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# Do Zambian farmers manage climate risks?

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**Abstract**

This study investigates production responses to climate risk among farmers in Zambia by combining historical rainfall with nationally representative household data. After identifying the importance of January and February rainfall in maize production, we define these months' historical rainfall variations as the climate risk index. We then relate this index to agricultural decisions. Results indicate little crop or plot diversifications in response to weather risks. Conversely, farmers in high-climate-risk regions apply less fertilizer and consequently achieve lower maize yields than their counterparts in low-risk regions. Overall, Zambian farmers manage climate risk by underinvesting risky inputs at the expense of returns.

**KEYWORDS**

agriculture, mediation analysis, self-insurance, weather risk, Zambia

**JEL CLASSIFICATION**

O12, O13, Q12

The impact of climate change has become increasingly conspicuous worldwide. Developing countries are vulnerable to climate change, and because small-scale farmers rely primarily on rainfed agriculture, they are particularly exposed to severe weather risks (Kurukulasuriya et al., 2006). Understanding climate risk management is critical to designing effective and appropriate adaptation policies.

According to the standard economic theory, risk-averse agents are willing to diversify their income risk in risky environments. Where the credit and insurance markets are underdeveloped, the most accessible risk diversification is the adjustment of income portfolios by increasing investments in low-risk assets in exchange for higher returns. Similarly, agents are likely to avoid profitable, albeit risky, investments. Although ensuring a secure income is a critical livelihood strategy for individuals living close to a subsistence level to bypass life-threatening scenarios in the short run, missing profitable opportunities may lock them into poverty traps in the long run. To derive welfare implications, this study investigates the nature of smallholders' production responses to climate risk and its consequences for productivity in Zambian agriculture.

Zambia provides an excellent setting for empirical analysis of farmers' risk management. First, agricultural production is prone to climate risks because irrigation facilities are almost nonexistent in rural areas; thus, farming is rainfed (Mendelsohn & Dinar, 2003). Second, the mono-production mode of maize crops continues to be dominant among Zambian smallholders despite the government's and aid organizations' efforts to promote crop diversification as a practical adaptation strategy against climate risks. Farmers' focus on maize production may be risky given the high weather uncertainty, providing an empirical puzzle motivating this study. Therefore, investigating household risk management in agricultural production offers valuable implications for future policy planning.

In the literature, previous studies on self-insurance empirically examined the production response of agricultural households to climate risk. Examples of such agricultural decisions include crop choices, seed choices, land adjustments, and farm investments in fertilizers and labor (Alem et al., 2010; Aragón et al., 2021; Arslan et al., 2018; Boucher et al., 2021; Emerick et al., 2016; Karlan et al., 2014). However, few empirical attempts have been made to discuss the consequences of farmers' weather risk management practices on their agricultural productivity. To fill this research gap, this study examines how climate risk affects farmers' agricultural decisions and, consequently, farm productivity in rural Zambia by combining nationally representative agricultural survey data and long-term pixel-level climate data.

Our analysis begins by defining a climate risk index based on historical variations in rainfall amounts that are crucial for agricultural production. We estimate the impact of precipitation on maize yield for each calendar month using district-level production records and rainfall estimates from 1990/1991 to 2019/2020 cropping seasons. Past production records were obtained from annual agricultural statistics aggregated at the district level using the Crop Forecast Survey (CFS) conducted by the Zambia Statistics Agency (ZamStats) in collaboration with the Ministry of Agriculture. For historical rainfall data, we aggregate the grid-level rainfall database, WorldClim, at the district level. Using these data, our estimation results identify the rainfall in January and February as the most influential determinants of maize yield. Based on this result, we define the coefficient of variation in the rainfall of these 2 months over 60 agricultural years (1960/1961 to 2019/2020) as the climate risk index for this study and construct it at the ward level.

We then relate this climate risk index to agricultural decisions concerning risk diversification and farm investments of 12,220 farm households from nationally representative CFS data for the 2020/2021 cropping season. As a suitable nature for this study, the CFS collected household-crop-plot level information on seed choices and fertilizer applications, allowing us to consider various risk management strategies. The estimation results reveal no evidence that farmers diversify their planted crops or plot locations in response to climate risks. Additionally, we find little evidence of growing drought-tolerant crops such as sorghum and millet in high-climate-risk regions. Conversely, the empirical results suggest that farmers react significantly to climate risks by reducing fertilizer application and adopting hybrid maize seeds that are typically drought-tolerant and early-maturing and, thus, risk-hedging inputs, which is consistent with theoretical predictions. These results are also economically significant; a one standard deviation increase in our rainfall risk measure reduces the fertilizer applied by 14.5 kg per hectare, corresponding to approximately 13% of its standard deviation, and increases the likelihood of planting hybrid maize seeds by 10.1% points, with a sample average of 74%. As our regressions control for recent weather shocks, these input responses directly capture the long-run behavioral reactions to location-specific rainfall risks.

Our findings that rainfall risk significantly changes household investment decisions in farming invite natural speculation that climate risk has consequences for productivity. The data indicate that, after accounting for soil conditions and recent climates, the maize yield gap is approximately 8% when the difference in our climate risk index equals one standard deviation. To quantify the cost of climate risks via household-level risk-management behavior, we conduct a mediation analysis to examine the extent to which the responses of fertilizer application and hybrid seed adoption to rainfall risks contribute to maize productivity (Acharya et al., 2016). Specifically, we estimate the average conditional direct effect of historical rainfall variations conditional on fertilizer and seed inputs and then compare these estimated coefficients to discuss the relative importance of these two channels. This empirical exercise demonstrates that risk-induced underinvestment in fertilizer reduces maize productivity by 43.1%, while encouraging hybrid seed adoption restores it by 71.8% in proportion to the total productivity loss owing to increased climate risks. Thus, risk avoidance through underinvestment in chemical fertilizers is costly for Zambian farmers, whereas risk hedging by planting hybrid seeds has positive productivity consequences as a by-product.

This study contributes to the literature on climate risk's impact on farmers' welfare in developing countries. Previous studies have examined land values, crop yields, and agricultural productivity (Chen et al., 2016; Kurukulasuriya et al., 2006; Lobell et al., 2011; Taraz, 2018; Welch et al., 2010) as welfare indicators influenced by climate change. Instead of estimating the reduced-form impacts of weather conditions, this study conducts a mediation analysis to uncover the impact of risk-induced household behavior as a channel through which climate risk affects agricultural productivity. Our closest study is that of Chen and Gong (2021). They use a county-year panel over the past 35 years in China and decompose the impact of climate change on crop yields into the effect of changes in total factor productivity and agricultural input utilization. Although both studies investigate the mechanisms underlying climate adaptation, they are distinct in two important ways. First, Chen and Gong (2021) unpack the impacts of climate change on agricultural outputs but do not quantify the relative importance of the two channels in productivity consequences. Our results indicate that the adoption of hybrid maize seeds has yield-enhancing effects. However, these favorable effects are attenuated by the negative effects of underinvestment in fertilizers in response to rainfall risks. The second significant difference is the unit of analysis. While Chen and Gong (2021) use aggregated data at the county level, this study examines plot-level data to obtain more precise estimates by controlling for essential determinants of agricultural decisions such as household demographics and plot characteristics. This difference between the two studies may generate different findings on labor responses to climate factors, with no significant results in this study.[i]

Another contribution of this study is the addition of new evidence to the rich literature on smallholder household behavior in risky environments in developing countries. One strand of the literature identifies various agricultural decisions as a response to climate risks.[ii] Among them, the study by Arslan et al. (2018) is notable. Using different data sources from our study, they examine the relationship between long-term precipitation risks and three types of diversification (crop, livestock, and income) in Zambia and find crop portfolio diversification as a response to rainfall risks in dry regions. In contrast to their findings, we find no significant risk management through diversification strategies among Zambian farmers. Although the varied results may be attributed to different data sources and empirical samples, the current assessment of farmers' risk management in Zambia requires further data collection and empirical investigation. Furthermore, our finding of no evidence for crop and plot diversifications warrants future investigations into the potential hindrances to traditional self-insurance in agricultural production.

The remainder of this paper is organized as follows: Risk management in agricultural production describes the theoretical motivation for this study. Context and Data provides background information on Zambian agriculture and discusses the nature of the data used in the subsequent empirical analysis. After constructing the climate risk index used in this study in Constructing rainfall risk index, Farmers' risk mitigation in agricultural decisions as a response to rainfall risks investigates household production responses to climate risks. Mediation analysis discusses the productivity consequences of risk-induced household production behaviors through a mediation analysis. Finally, Conclusion summarizes the findings and proposes a future research agenda.

## RISK MANAGEMENT IN AGRICULTURAL PRODUCTION

People in developing countries are vulnerable to unpredictable shocks owing to extreme weather conditions. While some production risks are beyond farmers' control (e.g., rainfall risks), farmers can control the consequences in advance through self-insurance. As self-insurance methods spread the risks faced in household production across activities, issues relating to asymmetric information and contract enforcement are less concerning than formal insurance and informal risk arrangements. Although its effectiveness remains an empirical question, self-insurance is the most accessible risk-hedging method for small-scale farmers in developing countries. Therefore, understanding the nature of self-insurance is indispensable for designing policies to enhance the resilience of people's livelihoods against unexpected shocks. Among the several forms of self-insurance,[iii] this study examines *ex ante* risk management in agricultural production. Specifically, we focus on diversification and investment choices.

Risk diversification through crop choice is a traditional risk-management strategy in agrarian settings. Agricultural production is inherently risky, primarily because of unforeseen climatic conditions. The risk to production becomes salient, particularly when agriculture is rainfed. With distinct production responses to weather conditions, each crop has different expected returns and variances (Kurukulasuriya et al., 2006). Thus, farmers select an optimal crop portfolio by balancing the trade-off between expected profits and production risks, given their risk attitudes and the nature of the risks in their production environments. Crop diversification can reduce total production risk in the absence of a perfect yield correlation between crops (Newbery, 1991). Similarly, plot diversification is another way to spread production risks within a production mode (Morduch, 1995). Farm households can minimize production loss from crop disease and livestock/bird attacks by planting the same crop on multiple plots. Although aggregate weather risks cannot be insured by nature, this risk management strategy is also effective if the microclimates are salient.

Changing the production mode to a safer one is an alternative risk-management strategy for agricultural production. Similar to crop types, returns on inputs respond differently to production risks. If the returns on investment in farm inputs respond negatively to shocks, risk-averse farmers hesitate to use these inputs. The leading example is chemical fertilizer, because its net return is small when weather shocks (e.g., drought) occur. Thus, we hypothesize that fertilizer application decreases in areas with high climate risk.

In contrast, some inputs can contribute to hedging production risks. For instance, the variance in the profits from planting drought-tolerant crops and seed varieties is lower than those from planting regular crops and varieties. Another example of reducing the variance is planting early-maturing varieties because quicker crop cycles can minimize the ill effects of erratic rainfall patterns and drought. Overall, we add the positive response of planting drought-tolerant crops and early maturing seeds to climate risks to our empirical hypotheses.

Finally, the responses of land and labor investments to production risks are theoretically ambiguous. As land rental and labor costs are minimal where outside options are limited, the responses of investment returns may be neutral to climate shocks. Thus, the direction in which they respond to climate risks depends on their production relationships with other inputs, such as fertilizer. For example, if labor and fertilizer are complements (substitutes), weather risks discourage (encourage) farmers from applying labor. Therefore, the relationship between climate risks and investments in land and labor is an empirical question.

In summary, the theory suggests that farmers in high-climate-risk regions are more likely to diversify crops and plots, plant drought-tolerant crops and varieties, and plant early-maturing varieties than their counterparts in low-risk regions. Moreover, farmers in high-climate-risk regions are less likely to apply fertilizers than their counterparts, while predictions regarding labor and land inputs are ambiguous *ex ante*. This study tests these empirical hypotheses by combining historical climate estimates with household production data from Zambia.

# CONTEXT AND DATA

## Context

As in the rest of the Sub-Saharan African countries, Zambia is agriculture-based. In 2022, 54% of the population lived in rural areas, and agricultural employment accounted for 59% of the total employment in 2021. However, the value added from the agriculture, forestry, and fishing sectors accounted for only 3.4% in 2022, suggesting that most farmers engage in subsistence farming.[iv]

Environmental conditions are heterogeneous across the country. Based on the rainfall distribution and soil quality, the country is divided into agroecological zones I, II, and III (Ministry of Agriculture and Ministry of Fisheries and Livestock, 2016) (Figure 1). Region I in southern, eastern, and western Zambia, accounting for 12% of the country's total area, receives less than 800 mm of rainfall on average per year and has loamy to clayey soil on the valley floor and course and shallow loamy soils on the escarpment. Therefore, Region I is the driest zone, with frequent droughts. Region II accounts for 42% of the country, where the expected annual rainfall ranges between 800 and 1000 mm, and is further divided into Region IIa with relatively fertile soils and Region IIb with sandy soils. Region III accounts for 46% of the country, and its average annual rainfall ranges between 1000 and 1500 mm. Despite the high rainfall, agricultural productivity is low because Region III has acidic soils caused by leaching.

Smallholders rarely have access to irrigation facilities in rural Zambia. The Food and Agriculture Organization (FAO) has estimated the constant proportion of land irrigated to total

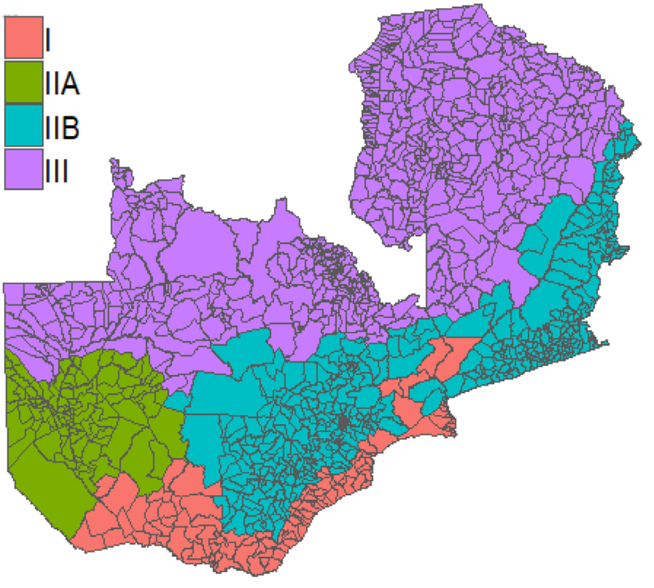


**FIGURE 1** Agroecological zones in Zambia. *Source*: Shapefiles depicting this map are available at http://landscapesportal.org/layers/geonode:agroecological_zones for agroecological zones and at https://maps.princeton.edu/catalog/ stanford-yc436vm9005 for ward boundaries.

arable land at 4%–6% in the last two decades (FAO AQUASTAT). Thus, most agricultural production systems are rainfed. As formal insurance and social safety nets are underdeveloped, weather shocks often depress food production and threaten national food security. Climate risk poses a major threat to Zambian farmers, and the government promotes investments in irrigation and crop diversification to enhance their resilience to climate change (ZVAC, 2015).

Although detailed crop calendars should be specific to each region, the main agricultural season generally corresponds to the rainy season from November to April. Most farmers cultivate maize, a staple food in Zambia, during the rainy season. According to the CFS, in the 2020/2021 agricultural season, 94% of farmers cultivated maize, and approximately 80% cultivated only maize rather than other cereals such as sorghum, rice, and millet. Despite salient weather risks, the dominant mono-production mode of maize characterizes agriculture in rural Zambia, motivating this study. Conversely, during the dry season between May and October, agricultural activities are limited to winter maize and vegetable production in the wetlands and riverbanks because it rarely rains.

Before proceeding, it is worthwhile to touch on other essential crops in risk management strategies within agricultural production. Notably, millet and sorghum are more drought-tolerant than maize due to their generally lower water requirements. Figure A1 shows the relationship between total precipitation during the rainy season and yield at the district level by crop. As illustrated, yield responses to rainfall are milder for millet and sorghum than for maize. We expect a high prevalence of millet and sorghum cultivation in high-climate-risk regions.

## Data

This subsection describes the data sources used in the study.

## Agricultural survey data

The primary empirical analysis uses household data from the CFS for the 2020/2021 agricultural year. The CFS is conducted by ZamStats in collaboration with the Ministry of Agriculture during March and April every year to provide a basis for inferring national food security in a given agricultural season. The CFS covers all provinces and provides a nationally representative sample through a two-stage stratified cluster sample design to select interviewed households. First, a sample of the Enumeration Areas (EA) is selected in proportion to the number of households based on the 2010 Census of Population and Housing.[v] The sampling procedure selected 680 Census EAs nationwide for the 2020/2021 CFS.

Stratification was based on the total crop area. In the second stage of the sampling, after listing all the households for each selected EA, 20 households cultivating less than 20 hectares are randomly sampled for interviews from each list. Thus, the CFS targets 13,600 households every year. The 2020/2021 CFS interviewed 13,553 households.

The CFS questionnaire starts with basic demographics. The agricultural module then collects detailed information on plot characteristics, farming practices (e.g., tillage methods), inputs such as seeds and fertilizers, and the expected production and sales for each field and crop in the corresponding agricultural season. Since CFS interviews usually occur before harvest completion, respondents provide estimated values recorded as the harvested quantities.

To investigate farmers' risk-management behavior, we construct outcomes at the household level based on plot-level data. The outcomes of interest include crop-specific yields in quantity per hectare; risk diversification indices, such as the number of crops cultivated and the Gini–Simpson index of crop-specific areas; and per-hectare quantities of farm inputs, such as fertilizer and labor. We also calculate the share of maize plot areas planted with hybrid seeds over the total maize field areas to capture households' hybrid maize seed adoption.

Table 1 presents the descriptive statistics of the outcomes and the main explanatory variables used in the household-level analysis. Table 1 indicates that the average household cultivates approximately three crops in more than three fields. Only 9% and 6% of the sample households grew millet and sorghum during the 2020/2021 rainy season. In Zambia, farmers commonly apply Compound D with NPK = 10-20-10 as basal fertilizer and urea with NPK = 46-0-0 as top dressing (Donovan et al., 2000). For example, the government's Farmer Input Support Program (FISP) recommends 200 kg/ha for both fertilizer types for maize production (Chapoto et al., 2016). Table 1 shows that the application rate of fertilizer among average farmers is 50 kg/ha, far lower than the recommended amount, for both types. Also, its high standard deviations suggest significant variations across the farm households. Finally, three to four adult family members work on farming in an average household.

## Historical rainfall data

This study uses the grid cell level precipitation data from WorldClim for 1960–2020 (Fick & Hijmans, 2017; Harris et al., 2020).[vi] The dataset offers rainfall estimates covering the entire country. The spatial resolution is 2.5 min (≈21 km$^2$ at the equator), allowing for detailed historical rainfall estimates. Consequently, each ward—the smallest geographical unit in the CFS data, with an average area of 555 km$^2$—encompasses many pixels.[vii] This study also incorporates rainfall estimates from TAMSAT v3.1, which provides spatial resolution of approximately 16 km$^2$ for 2019–2021, to account for recent climatic conditions at a more granular level

**TABLE 1** Summary statistics.

| Variable | Mean | Std. dev. | Min | Max | *N* |
|---|---|---|---|---|---|
| Number of crops | 2.90 | 1.60 | 1.00 | 16.00 | 12,220 |
| Gini–Simpson index | 0.42 | 0.26 | 0.00 | 0.92 | 12,220 |
| Number of plots | 3.20 | 1.70 | 1.00 | 16.00 | 12,220 |
| Cultivate millet = 1 | 0.09 | 0.29 | 0.00 | 1.00 | 12,220 |
| Cultivate sorghum = 1 | 0.06 | 0.23 | 0.00 | 1.00 | 12,220 |
| Basal fertilizer (kg/ha) | 50.00 | 59.00 | 0.00 | 1675.00 | 12,220 |
| Top dress fertilizer (kg/ha) | 50.00 | 61.00 | 0.00 | 1750.00 | 12,220 |
| Total fertilizer (kg/ha) | 100.00 | 118.00 | 0.00 | 3425.00 | 12,220 |
| Hybrid maize seed share | 0.74 | 0.43 | 0.00 | 1.00 | 12,220 |
| Area planted/area field | 0.91 | 0.19 | 0.02 | 1.00 | 12,220 |
| Number of family labor | 3.30 | 1.80 | 0.00 | 14.00 | 12,220 |
| Number of female family labor | 1.60 | 1.10 | 0.00 | 10.00 | 12,220 |
| Number of male family labor | 1.70 | 1.20 | 0.00 | 9.00 | 12,220 |
| CoV (Jan, Feb) | 0.19 | 0.07 | 0.08 | 0.31 | 12,220 |
| CoV (Nov–Apr) | 0.15 | 0.04 | 0.09 | 0.24 | 12,220 |

*Note*: All variables are at the household level. The hybrid maize seed share is the share of maize plot areas planted with hybrid seeds over the total maize field areas. CoV of Prec is the coefficient of variation of historical rainfall in the denoted period at the ward level and assigned to each household.

(Maidment et al., 2014, 2017; Tarnavsky et al., 2014).[viii] By mapping these historical rainfall data onto administrative boundary data in Zambia, we calculate monthly precipitation at the district and ward levels as its weighted average using pixel area as the weight.

# CONSTRUCTING RAINFALL RISK INDEX

This section defines the index to quantify rainfall risk. We first examine which monthly rainfall significantly impacts maize yield, using historical rainfall and production data at the district level. In particular, we use the expected quantity of harvest and planted area from aggregated district-level CFS data published since 1990. We then calculate the long-term variability in monthly rainfall that is important for farming and define this as the rainfall risk index.

## Specifications

We specify the district-level relationship between the maize yield and monthly rainfall as follows[ix]:

$$\text{Yield}_{dt} = \beta_1 R_{dt}^{\text{Jan}} + \beta_2 R_{dt}^{\text{Feb}} + \cdots + \beta_{11} R_{dt}^{\text{Nov}} + \beta_{12} R_{dt}^{\text{Dec}} + \beta_l t + \beta_q t^2 + \delta_p + \epsilon_{dt}, \tag{1}$$

where $\text{Yield}_{dt}$ represents maize yield (defined as expected maize harvest quantity divided by area planted) in tons per hectare of district $d$ in agricultural year $t$ and $R_{dt}^m$ is the rainfall amount of district $d$ in month $m$ of agricultural year $t$. Thus, regression model (1) assumes that all monthly rainfall amounts affect maize yields additively and linearly. We include linear and quadratic time trends $t$ and $t^2$ to control for agricultural technological progress over the study period. $\delta_p$ represents province fixed effects to capture time-invariant geographic conditions (e.g., soil qualities, biomass, and market access).[x] $\epsilon_{dt}$ is an error term. Due to the lack of district-level data, we cannot directly control other potential determinants (e.g., input prices and farming practices). Thus, we will estimate the gross effect of rainfall on maize yield by exploiting climate variations across agricultural years.

We define November and December as the planting season and January and February as the weeding season, based on the crop calendar in Zambia. Using season-specific rainfall variables, we also specify and run the following regression equation:

$$\begin{aligned}\text{Yield}_{dt} = \beta_{Pl} R_{dt}^{\text{Plant}} + \beta_{Wd} R_{dt}^{\text{Weed}} + \beta_{PW} R_{dt}^{\text{Plant}} \times R_{dt}^{\text{Weed}} + \beta_3 R_{dt}^{\text{Mar}} + \beta_4 R_{dt}^{\text{Apr}} \\ + \beta_l t + \beta_q t^2 + \delta_p + \epsilon_{dt},\end{aligned} \tag{2}$$

where $R_{dt}^{\text{Plant}}$ ($R_{dt}^{\text{Weed}}$) is rainfall during the planting (weeding) season in district $d$ in agricultural year $t$. In addition to the independent effects on the maize yield in each season, we allow for the complementarity of rainfall across seasons by including their interaction term. Finally, we include March and April rainfall $R_{dt}^{\text{Mar}}$ and $R_{dt}^{\text{Apr}}$ as controls.

We run regression Equations (1) and (2) using unbalanced panel data from 76 districts for 28 cropping seasons between 1990/1991 and 2019/2020.[xi]

## Results

Table 2 presents the estimation results for the regression Equation (1) in Column (1) and Equation (2) in Columns (2) and (3), respectively.[xii] Regression results in Column (1) display positive and statistically significant impacts of rainfall in December, January, and February on maize yields. By comparing the magnitudes of the estimated coefficients, the results also suggest that February rainfall has the most significant effect on maize production.

The estimation results in Column (2) suggest the relative importance of weeding season rainfall (January–February) compared with planting season rainfall (November–December). The rainfall during the weeding season presents positive and significant correlations with maize yields. In contrast, the planting season rainfall indicates a null association after controlling for weeding season rainfall. Adding the interaction terms of rainfall from the two seasons confirms the substitutability of rainfall impacts across seasons (Column 3). A more important observation is that the independent impact of weeding season rainfall is approximately twice as significant as that of planting season rainfall. Tables A2 and A3 confirm that neither adding year dummies instead of time trends nor including fixed effects for districts instead of provinces qualitatively change the results.[xiii]

Overall, estimating maize yield responses to rainfall using historical data suggests the crucial role of weeding season rainfall in maize yield. This finding is consistent with field observations and previous studies (Waldman et al., 2017). Even if drought hits in the early stage of the rainy season, local farmers can replant early maturing seed varieties to offset losses. Conversely, erratic dry spells during the weeding season significantly limit crop growth, leading to poor maize harvest.

**TABLE 2** Rainfall and maize yield, 1990/1991 and 2019/2020.

| | (1) | (2) | (3) |
|---|---|---|---|
| Prec Nov (1000 mm) | 0.63 | | |
| | (0.56) | | |
| Prec Dec (1000 mm) | 0.93* | | |
| | (0.47) | | |
| Prec Jan (1000 mm) | 0.74** | | |
| | (0.34) | | |
| Prec Feb (1000 mm) | 3.24*** | | |
| | (0.38) | | |
| Prec Plant (1000 mm) | | −0.028 | 1.20*** |
| | | (0.22) | (0.35) |
| Prec Weed (1000 mm) | | 1.10*** | 2.23*** |
| | | (0.19) | (0.28) |
| Prec plant (1000 mm) × Prec weed (1000 mm) | | | −2.07*** |
| | | | (0.53) |
| Prec Mar (1000 mm) | −0.23 | 0.75* | 0.49 |
| | (0.43) | (0.45) | (0.44) |
| Prec Apr (1000 mm) | −1.61** | −1.43** | −1.35** |
| | (0.63) | (0.66) | (0.66) |
| Linear trend in year | −0.049*** | −0.039*** | −0.039*** |
| | (0.011) | (0.011) | (0.011) |
| Square trend in year | 0.0024*** | 0.0023*** | 0.0022*** |
| | (0.00036) | (0.00036) | (0.00037) |
| Adj. *R*-squared | 0.40 | 0.38 | 0.39 |
| Observations | 1807 | 1807 | 1807 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Province fixed effects are included, but not reported. We control for the precipitation in May, June, and October in Column (1).
****p* <0.01; ***p* <0.05; **p* <0.1.

Based on the observed relative importance of weeding season rainfall to planting season rainfall, the coefficient of variation (CV) for January and February rainfall is defined as the precipitation risk index.[xiv] We calculate the rainfall risk index for each ward using WorldClim's monthly rainfall estimates over 60 years between the 1960/1961 and 2019/2020 cropping seasons. A similar approach to calculating CV based on historical data as a measure of rainfall risk is taken by Arslan et al. (2018), Alem et al. (2010), and Ito and Kurosaki (2009) among others. By definition, the CV is a standardized measure. Thus, the interpretation should take into account the average rainfall amounts. The regression analysis using our defined rainfall risk index always controls the average rainfall over the same 60 years to address this potential downside.

Figure 2 plots the CV of January and February rainfall for 60 cropping seasons at the ward level (left), the average Gini–Simpson index of areas planted by crop as the crop diversification

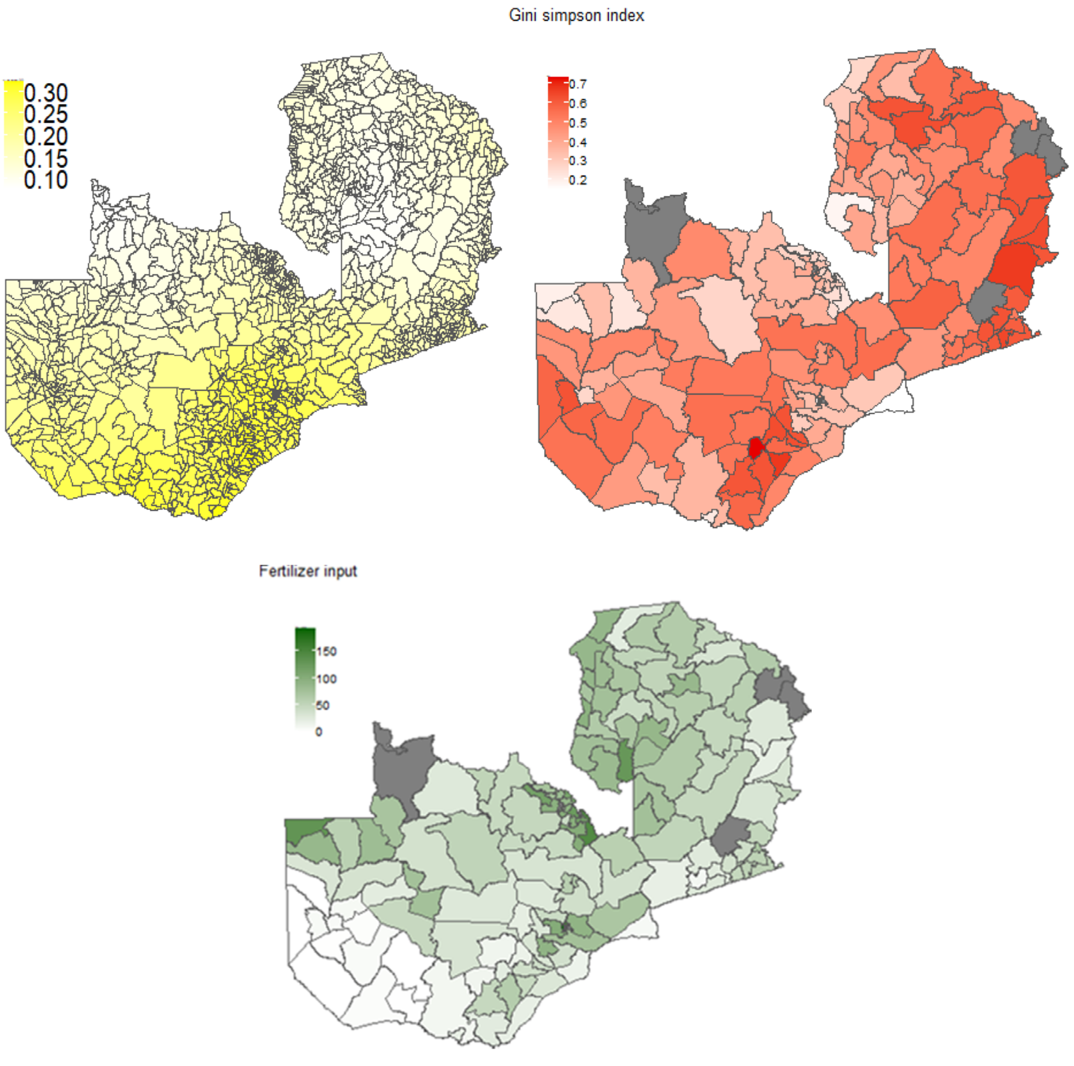


**FIGURE 2** Rainfall variations, crop diversification, and fertilizer applications. The upper-left map plots the coefficient of variation of January and February rainfall for 60 years between the 1960/1961 and 2019/2020 cropping seasons by ward. The upper-right figure plots the average Gini–Simpson index of planted areas by crop as the crop diversification indicator for each constituency. The lower-middle map displays the average amount of fertilizer applied in kilograms per hectare for each constituency. Data are missing in the gray shaded areas.

indicator (right), and the average amount of fertilizer applied in kilograms per hectare (middle) for each constituency. The left panel presents high rainfall variations in southern Zambia, corresponding to Region I of the agroecological zone classification. While the relationship between the crop diversification indicator and rainfall risk index is unclear, the average quantity of fertilizer applied tends to be high in the Copperbelt and Luapula provinces and low in the Western and Southern provinces, suggesting a negative association with climate risk. The regression analysis in the next section formally tests these observations.

## Specification

This section tests the response of farmers' risk management to location-specific rainfall risks by exploiting cross-sectional variations in interannual rainfall variability. To this end, we model farmers' agricultural decisions as follows[xv]:

$$Y_{iwp} = \beta_{\mathrm{CV}} \mathrm{CV}_{wp}^{12} + X'_{\mathrm{iwp}}\alpha + Z'_{wp}\gamma + \phi_p + \varepsilon_{\mathrm{iwp}}, \tag{3}$$

where $Y_{iwp}$ is the outcome of interest for household $i$ in ward $w$ of province $p$ during the 2020/2021 rainy season. The outcome variables include risk diversification measures and agricultural investments. For risk diversification, we analyze the number of crops, the Gini–Simpson index of the area cultivated for different crops, and the number of plots cultivated. Additionally, the regression analysis examines the cultivation of sorghum and millet, which are more drought-tolerant than maize, as another diversification measure (see Figure A1). For farm investments, we investigate fertilizer applications per hectare, hybrid maize seed shares, family labor, and the land utilization rate, defined as the ratio of areas cultivated to total areas owned.

The primary explanatory variable is $\mathrm{CV}_{wp}^{12}$, the CV of January and February rainfall in ward $w$ calculated using historical rainfall estimates from the WorldClim database for 60 years between the 1960/1961 and 2019/2020 cropping seasons.[xvi] Therefore, the parameter of interest is $\beta_{\mathrm{CV}}$, which captures the impact of location-specific rainfall risks on farmers' risk management and farm investments. The sign of $\beta_{\mathrm{CV}}$ depends on the outome variables. On the one hand, we expect $\beta_{\mathrm{CV}} > 0$ in the regression with the risk diversification index as the outcome variable if Zambian households manage weather risks by diversifying crops and plot locations. On the other hand, the theory predicts $\beta_{\mathrm{CV}} < 0$ in the regression with fertilizer applied per hectare as the outcome variable if farmers respond to climate risks by hesitating risky investments.

$X_{iwp}$ is the vector of household-level controls, including the total size of land owned, subjective land soil quality, family size (as a proxy for labor endowments), and household head characteristics, such as gender, age, and educational attainment. In contrast, $Z_{wp}$ represents the vector of ward-level controls, such as the average annual rainfall over 60 agricultural years (1960/1961–2019/2020) and objective soil quality measures.[xvii] We also add maximum and minimum temperatures from WorldClim and rainfall from TAMSAT data between November 2019 and February 2020 to capture transitory income shocks that may restrict farmers' agricultural decisions for the 2020/2021 cropping season. By controlling for these immediate weather shocks, $\beta_{\mathrm{CV}}$ directly captures long-run behavioral reactions to rainfall risks. Finally, $\phi_p$ stands for province fixed effects, and $\varepsilon_{iwp}$ is an error term. Table A5 reports the summary statistics of the control variables.

The key identification assumption for the estimation of $\beta_{\mathrm{CV}}$ is that rainfall variability measured on historical data ($\mathrm{CV}_{wp}^{12}$) should be uncorrelated with other determinants omitted from the right-hand side variables of regression Equation (3). This exogeneity assumption of $\mathrm{CV}_{wp}^{12}$ is violated if systematic differences exist among wards that are correlated with $\mathrm{CV}_{wp}^{12}$ and determine the average agricultural decisions in the area. For example, selective migration (e.g., when some households are more likely to migrate away from high-climate-risk regions) may induce this empirical concern. Robustness check examines the possibility of selective migration based on climate risk to ensure the validity of the identification assumption.

## Results

Table 3 presents the estimation results for risk-diversification strategies in agricultural production. These results do not support farmers' management of rainfall risk through crop and plot location choices. These findings contradict the theoretical predictions of risk-averse households' behavior in developing countries. Moreover, the null or even negative results for diversification outcomes are inconsistent with prior empirical evidence from Zambia (Arslan et al., 2018). Columns (4) and (5) do not support planting millet and sorghum as risk-management strategies.

Table 4 presents the regression results for agricultural investments in fertilizers and seeds. Columns (1)–(3) suggest that farmers facing high rainfall risk apply less fertilizer, particularly basal fertilizers (e.g., Compound D), than their counterparts facing low rainfall risk. This result is also economically significant: A one standard deviation increase of CV by 0.07 reduces the fertilizer applied by 14.5 kg per hectare, corresponding to approximately 13% of its standard deviation. As the regression controls for transitory income shocks by including rainfall amounts and temperature in the previous season, these results capture farmers' long-term reactions to weather risks, rather than their short-term responses to climate shocks.

To examine household-level investments in maize seeds, we use the share of maize plot areas planted with hybrid seeds over the total maize field areas. The results in Column (4) indicate that farm households in regions with high rainfall variability are more likely to adopt hybrid maize seeds than those in regions with mild variability. For example, we anticipate an increase in the likelihood of planting hybrid seeds by 10.1 percentage points if the rainfall risk index increases by one standard deviation, whereas the sample average is 74%. This result is counterintuitive, given that hybrid seeds are relatively costly. However, the following features of hybrid maize seeds provide meaningful interpretations of their high adoption rates in high-rainfall-risk regions. First, hybrid varieties are more drought-tolerant than traditional varieties. Hence, we consider planting hybrid varieties a risk-mitigating technology. Second, hybrid varieties grow faster than the local varieties; thus, hybrid seeds can be replanted even after germination failure during the first planting. Therefore, planting hybrid maize can be a risk-coping method in the early stages of the agricultural season. Combining these observations with the lack of significant results for the seedling rate (not reported), we speculate that Zambian farmers consider planting hybrid maize a risk-hedging option rather than a risky investment option.

The discussion now turns to agricultural investments in family labor and land (Table 5). The estimation results do not support the idea that agricultural households adjust their family labor in response to climate risks (Columns 1–3). By contrast, the operating rate of agricultural land in the rainy season is higher among farm households in high-climate-risk regions than among their counterparts in low-climate-risk regions, although the coefficient is marginally significant. Given that its sample average is 91%, rainfall risks encourage farmers to make full use of accessible fields.[xviii] The full use of land may be motivated by compensation for the production loss from hesitant fertilizer applications because of uninsured rainfall risks.

Robustness check confirms the main empirical results' robustness to alternative definitions of rainfall risk. We also find no supporting evidence for possible selective migration as a source of endogenous climate risk.

**TABLE 3** Rainfall risk and diversification.

| | # of crop | Gini–Simpson index | # of plot | Millet | Sorghum |
|---|---|---|---|---|---|
| CoV (Jan, Feb) | 0.38 | 0.18 | −1.13 | 0.38 | −0.67* |
| | (1.57) | (0.34) | (1.89) | (0.52) | (0.40) |
| Average precipitation | 0.094* | 0.027** | 0.27*** | 0.026* | −0.0084 |
| | (0.052) | (0.010) | (0.059) | (0.015) | (0.0072) |
| Prec Nov, 19 | −0.033 | −0.054 | −0.0036 | −0.056 | −0.049 |
| | (0.21) | (0.046) | (0.25) | (0.063) | (0.038) |
| Prec Dec, 19 | 0.37*** | 0.059* | 0.26* | 0.11** | 0.029 |
| | (0.13) | (0.033) | (0.15) | (0.043) | (0.044) |
| Prec Jan, 20 | −0.34** | −0.037 | −0.33** | −0.083* | −0.016 |
| | (0.15) | (0.031) | (0.15) | (0.043) | (0.038) |
| Prec Feb, 20 | −0.26** | −0.036 | −0.39*** | 0.0067 | −0.0020 |
| | (0.13) | (0.031) | (0.13) | (0.034) | (0.032) |
| Temp (min) Nov, 19 | −0.39*** | −0.078*** | −0.33*** | 0.0084 | 0.034 |
| | (0.11) | (0.024) | (0.12) | (0.037) | (0.037) |
| Temp (max) Nov, 19 | 0.20** | 0.018 | 0.089 | −0.044 | −0.014 |
| | (0.092) | (0.019) | (0.11) | (0.026) | (0.017) |
| Temp (min) Dec, 19 | 0.26** | 0.060** | 0.27** | 0.024 | 0.052 |
| | (0.12) | (0.028) | (0.12) | (0.034) | (0.035) |
| Temp (max) Dec, 19 | −0.18 | −0.020 | −0.33** | 0.063* | 0.043 |
| | (0.15) | (0.031) | (0.16) | (0.037) | (0.029) |
| Temp (min) Jan, 20 | 0.18 | 0.029 | 0.012 | 0.038 | −0.0022 |
| | (0.16) | (0.036) | (0.17) | (0.052) | (0.035) |
| Temp (max) Jan, 20 | 0.16 | 0.047 | 0.25 | 0.0045 | 0.061 |
| | (0.18) | (0.039) | (0.20) | (0.057) | (0.045) |

TABLE 3 (Continued)

| | # of crop | Gini–Simpson index | # of plot | Millet | Sorghum |
|---|---|---|---|---|---|
| Temp (min) Feb, 20 | −0.081 | −0.0069 | 0.090 | −0.047 | −0.065** |
| | (0.13) | (0.029) | (0.12) | (0.057) | (0.028) |
| Temp (max) Feb, 20 | −0.15 | −0.045 | −0.043 | −0.044 | −0.092** |
| | (0.14) | (0.031) | (0.17) | (0.045) | (0.044) |
| Soil condition = medium | −0.020 | 0.000028 | −0.017 | −0.0084 | −0.0046 |
| | (0.041) | (0.0083) | (0.042) | (0.0053) | (0.0038) |
| Soil condition = high | 0.12** | 0.024** | 0.17*** | 0.0080 | −0.00069 |
| | (0.051) | (0.010) | (0.051) | (0.0085) | (0.0050) |
| Total nitrogen (ppm) | −0.00015 | −0.000042 | −0.000034 | −0.00017 | −0.00012 |
| | (0.00051) | (0.00012) | (0.00052) | (0.00012) | (0.000100) |
| Total phosphorus (ppm) | −0.0023*** | −0.00054*** | −0.0025*** | −0.00043** | −0.00020 |
| | (0.00061) | (0.00015) | (0.00079) | (0.00020) | (0.00014) |
| Extractable potassium (ppm) | 0.0011 | 0.00029 | 0.0010 | 0.00094** | 0.0010*** |
| | (0.0013) | (0.00029) | (0.0019) | (0.00046) | (0.00037) |
| Water holding capacity (mm) | 0.0015 | 0.00029 | 0.0026 | 0.0012* | 0.00100* |
| | (0.0022) | (0.00055) | (0.0023) | (0.00058) | (0.00058) |
| Soil pH (depth 0–5 cm) | −0.041 | −0.0033 | 0.0099 | 0.019** | 0.011 |
| | (0.032) | (0.0069) | (0.037) | (0.0084) | (0.0075) |
| Adj. $R$-squared | 0.39 | 0.27 | 0.39 | 0.19 | 0.14 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and province fixed effects are included but not reported.
***$p$ <0.01; **$p$ <0.05; *$p$ <0.1.

**TABLE 4** Rainfall risk and investments in fertilizers and seeds.

| | Basal (/ha) | Top (/ha) | Total (/ha) | Hybrid seed |
|---|---|---|---|---|
| CoV (Jan, Feb) | −122.2** | −84.4 | −206.6* | 1.44*** |
| | (57.4) | (59.2) | (115.4) | (0.45) |
| Average precipitation | 7.53*** | 9.10*** | 16.6*** | 0.026 |
| | (2.03) | (2.08) | (4.04) | (0.017) |
| Prec Nov, 19 | −13.4** | −10.9* | −24.3* | 0.045 |
| | (6.19) | (6.28) | (12.4) | (0.065) |
| Prec Dec, 19 | 15.9*** | 16.3*** | 32.2*** | 0.13*** |
| | (5.29) | (5.33) | (10.6) | (0.040) |
| Prec Jan, 20 | 2.17 | −0.55 | 1.62 | 0.079 |
| | (6.15) | (6.14) | (12.2) | (0.050) |
| Prec Feb, 20 | −20.5*** | −23.2*** | −43.7*** | −0.16*** |
| | (4.02) | (3.84) | (7.60) | (0.035) |
| Temp (min) Nov, 19 | 3.81 | 3.27 | 7.08 | −0.015 |
| | (3.94) | (4.25) | (8.10) | (0.032) |
| Temp (max) Nov, 19 | −0.57 | 0.53 | −0.045 | 0.029 |
| | (3.39) | (3.64) | (6.99) | (0.027) |
| Temp (min) Dec, 19 | 1.84 | 0.34 | 2.18 | 0.016 |
| | (5.44) | (5.52) | (10.9) | (0.040) |
| Temp (max) Dec, 19 | −1.56 | −1.70 | −3.26 | 0.0064 |
| | (6.63) | (6.86) | (13.4) | (0.062) |
| Temp (min) Jan, 20 | −17.0** | −14.7** | −31.8** | −0.052 |
| | (6.49) | (6.83) | (13.2) | (0.057) |
| Temp (max) Jan, 20 | 1.78 | 1.34 | 3.11 | 0.019 |
| | (6.02) | (5.96) | (11.9) | (0.051) |
| Temp (min) Feb, 20 | 7.21 | 7.73 | 14.9 | −0.0054 |
| | (5.32) | (5.50) | (10.7) | (0.049) |
| Temp (max) Feb, 20 | −0.42 | −1.94 | −2.36 | −0.046 |
| | (6.34) | (6.45) | (12.7) | (0.059) |
| Soil condition = Medium | 6.99*** | 7.49*** | 14.5*** | 0.066*** |
| | (1.75) | (1.55) | (3.24) | (0.017) |
| Soil condition = High | 5.61*** | 6.40*** | 12.0*** | 0.079*** |
| | (1.93) | (1.83) | (3.69) | (0.020) |
| Total Nitrogen (ppm) | 0.038* | 0.030 | 0.068* | 0.00024 |
| | (0.019) | (0.020) | (0.039) | (0.00017) |
| Total Phosphorus (ppm) | −0.11*** | −0.097*** | −0.20*** | −0.00045** |
| | (0.026) | (0.028) | (0.054) | (0.00022) |
| Extractable potassium (ppm) | 0.0088 | 0.011 | 0.019 | 0.00077* |
| | (0.054) | (0.059) | (0.11) | (0.00045) |

TABLE 4 (Continued)

| | Basal (/ha) | Top (/ha) | Total (/ha) | Hybrid seed |
|---|---|---|---|---|
| Water holding capacity (mm) | 0.083 | 0.097 | 0.18 | 0.0022*** |
| | (0.090) | (0.092) | (0.18) | (0.00078) |
| Soil pH (depth 0–5 cm) | 0.24 | −0.0070 | 0.23 | −0.0028 |
| | (1.26) | (1.31) | (2.56) | (0.0090) |
| Adj. *R*-squared | 0.26 | 0.26 | 0.27 | 0.24 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and province fixed effects are included but not reported.
***$p$ <0.01; **$p$ <0.05; *$p$ <0.1.

In summary, the estimation results find no evidence that precipitation risks promote crop and plot diversifications or the adoption of drought-tolerant crops (e.g., millet and sorghum). Instead, farmers respond to climate risks by reducing risky investments in fertilizers at the cost of high returns, making full use of accessible agricultural lands to compensate for the loss, and adopting hybrid maize seeds as risk management strategies.[xix]

The natural question is: Why do Zambian farmers fail to pursue risk diversification through crop choices? One possible explanation for this is the regional heterogeneity. For example, Arslan et al. (2018) show that in Zambia, farmers in relatively heavy precipitation regions diversify their crops, while farmers in other regions diversify their income sources and livestock portfolios. Thus, households may spread their income risks owing to climate variability in other dimensions. Moreover, each crop's agronomic growing conditions differ, which innately restricts available crop options. The ineffectiveness of crop diversification, misunderstanding of the effectiveness of diversification among farmers, and strong preferences for maize as a food crop also provide alternative explanations. Data constraints did not allow us to examine the reasons for the negligible crop diversification in response to climate risks. Determining the reasons for this phenomenon is a promising avenue for future research.

Instead, our discussion raises a different question. Our empirical results reveal that rainfall risk significantly affects investment decisions in farming, suggesting that it affects agricultural productivity. By quantifying the productivity impacts of rainfall risks, we can determine the cost of climate risks and the potential benefits of mitigating them. Thus, the extent to which behavioral changes induced by climate risk miss agricultural outputs is an attractive question for policymakers. The mediation analysis in the next section answers this question.

# MEDIATION ANALYSIS

## Estimating mediating effects

In this section, we examine how risk avoidance in agricultural decisions affects farm productivity by estimating the mediating effects. The mediation analysis focuses on fertilizer adjustments and hybrid seed adoption as risk-induced responses in the form of agricultural investments. We select these two inputs as our focus for the following reasons. First, the regression analysis in the previous section finds significant associations with rainfall risk. Second, these two inputs

**TABLE 5** Rainfall risk, family labor, and land utilization.

| | Labor | Female labor | Male labor | Area planted/area field |
|---|---|---|---|---|
| CoV (Jan, Feb) | 0.97 | 0.098 | 0.87 | 0.52 |
| | (1.09) | (0.70) | (0.78) | (0.34) |
| Average precipitation | 0.035 | 0.027 | 0.0083 | −0.034*** |
| | (0.038) | (0.025) | (0.022) | (0.0081) |
| Prec Nov, 19 | 0.31* | 0.093 | 0.22** | −0.000043 |
| | (0.16) | (0.096) | (0.096) | (0.030) |
| Prec Dec, 19 | −0.073 | −0.047 | −0.025 | 0.035* |
| | (0.099) | (0.060) | (0.061) | (0.020) |
| Prec Jan, 20 | 0.15* | 0.14** | 0.016 | −0.014 |
| | (0.091) | (0.058) | (0.063) | (0.020) |
| Prec Feb, 20 | −0.15* | −0.054 | −0.098* | 0.025 |
| | (0.087) | (0.057) | (0.057) | (0.020) |
| Temp (min) Nov, 19 | −0.076 | −0.0069 | −0.069 | −0.028 |
| | (0.077) | (0.041) | (0.056) | (0.019) |
| Temp (max) Nov, 19 | 0.098* | −0.013 | 0.11*** | 0.049*** |
| | (0.056) | (0.036) | (0.036) | (0.016) |
| Temp (min) Dec, 19 | −0.012 | −0.052 | 0.041 | 0.0052 |
| | (0.085) | (0.054) | (0.052) | (0.020) |
| Temp (max) Dec, 19 | −0.19** | −0.062 | −0.13** | 0.0088 |
| | (0.092) | (0.058) | (0.056) | (0.022) |
| Temp (min) Jan, 20 | −0.30*** | −0.056 | −0.24*** | 0.063** |
| | (0.11) | (0.063) | (0.071) | (0.030) |
| Temp (max) Jan, 20 | −0.090 | −0.030 | −0.060 | −0.032 |
| | (0.13) | (0.070) | (0.083) | (0.024) |
| Temp (min) Feb, 20 | 0.39*** | 0.099 | 0.29*** | −0.061** |
| | (0.11) | (0.062) | (0.070) | (0.023) |
| Temp (max) Feb, 20 | 0.17 | 0.10 | 0.069 | −0.017 |
| | (0.11) | (0.065) | (0.076) | (0.022) |
| Soil condition = medium | 0.011 | −0.0036 | 0.014 | 0.0021 |
| | (0.047) | (0.026) | (0.031) | (0.0047) |
| Soil condition = high | −0.0041 | 0.015 | −0.019 | −0.0035 |
| | (0.055) | (0.031) | (0.036) | (0.0065) |
| Total nitrogen (ppm) | −0.00031 | −0.00016 | −0.00015 | −0.000040 |
| | (0.00043) | (0.00027) | (0.00022) | (0.00011) |
| Total phosphorus (ppm) | 0.00062 | 0.00014 | 0.00049 | −0.00012 |
| | (0.00056) | (0.00035) | (0.00029) | (0.00019) |
| Extractable potassium (ppm) | 0.00043 | 0.00083 | −0.00040 | 0.00036 |
| | (0.0011) | (0.00078) | (0.00068) | (0.00037) |

**TABLE 5** (Continued)

| | Labor | Female labor | Male labor | Area planted/area field |
|---|---|---|---|---|
| Water holding capacity (mm) | −0.0015 | −0.00090 | −0.00062 | 0.00015 |
| | (0.0019) | (0.0012) | (0.0012) | (0.00042) |
| Soil pH (depth 0–5 cm) | −0.015 | 0.0041 | −0.019* | −0.0076 |
| | (0.018) | (0.011) | (0.012) | (0.0050) |
| Adj. *R*-squared | 0.54 | 0.37 | 0.38 | 0.43 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and province fixed effects are included but not reported.
***$p$ <0.01; **$p$ <0.05; *$p$ <0.1.

are the primary policy target. For example, the government's FISP provides a package of maize hybrid seeds and chemical fertilizer at a subsidized price. Thus, we expect rich policy implications for future agricultural policy designs from the mediation analysis.

Following Acharya et al. (2016), we apply the two-stage derivation of the regression-based estimator to our empirical setting. This exercise uses plot-level CFS data because plot characteristics important for maize yield can be controlled in the regression analysis. The first-stage regression estimates the impact of the mediators (hybrid seed and fertilizer) on the outcome (maize yield). Specifically, we run the following regression equation in the first stage[xx]:

$$\ln \text{Yield}_{\text{liwp}} = \beta_1 \text{CV}_{wp}^{12} + M'_{\text{liwp}}\beta_2 + X'\beta_3 + Z'\beta_4 + \delta_p + \epsilon_{\text{liwp}}, \tag{4}$$

where $\ln \text{Yield}_{\text{liwp}}$ is the logarithm of (expected) maize yield in plot $l$ of household $i$ in ward $w$ and $M_{\text{liwp}}$ is a vector of the dummy taking one if household $i$ plants hybrid maize seeds in plot $l$ and the amount of fertilizer applied per hectare to plot $l$ by household $i$. $\boldsymbol{X}$ contains predetermined covariates at the plot (soil conditions), household (e.g., sex and age of household $i$'s head), and ward levels (rainfall and temperatures from November 2020 to February 2021 to control for productivity shocks). $\boldsymbol{Z}$ contains post-determined covariates including the family size of household $i$ in ward $w$. $\delta_p$ stands for fixed effects for province $p$, and $\epsilon_{\text{liwp}}$ is an error term.

In the second stage, we regress the demediated outcome as $\ln \widetilde{\text{Yield}}_{\text{liwp}} = \ln \text{Yield}_{\text{liwp}} - M'_{\text{liwp}}\widehat{\beta_2}$ on the treatment and controls:

$$\ln \widetilde{\text{Yield}}_{\text{liwp}} = \alpha_1 \text{CV}_{wp}^{12} + X'\alpha_3 + Z'\alpha_4 + \delta_p + \varepsilon_{\text{liwp}}. \tag{5}$$

The coefficient $\alpha_1$ represents the average conditional direct effect (ACDE) of the rainfall risk $\text{CV}_{wp}^{12}$. As the standard errors in the second regression are biased owing to the estimation error in the first-stage regression, we use standard nonparametric bootstrap methods in both stages.

## Results

Table 6 summarizes the mediation analysis results.[xxi] In the first column, the estimated ATE suggests that a one standard deviation increase in the rainfall index by 0.07 diminishes maize

**TABLE 6** Estimated average treatment effect and average conditional direct effects.

| | Total | Fertilizer | Hybrid seed |
|---|---|---|---|
| CoV (Jan, Feb) | −1.213** | −0.690* | −2.084*** |
| | (0.469) | (0.405) | (0.421) |
| Observations | 11,429 | 11,429 | 11,429 |

*Note*: Column 1 reports the average treatment effect of the coefficient of variation for the rainfall in January and February. Robust standard errors clustered by household are reported in parenthesis. Columns 2 and 3 report the average conditional direct effects of the coefficient of variation for the rainfall in January and February, conditional on fertilizer (Column 2) and hybrid seed adoption (Column 3). Nonparametric bootstrap standard errors based on 1000 replications are reported in parentheses in Columns 2 and 3.
****p* <0.01; ***p* <0.05; **p* <0.1.

yields by 8.1 $(= \exp(-1.213 \times 0.07) - 1 \times 100)$ percent. The long-term rainfall risk is the sole cause of this 8.1% gap in maize yield as the regression controls for soil conditions and weather-related productivity shocks. Given that a non-negligible number of Zambian farmers live near subsistence levels, the estimated risk impacts on staple food production are significant in absolute terms. The key observation is that the direct effect of precipitation risk on yield may come from additional factors that affect productivity other than soil conditions, rainfall conditions in that year, and endogenous risk management strategies.

The second and third columns present the ACDE of historical rainfall variations conditional on fertilizer and seed inputs. The estimated coefficient in the second column represents the effects of rainfall risk when the amount of fertilizer applied is fixed to the sample average. Conversely, the third column shows the impact of rainfall risk when no adoption of hybrid maize seeds is assumed. The estimation results imply that maize yields decrease by 4.8% after a one-standard-deviation increase in rainfall risk when fertilizer inputs are conditioned at the sample average. The same increase in rainfall risk depresses the maize yield by 14.6% when hybrid maize is not planted. In other words, if farmers do not use fertilizers in both the high- and low-risk regions, the impact of rainfall risk on maize productivity decreases by approximately 43.1% $\left(\frac{1.213-0.690}{1.213} \times 100\right)$ relative to the ATE. In contrast, if farmers use hybrid seeds in both high- and low-risk regions, the treatment effect of rainfall risk on maize productivity increases by approximately 71.8% $\left(\frac{2.084-1.213}{1.213} \times 100\right)$ relative to the ATE.

The credibility of the mediation analysis depends on the specification of Equation (5) and the validity of the identification assumptions. Robustness Check tests the robustness of these results through a sensitivity analysis, underscoring significant productivity consequences from household responses to climate risk via fertilizer investment.

## CONCLUSION

Active debates in the climate policy arena require a comprehensive understanding of farmers' responses to weather risks in developing countries. This study contributes to the literature by providing micro-level evidence for risk management in agricultural production among Zambian farmers. Our empirical results found no evidence that rainfall risks promote crop and plot diversification strategies or the adoption of drought-tolerant crops, such as sorghum and millet. Instead, they respond to climate risks by reducing fertilizer application as a risky investment, expanding planted agricultural land as a less costly investment, and adopting hybrid maize seeds as risk mitigation strategies. We also found that, after accounting for soil conditions and recent climate-related productivity shocks, the maize yield gap is 8.1% when the difference in our climate risk index equals one standard deviation. Our mediation analysis focused on fertilizer application and hybrid seed adoption as essential pathways through which climate risk affects household maize production. Although the results indicate that adopting hybrid maize seeds generates yield-enhancing effects, their favorable impacts are attenuated by the adverse impacts of underinvestment in fertilizers in response to rainfall risks. Overall, the empirical evidence suggests that household-level climate adaptations are made primarily through adjustments in the agricultural input portfolio rather than through risk diversification strategies in Zambia.

We conclude the paper by suggesting three promising avenues for future research. First, our finding of no diversification in response to rainfall risk raises the question of why Zambian farmers fail to pursue risk diversification through their crop choices. Future research should provide rational explanations for this empirical puzzle and propose policy interventions to relax these constraints. Second, one limitation of this study is the weak generalizability of our empirical results because they only come from the 2020/2021 season when maize production with the national average yield of 2.13 tons per hectare was relatively bumper. Future work will use data from different survey years to investigate the robustness of the empirical regularity observed in this study and assess this study's external validity. Finally, this study did not consider heterogeneity in responses to climate risks. For example, access to off-farm activities may cushion the impact of climate risk on farm income, allowing farmers to make different agricultural decisions. This potential interplay of risk management strategies suggests the importance of identifying cost-effective ways to control the consequences of climate risks faced by smallholders. The data constraints prevented us from exploring these critical possibilities. Incorporating other income-generating activities into the empirical analysis along with further data collection will enrich our understanding of farmers' risk management in developing countries.

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## ENDNOTES

[i] Both studies confirm household responses through fertilizer adjustment. In addition, our observed hybrid seed utilization and fewer fertilizer applications in high climate-risk areas may suggest that farmers adapt to uncertain environments by adopting agricultural technologies suitable for risky production, which is consistent with adaptations in the agricultural input portfolio, highlighted by the findings of Chen and Gong (2021).

[ii] The examples include Dercon (1996) for crop choice, Aragón et al. (2021) and Liu et al. (2023) for land adjustment, Alem et al. (2010) for farm investments in fertilizers, Ito and Kurosaki (2009) for agricultural labor adjustment, and Cui and Xie (2022) for changing the growing season.

iii Precautionary saving through the accumulation of liquid assets such as livestock and jewelry can provide effective self-insurance against negative income shocks in developing countries (Fafchamps et al., 1998; Miura et al., 2012). However, the data constraint did not allow us to investigate their empirical roles in this study.

iv All the statistics in this paragraph come from the World Bank Indicators. Data are retrieved from https://data.worldbank.org/indicator.

v The EA is the geographical unit used by ZamStats. At the time of the 2010 Population and Housing Census, ZamStats demarcated each ward such that each EA had 60–120 households in rural areas. The sampling frame for the Census contained 25,631 EAs. These EAs were used as sampling frames for the CFS after 2010.

vi The historical monthly weather data from the WorldClim database is the CRU-TS 4.06 (Harris et al., 2020) downscaled with WorldClim 2.1 (Fick & Hijmans, 2017). These data are publicly available at https://www.worldclim.org/data/monthlywth.html.

vii As administrative units, the country has 10 provinces, each divided into districts and further subdivided into wards.

viii We do not use TAMSAT data to gauge rainfall risk because it is available for a shorter period than WorldClim.

ix This analysis assesses the impact of monthly rainfall rather than estimates the specific form of the production function or explains all the historical variations in maize yield.

x We will also account more for such regional differences by including district fixed effects in the robustness check.

xi District-level production data for 1998/1999 and 2015/2016 are unavailable. Thus, we use data for 28 agricultural years.

xii Table A1 presents summary statistics for empirical variables used for the estimation.

xiii Another approach to the current reduced-form specification is modeling the maize production function more comprehensively with farm inputs and estimating rainfall effects net of input adjustment responses to current rainfall. Unfortunately, the historical production dataset aggregated at the district level does not publicize information on inputs except for fertilizer. Even data for fertilizer are missing before 2007, accounting for 45% (=774/1974) of the current estimation sample. For this reason, instead of partially controlling for available fertilizer information in the production function estimation, we decided to take the reduced-form approach. With the restricted sample, we also confirmed the significance of weeding season rainfall over the planting season, even after controlling for basal and top-dressing fertilizer amounts (Tables A4 and A5).

xiv Throughout all the specifications in Table 2, April rainfall is negatively correlated with maize yields. This consistent finding raises the risk of focusing only on weeding season rainfall. To ease this concern, we also use the historical variation of annual rainfall amounts between November and next April as an alternative rainfall risk index to check the robustness of the main results.

xv This analysis aims to understand the relationship between rainfall risk and agricultural decisions by focusing on a partial picture of the outcome rather than fully predicting farmers' input choices.

xvi We use ward boundary data as of 2010 because the 2020/2021 CFS relies on EAs from the 2010 census as the sampling unit, and geographical information, such as wards and constituencies, refers to information from the 2010 census. We could not match the CFS data from a few wards with the historical rainfall data because of a mismatch between the 2010 ward boundary data and the information provided in the CFS. The main analysis omits observations that could not be linked to the precipitation data.

xvii As for soil quality measures, we include estimated amounts of nitrogen, phosphorus, potassium, water holding capacity, and soil pH from the soil nutrient maps of Sub-Saharan Africa available at the ISRIC–World Soil Information website.

xviii The total land size, used as the outcome's denominator, might automatically create a negative correlation with the share of the area planted. However, removing it from $X_{iwp}$ did not change the results qualitatively.

xix We also examine specifications with fixed effects for districts instead of provinces to isolate responses to climate risk from other geographical differences. Tables A6–A8 report the regression results. Because of a few cases where sampled districts have multiple wards in the estimation sample, statistical significance is lost for fertilizer applications due to substantially reduced variations in the rainfall risk index. Nevertheless, the coefficient on the risk index is still significant and negative for the take-up of hybrid seeds. We use the regression equation with province fixed effects as the main specification to maintain meaningful variations in the constructed rainfall risk index.

[xx] This specification assumes that technologies mapping inputs to the output are universe across locations. However, it is natural that adopted technologies differ from place to place. In addition, pathways from rainfall risk to maize yield would depend on factors such as the availability of extension services and farmers' operational skills. We acknowledge that this specification builds on the strong assumption of the uniform technological relationship between farm output and input, irrespective of region. Accounting for such potential functional form specification errors is left for future work.

[xxi] Table A15 presents summary statistics for empirical variables used for the estimation.

[xxii] The two sources of the intermediate variable bias are the classical omitted variable bias and the bias from blocking the path of $D \rightarrow Z \rightarrow Y$ due to the inclusion of intermediate confounders $Z$.

[xxiii] Semi-parametric and nonparametric estimators do not require the assumption of no intermediate interactions (Assumption 2). However, these alternative estimators are unsuitable when the treatment and mediator variables are continuous, as is the case in our empirical setting. See Acharya et al. (2016) for further details.

[xxiv] The 10% sample microdata of the Zambian Census of Population and Housing are available at https://international.ipums.org/international/.

[xxv] For the 2000 Census data, we use the following durable goods as components of the asset index: refrigerators, radios, kitchens, motorcycles, motor vehicles, telephones, and roof materials. In addition to these durable assets, we add the following to the list of score components when calculating the asset index using 2010 Census data: televisions, bicycles, Internet facilities, computers, and mobile phones. Although the sources of the asset index differ across census years, using the same set of durable assets is not necessary because we compare the rankings of the constituency based on asset scores rather than comparing the asset indexes per se.

[xxvi] Constituencies are the finest geographic units available in the census for both survey years.

[xxvii] Given the following equation,

$$M_l = \gamma_0 + \gamma_1 CV_w^{12} + X_l'\gamma_2 + Z_l'\gamma_3 + \delta_p + \xi_l \tag{A2}$$

Acharya et al. (2016) demonstrate that the bias of the estimator of the ACDE is:

$$\text{plim}\widehat{\text{ACDE}} - \text{ACDE} = -\tilde{\delta}\frac{\tilde{\delta}_y}{\delta_m}\sqrt[2]{\left(1-\tilde{\rho^2}\right)/(1-\rho^2)},$$

where $\rho$ is the correlation coefficient between the error terms of Equation (4) and Equation (A2) and $\delta$ is the effect of the treatment on the mediator.

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## APPENDIX A

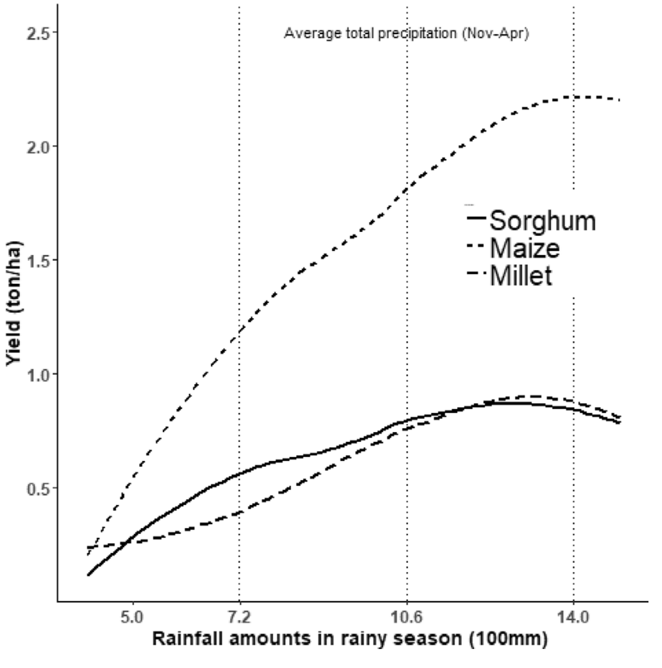


**FIGURE A1** Rainfall and crop yields. This figure depicts the district-level relationship between rainfall from November to February during the rainy season and average crop yields. Agricultural statistics aggregated at the district level from the crop forecast survey are used for the estimation.

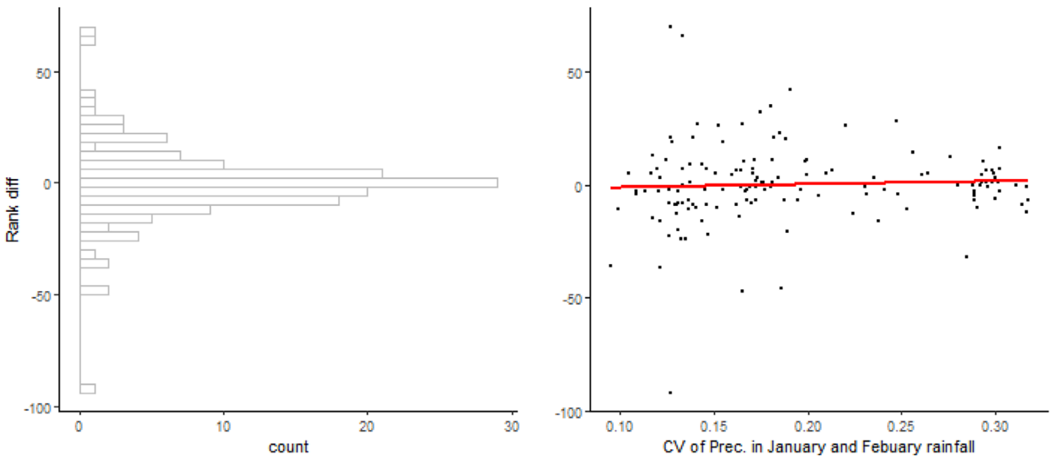


**FIGURE A2** Asset scores and climate risk by constituency, 2000 and 2010. The left figure is a histogram of the change in the ranking of the asset index based on the first principal components of durable goods from 2000 to 2010. The figure on the right depicts the relationship between the change in the ranking of the asset index and the coefficient of variation for the rainfall in January and February over the past 60 years between the 1960/1961 and 2019/2020 cropping seasons.

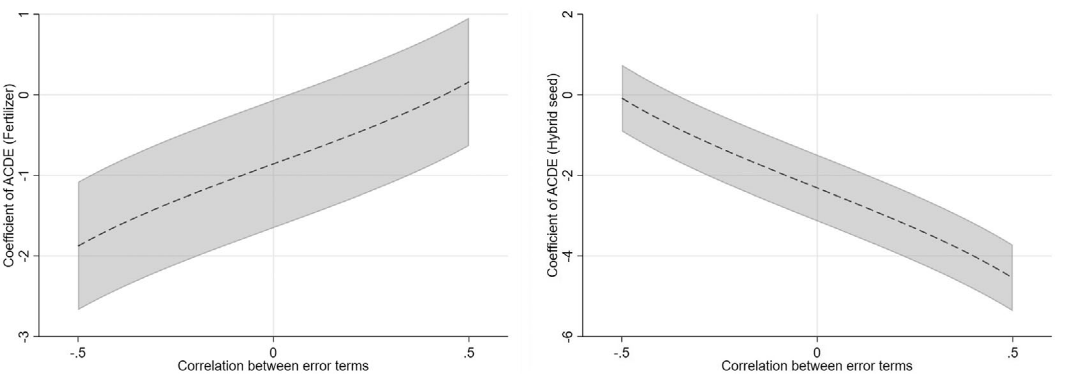


**FIGURE A3** Estimated average conditional direct effects (ACDEs) for different correlations between error terms. This figure depicts the relationship between the correlation of error terms and ACDEs, conditional on fertilizer input (left) and hybrid seed usage (right). The gray shaded regions represent the 95% confidence interval of the ACDE. The construction of confidence intervals does not consider the sample uncertainty of the bias.

## MEDIATION ANALYSIS

One natural estimand for examining mediation effects is the average natural directed effect (ANDE), which is the impact of precipitation risk on yield conditional on seed choice or fertilizer application. However, estimating the ANDE without bias is empirically challenging. To examine this, we consider a naïve regression model to estimate the effects of treatment $D$ (CV of January and February rainfall in our case) on outcome $Y$ (maize yield) conditional on mediator $M$ (hybrid seeds and fertilizer):

**TABLE A1** Summary statistics: variables used for the estimation of maize yield responses to rainfall at the district level.

| Variable | Mean | Std. dev. | Min | Max | Obs |
|---|---|---|---|---|---|
| Yield (1000 kg/ha) | 1.70 | 0.99 | 0.00 | 11.68 | 1807 |
| Prec Jan (1000 mm) | 0.24 | 0.07 | 0.07 | 0.48 | 1807 |
| Prec Feb (1000 mm) | 0.20 | 0.06 | 0.03 | 0.42 | 1807 |
| Prec Mar (1000 mm) | 0.17 | 0.07 | 0.01 | 0.49 | 1807 |
| Prec Apr (1000 mm) | 0.05 | 0.03 | 0.00 | 0.21 | 1807 |
| Prec May (1000 mm) | 0.01 | 0.01 | 0.00 | 0.14 | 1807 |
| Prec Jun (1000 mm) | 0.00 | 0.00 | 0.00 | 0.01 | 1807 |
| Prec Oct (1000 mm) | 0.02 | 0.02 | 0.00 | 0.12 | 1807 |
| Prec Nov (1000 mm) | 0.12 | 0.05 | 0.02 | 0.34 | 1807 |
| Prec Dec (1000 mm) | 0.23 | 0.07 | 0.06 | 0.42 | 1807 |
| Prec weed (1000 mm) | 0.46 | 0.15 | 0.12 | 1.73 | 1807 |
| Prec plant (1000 mm) | 0.37 | 0.13 | 0.13 | 1.32 | 1807 |

*Note*: Maize yield was calculated using the aggregated district-level CFS data. Rainfall variables were historical precipitation estimates aggregated at the district level using the WorldClim database.

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 M_i + \beta_3 X_i + \beta_4 Z_i + \epsilon_i, \tag{A1}$$

where $X_i$ and $Z_i$ represent the pretreatment and intermediate confounders, respectively (Acharya et al., 2016). The estimation problem to identify the regression estimator for $\beta_1$ is that it may contain the intermediate variable bias, selection bias that can arise from the inclusion of variables affected by treatment as controls in the regression model.[xxii] Under this potential bias, the OLS estimator for $\beta_1$ representing the ANDE of treatment cannot be consistent and unbiased.

Another parameter of interest is the average natural indirect effect (ANIE), which captures the impact of the subsequent change in mediator $M$ induced by the change in treatment $D$ while fixing the effect of the treatment. Denoting $Y(d, m)$ as the potential outcome for the realized treatment $D = d$ and mediator $M = m$, the ANIE can be represented as:

$$\text{ANIE}(d,d') = E[Y_i(d, M_i(d)) - Y_i(d, M_i(d'))].$$

However, the ANIE is not identified in the presence of intermediate confounders, that are affected by the intervention and affect the outcome. To get around the issue, we indirectly estimate the ANIE as a residual by exploiting the fact that the average treatment effect (ATE) can be decom- posed into a linear sum of the average conditional direct effect (ACDE), the ANIE, and interaction effects. ACDE is the average causal effect of the treatment when the mediator variables are fixed for all observations at a specific value (Acharya et al., 2016). For example, the ACDE of the change in treatment from $d$ to $d'$ is represented as:

$$\text{ACDE}(d,d',m) = E[Y_i(d,m) - Y_i(d',m)].$$

**TABLE A2** Robustness to adding time fixed effects.

| | (1) | (2) | (3) |
|---|---|---|---|
| Prec Nov (1000 mm) | 0.67 | | |
| | (0.72) | | |
| Prec Dec (1000 mm) | −0.44 | | |
| | (0.49) | | |
| Prec Jan (1000 mm) | 0.65 | | |
| | (0.40) | | |
| Prec Feb (1000 mm) | 2.60*** | | |
| | (0.52) | | |
| Prec plant (1000 mm) | | −0.37* | 0.28 |
| | | (0.22) | (0.32) |
| Prec weed (1000 mm) | | 0.63*** | 1.24*** |
| | | (0.19) | (0.29) |
| Prec plant (1000 mm) × prec weed (1000 mm) | | | −1.05** |
| | | | (0.41) |
| Prec Mar (1000 mm) | 0.84* | 1.68*** | 1.49*** |
| | (0.49) | (0.53) | (0.52) |
| Prec Apr (1000 mm) | −3.30*** | −3.14*** | −3.05*** |
| | (0.97) | (1.09) | (1.08) |
| Adj. $R$-squared | 0.55 | 0.54 | 0.54 |
| Observations | 1807 | 1807 | 1807 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Province fixed effects are included, but not reported. We control for the precipitation in May, June, and October in Column 1.
***$p$ <0.01; **$p$ <0.05; *$p$ <0.1.

Conversely, the interaction effect is the average extent to which the direct effect differs according to the mediators. Mathematically, the interaction effect is defined as:

$$E[M(d')[CDE(d,d',m)-CDE(d,d',m)]].$$

With these definitions, the ANIE estimation involves two steps. After estimating the ATE and ACDE in the first step, subtracting the ACDE from the ATE provides the estimator for the ANIE plus the interaction effect, which is an approximation of the indirect effect when the interaction effect is not substantial.

In the first step of the estimation procedure, the consistency of a regression-based estimator for the ACDE requires the following two identification conditions.[xxiii] The first assumption is called sequential unconfoundedness. Formally, the assumption of sequential unconfoundedness can be expressed as:

**Assumption 1.** Sequential unconfoundedness

$$Y_i(d,m),M_i(d)\perp D_i \mid X_i,$$

**TABLE A3** Robustness to using district fixed effects.

| | (1) | (2) | (3) |
|---|---|---|---|
| Prec Nov (1000 mm) | 1.04** | | |
| | (0.47) | | |
| Prec Dec (1000 mm) | 0.66 | | |
| | (0.49) | | |
| Prec Jan (1000 mm) | 0.38 | | |
| | (0.35) | | |
| Prec Feb (1000 mm) | 2.95*** | | |
| | (0.32) | | |
| Prec plant (1000 mm) | | −0.024 | 1.10*** |
| | | (0.24) | (0.31) |
| Prec weed (1000 mm) | | 0.93*** | 1.95*** |
| | | (0.19) | (0.22) |
| Prec plant (1000 mm) × prec weed (1000 mm) | | | −1.87*** |
| | | | (0.40) |
| Prec Mar (1000 mm) | −0.19 | 0.50 | 0.32 |
| | (0.34) | (0.34) | (0.33) |
| Prec Apr (1000 mm) | −0.69 | −0.49 | −0.50 |
| | (0.65) | (0.59) | (0.61) |
| Linear trend in year | −0.044*** | −0.035*** | −0.036*** |
| | (0.012) | (0.013) | (0.013) |
| Square trend in year | 0.0023*** | 0.0022*** | 0.0022*** |
| | (0.00040) | (0.00041) | (0.00042) |
| Adj. $R$-squared | 0.49 | 0.48 | 0.49 |
| Observations | 1807 | 1807 | 1807 |

*Note*: Robust standard errors clustered by district are reported in parentheses. District dummies are included, but not reported. We control for the precipitation in May, June, and October in Column 1.
***$p$ <0.01; **$p$ <0.05.

$$Y_i(d,m) \perp M_i(d) \mid D_i, X_i, Z_i.$$

Assumption 1 does not allow for two types of omitted variables: Those for the effect of treatment on the outcome, conditional on the pretreatment confounders, and those for the effect of the mediator on the outcome, conditional on the treatment, pretreatment confounders, and intermediate confounders. This condition ensures a separate estimation of the impact of the treatment and the mediator on the outcome.

The second assumption for ACDE identification is the absence of intermediate interactions. This assumption can be stated as follows:

**Assumption 2.** No intermediate interaction

$$E[Y_i(d,m) - Y_i(d,m')|D_i, X_i, Z_i] = E[Y_i(d,m) - Y_i(d,m')|D_i, X_i].$$

**TABLE A4** Robustness to controlling for fertilizer.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Prec Nov (1000 mm) | 2.84*** | 3.30*** | | | | |
| | (0.85) | (0.68) | | | | |
| Prec Dec (1000 mm) | 0.22 | −0.45 | | | | |
| | (0.72) | (0.77) | | | | |
| Prec Jan (1000 mm) | 1.75*** | 1.36*** | | | | |
| | (0.45) | (0.46) | | | | |
| Prec Feb (1000 mm) | 2.15*** | 1.30** | | | | |
| | (0.61) | (0.57) | | | | |
| Prec plant (1000 mm) | | | 1.11*** | 1.05*** | 1.90 | 0.79 |
| | | | (0.32) | (0.38) | (1.44) | (1.88) |
| Prec weed (1000 mm) | | | 1.70*** | 1.08*** | 2.35* | 0.88 |
| | | | (0.35) | (0.37) | (1.28) | (1.62) |
| Prec plant (1000 mm) × prec weed (1000 mm) | | | | | −1.66 | 0.52 |
| | | | | | (3.01) | (3.96) |
| Prec Mar (1000 mm) | 0.70 | 0.58 | 1.12** | 0.87* | 1.14** | 0.86* |
| | (0.51) | (0.51) | (0.47) | (0.45) | (0.48) | (0.48) |
| Prec Apr (1000 mm) | −2.19* | 0.078 | −2.38** | −0.75 | −2.41** | −0.77 |
| | (1.11) | (1.26) | (1.10) | (1.23) | (1.11) | (1.21) |
| Linear trend in year | 0.22*** | 0.22*** | 0.23*** | 0.23*** | 0.23*** | 0.23*** |
| | (0.026) | (0.026) | (0.026) | (0.027) | (0.023) | (0.023) |
| Square trend in year | −0.0039*** | −0.0040*** | −0.0043*** | −0.0041*** | −0.0042*** | −0.0042*** |
| | (0.00069) | (0.00067) | (0.00064) | (0.00065) | (0.00058) | (0.00058) |
| Basal fertilizer (MT*10$^{-6}$) | −0.17* | −0.28* | −0.16 | −0.27* | −0.16 | −0.27* |
| | (0.097) | (0.15) | (0.10) | (0.15) | (0.10) | (0.15) |
| Top fertilizer (MT*10$^{-6}$) | −0.025*** | −0.015*** | −0.025*** | −0.014*** | −0.026*** | −0.014*** |
| | (0.0039) | (0.0048) | (0.0037) | (0.0045) | (0.0039) | (0.0047) |
| Adj. *R*-squared | 0.52 | 0.63 | 0.52 | 0.63 | 0.52 | 0.63 |
| Observations | 959 | 959 | 959 | 959 | 959 | 959 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Province fixed effects are included in odd columns, but not reported. District fixed effects are included in odd columns, but not reported. We control for the precipitation in May, June, and October in Columns 1 and 2.
***$p$ <0.01; **$p$ <0.05; *$p$ <0.1.

Assumption 2 requires the effect of the mediator on the outcome and the intermediate confounders to be independent. These two assumptions are necessary for an unbiased mediation analysis.

Under these two assumptions by defining the following the demediation function and using its property,

**TABLE A5** Summary statistics: control variables.

| Variable | Mean | Std. dev. | Min | Max | Obs |
|---|---|---|---|---|---|
| Total land size (ha) | 2.90 | 2.70 | 0.01 | 32.0 | 12,220 |
| Family size | 5.90 | 2.70 | 1.00 | 24.0 | 12,220 |
| Educ years, head | 7.60 | 3.00 | 1.00 | 15.0 | 12,220 |
| Age, head | 46.00 | 14.00 | 13.00 | 99.0 | 12,220 |
| Female head dummy | 0.17 | 0.38 | 0.00 | 1.0 | 12,220 |
| Average precipitation | 10.00 | 2.00 | 5.50 | 15.0 | 12,220 |
| Prec Jan, 20 | 2.20 | 0.36 | 1.20 | 3.1 | 12,220 |
| Prec Feb, 20 | 2.50 | 0.47 | 1.50 | 4.0 | 12,220 |
| Prec Nov, 19 | 1.00 | 0.45 | 0.21 | 2.2 | 12,220 |
| Prec Dec, 19 | 2.40 | 0.35 | 1.60 | 3.8 | 12,220 |
| Temp (max) Jan, 20 | 27.00 | 1.80 | 17.00 | 42.0 | 12,220 |
| Temp (max) Feb, 20 | 28.00 | 1.90 | 18.00 | 43.0 | 12,220 |
| Temp (max) Nov, 19 | 31.00 | 2.40 | 19.00 | 48.0 | 12,220 |
| Temp (max) Dec, 19 | 27.00 | 1.80 | 18.00 | 42.0 | 12,220 |
| Temp (min) Jan, 20 | 17.00 | 1.60 | 9.90 | 26.0 | 12,220 |
| Temp (min) Feb, 20 | 17.00 | 1.50 | 10.00 | 26.0 | 12,220 |
| Temp (min) Nov, 19 | 18.00 | 1.90 | 10.00 | 28.0 | 12,220 |
| Temp (min) Dec, 19 | 17.00 | 1.60 | 9.20 | 27.0 | 12,220 |
| Soil condition = medium | 0.63 | 0.48 | 0.00 | 1.00 | 12,220 |
| Soil condition = high | 0.21 | 0.41 | 0.00 | 1.00 | 12,200 |
| Total nitrogen (ppm) | 759.00 | 106.00 | 523.00 | 1345.0 | 12,220 |
| Total phosphorus (ppm) | 235.00 | 62.00 | 142.00 | 669.0 | 12,220 |
| Extractable potassium (ppm) | 121.00 | 37.00 | 56.00 | 299.0 | 12,220 |
| Water holding capacity (mm) | 95.00 | 22.00 | 8.90 | 131.0 | 12,220 |
| Soil pH (depth 0–5 cm) | 59.00 | 2.70 | 54.00 | 66.0 | 12,220 |

*Note*: This table presents the summary statistics of the control variables in the regression used to estimate household production responses to climate risk.

$$\gamma(r,m,x) = E[Y_i(r,m) - Y_i(r,m')|X_i] = E[Y_i(r,m)|X_i,Z_i,R_i] - E[Y_i(r,m')|X_i,Z_i,R_i],$$

$$E[Y_i - \gamma(r,m,x)|R_i,X_i] = E[Y_i(r,m')|X_i],$$

the ACDE can be identified

$$E[Y_i - \gamma(r,M_i,x)|R_i,X_i] - E[Y_i - \gamma(r',M_i,x)|R_i,X_i] = E[Y_i(r,M_i)|X_i] - E[Y_i(r',M_i)|X_i] = ACDE(x).$$

## ROBUSTNESS CHECK

This section confirms the robustness of the main empirical results by altering the proxy for rainfall risk, discussing the possibility of selective migration as a source of endogenous climate risk,

**TABLE A6** Robustness to using district-level fixed effects: diversification.

| | # of crop | Gini–Simpson index | # of plot | Millet | Sorghum |
|---|---|---|---|---|---|
| CoV (January, February) | −2.78 | −0.53 | −3.83* | 1.12* | 0.013 |
| | (2.53) | (0.63) | (2.20) | (0.59) | (0.54) |
| Average precipitation | 0.12** | 0.028** | 0.21*** | 0.0066 | −0.013 |
| | (0.061) | (0.011) | (0.067) | (0.016) | (0.010) |
| Prec Nov, 19 | −0.36 | −0.080* | −0.42* | −0.094 | 0.062 |
| | (0.23) | (0.048) | (0.24) | (0.069) | (0.052) |
| Prec Dec, 19 | 0.22 | 0.050 | 0.29 | 0.070** | 0.030 |
| | (0.17) | (0.041) | (0.19) | (0.034) | (0.033) |
| Prec Jan, 20 | −0.16 | −0.031 | −0.25 | −0.16*** | −0.031 |
| | (0.16) | (0.039) | (0.20) | (0.057) | (0.042) |
| Prec Feb, 20 | −0.26* | −0.046 | −0.30* | 0.025 | −0.0034 |
| | (0.14) | (0.032) | (0.17) | (0.034) | (0.034) |
| Temp (min) Nov, 19 | −0.086 | −0.020 | −0.0031 | 0.013 | 0.024 |
| | (0.10) | (0.025) | (0.12) | (0.039) | (0.041) |
| Temp (max) Nov, 19 | 0.13 | 0.013 | −0.018 | −0.050 | −0.0096 |
| | (0.11) | (0.020) | (0.11) | (0.032) | (0.026) |
| Temp (min) Dec, 19 | 0.38*** | 0.078*** | 0.40*** | 0.055* | 0.037 |
| | (0.11) | (0.026) | (0.13) | (0.032) | (0.035) |
| Temp (max) Dec, 19 | −0.34** | −0.030 | −0.38** | 0.039 | 0.048 |
| | (0.15) | (0.034) | (0.17) | (0.032) | (0.046) |
| Temp (min) Jan, 20 | −0.099 | −0.056 | −0.071 | −0.013 | −0.016 |
| | (0.15) | (0.036) | (0.18) | (0.045) | (0.034) |
| Temp (max) Jan, 20 | 0.32* | 0.058 | 0.44** | −0.023 | −0.046 |
| | (0.18) | (0.035) | (0.21) | (0.041) | (0.038) |
| Temp (min) Feb, 20 | −0.071 | −0.0022 | −0.14 | −0.044 | −0.032 |
| | (0.15) | (0.030) | (0.16) | (0.051) | (0.028) |
| Temp (max) Feb, 20 | −0.17 | −0.037 | −0.13 | 0.039 | 0.0028 |
| | (0.16) | (0.037) | (0.20) | (0.040) | (0.029) |
| Soil condition = medium | −0.022 | 0.00052 | −0.040 | −0.0076 | −0.0021 |
| | (0.039) | (0.0075) | (0.039) | (0.0046) | (0.0035) |
| Soil condition = high | 0.097** | 0.022** | 0.12** | 0.0042 | −0.00076 |
| | (0.048) | (0.0094) | (0.047) | (0.0078) | (0.0052) |
| Total nitrogen (ppm) | −0.00067 | −0.00011 | −0.00063 | −0.00022 | −0.00011 |
| | (0.00051) | (0.00011) | (0.00055) | (0.00016) | (0.00014) |
| Total phosphorus (ppm) | −0.00028 | −0.000071 | −0.00068 | −0.0000017 | −0.00014 |
| | (0.00061) | (0.00015) | (0.00094) | (0.00017) | (0.00011) |

TABLE A6 (Continued)

| | # of crop | Gini–Simpson index | # of plot | Millet | Sorghum |
|---|---|---|---|---|---|
| Extractable potassium (ppm) | 0.00053 | 0.000098 | 0.0011 | 0.00066 | 0.00069 |
| | (0.0017) | (0.00032) | (0.0025) | (0.00051) | (0.00046) |
| Water holding capacity (mm) | 0.00047 | 0.00041 | −0.00061 | 0.00033 | 0.00092 |
| | (0.0023) | (0.00054) | (0.0027) | (0.00059) | (0.00057) |
| Soil pH (depth 0–5 cm) | −0.031 | 0.0014 | −0.0096 | −0.0057 | 0.014* |
| | (0.043) | (0.0081) | (0.047) | (0.0096) | (0.0077) |
| Adj. *R*-squared | 0.42 | 0.32 | 0.42 | 0.26 | 0.21 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and district fixed effects are included but not reported.
***$p$ <0.01; **$p$ <0.05; *$p$ <0.1.

and verifying the sensitivity of the mediation analysis results to violations of the sequential unconfoundedness assumption.

### Alternative definition of precipitation risk

The first concern is the misspecification of precipitation risk measures defined in Constructing rainfall risk index. Instead of the coefficient of variation for the rainfall in January and February over 60 years, we check the robustness of the main results to alternative definitions of precipitation risk. Particularly, we use (1) rainfall during the entire agricultural season between November and April or (2) rainfall during the planting and weeding seasons between November and February, and then calculate the coefficient of variation for each alternative definition. The regression results in Tables A9–A14 While coefficients for fertilizer lost statistical significance, the expected signs are maintained if we use CV based on November and February, which is more sounding alternatives for farm production (Table A12).

### Endogeneity in climate risk: Migration

Another empirical concern is the potential endogeneity of the precipitation risk. Selective migration is a potential source of endogeneity. A possible scenario is that if better-off households migrate away from high-risk regions, only resource-poor households will remain concentrated in disadvantaged regions. This scenario systematically differentiates between low- and high-rainfall- risk regions in terms of the production resources that determine agricultural decisions.

As a simple empirical test for this possibility, we examine if the change in the regional average of asset levels is correlated with our rainfall risk index using data from the Census of Population and Housing in 2000 and 2010.[xxiv] To construct the asset index, the principal component analysis calculates the asset score based on the ownership of durable goods for each household, and then we aggregate them at the constituency level.[xxv,xxvi]

**TABLE A7** Robustness to using district-level fixed effects: investments in fertilizer and seeds.

| | Basal (/ha) | Top (/ha) | Total (/ha) | Hybrid seed |
|---|---|---|---|---|
| CoV (Jan, Feb) | 39.3 | 46.5 | 85.8 | 2.07*** |
| | (77.5) | (84.9) | (161.1) | (0.61) |
| Average precipitation | 6.78** | 7.77*** | 14.5** | 0.018 |
| | (2.91) | (2.74) | (5.63) | (0.017) |
| Prec Nov, 19 | −2.30 | −3.37 | −5.67 | 0.041 |
| | (9.38) | (9.32) | (18.5) | (0.061) |
| Prec Dec, 19 | 8.38 | 8.29 | 16.7 | 0.11** |
| | (6.53) | (6.38) | (12.8) | (0.053) |
| Prec Jan, 20 | 1.15 | −0.61 | 0.54 | 0.042 |
| | (7.91) | (7.73) | (15.5) | (0.063) |
| Prec Feb, 20 | −9.47 | −14.0** | −23.4* | −0.087 |
| | (7.27) | (6.60) | (13.7) | (0.052) |
| Temp (min) Nov, 19 | 2.51 | 1.68 | 4.19 | −0.050 |
| | (5.19) | (5.37) | (10.5) | (0.034) |
| Temp (max) Nov, 19 | −2.67 | −1.32 | −3.99 | 0.047 |
| | (4.08) | (4.19) | (8.22) | (0.032) |
| Temp (min) Dec, 19 | 4.49 | 3.62 | 8.12 | 0.050 |
| | (4.59) | (5.21) | (9.65) | (0.040) |
| Temp (max) Dec, 19 | −6.27 | −4.78 | −11.1 | −0.052 |
| | (8.03) | (8.03) | (15.9) | (0.070) |
| Temp (min) Jan, 20 | −10.2 | −8.68 | −18.8 | −0.055 |
| | (7.30) | (7.58) | (14.7) | (0.058) |
| Temp (max) Jan, 20 | 6.29 | 7.05 | 13.3 | 0.098 |
| | (6.52) | (5.85) | (12.1) | (0.064) |
| Temp (min) Feb, 20 | −0.84 | 0.29 | −0.55 | 0.046 |
| | (6.03) | (6.20) | (12.1) | (0.051) |
| Temp (max) Feb, 20 | 2.61 | −1.82 | 0.79 | −0.11* |
| | (5.72) | (5.73) | (11.3) | (0.057) |
| Soil condition = medium | 5.87*** | 6.33*** | 12.2*** | 0.053*** |
| | (1.72) | (1.53) | (3.20) | (0.016) |
| Soil condition = high | 4.29** | 5.18*** | 9.47** | 0.065*** |
| | (1.89) | (1.81) | (3.63) | (0.020) |
| Total nitrogen (ppm) | 0.030* | 0.024 | 0.054 | 0.00031* |
| | (0.018) | (0.019) | (0.037) | (0.00017) |
| Total phosphorus (ppm) | −0.10*** | −0.088** | −0.19*** | −0.00046** |
| | (0.034) | (0.036) | (0.070) | (0.00023) |
| Extractable potassium (ppm) | 0.060 | 0.054 | 0.11 | −0.0000087 |
| | (0.073) | (0.077) | (0.15) | (0.00049) |

**TABLE A7** (Continued)

| | Basal (/ha) | Top (/ha) | Total (/ha) | Hybrid seed |
|---|---|---|---|---|
| Water holding capacity (mm) | 0.047 | 0.073 | 0.12 | 0.000067 |
| | (0.12) | (0.12) | (0.23) | (0.00084) |
| Soil pH (depth 0–5 cm) | 0.78 | 0.53 | 1.31 | −0.014 |
| | (1.32) | (1.34) | (2.64) | (0.012) |
| Adj. $R$-squared | 0.28 | 0.28 | 0.29 | 0.27 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and district fixed effects are included but not reported.
$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$.

While the left panel in Figure A2 plots the change in the ranking of asset scores at the constituency level, the right panel presents a scatter plot between the rank change and our rainfall risk index, that is, the CV of the January and February rainfall based on historical rainfall data at the constituency level. We find no correlation between ranking changes based on asset scores and climate risk. Thus, this empirical exercise does not provide supporting evidence for selective migration based on production resources.

## Sensitivity analysis of mediation analysis

The credibility of the ADCE estimation depends on the validity of Assumptions 1 and 2 and the specifications of regression Equation (4). Among these, we can assess the violations of Assumption 1, which is *sequential unconfoundedness*. This assumption requires that the treatment assignment of rainfall risks $CV_{wp}^{12}$ should be uncorrelated with potential outcomes and potential mediators after conditioning on pretreatment covariates, and that mediators should be uncorrelated with potential outcomes after controlling for treatment, pretreatment confounders, and intermediate confounders. In other words, these conditions allow us to consistently estimate the effects of rainfall risk, fertilizer input, and hybrid seed utilization on maize yield using OLS. However, because input choices, such as hybrid seeds and chemical fertilizers, are part of complicated household decisions, some unobservables may violate the latter condition.

Acharya et al. (2016) propose a sensitivity analysis to violate sequential unconfoundedness. The sensitivity analysis is based on the observation that bias arises from the correlation between the error terms in Equations (4) and (A2).[xxvii] Therefore, we can characterize the violation of the sequential unconfoundedness assumption by estimating the ACDE for different hypothetical values of the correlation between the mediator and outcome errors.

Figure A3 depicts the estimated ACDE under different correlation-level assumptions. If unmeasured factors make both fertilizer applications and maize yields positively correlated (considered more plausible in this case), the impact of climate risks on yields at a constant level of fertilizer input will become smaller in absolute terms than when there is no such bias. The convergence of the estimated ACDE to zero as the positive correlation between fertilizer application and yield becomes strong implies that climate adaptations are made primarily through adjustments in the agricultural input portfolio, particularly when agricultural decisions are

**TABLE A8** Robustness to using district level fixed effect: family labor and land utilization.

| | Labor | Female labor | Male labor | Area planted/area field |
|---|---|---|---|---|
| CoV (Jan, Feb) | −2.08 | −0.95 | −1.13 | 0.40 |
| | (1.85) | (1.36) | (1.19) | (0.53) |
| Average precipitation | 0.016 | 0.039 | −0.023 | −0.014 |
| | (0.047) | (0.030) | (0.028) | (0.011) |
| Prec Nov, 19 | 0.21 | 0.098 | 0.11 | 0.0060 |
| | (0.21) | (0.12) | (0.15) | (0.026) |
| Prec Dec, 19 | −0.014 | −0.061 | 0.047 | −0.026 |
| | (0.12) | (0.075) | (0.071) | (0.023) |
| Prec Jan, 20 | 0.093 | 0.17** | −0.077 | 0.033 |
| | (0.11) | (0.075) | (0.090) | (0.028) |
| Prec Feb, 20 | −0.13 | −0.045 | −0.089 | 0.010 |
| | (0.11) | (0.087) | (0.083) | (0.019) |
| Temp (min) Nov, 19 | 0.043 | 0.059 | −0.016 | −0.020 |
| | (0.083) | (0.054) | (0.066) | (0.017) |
| Temp (max) Nov, 19 | 0.064 | −0.059 | 0.12** | 0.059*** |
| | (0.073) | (0.045) | (0.048) | (0.020) |
| Temp (min) Dec, 19 | 0.015 | −0.027 | 0.042 | 0.00042 |
| | (0.098) | (0.060) | (0.063) | (0.014) |
| Temp (max) Dec, 19 | −0.21** | −0.060 | −0.15** | −0.017 |
| | (0.098) | (0.053) | (0.075) | (0.023) |
| Temp (min) Jan, 20 | −0.41*** | −0.11 | −0.30*** | −0.017 |
| | (0.12) | (0.075) | (0.083) | (0.028) |
| Temp (max) Jan, 20 | 0.100 | 0.053 | 0.047 | −0.028 |
| | (0.15) | (0.087) | (0.096) | (0.020) |
| Temp (min) Feb, 20 | 0.36*** | 0.040 | 0.32*** | 0.022 |
| | (0.13) | (0.083) | (0.076) | (0.020) |
| Temp (max) Feb, 20 | 0.034 | 0.067 | −0.033 | −0.013 |
| | (0.12) | (0.068) | (0.084) | (0.023) |
| Soil condition = medium | 0.0028 | −0.0069 | 0.0097 | 0.0045 |
| | (0.047) | (0.026) | (0.031) | (0.0040) |
| Soil condition = high | −0.014 | 0.0067 | −0.021 | −0.0029 |
| | (0.056) | (0.032) | (0.036) | (0.0053) |
| Total nitrogen (ppm) | −0.0012** | −0.00056* | −0.00063** | −0.0000036 |
| | (0.00050) | (0.00031) | (0.00025) | (0.000098) |
| Total phosphorus (ppm) | 0.00092 | 0.00025 | 0.00067* | 0.00011 |
| | (0.00065) | (0.00042) | (0.00038) | (0.00017) |
| Extractable potassium (ppm) | 0.0013 | 0.0013 | −0.000053 | −0.00013 |
| | (0.0015) | (0.00097) | (0.0011) | (0.00030) |

TABLE A8 (Continued)

| | Labor | Female labor | Male labor | Area planted/area field |
|---|---|---|---|---|
| Water holding capacity (mm) | −0.0032 | −0.00081 | −0.0024 | 0.000093 |
| | (0.0020) | (0.0015) | (0.0016) | (0.00035) |
| Soil pH (depth 0–5 cm) | −0.010 | 0.022 | −0.033** | −0.0033 |
| | (0.023) | (0.017) | (0.015) | (0.0050) |
| Adj. *R*-squared | 0.55 | 0.38 | 0.39 | 0.50 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and district fixed effects are included but not reported.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

interconnected and complementary. Thus, this sensitivity analysis result highlights the significant productivity implications of household responses to climate risk through fertilizer investment. Conversely, the sensitivity analysis results for the ACDE, conditional on the lack of hybrid maize seeds in the right panel of Figure A3 suggest that accounting only for maize seed choice leaves significant and independent climate risk impacts unexplained.

**TABLE A9** Robustness to using the coefficient of variation of rainfall between November and February: diversification.

| | # of crop | Gini–Simpson index | # of plot | Millet | Sorghum |
|---|---|---|---|---|---|
| CoV (Nov–Feb) | 3.64 | 0.88* | 2.34 | 0.35 | −0.84 |
| | (2.61) | (0.51) | (3.07) | (0.71) | (0.62) |
| Average precipitation | 0.12** | 0.032*** | 0.30*** | 0.026* | −0.0087 |
| | (0.054) | (0.011) | (0.060) | (0.014) | (0.0077) |
| Prec Nov, 19 | −0.063 | −0.061 | −0.028 | −0.058 | −0.044 |
| | (0.21) | (0.046) | (0.25) | (0.062) | (0.039) |
| Prec Dec, 19 | 0.35*** | 0.055 | 0.24 | 0.11** | 0.029 |
| | (0.13) | (0.033) | (0.15) | (0.044) | (0.043) |
| Prec Jan, 20 | −0.30* | −0.028 | −0.29* | −0.082* | −0.020 |
| | (0.15) | (0.032) | (0.15) | (0.044) | (0.035) |
| Prec Feb, 20 | −0.27** | −0.037 | −0.38*** | 0.0059 | −0.00055 |
| | (0.13) | (0.031) | (0.13) | (0.034) | (0.032) |
| Temp (min) Nov, 19 | −0.46*** | −0.091*** | −0.41*** | 0.013 | 0.030 |
| | (0.12) | (0.024) | (0.13) | (0.037) | (0.037) |
| Temp (max) Nov, 19 | 0.21** | 0.020 | 0.094 | −0.043 | −0.016 |
| | (0.094) | (0.020) | (0.11) | (0.026) | (0.017) |
| Temp (min) Dec, 19 | 0.28** | 0.064** | 0.29** | 0.024 | 0.050 |
| | (0.12) | (0.028) | (0.12) | (0.034) | (0.037) |
| Temp (max) Dec, 19 | −0.20 | −0.026 | −0.33* | 0.058 | 0.053* |
| | (0.16) | (0.034) | (0.18) | (0.037) | (0.031) |
| Temp (min) Jan, 20 | 0.18 | 0.030 | 0.020 | 0.038 | −0.0016 |
| | (0.16) | (0.036) | (0.17) | (0.053) | (0.035) |
| Temp (max) Jan, 20 | 0.16 | 0.047 | 0.25 | 0.0060 | 0.058 |
| | (0.18) | (0.038) | (0.20) | (0.057) | (0.044) |

**TABLE A9** (Continued)

| | # of crop | Gini–Simpson index | # of plot | Millet | Sorghum |
|---|---|---|---|---|---|
| Temp (min) Feb, 20 | −0.019 | 0.0052 | 0.17 | −0.052 | −0.060** |
| | (0.14) | (0.029) | (0.13) | (0.052) | (0.027) |
| Temp (max) Feb, 20 | −0.15 | −0.043 | −0.056 | −0.040 | −0.099** |
| | (0.13) | (0.030) | (0.16) | (0.043) | (0.043) |
| Soil condition = medium | −0.025 | −0.00088 | −0.022 | −0.0083 | −0.0046 |
| | (0.041) | (0.0083) | (0.042) | (0.0053) | (0.0037) |
| Soil condition = high | 0.12** | 0.024** | 0.17*** | 0.0081 | −0.00072 |
| | (0.050) | (0.010) | (0.052) | (0.0085) | (0.0051) |
| Total nitrogen (ppm) | −0.00013 | −0.000035 | −0.000061 | −0.00016 | −0.00014 |
| | (0.00052) | (0.00012) | (0.00051) | (0.00011) | (0.000096) |
| Total phosphorus (ppm) | −0.0022*** | −0.00051*** | −0.0025*** | −0.00043** | −0.00022 |
| | (0.00062) | (0.00015) | (0.00081) | (0.00020) | (0.00014) |
| Extractable potassium (ppm) | 0.00099 | 0.00026 | 0.0011 | 0.00089* | 0.0011*** |
| | (0.0013) | (0.00029) | (0.0019) | (0.00046) | (0.00037) |
| Water holding capacity (mm) | 0.0017 | 0.00032 | 0.0031 | 0.0011* | 0.0011* |
| | (0.0022) | (0.00056) | (0.0023) | (0.00059) | (0.00062) |
| Soil pH (depth 0–5 cm) | −0.045 | −0.0039 | 0.0016 | 0.021** | 0.0095 |
| | (0.030) | (0.0067) | (0.036) | (0.0080) | (0.0071) |
| Adj. *R*-squared | 0.39 | 0.27 | 0.39 | 0.19 | 0.14 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and province fixed effects are included but not reported.
***$p$ <0.01; **$p$ <0.05; *$p$ <0.1.

**TABLE A10** Robustness to using the coefficient of variation of rainfall between November and April: diversification.

| | # of crop | Gini–Simpson index | # of plot | Millet | Sorghum |
|---|---|---|---|---|---|
| CoV (Nov–Apr) | 0.47 | 0.053 | −0.87 | 0.15 | −0.99* |
| | (2.61) | (0.55) | (3.12) | (0.74) | (0.59) |
| Average precipitation | 0.094* | 0.025** | 0.28*** | 0.024 | −0.0097 |
| | (0.055) | (0.011) | (0.061) | (0.014) | (0.0071) |
| Prec Nov, 19 | −0.033 | −0.053 | −0.0048 | −0.055 | −0.048 |
| | (0.21) | (0.046) | (0.25) | (0.063) | (0.038) |
| Prec Dec, 19 | 0.37*** | 0.060* | 0.25* | 0.12** | 0.029 |
| | (0.13) | (0.033) | (0.15) | (0.044) | (0.044) |
| Prec Jan, 20 | −0.34** | −0.038 | −0.33** | −0.085* | −0.022 |
| | (0.15) | (0.032) | (0.15) | (0.044) | (0.037) |
| Prec Feb, 20 | −0.27** | −0.037 | −0.38*** | 0.0048 | 0.0062 |
| | (0.13) | (0.031) | (0.13) | (0.035) | (0.032) |
| Temp (min) Nov, 19 | −0.39*** | −0.074*** | −0.35*** | 0.017 | 0.034 |
| | (0.11) | (0.024) | (0.13) | (0.037) | (0.038) |
| Temp (max) Nov, 19 | 0.20** | 0.018 | 0.090 | −0.044* | −0.014 |
| | (0.092) | (0.019) | (0.11) | (0.026) | (0.017) |
| Temp (min) Dec, 19 | 0.26** | 0.059** | 0.27** | 0.023 | 0.048 |
| | (0.12) | (0.029) | (0.12) | (0.035) | (0.036) |
| Temp (max) Dec, 19 | −0.18 | −0.021 | −0.32* | 0.060 | 0.050 |
| | (0.16) | (0.033) | (0.17) | (0.037) | (0.030) |
| Temp (min) Jan, 20 | 0.18 | 0.028 | 0.015 | 0.037 | −0.00094 |
| | (0.16) | (0.036) | (0.17) | (0.053) | (0.035) |
| Temp (max) Jan, 20 | 0.16 | 0.048 | 0.25 | 0.0063 | 0.057 |
| | (0.18) | (0.039) | (0.20) | (0.058) | (0.044) |

**TABLE A10** (Continued)

| | # of crop | Gini–Simpson index | # of plot | Millet | Sorghum |
|---|---|---|---|---|---|
| Temp (min) Feb, 20 | −0.085 | −0.012 | 0.11 | −0.056 | −0.062** |
| | (0.13) | (0.028) | (0.12) | (0.051) | (0.028) |
| Temp (max) Feb, 20 | −0.15 | −0.043 | −0.052 | −0.040 | −0.097** |
| | (0.14) | (0.032) | (0.17) | (0.044) | (0.044) |
| Soil condition = medium | −0.020 | 0.00028 | −0.018 | −0.0079 | −0.0049 |
| | (0.041) | (0.0084) | (0.042) | (0.0054) | (0.0037) |
| Soil condition = high | 0.12** | 0.025** | 0.17*** | 0.0082 | −0.0011 |
| | (0.050) | (0.010) | (0.051) | (0.0086) | (0.0052) |
| Total nitrogen (ppm) | −0.00013 | −0.000037 | −0.000068 | −0.00016 | −0.00014 |
| | (0.00051) | (0.00012) | (0.00051) | (0.00011) | (0.000096) |
| Total phosphorus (ppm) | −0.0023*** | −0.00054*** | −0.0025*** | −0.00043** | −0.00020 |
| | (0.00061) | (0.00015) | (0.00079) | (0.00020) | (0.00014) |
| Extractable potassium (ppm) | 0.0011 | 0.00027 | 0.0011 | 0.00090* | 0.0011*** |
| | (0.0013) | (0.00029) | (0.0019) | (0.00046) | (0.00037) |
| Water holding capacity (mm) | 0.0014 | 0.00024 | 0.0028 | 0.0011* | 0.0011* |
| | (0.0022) | (0.00056) | (0.0022) | (0.00058) | (0.00061) |
| Soil pH (depth 0–5 cm) | −0.041 | −0.0026 | 0.0072 | 0.021** | 0.010 |
| | (0.031) | (0.0068) | (0.037) | (0.0082) | (0.0074) |
| Adj. *R*-squared | 0.39 | 0.27 | 0.39 | 0.19 | 0.14 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and province fixed effects are included but not reported.

***$p$ <0.01; **$p$ <0.05; *$p$ <0.1.

**TABLE A11** Robustness to using the coefficient of variation of rainfall between November and February: investments in fertilizer and seeds.

| | Basal (/ha) | Top (/ha) | Total (/ha) | Hybrid seed |
|---|---|---|---|---|
| CoV (Nov–Feb) | −29.3 | 39.3 | 9.99 | 2.43*** |
| | (92.6) | (96.3) | (186.8) | (0.70) |
| Average precipitation | 8.43*** | 10.2*** | 18.6*** | 0.031* |
| | (2.04) | (2.13) | (4.10) | (0.018) |
| Prec Nov, 19 | −13.6** | −11.6* | −25.2** | 0.030 |
| | (6.26) | (6.41) | (12.5) | (0.065) |
| Prec Dec, 19 | 15.2*** | 15.4*** | 30.6*** | 0.13*** |
| | (5.51) | (5.46) | (10.9) | (0.038) |
| Prec Jan, 20 | 2.96 | 0.71 | 3.67 | 0.095* |
| | (6.23) | (6.32) | (12.5) | (0.049) |
| Prec Feb, 20 | −20.2*** | −23.1*** | −43.3*** | −0.17*** |
| | (4.02) | (3.80) | (7.56) | (0.036) |
| Temp (min) Nov, 19 | 0.57 | −0.19 | 0.38 | −0.020 |
| | (4.03) | (4.25) | (8.19) | (0.028) |
| Temp (max) Nov, 19 | −0.58 | 0.63 | 0.057 | 0.033 |
| | (3.47) | (3.72) | (7.15) | (0.026) |
| Temp (min) Dec, 19 | 2.24 | 0.94 | 3.17 | 0.023 |
| | (5.28) | (5.29) | (10.5) | (0.039) |
| Temp (max) Dec, 19 | −0.44 | −1.27 | −1.70 | −0.019 |
| | (6.15) | (6.38) | (12.5) | (0.060) |
| Temp (min) Jan, 20 | −16.7** | −14.4** | −31.1** | −0.052 |
| | (6.63) | (6.96) | (13.5) | (0.056) |
| Temp (max) Jan, 20 | 1.23 | 0.90 | 2.13 | 0.023 |
| | (6.04) | (5.94) | (11.9) | (0.049) |
| Temp (min) Feb, 20 | 10.6* | 11.3* | 21.9* | −0.0029 |
| | (5.78) | (5.88) | (11.6) | (0.053) |
| Temp (max) Feb, 20 | −1.68 | −2.85 | −4.53 | −0.032 |
| | (6.51) | (6.52) | (13.0) | (0.058) |
| Soil condition = medium | 6.83*** | 7.31*** | 14.1*** | 0.065*** |
| | (1.78) | (1.57) | (3.29) | (0.017) |
| Soil condition = high | 5.57*** | 6.36*** | 11.9*** | 0.079*** |
| | (1.97) | (1.87) | (3.78) | (0.020) |
| Total nitrogen (ppm) | 0.035* | 0.028 | 0.063 | 0.00028 |
| | (0.020) | (0.021) | (0.040) | (0.00017) |
| Total phosphorus (ppm) | −0.11*** | −0.096*** | −0.20*** | −0.00039* |
| | (0.026) | (0.028) | (0.053) | (0.00022) |

TABLE A11 (Continued)

| | Basal (/ha) | Top (/ha) | Total (/ha) | Hybrid seed |
|---|---|---|---|---|
| Extractable potassium (ppm) | 0.025 | 0.021 | 0.046 | 0.00054 |
| | (0.056) | (0.061) | (0.12) | (0.00047) |
| Water holding capacity (mm) | 0.11 | 0.12 | 0.24 | 0.0020** |
| | (0.089) | (0.090) | (0.18) | (0.00077) |
| Soil pH (depth 0–5 cm) | −0.22 | −0.42 | −0.64 | −0.00053 |
| | (1.27) | (1.30) | (2.56) | (0.0087) |
| Adj. *R*-squared | 0.26 | 0.26 | 0.27 | 0.24 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and province fixed effects are included but not reported.
****p* <0.01; ***p* <0.05; **p* <0.1.

TABLE A12 Robustness to using the coefficient of variation of rainfall between November and April: Investments in fertilizer and seeds.

| | Basal (/ha) | Top (/ha) | Total (/ha) | Hybrid seed |
|---|---|---|---|---|
| CoV (Nov–Apr) | −111.4 | −46.7 | −158.1 | 2.29*** |
| | (83.9) | (87.3) | (169.4) | (0.64) |
| Average precipitation | 7.81*** | 9.52*** | 17.3*** | 0.030 |
| | (2.09) | (2.13) | (4.16) | (0.018) |
| Prec Nov, 19 | −13.5** | −11.1* | −24.5* | 0.043 |
| | (6.20) | (6.33) | (12.4) | (0.065) |
| Prec Dec, 19 | 15.6*** | 15.9*** | 31.5*** | 0.13*** |
| | (5.51) | (5.49) | (10.9) | (0.040) |
| Prec Jan, 20 | 1.99 | −0.31 | 1.67 | 0.093* |
| | (6.25) | (6.35) | (12.5) | (0.050) |
| Prec Feb, 20 | −19.5*** | −22.7*** | −42.2*** | −0.18*** |
| | (4.03) | (3.81) | (7.60) | (0.036) |
| Temp (min) Nov, 19 | 2.28 | 1.59 | 3.87 | −0.018 |
| | (3.94) | (4.19) | (8.04) | (0.029) |
| Temp (max) Nov, 19 | −0.48 | 0.58 | 0.098 | 0.028 |
| | (3.46) | (3.70) | (7.12) | (0.026) |
| Temp (min) Dec, 19 | 1.66 | 0.41 | 2.07 | 0.025 |
| | (5.46) | (5.50) | (10.9) | (0.039) |
| Temp (max) Dec, 19 | −0.41 | −0.96 | −1.37 | −0.0088 |
| | (6.37) | (6.60) | (12.9) | (0.058) |
| Temp (min) Jan, 20 | −16.7** | −14.5** | −31.3** | −0.054 |
| | (6.52) | (6.88) | (13.3) | (0.056) |

(Continues)

**TABLE A12** (Continued)

| | Basal (/ha) | Top (/ha) | Total (/ha) | Hybrid seed |
|---|---|---|---|---|
| Temp (max) Jan, 20 | 1.17 | 0.92 | 2.09 | 0.026 |
| | (6.07) | (6.00) | (12.0) | (0.051) |
| Temp (min) Feb, 20 | 9.08 | 9.61* | 18.7* | −0.0088 |
| | (5.52) | (5.70) | (11.1) | (0.051) |
| Temp (max) Feb, 20 | −1.40 | −2.70 | −4.11 | −0.037 |
| | (6.56) | (6.56) | (13.1) | (0.058) |
| Soil condition = medium | 6.88*** | 7.39*** | 14.3*** | 0.066*** |
| | (1.78) | (1.56) | (3.28) | (0.017) |
| Soil condition = high | 5.55*** | 6.36*** | 11.9*** | 0.080*** |
| | (1.95) | (1.85) | (3.74) | (0.020) |
| Total nitrogen (ppm) | 0.034* | 0.028 | 0.062 | 0.00029* |
| | (0.020) | (0.021) | (0.040) | (0.00017) |
| Total phosphorus (ppm) | −0.11*** | −0.097*** | −0.20*** | −0.00044** |
| | (0.026) | (0.028) | (0.053) | (0.00022) |
| Extractable potassium (ppm) | 0.022 | 0.020 | 0.042 | 0.00064 |
| | (0.055) | (0.059) | (0.11) | (0.00046) |
| Water holding capacity (mm) | 0.11 | 0.12 | 0.22 | 0.0020*** |
| | (0.088) | (0.089) | (0.18) | (0.00076) |
| Soil pH (depth 0–5 cm) | −0.011 | −0.25 | −0.26 | −0.0021 |
| | (1.29) | (1.33) | (2.61) | (0.0088) |
| Adj. *R*-squared | 0.26 | 0.26 | 0.27 | 0.24 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and province fixed effects are included but not reported.
***$p$ <0.01; **$p$ <0.05; *$p$ <0.1.

**TABLE A13** Robustness to using the coefficient of variation of rainfall between November and February: family labor and land utilization.

| | Labor | Female labor | Male labor | Area planted/area field |
|---|---|---|---|---|
| CoV (Nov–Feb) | 0.61 | −1.12 | 1.73* | 0.51 |
| | (1.30) | (0.88) | (0.94) | (0.45) |
| Average precipitation | 0.031 | 0.017 | 0.014 | −0.035*** |
| | (0.035) | (0.024) | (0.021) | (0.0087) |
| Prec Nov, 19 | 0.31* | 0.10 | 0.21** | −0.0025 |
| | (0.16) | (0.095) | (0.098) | (0.029) |
| Prec Dec, 19 | −0.069 | −0.039 | −0.030 | 0.036* |
| | (0.097) | (0.060) | (0.059) | (0.021) |

**TABLE A13** (Continued)

| | Labor | Female labor | Male labor | Area planted/area field |
|---|---|---|---|---|
| Prec Jan, 20 | 0.15 | 0.12** | 0.028 | −0.013 |
| | (0.092) | (0.057) | (0.061) | (0.021) |
| Prec Feb, 20 | −0.15* | −0.054 | −0.100* | 0.024 |
| | (0.086) | (0.058) | (0.056) | (0.020) |
| Temp (min) Nov, 19 | −0.058 | 0.019 | −0.077 | −0.022 |
| | (0.075) | (0.040) | (0.054) | (0.019) |
| Temp (max) Nov, 19 | 0.099* | −0.015 | 0.11*** | 0.050*** |
| | (0.056) | (0.037) | (0.036) | (0.016) |
| Temp (min) Dec, 19 | −0.013 | −0.059 | 0.046 | 0.0057 |
| | (0.084) | (0.052) | (0.053) | (0.021) |
| Temp (max) Dec, 19 | −0.20** | −0.056 | −0.14*** | 0.0019 |
| | (0.090) | (0.062) | (0.053) | (0.023) |
| Temp (min) Jan, 20 | −0.30*** | −0.059 | −0.24*** | 0.063** |
| | (0.11) | (0.062) | (0.070) | (0.031) |
| Temp (max) Jan, 20 | −0.086 | −0.029 | −0.057 | −0.030 |
| | (0.13) | (0.069) | (0.082) | (0.025) |
| Temp (min) Feb, 20 | 0.37*** | 0.072 | 0.29*** | −0.068*** |
| | (0.12) | (0.062) | (0.072) | (0.023) |
| Temp (max) Feb, 20 | 0.18 | 0.10 | 0.077 | −0.011 |
| | (0.11) | (0.065) | (0.076) | (0.022) |
| Soil condition = medium | 0.011 | −0.0019 | 0.013 | 0.0023 |
| | (0.047) | (0.026) | (0.031) | (0.0047) |
| Soil condition = high | −0.0040 | 0.015 | −0.019 | −0.0035 |
| | (0.055) | (0.031) | (0.036) | (0.0065) |
| Total nitrogen (ppm) | −0.00028 | −0.00016 | −0.00012 | −0.000025 |
| | (0.00042) | (0.00026) | (0.00023) | (0.00011) |
| Total phosphorus (ppm) | 0.00064 | 0.00011 | 0.00053* | −0.00010 |
| | (0.00057) | (0.00034) | (0.00030) | (0.00019) |
| Extractable potassium (ppm) | 0.00030 | 0.00084 | −0.00054 | 0.00029 |
| | (0.0011) | (0.00078) | (0.00069) | (0.00035) |
| Water holding capacity (mm) | −0.0017 | −0.0010 | −0.00070 | 0.000052 |
| | (0.0018) | (0.0011) | (0.0012) | (0.00041) |
| Soil pH (depth 0–5 cm) | −0.012 | 0.0062 | −0.018 | −0.0062 |
| | (0.019) | (0.012) | (0.012) | (0.0050) |
| Adj. *R*-squared | 0.54 | 0.37 | 0.38 | 0.43 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and province fixed effects are included but not reported.

***$p$ <0.01; **$p$ <0.05; *$p$ <0.1.

**TABLE A14** Robustness to using the coefficient of variation of rainfall between November and April: family labor and land utilization.

| | Labor | Female labor | Male labor | Area planted/area field |
|---|---|---|---|---|
| CoV (Nov–Apr) | 0.26 | −0.61 | 0.87 | 0.61 |
| | (1.38) | (0.86) | (0.90) | (0.54) |
| Average precipitation | 0.028 | 0.021 | 0.0069 | −0.034*** |
| | (0.036) | (0.024) | (0.020) | (0.0086) |
| Prec Nov, 19 | 0.31* | 0.095 | 0.22** | −0.00027 |
| | (0.16) | (0.096) | (0.096) | (0.030) |
| Prec Dec, 19 | −0.067 | −0.043 | −0.024 | 0.036* |
| | (0.098) | (0.060) | (0.060) | (0.021) |
| Prec Jan, 20 | 0.15 | 0.13** | 0.018 | −0.011 |
| | (0.092) | (0.059) | (0.061) | (0.021) |
| Prec Feb, 20 | −0.16* | −0.050 | −0.11* | 0.020 |
| | (0.085) | (0.056) | (0.056) | (0.021) |
| Temp (min) Nov, 19 | −0.051 | 0.0089 | −0.060 | −0.024 |
| | (0.077) | (0.040) | (0.056) | (0.019) |
| Temp (max) Nov, 19 | 0.098* | −0.012 | 0.11*** | 0.048*** |
| | (0.056) | (0.037) | (0.036) | (0.016) |
| Temp (min) Dec, 19 | −0.014 | −0.057 | 0.043 | 0.0069 |
| | (0.083) | (0.053) | (0.052) | (0.022) |
| Temp (max) Dec, 19 | −0.20** | −0.061 | −0.13** | 0.0037 |
| | (0.091) | (0.060) | (0.054) | (0.022) |
| Temp (min) Jan, 20 | −0.30*** | −0.057 | −0.25*** | 0.062** |
| | (0.10) | (0.063) | (0.069) | (0.031) |
| Temp (max) Jan, 20 | −0.085 | −0.030 | −0.055 | −0.030 |
| | (0.13) | (0.070) | (0.083) | (0.025) |
| Temp (min) Feb, 20 | 0.36*** | 0.084 | 0.28*** | −0.066*** |
| | (0.12) | (0.060) | (0.078) | (0.023) |
| Temp (max) Feb, 20 | 0.18 | 0.11 | 0.076 | −0.013 |
| | (0.12) | (0.065) | (0.078) | (0.022) |
| Soil condition = medium | 0.012 | −0.0029 | 0.015 | 0.0025 |
| | (0.047) | (0.026) | (0.031) | (0.0048) |
| Soil condition = high | −0.0038 | 0.015 | −0.018 | −0.0033 |
| | (0.055) | (0.031) | (0.036) | (0.0065) |
| Total nitrogen (ppm) | −0.00028 | −0.00016 | −0.00012 | −0.000023 |
| | (0.00042) | (0.00026) | (0.00023) | (0.00011) |
| Total phosphorus (ppm) | 0.00062 | 0.00013 | 0.00049* | −0.00011 |
| | (0.00056) | (0.00034) | (0.00029) | (0.00019) |

TABLE A14 (Continued)

| | Labor | Female labor | Male labor | Area planted/area field |
|---|---|---|---|---|
| Extractable potassium (ppm) | 0.00031 | 0.00081 | −0.00049 | 0.00031 |
| | (0.0011) | (0.00078) | (0.00069) | (0.00036) |
| Water holding capacity (mm) | −0.0018 | −0.00098 | −0.00078 | 0.000058 |
| | (0.0018) | (0.0011) | (0.0012) | (0.00041) |
| Soil pH (depth 0–5 cm) | −0.012 | 0.0059 | −0.018 | −0.0068 |
| | (0.019) | (0.012) | (0.012) | (0.0049) |
| Adj. *R*-squared | 0.54 | 0.37 | 0.38 | 0.43 |
| Observations | 12,220 | 12,220 | 12,220 | 12,220 |

*Note*: Robust standard errors clustered by district are reported in parentheses. Total land size, family size, head's gender, age, years of education, and province fixed effects are included but not reported.
$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$.

TABLE A15 Summary statistics: mediation analysis.

| Variables | (1) Mean | (2) SD | (3) Min | (4) Max | (5) Obs |
|---|---|---|---|---|---|
| Log yield (log kg/ha) | 7.363 | 0.979 | 2.197 | 9.293 | 11,429 |
| Fertilizer (kg/ha) | 101.7 | 118.7 | 0 | 3425 | 11,429 |
| Hybrid seed = 1 | 0.739 | 0.439 | 0 | 1 | 11,429 |
| Self-reported soil quality, low = 1 | 0.147 | 0.354 | 0 | 1 | 11,429 |
| Self-reported soil quality, medium = 1 | 0.672 | 0.469 | 0 | 1 | 11,429 |
| Self-reported soil quality, high = 1 | 0.180 | 0.385 | 0 | 1 | 11,429 |
| Total nitrogen (ppm) | 758.4 | 105.4 | 522.6 | 1345 | 11,429 |
| Total phosphorus (ppm) | 234.9 | 60.45 | 142.0 | 669.3 | 11,429 |
| Extractable potassium (ppm) | 121.3 | 37.15 | 55.91 | 298.6 | 11,429 |
| Water holding capacity (mm) | 94.45 | 21.50 | 8.926 | 131.2 | 11,429 |
| Soil pH (depth 0–5 cm) | 59.02 | 2.708 | 53.67 | 65.93 | 11,429 |

*Note*: This table presents the summary statistics of the plot-level variables used in the mediation analysis.