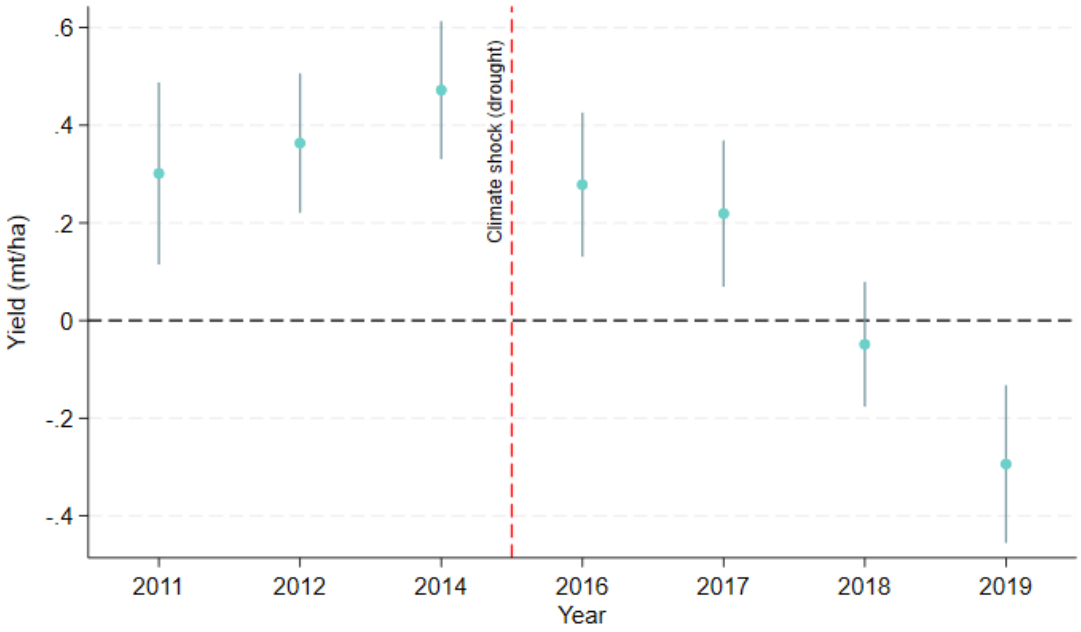

Figure 4: The figure illustrates that maize yields declined sharply following the 2015 drought, with losses becoming evident from 2016 onward. The decline appears after the drought rather than during it, reflecting the timing of the agricultural season, as poor rainfall conditions in 2015 led to reduced harvests and lower yields in subsequent years.

8.3. Charcoal market conditions

Charcoal prices show little seasonal fluctuation, suggesting that rising production is not a response to stronger market incentives. Rather, it reflects supply-side pressures: when households face income losses from droughts and floods, they turn to charcoal production as a fallback strategy to make ends meet (see Figure 5).

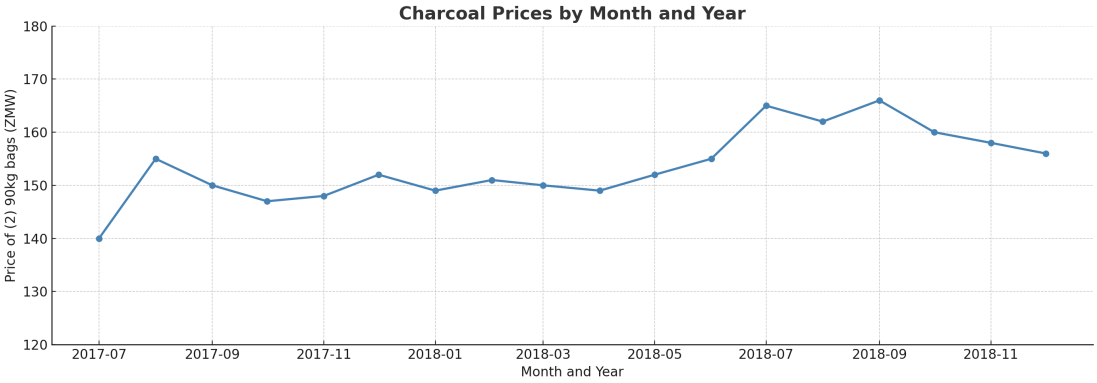

Figure 5: Average retail price of charcoal across seasons

Source: HICPS survey and retail price monitoring data Adopted from (**hadunka2022staple.**)

8.4. Balance of baseline characteristics

Table 2 reports baseline means and balance tests for households exposed to a rainfall shock compared to those that were not during the 2015/16 agricultural season. The two groups are broadly comparable across demographic, landholding, and income characteristics, with only modest differences in a few variables. This balance supports the validity of subsequent comparisons between households affected by rainfall shocks and those unaffected.

Table 2: Baseline (2015/16 agricultural season) means and balance

	Means [SD]		Normalized difference
	No rainfall shock	Rainfall shock	Difference
Age (years)	47.20	46.05	0.025*
	[14.80]	[15.10]	
Gender (1 = male)	0.82	0.79	0.019
	[0.38]	[0.41]	
Education (years)	4.05	3.76	0.092
	[2.01]	[1.68]	
Weather index (std)	0.02	-0.03	0.045
	[1.00]	[1.00]	
Charcoal (1=yes)	0.14	0.20	-0.051
	[0.35]	[0.40]	
Total landholding (ha)	5.12	5.54	-0.121
	[8.92]	[7.46]	
Cultivated land (ha)	2.60	2.85	-0.148
	[2.35]	[2.52]	
Distance to market (km)	14.8	15.3	-0.032
	[9.5]	[10.1]	
Maize yield (kg/ha)	1640.32	1705.11	0.203
	[1685.74]	[1423.89]	
Total income (ZMW)	7650.25	8025.47	0.162
	[12954.12]	[13560.44]	
Food consumption score	32.5	31.1	-0.058
	[8.7]	[9.1]	
Access to credit (1=yes)	0.69	0.71	0.014
	[0.46]	[0.45]	
Asset index	128.54	93.27	0.073
	[410.72]	[63.55]	
N	**975**	**975**	

Robust standard errors in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

9. Results

9.1. First stage – rainfall shocks and maize yields

I estimate the causal impact of rainfall shocks on maize yields using a DiD framework with household and year fixed effects. This approach compares changes in maize yields for households exposed to rainfall shocks with those unexposed before and after the shock, while controlling for time-invariant household characteristics and year-specific factors that affect all households equally.

Rainfall shocks are defined as standardized anomalies relative to each household's 30-year rain-

fall record. For each household and year, seasonal rainfall is extracted from CHIRPS precipitation data matched to household GPS coordinates and normalized against the local 30-year mean and standard deviation. A drought occurs when the standardized anomaly is less than or equal to -1, a flood when it is greater than or equal to 1, and severe events correspond to absolute values greater than or equal to 2 (Hersbach et al., 2020; Funk et al., 2015; Muñoz-Sabater et al., 2021). This household-specific normalization allows shocks to be measured relative to long-term local rainfall patterns, capturing truly anomalous weather events.

Across all model specifications, I find strong evidence that rainfall shocks reduce maize yields. In the baseline model without controls, yields decline by about 22%. After accounting for household and year fixed effects, the estimated loss increases to roughly 32%. Including additional controls does not change this conclusion, with yield reductions ranging between 18 and 32% (see Table 3). These results align with national evidence from Zambia, where maize production during the 2019 drought was about one-third lower than in subsequent non-drought years (Boer et al., 2024).

By framing rainfall shocks within a DiD structure and anchoring anomalies to local long-term rainfall baselines, I isolate the causal effect of drought on yields and show the vulnerability of rainfed smallholder agriculture to climate variability.

Table 3: Impact of Rainfall Shocks on Maize Yields

	(1) Maize yields	(2) Maize yields	(3) Maize yields	(4) Maize yields
Post × Treated (Rainfall shock)	-0.186***	-0.298***	-0.215***	-0.324***
	(0.045)	(0.060)	(0.051)	(0.058)
Household fixed effects		✓		✓
Year fixed effects		✓		✓
Controls			✓	✓
Observations	2,376	2,376	2,376	2,376
R-squared	0.35	0.37	0.39	0.38

Dependent variable: ln(maize yield, kg/ha). Robust SEs in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

9.2. Extensive margin – participation in charcoal production

Using the DiD framework to examine how rainfall shocks, measured relative to each household's long-run climate baseline, influence participation in charcoal production.

The results show that severe droughts increase the probability of household participation in charcoal production by about 3 percentage points, relative to an average participation rate of 20 percent in the sample. Because charcoal prices remain relatively stable across seasons, this increase reflects a supply-side coping response to lower agricultural income rather than changes in demand (Vorlaufer et al., 2017; Adnan et al., 2017).

Access to productive land helps cushion this response. Each additional hectare of cultivated land reduces the likelihood of charcoal participation by about 0.8 percentage points, suggesting that households with larger farms are less likely to divert labor toward forest extraction (Hichaambwa and Jayne, 2012). The effects are strongest among asset-poor households and those closer to markets, consistent with the broader socioeconomic profile of charcoal producers in the region (Hadunka and Baylis, 2022; Zulu and Richardson, 2010). These findings are robust to alternative definitions of rainfall shocks, and DiD event-study checks show no evidence of differential pre-trends before exposure.

Table 4: Effect of rainfall shocks on charcoal production (participation)

	(1) Probit	(2) CRE-Probit	(3) LPM	(4) DiD (LPM + FE)
Post × Treated (Rainfall Shock)	0.034***	0.037***	0.032***	0.035***
	(0.011)	(0.013)	(0.012)	(0.013)
Cultivated land (ha)	-0.009**	-0.008**	-0.009**	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Asset index (std)	-0.004*	-0.003	-0.004*	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Household FE		✓		✓
Year FE		✓		✓
Controls	✓	✓	✓	✓
Observations	2,300	2,300	2,300	2,300
R-squared	0.23	0.26	0.25	0.27

Robust standard errors clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

9.3. Intensive margin – quantity of charcoal produced

To examine how rainfall shocks influence the intensity of charcoal production among households already engaged in the activity, I employ a DiD framework. The dependent variable is the annual quantity of charcoal produced (in kgs), with non-producing households coded as zero to capture

both participation and intensity effects.

The DiD model compares changes in charcoal output for treated households before and after a rainfall shock, relative to control households not exposed to the shock. Household and year fixed effects control for unobserved time-invariant factors and time-varying shocks, isolating the causal impact of drought exposure (Wooldridge, 2010).

Results show that rainfall shocks increase charcoal output by roughly 900–1,100 kilograms on average, particularly in the post-harvest season when liquidity constraints are most binding (Adnan et al., 2017; Mulenga et al., 2019; Hadunka and Baylis, 2022). These effects remain robust to controls for market access, landholding, and forest proximity, and event-study evidence shows no pre-trend differences. In general, droughts not only increase the entry into charcoal production, but also increase the intensity of production, strengthening short-term coping behavior with long-term environmental costs (Wooldridge, 2019; Hsiao, 2022).

Table 5: DiD estimates: Effect of rainfall shocks on quantity of charcoal produced

	(1) DiD (OLS)	(2) DiD (FE)	(3) DiD (FE + Controls)
Post × Treated (Rainfall Shock)	940***	1025***	1100***
	(270)	(285)	(298)
Household FE		✓	✓
Year FE	✓	✓	✓
Controls			✓
Observations	740	740	740
R-squared	0.23	0.26	0.28

Dependent variable: Charcoal output (kg). Robust SEs in parentheses, clustered at district level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

9.4. Poverty consequences

I then analyze whether rainfall shocks and the resulting increase in charcoal production push households deeper into poverty. The analysis compares changes in welfare for households exposed to rainfall shocks (treated) before and after the event, relative to those that were not exposed (controls). By including household and year fixed effects, I control for unobserved household traits and broader time effects that might otherwise bias the results.

I focus on three indicators of household well-being: (i) a standardized wealth index based on assets, housing, and livestock; (ii) a food consumption score capturing dietary quantity and diversity; and (iii) the share of income spent on food (Coates et al., 2007; Deaton, 1997; Deaton and Muellbauer, 1980). This follows the broader poverty and risk literature showing that short-term shocks can lead to lasting losses in assets and consumption, especially for households with limited access to credit or insurance (Carter and Barrett, 2006; Dercon, 2004; Barrett et al., 2016).

As shown in Table 6, the DiD results show clear welfare declines after rainfall shocks. Treated households experience about a 0.05 standard deviation drop in the wealth index and a 0.06 reduction in food consumption scores, reflecting both asset erosion and lower food quality. At the same time, the food budget share rises by around 0.07 log points, suggesting that households divert limited income toward food to cushion consumption losses (Boer et al., 2024).

These patterns are consistent and statistically significant across specifications. Including household and year fixed effects strengthens the causal interpretation. Generally, the results show that even temporary rainfall shocks can cause meaningful welfare setbacks, reducing assets, narrowing diets, and tightening liquidity, emphasizing the importance of policies that improve access to credit, strengthen safety nets, and protect household assets during climate shocks.

Table 6: DiD estimates: Effect of rainfall shocks on poverty indicators

	(1) OLS	(2) OLS + Controls	(3) FE	(4) FE + Controls
Panel A: Wealth Index (std)				
Post × Treated (Rainfall Shock)	-0.045**	-0.048**	-0.050**	-0.046**
	(0.021)	(0.020)	(0.018)	(0.019)
Household FE			✓	✓
Year FE			✓	✓
Controls		✓		✓
Observations	2,531	2,531	2,531	2,531
Panel B: Log Food Consumption Score				
Post × Treated (Rainfall Shock)	-0.052**	-0.055**	-0.058**	-0.050**
	(0.022)	(0.021)	(0.020)	(0.019)
Household FE			✓	✓
Year FE			✓	✓
Controls		✓		✓
Observations	2,400	2,400	2,400	2,400
Panel C: Log Food Expenditure Share (%)				
Post × Treated (Rainfall Shock)	0.070**	0.073**	0.072**	0.065**
	(0.034)	(0.032)	(0.031)	(0.030)
Household FE			✓	✓
Year FE			✓	✓
Controls		✓		✓
Observations	2,300	2,300	2,300	2,300

Notes: Dependent variables include standardized wealth index (Panel A), log food consumption score (Panel B), and log food expenditure share (Panel C). Robust standard errors clustered at the district level in parentheses. FE models include household and year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

9.5. Dynamic effects and feedback loop

I explore how the link between charcoal production, poverty, and deforestation continues and reinforces itself over time. By including lagged rainfall shocks and measures of charcoal participation, I assess whether a one-time climate shock sets in motion a longer trajectory of charcoal dependence, forest loss, and asset depletion (Angelsen and Kaimowitz, 1999; Barrett et al., 2016). The DiD design compares changes in outcomes for households exposed to rainfall shocks (treated) before and after the shock with those of unexposed households (controls), while accounting for household and year fixed effects to remove unobserved heterogeneity and time shocks common to all households.

As shown in Table 7, the DiD estimates reveal that the effects of rainfall shocks extend well beyond the year of occurrence. In the year of a drought, treated households are about 10 percentage points more likely to produce charcoal, deforestation increases by roughly 2 percentage points, and household wealth declines by 0.12 standard deviations. These impacts persist over time: one year after the shock, treated households remain around 7 percentage points more likely to engage in charcoal production, deforestation remains elevated by nearly 2 percentage points, and asset losses continue to deepen. Even two years later, although the magnitude declines, the effects remain statistically significant.

This persistence suggests that short-term coping responses can evolve into structural livelihood changes. Once households divert labor toward charcoal and other low-return activities, they face barriers to re-entry into higher productivity farming, reinforcing poverty and environmental degradation (Zulu and Richardson, 2010; Hadunka and Baylis, 2022; Dewees et al., 2010).

Feedback loop: The DiD results reveal a clear reinforcing cycle. When rainfall shocks occur, farm income declines and households turn to charcoal as a coping strategy. Increased charcoal production accelerates deforestation, eroding both natural and physical capital. As wealth declines, households become even more vulnerable to subsequent shocks, creating a poverty–environment trap. This feedback loop emphasizes how short-term climate events can trigger long-lasting livelihood and ecological consequences in rural economies dependent on natural resources.

Table 7: Dynamic effects of rainfall shocks on charcoal, deforestation, and assets

	(1) Charcoal participation (Percentage points)	(2) Deforestation (Forest loss, %)	(3) Wealth index (Std. dev. units)
Post × Treated (Year t)	0.098***	0.021***	-0.124***
	(0.022)	(0.006)	(0.039)
Post × Treated (Year $t-1$)	0.071**	0.018**	-0.097**
	(0.028)	(0.008)	(0.045)
Post × Treated (Year $t-2$)	0.034*	0.012*	-0.054*
	(0.019)	(0.007)	(0.032)
Year FE	✓	✓	✓
Household controls	✓	✓	✓
Observations	2,189	2,211	2,211

Robust standard errors in parentheses, clustered at the camp level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

9.6. Charcoal, deforestation, and poverty dynamics

In this section I use a DiD framework to examine how household engagement in charcoal production affects poverty and environmental outcomes after climate shocks. The DiD design compares changes in welfare and deforestation outcomes for households that turn to charcoal following a rainfall shock against those that do not, before and after the shock. By including household and year fixed effects, the model isolates the causal impact of charcoal reliance on household assets, food security, and local forest loss.

The DiD estimates reveal a recursive process that is difficult to break. When rainfall shocks reduce farm income, treated households increase charcoal production as a short-term coping strategy. While this response provides temporary liquidity, it diverts time and labor away from farming, accelerates forest clearing, and undermines future productivity. As shown in Table 8, households engaged in charcoal production experience a 0.05 standard deviation decline in their wealth index and a 0.06 reduction in food consumption scores, alongside an increase of about 0.07 log points in the food expenditure share. In the same breath, deforestation within 5 km rises by nearly 0.09 percentage points, emphasizing the link between coping strategies and environmental degradation.

These DiD results point to a poverty–deforestation trap in which households oscillate between short-term survival and deepening vulnerability (Barrett et al., 2016; Zulu and Richardson, 2010;

Kiruki et al., 2020). Charcoal production offers an immediate buffer against income shocks but erodes natural capital and asset wealth, leaving households more exposed to subsequent droughts and floods. This feedback loop highlights how even short-lived shocks can produce long-term consequences for both rural livelihoods and the environment.

Table 8: Deforestation, and poverty outcomes

	Ialth Index (std)	Food Cons. Score	Food Exp. Share	Deforestation (%)
Post × Treated (Charcoal)	-0.050**	-0.060**	0.072**	0.089**
	(0.022)	(0.025)	(0.031)	(0.041)
Household FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	2,321	2,389	2,300	2,321

Notes: Robust standard errors clustered at the district level in parentheses. Dependent variables are standardized. Charcoal production is binary (0/1). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

9.7. Heterogeneous responses by shock severity and household characteristics

I then analyze how the effects of rainfall shocks on charcoal participation vary by shock severity and household characteristics. The DiD model interacts the treatment indicator with different levels of shock intensity (low, moderate, and high) to capture how the magnitude of exposure influences household responses. By comparing changes in outcomes for treated and control households before and after shocks, and including household and year fixed effects, I isolate the causal effect of varying rainfall severity on the likelihood of producing charcoal.

The DiD results reveal a clear stepwise pattern. As shown in Table 9, households exposed to mild rainfall shocks are about 4.8 percentage points more likely to produce charcoal after the event relative to unexposed controls. Under moderate shocks, this likelihood nearly doubles to 8.5 points, and during severe shocks it rises further, to over 12 points. All effects are statistically significant and consistent with the intuition that the larger the shock to farm income, the greater the reliance on charcoal as a coping strategy. This pattern aligns with evidence from other rural settings, where households under stress turn to environmentally taxing activities such as fuelwood and charcoal extraction to sustain consumption (Chidumayo and Gumbo, 2013).

I further extend the DiD analysis to explore heterogeneity by household wealth, landholding, and market proximity. Interaction terms between the rainfall shock and these characteristics identify who is most vulnerable to being drawn into the charcoal, poverty, and deforestation cycle. The results show that poorer households and those located closer to markets are significantly more likely to increase charcoal production after shocks, reflecting both limited coping options and easier access to buyers. In contrast, households with larger landholdings are less likely to turn to charcoal, as cultivated land provides a buffer that stabilizes income and reduces reliance on forest extraction. These findings suggest that vulnerability is not evenly distributed but is concentrated among households with fewer assets, smaller farms, and greater exposure to urban demand.

Table 9: DiD estimates: Heterogeneous effects of rainfall shocks on charcoal participation

	(1) Probit	(2) LPM	(3) CRE-Probit	(4) CRE
Post × Low severity shock	0.048**	0.047**	0.048**	
	(0.019)	(0.020)	(0.020)	
Post × Moderate shock	0.084***	0.086***	0.085***	
	(0.021)	(0.022)	(0.022)	
Post × High shock	0.122***	0.124***	0.123***	
	(0.025)	(0.026)	(0.026)	
Wealth (bottom quartile) × Post × Shock				0.061**
				(0.024)
Landholding (per ha) × Post × Shock				-0.009*
				(0.005)
Market proximity × Post × Shock				0.045***
				(0.017)
Year FE		✓	✓	✓
Household controls	✓	✓	✓	✓
Observations	2,351	2,351	2,332	2,332

Average partial effects reported. Robust standard errors clustered at the district level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

9.8. Effect of Drought on Cultivated Land Area

According to Table 10, drought has no statistically significant effect on the area of land cultivated. This indicates that households do not respond to drought by expanding cropland, reinforcing that the pathway from drought to forest loss does not operate through agricultural land expansion. This result is consistent with Ordóñez et al. (2025), who similarly find that households do not increase cultivated land in response to production shocks.

Table 10: Effect of Drought on Cultivated Land Area

	Coefficient
Drought (t-1) × Treated	0.015
	(0.040)
Observations	2,267
R-squared	0.18

Dependent variable: Land cultivated (ha).
Robust standard errors clustered at the district level.

9.9. Environmental outcomes – Can charcoal be harvested sustainably?

In this specification, I examine whether dependence on charcoal production necessarily leads to unsustainable forest loss, or whether it can occur under conditions that mitigate environmental harm. Using the Global Forest Change dataset (Hansen et al., 2013), I track annual tree-cover loss within a 5 km buffer around each household. The DiD design compares changes in deforestation before and after households engage in charcoal production relative to those that do not, while including buffer and year fixed effects to account for unobserved spatial and temporal variation in forest conditions.

The results in Table 11 show that in models without controls, areas near charcoal-producing households experience about a 28% increase in deforestation compared to non-producing areas. When household controls and fixed effects are added, the estimated impact drops to around 8–10% and becomes less precise. This suggests that much of the observed relationship between charcoal production and forest loss is explained by underlying differences across locations, such as land use, forest cover, or household wealth, rather than charcoal production alone.

The DiD results suggest that charcoal production does not inevitably lead to widespread deforestation. When production occurs in areas with regulated harvesting zones, improved kiln technologies, and replanting initiatives, its environmental footprint can be substantially reduced (Chidumayo and Gumbo, 2013; Hadunka and Baylis, 2022). In this regard, today's deforestation pressures stem less from charcoal itself than from unregulated practices and limited forest management capacity.

Table 11: Effect of charcoal production on deforestation rates

	(1) Deforestation Rates	(2) Deforestation Rates	(3) Deforestation Rates	(4) Deforestation Rates
Post × Treated (Charcoal)	0.276***	0.142**	0.131**	0.089*
	(0.062)	(0.057)	(0.055)	(0.051)
Year FE			✓	✓
Household controls		✓		✓
Observations	2,321	2,321	2,321	2,321

Dependent variable: Annual forest loss rate (% within 5 km). Robust SEs clustered at the district level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

10. Conclusion

Deforestation in Sub-Saharan Africa is accelerating, with charcoal production remaining a leading driver of forest loss. This study provides causal evidence that rainfall shocks, particularly droughts, push smallholder farmers into charcoal production as a coping mechanism for lost agricultural income. Using four years of household panel data linked to satellite observations of forest cover, I trace a chain of impacts from rainfall variability to livelihoods and deforestation.

Three main findings emerge. First, drought exposure reduces maize yields by about 32%, significantly lowering farm income in rainfed systems. Second, these income losses increase the likelihood of charcoal production by 3-4 percentage points from a 20% baseline, with the largest effects among poorer and more market-accessible households. Among existing producers, severe shocks raise charcoal output by roughly 1,100 kilograms, particularly during post-harvest and pre-planting months when liquidity constraints are most binding. Third, this reallocation of labor drives forest degradation: charcoal production is associated with a 28% rise in local tree cover loss in simple models and around 8-10% after controlling for household fixed effects.

The welfare impacts mirror these environmental effects. Asset wealth declines by about 0.05 standard deviations, food consumption scores fall by 5-6%, and the share of income spent on food rises by roughly 7%. These results point to a self-reinforcing cycle in which rainfall shocks depress agricultural income, prompting households to produce charcoal, which accelerates deforestation and deepens poverty. The persistence of this pattern, as households remain 7 percentage points more likely to produce charcoal one year after a drought, indicates that short-term coping responses can evolve into structural traps.

Breaking this cycle requires integrated policies that build resilience and protect natural capital. Expanding access to shock-responsive safety nets, drought-tolerant crops, and irrigation can stabilize farm incomes, while clean energy initiatives can reduce reliance on charcoal. Strengthening forest governance and community-based management can further prevent overextraction during crises.

In short, rainfall shocks trigger a chain reaction in which falling farm income fuels charcoal production, forest loss, and poverty. Without intervention, this feedback loop risks locking households into long-term vulnerability. With targeted support combining income stabilization, clean energy,

and forest protection, charcoal dependence can instead be managed as part of a transition toward more sustainable and climate-resilient rural livelihoods.

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