Conservation Agriculture and Climate Resilience

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Abstract:

Climate change is predicted to increase the number and severity of extreme rainfall events, especially in Sub-Saharan Africa. In response, development agencies are encouraging the adoption of `climate-smart' agricultural techniques, such as conservation agriculture (CA). However, little rigorous evidence exists to demonstrates the effect of CA on production or climate resilience, and what evidence there is, is hampered by selection bias. Using panel data from Zimbabwe, we test how CA performs during extreme rainfall events - both shortfalls and surpluses. We control for the endogenous adoption decision and find that while CA has little, or if anything, a negative effect on yields during periods of average rainfall, it is effective in mitigating the negative impacts of rainfall shocks. Households that practice CA tend to receive higher yields compared to households using conventional methods in years of both low and high rainfall. We conclude that the lower yields during normal rainfall seasons may be a proximate factor in low uptake of CA. Policy should focus promotion of CA on these climate resiliency benefits.

Acknowledegment:

JEL Codes: O13, Q12

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Abstract

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JEL Classification: O12, O13, Q12, Q54, Q56

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1 Introduction

Climate change is expected to increase the frequency and severity of weather events. Agricultural productivity in Sub-Saharan Africa is particularly under threat, with expected loses between two to seven percent of GDP by 2100. (IPCC, 2014). In response, governments and development agencies are encouraging the adoption of 'climate smart' agricultural technologies, including conservation agriculture (FAO, 2011).[1] Conservation agriculture (CA) is based on three practices promoted as a means for sustainable agricultural intensification: minimum soil disturbance (no-till), mulching with crop residue, and crop rotation. The goal of these practices is to provide a variety of benefits to farmers, including increased soil fertility, reduced input demand, and reduced risk to yields from rainfall shocks (Brouder and Gomez-Macpherson, 2014). This last benefit comes, in the case of sub-optimal rainfall, through the use of planting basins to achieve minimum tillage, in combination with mulching, which increases water infiltration and moisture conservation (Thierfelder and Wall, 2009). In the case of excess rainfall, the retention of crop residue reduces water-driven soil erosion rates (Schuller et al., 2007). Yet little evidence exists regarding CA's 'climate smart' properties (Andersson and D'Souza, 2014). Further, adoption rates of CA have been low, and dis-adoption rates are high, raising the question of whether farmers receive the promised agronomic benefits (Pedzisa et al., 2015a). Most studies explore the effect of CA on yields during normal rainfall years, but many of these rely on agronomic analysis of field station trials, missing potential effects of farmer behavior. As Pannell et al. (2014) argue, the few studies that do use observational data often fail to account for selection bias or fully control for all potential sources of endogeneity.

In this paper, we examine CA's ability to reduce yield loss due to deviations in average rainfall, while controlling for potential selection bias. While CA is hypothesized to be 'climate smart,' increased resiliency during periods of rainfall stress may come at the cost of yields during regular growing conditions. We follow Di Falco and Chavas (2008) in defining resilience in terms of practices that limit productivity loss when challenged by climatic events. We use four years of plot-level panel data covering $4,171$ plots from 729 households across Zimbabwe to estimate how yields respond

[1] FAO (2013) broadly defines climate smart agriculture (CSA) as an approach to agriculture designed to help farmers effectively respond to climate change.

during periods of high and low rainfall shocks, compared to the norms households experience over time. The data include plot-level inputs and outputs for five different crops: maize, sorghum, millet, groundnut, and cowpea. Unlike earlier work that estimates CA's effect on a single crop, this rich set of production data allows us to examine how the impacts of CA vary in the multi-cropping system common to Sub-Saharan Africa.

Causal identification of CA's impact on yields is complicated by non-random adoption of the technology. We identify two potential sources of endogeneity that might bias our results. First is the presence of unobserved household heterogeneity that influences both adoption and yields, which we control for with household fixed effects. Second is the possible presence of unobserved time-varying shocks that might affect a household's access to and use of CA while being correlated with yields. To instrument for household adoption of CA, we use data on CA promotion through the distribution of input subsidies as part of the Zimbabwe Protracted Relief Programme (PRP). The Zimbabwe PRP was a multi-faceted, four year, £28 million project aimed at providing short-term nutritional, economic, and agricultural interventions to one-third of all smallholder households in the country, about 1.7 million people (Jennings et al., 2013). In addition to these two primary concerns, we test for other potential factors that could confound the causal identification of CA on yields. Because households do not use CA on their entire farm, the choice of which plots to use for CA might be endogenous. To test this concern, we use a subset of our data for which we have consistent plot identifiers and estimate regressions controlling for plot-level unobservables.

In our data, we find that adoption of CA in years of average rainfall results in no yield gains, and in some cases yield loses, compared to conventional practices. Where CA is effective is in mitigating the negative impacts of deviations in rainfall. For all crops, except millet, CA generates yields that are more resilient to rainfall shocks than conventional farming methods. The magnitude of these positive yield effects vary by crop, and whether rainfall is in shortfall or surplus, but persist when we include plot-level effects. We then use the estimated coefficients on the CA terms to predict the returns to CA at various values of rainfall. We find that a one standard deviation decrease or increase in rainfall is required before the returns to CA become positive. Using rainfall realizations over the past 15 years, we find that the mean return to CA is positive, though the median value is negative. Our results, using observational data, support a recent meta-analysis of agronomic field experiments which found that, on average, CA reduces yields but can enhance yields in dry climates (Pittelkow et al., 2015).

Pannell et al. (2014) discuss several limitations with the state of economic research on CA. A key limitation is a lack of clarity regarding what qualifies as CA adoption. Our survey data only allow us to partially address this concern. While the data cover four cropping seasons, only in the final two seasons (2010 and 2011) were households asked about which specific practices they implemented on plots that they identified as cultivating with CA. Among households that used CA in the last two years of the survey, 97 percent of them used planting basins to achieve minimum soil disturbance, 27 percent mulched with crop residuals, and 36 percent practiced crop rotation. In total, 22 percent of self-identified CA adopters engaged in at least two practices while only five percent of CA adopters actually engaged in all three practices. Therefore, in our context, we use a practical definition of CA as, at the very least, minimum tillage, the original and central principle of CA. We then define traditional cultivation practices as everything other than self-identified CA adoption, which for the majority of plots amounts to conventional tillage practices. While our pragmatic approach is not ideal, it is in line with previous literature at the farm level and with meta-analyses of agronomic field experiment data.[2]

This paper makes three contributions to the literature. First, by interacting the instrumented measure of CA adoption with deviations in rainfall we test whether CA can help mitigate yield loss due to adverse weather events. The only evidence of the resilience of yields under CA comes from station and on-farm field trial data or from observational data that fails to adequately control for both time-variant and time-invariant sources of endogeneity. In this literature, researchers acknowledge that selection bias is a problem because farmers choose the technology based on its expected benefits, which are heterogeneous. Much of the literature relies on cross-sectional data and two-stage techniques that involve estimating selection correction terms (Kassie et al., 2009; Teklewold et al., 2013; Teklewold et al., 2013; Kassie et al., 2015; Kassie et al., 2015; Abdulai, 2016; Manda et al., 2016). Like any other IV, selection models rely on exclusion restrictions for proper

[2]Using the last two years of the data, we test how the individual practices, singly and in combinations, impact yields during periods of rainfall stress. Results are not significantly different from our broader measure of CA.

identification of time-variant endogenous choice variables. However, reliance on cross-sectional data means that one cannot easily control for endogeneity coming from time-invariant sources. A second set of literature relies on panel data to control for time-invariant heterogeneity (Arslan et al., 2014; Ndlovu et al., 2014; Arslan et al., 2015; Pedzisa et al., 2015a; Pedzisa et al., 2015b). This literature, though, fails to control for time-variant factors causing endogeneity in the adoption decision. We use realizations of on-farm yields over four years and control for both sources of endogeneity. Ours is one of the first papers to test the 'climate smart' properties of CA as they are experienced by farm households.

Second, we expand the analysis of CA by encompassing a variety of crops. Most previous work focuses on the impact of CA on yields for a single crop, often maize (Teklewold et al., 2013; Brouder and Gomez-Macpherson, 2014; Kassie et al., 2015; Manda et al., 2016). But, farmers in Sub-Saharan Africa frequently grow multiple crops in a single season, meaning decisions regarding cultivation method and input use are made at the farm level, not the crop level. To examine the farm-wide impacts, we adopt a flexible yield function that allows coefficients on inputs to vary across crops. This approach accommodates heterogeneity in the input-response curves by allowing slopes and intercepts to vary across crops without forcing us to split the random sample based on non-random criteria. Our results provide new insight on the use and impact of CA in a multi-cropping environment.

Third, we provide suggestive evidence on the reason for the low adoption rate of CA among farmers in Sub-Saharan Africa. Given early evidence on the positive correlation between CA and yields (Mazvimavi and Twomlow, 2009), and its promotion by research centers, donor agencies, and policymakers (Andersson and D'Souza, 2014), the slow uptake of CA has presented the adoption literature with an empirical puzzle. We find that once we control for endogeneity in the adoption decision, CA no longer has any impact on yields during periods of average rainfall. We conclude that the lack of yield gains during average rainfall seasons may be a limiting factor in the uptake of CA. Focusing on CA's potential as a 'climate smart' agricultural technology by advertising the resilience benefits of CA marks a path forward for the promotion of CA in regions facing climate extremes.

2 Theoretical Framework

We begin by defining two stochastic Cobb-Douglas yield functions along the lines of Just and Pope (1978), Barrett et al. (2004), and Suri (2011):

$$Y_{kit}^{\text{CA}} = e^{\beta_{kt}^{\text{CA}}} \left(\prod_{j=1}^{J} X_{jkit}^{\gamma_{jk}^{\text{CA}}} \right) e^{u_{kit}^{\text{CA}}} , \tag{1}$$

$$Y_{kit}^{\text{TC}} = e^{\beta_{kt}^{\text{TC}}} \left(\prod_{j=1}^{J} X_{jkit}^{\gamma_{jk}^{\text{TC}}} \right) e^{u_{kit}^{\text{TC}}} , \tag{2}$$

where Y_{kit} is yield for crop k cultivated by household i at time t and X_{jkit} is a set of j measured inputs, including a crop specific intercept, used on the k^{th} crop by household i at time t. We allow the yield functions for conservation agriculture (CA) and traditional cultivation (TC) to have different parameters for inputs (γ_j^{CA} and γ_j^{TC}), although the same set of potential inputs are used in both cultivation methods. The disturbance terms (u_{kit}^{CA} and u_{kit}^{TC}) are sector-specific errors composed of time-invariant farm and household characteristics and time-variant production shocks.

Taking logs of equations (1) and (2) gives us:

$$y_{kit}^{\text{CA}} = \beta_{kt}^{\text{CA}} + x'_{jkit}\gamma_{jk}^{\text{CA}} + u_{kit}^{\text{CA}} , \tag{3}$$

$$y_{kit}^{\text{TC}} = \beta_{kt}^{\text{TC}} + x'_{jkit}\gamma_{jk}^{\text{TC}} + u_{kit}^{\text{TC}} , \tag{4}$$

where we can decompose the disturbance terms into:

$$u_{kit}^{\text{CA}} = \theta_{ki}^{\text{CA}} + \xi_{kit}^{\text{CA}} , \tag{5}$$

$$u_{kit}^{\text{TC}} = \theta_{ki}^{\text{TC}} + \xi_{kit}^{\text{TC}} . \tag{6}$$

The θ_{ki}'s are crop-level productivity terms based on factors not chosen but known by the household.

The transitory errors (ξ^{CA}_{kit} and ξ^{TC}_{kit}) are assumed to be uncorrelated with each other, uncorrelated with the X_{jkit}'s, unknown by households, and have a zero mean and finite variance.

We can define the relative productivity of a plot cultivated using CA compared to traditional methods as $(\theta^{\text{CA}}_{ki} - \theta^{\text{TC}}_{ki})$, which relies on the decomposition of θ^{CA}_{ki} and θ^{TC}_{ki} into:

$$\theta^{\text{CA}}_{ki} = b^{\text{CA}}_{k}\left[\sum_{t=1}^{T}\left(\mathrm{R}^{\text{CA}}_{kit} - \mathrm{R}^{\text{TC}}_{kit}\right)\right] + \tau_i, \tag{7}$$

$$\theta^{\text{TC}}_{ki} = b^{\text{TC}}_{k}\left[\sum_{t=1}^{T}\left(\mathrm{R}^{\text{CA}}_{kit} - \mathrm{R}^{\text{TC}}_{kit}\right)\right] + \tau_i. \tag{8}$$

The b_k's are a measure of each crop's relative advantage under a given cultivation method and for a certain level of rainfall, R. The τ_i term is the household's absolute advantage in cultivating crops, which does not vary by crop type or cultivation method and is constant over time.

We can re-define this comparative advantage gain as $\theta_{ki} \equiv b^{\text{TC}}_{k}\left[\sum_{t=1}^{T}\left(\mathrm{R}^{\text{CA}}_{kit} - \mathrm{R}^{\text{TC}}_{kit}\right)\right]$ and define a new parameter, $\phi_k \equiv b^{\text{CA}}_{k}/b^{\text{TC}}_{k} - 1$. This allows us to re-write equations (7) and (8) as:

$$\theta^{\text{CA}}_{ki} = (\phi + 1)\theta_{ki} + \tau_i, \tag{9}$$

$$\theta^{\text{TC}}_{ki} = \theta_{ki} + \tau_i. \tag{10}$$

Substituting the decomposed error terms back into equations (3) and (4) results in:

$$y^{\text{CA}}_{kit} = \beta^{\text{CA}}_{kt} + x'_{jkit}\gamma^{\text{CA}}_{jk} + (\phi + 1)\theta_{ki} + \tau_i + \xi^{\text{CA}}_{kit}, \tag{11}$$

$$y^{\text{TC}}_{kit} = \beta^{\text{TC}}_{kt} + x'_{jkit}\gamma^{\text{TC}}_{jk} + \theta_{ki} + \tau_i + \xi^{\text{TC}}_{kit}. \tag{12}$$

Using a generalized yield function of the form

$$y_{kit} = h_{kit}y^{\text{CA}}_{kit} + (1 - h_{kit})y^{\text{TC}}_{kit}, \tag{13}$$

we can substitute equations (11) and (12) into equation (13) to get:

$$y_{kit} = \beta_{kt}^{\text{TC}} + \theta_{ki} + (\beta_{kt}^{\text{CA}} - \beta_{kt}^{\text{TC}})h_{kit} + x'_{jkit}\gamma_{jk}^{\text{TC}} + \phi_k\theta_{ki}h_{kit} + x'_{jkit}(\gamma_{jk}^{\text{CA}} - \gamma_{jk}^{\text{TC}})h_{kit} + \tau_i + \epsilon_{kit}. \quad (14)$$

Here h_{kit} is an indicator of whether or not crop k was cultivated by household i at time t using CA. The θ_{ki} term is the impact of rainfall, or rainfall shocks, on crop k grown by household i. We are primarily interested in the coefficient ϕ_k on the composite term $\theta_{ki}h_{kit}$, which measures the impact of rainfall on yield given a household was using CA. The expected gain from using CA is therefore:

$$B_{kit} = y_{kit}^{\text{CA}} - y_{kit}^{\text{TC}} = \phi_k\theta_{ki} + (\beta_{kt}^{\text{CA}} - \beta_{kt}^{\text{TC}}) + x'_{jkit}(\gamma_{jk}^{\text{CA}} - \gamma_{jk}^{\text{TC}}). \quad (15)$$

Neither the household fixed effect term nor the transitory error term appear in equation (15). This is because τ_i is restricted to impact yields identically regardless of cultivation method and because of the assumptions placed on ξ_{kit}^{CA} and ξ_{kit}^{TC}. These logarithmic representations of the yield function map back to a generalized Cobb-Douglas yield function in which returns are heterogeneous based on crop type and cultivation method. While it is recognized that the Cobb-Douglas is not a flexible functional form, in studies of developing country agriculture it is often still preferred to the translog due to data limitations, the simplicity of the production technology, and the frequent issue of multicollinearity in estimation (Michler and Shively, 2015).

Our primary empirical specification is contained in equation (14). To implement the estimation procedure we make two simplifying assumptions. First, we allow $\beta_{kt}^{\text{CA}} - \beta_{kt}^{\text{TC}} = \beta_{kt}$ and assume $\beta_{kt} = \beta_k \ \ \forall\, t$. This amounts to assuming that, holding rainfall constant, productivity gains from adoption of CA vary by crop but not over time. Second, we assume $\gamma_{jk}^{\text{CA}} = \gamma_{jk}^{\text{TC}} = \gamma_{jk}$. This allows the yield response curves to vary by input and by crop but not by cultivation method. We address this second assumption in greater detail in Section 4.1.

Finally, a potential issue with identifying the impact of CA adoption on yields is that the decision to adopt, h_{kit}, may be correlated with transitory shocks contained in ϵ_{kit}. In our empirical implementation we instrument for the likely endogeneity of the adoption term using an approach outlined by Wooldridge (2003). We discuss this approach more fully in Section 4.2.

3 Data

This study uses four years of panel data on smallholder farming practices in Zimbabwe collected by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). The data cover 783 households in 45 wards from 2007-2011.[3] The wards come from 20 different districts which were purposefully selected to provide coverage of high rainfall, medium rainfall, semi-arid, and arid regions. Thus the survey can be considered nationally representative of smallholder agriculture in Zimbabwe. For our analysis we use an unbalanced panel consisting of a subset of 728 randomly selected households. The 55 excluded households come from the 2007 round, which we drop completely, because in that year the survey only targeted households who had received NGO support as part of the Zimbabwe PRP.

3.1 Household Data

Our data provide us with detailed cultivation data for five crops on 4,171 unique plots (see Table 1). Maize, the staple grain of Zimbabwe, is the most commonly cultivated crop. Just over half of all observations are maize and 98 percent of households grow maize on at least one plot in every year. The next most common crop, in terms of observations, is groundnut, which is often grown in rotation with maize. The third most common crop is sorghum, which is frequently grown as an alternative to maize in the semi-arid regions of Zimbabwe. As an alternative to groundnut and sorghum, households will often grow cowpea or pearl millet, respectively. Both of these crops are much less common and combine to account for only 15 percent of observations.

Examining the production data by year reveals a high degree of annual variability (see Table 2). Yields in 2009 and 2010 were about 30 percent higher than yields in 2008 or in 2011, despite much higher levels of fertilizer and seed use in the low yield years. CA practices vary both by crop and over time (see Figure 1). In 2008, adoption of CA was at over 40 percent for those cultivating maize, sorghum, groundnut, and cowpea and it was about 30 percent for those cultivating millet.

[3] Wards are the smallest administrative district in rural Zimbabwe.

Since then, adoption of CA has declined for all crops so that the average adoption rate is now only 17 percent, although use of CA for maize cultivation remains relatively high at 25 percent. Previous literature has hypothesized that this abandonment of CA by households in Zimbabwe is due to the withdrawal of NGO input support as the PRP was scaled down (Ndlovu et al., 2014; Pedzisa et al., 2015b). We make use of this insight to help identify CA adoption.

3.2 Rainfall Data

To calculate rainfall shocks we use satellite imagery from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data. CHIRPS is a thirty year quasi-global rainfall dataset that spans 50°S-50°N, with all longitudes and incorporates 0.05° resolution satellite imagery with in-situ station data to create a gridded rainfall time series (Funk et al., 2015). The dataset provides daily rainfall measurements from 1981 up to the current year. We overlay ward boundaries on the 0.05° grid cells and take the average rainfall for the day within the ward. We then aggregate the ward level daily rainfall data to the seasonal level.[4]

Figure 2 shows historic seasonal rainfall distribution by ward over the 15 year period 1997-2011. We observe large seasonal fluctuations as well as longer term cycles in rainfall patterns. The four-year period 1997-2000 saw relatively high levels of rainfall. This was followed by a six-year period in which rainfall was relatively scarce. Since 2007, and throughout the survey period, rainfall was again relatively abundant. In addition to plotting the ward-level rainfall realization, we fit a linear trendline to the data. Over the last 15 years, despite the long term cycles, seasonal rainfall levels have been decreasing in Zimbabwe. To determine the degree of variation in realized rainfall over the four year study period, we draw the distribution of cumulative seasonal rainfall (see Figure 3). The distribution forms a fairly tight band, with half the observations (51 percent) falling within half a standard deviation of the mean and a majority of observations (71 percent) falling within one standard deviations of the mean.

We follow Ward and Shively (2015) in measuring rainfall shocks as normalized deviations in a single season's rainfall from expected seasonal rainfall over the 15 year period 1997-2011:

[4]The rainy season in Zimbabwe runs from November to March, with households planting immediately ahead of the first rains and harvesting in May or June.

$$\mathrm{R}_{wt} = \left| \frac{r_{wt} - \bar{r}_w}{\sigma_{r_w}} \right|. \tag{16}$$

Here shocks are calculated for each ward w in year t where r_{wt} is the observed amount of rainfall for the season, $\bar{r}_w$ is the average seasonal rainfall for the ward over the period, and σ_{r_w} is the standard deviation of rainfall during the same period.

Our rainfall shock variable treats too little rain as having the same effect as too much rain. While this may not appear to be meaningful in an agronomic sense, proponents of CA claim that CA will have a positive impact on yields in both abnormally wet and abnormally dry conditions (Thierfelder and Wall, 2009). TWe also calculate a measure of rainfall shortage as:

$$\underline{\mathrm{R}}_{wt} = \begin{cases} \left| \frac{r_{wt} - \bar{r}_w}{\sigma_{r_w}} \right| & \text{if } r_{wt} < \bar{r}_w \\ 0 & \text{otherwise} \end{cases}, \tag{17}$$

as well as a measure of rainfall surplus:

$$\overline{\mathrm{R}}_{wt} = \begin{cases} \left| \frac{r_{wt} - \bar{r}_w}{\sigma_{r_w}} \right| & \text{if } r_{wt} > \bar{r}_w \\ 0 & \text{otherwise} \end{cases}. \tag{18}$$

These measures help clarify if CA's impact on yield resilience is primarily due to mitigating loss from drought or from excess rainfall.

One potential concern with our rainfall terms is that they are measures of annual deviations in meteorological data which are designed to proxy for agricultural drought or overabundance of rainfall. In Zimbabwe, agricultural drought can takes the form of late onset of rains or mid-season dry spells. A further complication is that rainfall in Zimbabwe is often of high intensity but low duration and frequency, creating high runoff and little soil permeation. To test for this, we examine the impact of both seasonal and monthly deviations in rainfall on crop output. We find little empirical evidence that late onset of rainfall or mid-season dry spells reduce yields. Rainfall in the first month of the growing season only impacts maize and groundnut yields while deviations in the mid-season months tend to only effect maize, groundnut, and cowpea. By contrast, for all five crops, deviations in seasonal rainfall have a significant and negative impact on crop yields. Results from these regressions are presented in the Appendix, Table A1. Based on these results we conclude that our use of seasonal deviations is a strong proxy for rainfall induced stresses to agricultural production.

4 Identification Strategy

Our analysis is based on observational data from a setting in which households were randomly selected into the survey but adoption of CA was not random. Thus, care must be taken in understanding what constitutes the relevant comparable group for hypothesis testing. Additionally, identification of the impact of CA on yields is confounded by two potential sources of endogeneity. First, time-invariant unobserved household-level characteristics might influence both CA adoption and yields. Second, time-variant unobserved shocks captured in ϵ_{kit} may simultaneously affect the adoption decision and crop yields.

4.1 Establishing the Relevant Comparison Group

While we want to compare adopters to non-adopters, if CA requires different levels of inputs, or if yields respond in different ways to inputs under CA compared to traditional cultivation, we cannot simply compare across the two groups, irrespective of any selection issues.

In Table 3 we explore the differences in outputs and input use by crop across cultivation practices.[5] Mean yields for all crops are significantly higher under CA than under traditional cultivation methods. One obvious potential reason why CA is often associated with higher yields is that households increase the intensity of agricultural input application under CA. Compared to traditional cultivation methods, CA is associated with significantly higher levels of both basal and top applied fertilizer. Conversely, more seed and land is used in traditional cultivation compared to CA for all

[5] For each crop-cultivation pair we first test for normality of the data using the Shapiro-Wilk test. In every case we reject the null that the data is normally distributed. Because of this, we rely on the Mann-Whitney (MW) test instead of the standard t-test to determine if differences exist within crops across cultivation practices. Unlike the t-test, the MW test does not require the assumption of a normal distribution. In the context of summary statistics we also prefer the MW test to the the Kolmogorov-Smirnov (KS) test, since the MW test is a test of location while the KS test is a test for shape. Results using the KS test are equivalent to those obtained from the MW test.

crops, except for the seeding rate of groundnut. The different rates of input use between CA and traditional cultivation means that the two cultivation techniques are not directly comparable without taking into consideration measured inputs. Because we observe the quantity of fertilizer, seed applied, and the size of each plot, we can directly control for these differences in our econometric analysis.

Directly controlling for input use in our regression framework only allows us to compare CA adopters to non-CA adopters (ignoring issues of selection, for the moment), if the yield response curves are homogeneous across cultivation methods. We verify if this is the case by graphing the correlation between yields and inputs. In the top row of Figure 5 we draw scatter plots of yields and seeding rates in panel (1), yields and basal fertilizer application rates in panel (2), and yields and top fertilizer application rates in panel (3). We then fit a quadratic function to the data along with a 90 percent confidence interval band. While intercepts of the yield response curves differ by cultivation method for all three measured inputs, the slopes of the curves differ only for the two types of fertilizer application. Panels (1) - (3) imply that CA does not affect the responsiveness of yields to seed but may affect the responsiveness of yields to both basal and top applied fertilizer. Thus, we cannot compare yields of CA plots to non-CA plots, even when explicitly controlling for the amount of measured inputs applied to the plot.

Our data were collected during the implementation of the Zimbabwe Protracted Relief Program (PRP). The PRP simultaneously promoted CA and provided access to subsidized inputs such as fertilizer. The promotion and subsidy program provided nearly universal coverage at the district level, operating in 54 of the 59 districts in the country. But, within districts, program support varied from ward-to-ward. Thus, a household's access to information about CA, and their access to subsidized fertilizer, varies depending on which ward a household lives in. To examine if the difference in yield response to fertilizer across cultivation method is a result of access to inputs, and not a result of CA itself, we regress output and inputs on ward indicators.[6] We then plot the residuals from these different regressions and again fit a quadratic function to the data with confidence intervals drawn at 90 percent (see panels (4) - (6) in Figure 5). The result allows us to

[6]Specifically, we estimate four different regressions: log of yield on ward indicators, log of seed on ward indicators, log of basal fertilizer on ward indicators, and log of top fertilizer on ward indicators.

compare yield response by cultivation method within a ward, and thus control for different rates of access to inputs across wards. Comparing panels in the top of Figure 5 to panels in the bottom of the figure, much of the apparent differences in yield response to inputs based on cultivation method is a result of ward effects. While differences in yield response do not completely disappear, the differences that remain are small compared to differences coming from variation in access to inputs from ward-to-ward. Thus, after controlling for ward, differences in yield response appear to be largely driven by access to inputs, not the cultivation method *per se*.

In our regression analysis we control for differences in access to inputs resulting from ward location using household fixed effects. Additionally, household fixed effects remove any other unobserved time-invariant household effects, such as skill at farming, wealth, or risk aversion, that may be correlated with both the τ_i term, the decision to adopt, and yields in equation (14). Thus, we are estimating the yield response to CA within a household during periods of high and low rainfall shocks, compared to the norms a household experiences over time.

Within a household, farmers may choose to apply CA techniques to some plots and not others based on plot-level unobservables. To test whether this is a valid concern, we compare output and input use across two different "treatment" and "control" groups. In the first, we compare plots on which CA was used in all four rounds of the data with plots that were initially cultivated using CA but which had reverted to traditional cultivation practices by the final round. In the second, we compare plots that never experienced CA with plots on which CA was used in later rounds. The intuition behind comparing these plot-level adoption types is that if differences in output and input use exist only after adoption histories diverge, then plot-level unobservables are not a concern. Examining Table 4, we see that in the first year, 2008, always adopters and future dis-adopters have output and input use levels statistically indistinguishable from each other, as do never adopters and future adopters.[7] The two exceptions are the seeding rate between always adopters and future dis-adopters, and the rate of application of top fertilizer between the never adopters and the future adopters. By the last round, 2011, when adoption histories are different,

[7]Similar to our approach in Figure 5, we first regress each variable on ward indicators in order to control for differences in access to inputs across wards. The values displayed in each cell of the table are residuals from these regressions.

both yields and input use has diverged. The one exception is basal fertilizer, which is the same between never adopters and future adopters. Thus, there is *prima facie* evidence that differences in yields on CA and non-CA plots are due to differences in input use and not due to differences in unobserved plot-level characteristics.

In summary, Table 3 demonstrates that a naive comparison that does not consider differences in input use would lead to the erroneous conclusion that CA, by itself, increases yields for all crops. To address this issue, we include measured inputs by crop type in our regression analysis so that we are comparing CA plots to non-CA plots with similar input use. A second concern is that yields under CA might respond differently from yields under traditional cultivation. Figure 5 shows that controlling for different levels of access to inputs due to different levels of promotion and subsidies at the ward level explains most of the differences in yield response. Our use of household fixed effects controls for this and means that we are comparing yields on CA plots within a household during periods of high and low rainfall shocks, compared to the norms a household experiences over time. A final concern is that households may choose to apply CA to certain plots based on unobservable plot-level characteristics, thus making plot-level comparisons within a household invalid. Table 4 compares output and input use between plots on which CA was always used and plots where CA was initially used but eventually abandoned, along with a comparison between plots that never experienced CA and plots on which CA was eventually adopted. In only two of 16 cases do we see a statistically significant difference where we would expect to see differences if plot-level unobservables were indeed a concern. We take this as evidence that differences in yields are due to differences in input use and not differences in unobserved plot-level characteristics. As a robustness check, in subsection 5.3 we estimate yield functions using plot-level fixed effects, which allows us to compare yields under CA and traditional cultivation methods for plots whose adoption status changed over the period of study.

4.2 Selection Bias

Having established the relevant comparison group within our data, we next deal with the potential of selection bias. Because adoption of CA is not random, it is likely to be correlated with unobserved time-varying factors, such as government and NGO promotion of CA, that may simultaneously influence yields. In the particular case of Zimbabwe, CA was heavily promoted as one element in the PRP, which also included subsidies for improved inputs (Mazvimavi et al., 2008). Thus, adoption rates of CA within a ward are strongly correlated with the level of input subsidies distributed in the ward (Mazvimavi and Twomlow, 2009; Ndlovu et al., 2014; Pedzisa et al., 2015b). Because the intensity of promotion and the level of support changed from year-to-year, adoption of CA is neither random nor static and therefore is likely correlated with unobserved time-varying factors.

To address the endogeneity of CA we instrument for plot-level adoption using the number of households in the ward that receive NGO support as part of the PRP. An appropriate instrument for this model need not be random but must be correlated with the plot-level decision to adopt CA and uncorrelated with plot yields, except through the treatment. As Figure 4 shows, there is strong correlation between the probability that a household adopts CA and their receiving assistance from an NGO, as part of the PRP, in the form of input subsidies. According to the final report on the PRP, rural households were categorized into four standardized groups based on asset ownership, labor availability, and severity of cash constraints (Jennings et al., 2013). While the PRP provided support to 1.7 million people, those who were eligible for input subsidies, and thus most likely to adopt CA, were required to be households with land and labor but no cash. Eligibility for NGO support was well defined but not all eligible households received support, meaning that NGOs may have targeted individual households based on unobservable characteristics.

That not all eligible households received input subsidies from NGOs raises the concern that correlation exists among NGO targeting of households, CA adoption, and yields. To demonstrate that our instrument arguably satisfies the exclusion restriction, we must demonstrate that any correlation between our instrument and yields occurs only through the adoption of CA or can be explicitly controlled for in our regression framework. One potential pathway of contamination is through NGO targeting of households based on time-invariant characteristics, such as those defined in the eligibility criteria of the PRP. Our use of fixed effects controls for this possibility, making the use of NGO support a plausibly valid instrument. A second potential pathway of contamination is that input subsidies likely have a direct effect on yields, making it an invalid instrument. Here we can directly control for this pathway by including the amount of seed and fertilizer applied on each plot. A third potential pathway of contamination is that NGO targeting was based on some unobservable time-varying characteristics that are directly correlated with yields. While far from definitive proof, Figure 4 shows that there is little correlation from year-to-year between plot-level yields, CA adoption by household, and the number of households within a ward that received input subsidies as part of the PRP.[8] The level of support that neighboring households receive is correlated with a given household receiving NGO support but does not directly impact that household's plot-level yields, especially once we control for input use, household effects, and local conditions.[9] Thus, the number of households in the ward that receive NGO support arguably satisfies the exclusion restriction.

Given that adoption of CA, h_{it}, is interacted with either crop type (to give h_{kit}) or with crop type and the exogenous rainfall shock (to give $\theta_{ki}h_{kit}$), we follow Wooldridge (2003) in instrumenting for only the potentially endogenous term. We estimate a version of equation (14) in which CA and the CA interaction terms are instrumented using the number of households in the ward that receive NGO support. Specifically, we use a probit to predict $\hat{h}_{it}$ from the following equation:

$$h_{it} = 1\left[\zeta \mathrm{Z}_{it} + \theta_{ki} + \beta_k + x'_{jkit}\gamma_{jk} + \tau_i + v_{it} \geq 0\right], \tag{19}$$

where Z_{it} is the value of the instrument for household i at time t, ζ is the associated coefficient, and $v_{it} \sim \mathcal{N}(0, \sigma^2_{v_{it}})$ and is independent of u_{it} and τ_i. Since our first stage reduced form equation is nonlinear, we use a Mundlak-Chamblerain device to control for household unobservables instead of the fixed effects used in the second stage structural equation.[10] This amounts to replacing τ_i with its linear projection onto the time averages of observable choice variables $\tau_i = \bar{\mathbf{x}}_i\lambda + a_i$,

[8]Specifically, the correlation coefficient between CA and plot yields is $\rho = 0.1585$ while the correlation coefficient between our IV and plot yields is $\rho = 0.0018$.

[9]One may be concerned with potential spillover effects, in that a household that adopts CA due to NGO support might result in increased yields for a neighbor. For the case of CA in Zimbabwe this is unlikely for two reasons. First, the practices that constitute CA are location specific, in that use of planting basins or residue or rotation on one plot will have no impact on the productivity of another plot. Second, even if this was not the case, households in the survey are relatively dispersed throughout wards, meaning that the plots of one household are not contiguous with neighboring households.

[10]In the Appendix, Tables A7 and A8, we present results from a robustness check using a Tobit and household fixed effects for the first stage.

where $a_i \sim \mathcal{N}(0, \sigma^2_{a_i})$ (Mundlak, 1978; Chamberlain, 1984). Using the Mundlak-Chamblerain device allows us to avoid the incidental variable problem created by using fixed effects in a nonlinear model while still controlling for unobservables (Wooldridge, 2010). While our first stage and second stage equations take different approaches to controlling for τ_i, identification of h_{it} still fully relies on our instrumental variable Z_{it}. Any difference that exists between the fixed effects and the correlated random effects is captured in a_i, which in expectation has zero mean. Our use of correlated random effects will be less efficient than fixed effects to the extent that $\sigma^2_{a_i} > 0$, but this introduces no bias into our IV estimate of h_{it}.

We then calculate the Inverse Mills Ratio (IMR) and instrument h_{kit} with the IMR interacted with crop type and instrument $\theta_{ki}h_{kit}$ with the IMR interacted with crop type and the exogenous rainfall shock. Wooldridge (2003) shows that this approach produces consistent estimates and improves on efficiency when compared to instrumenting the entire interaction term.

To ensure correct hypothesis testing, we allow the variance structure of the error term to vary by household as well as by crop and cluster our standard errors at the household-crop level. This procedure is not without its critics. Bertrand et al. (2004) suggest that clustering at a single level is preferred to clustering at two levels. This provides two alternatives: cluster only at the crop-level or cluster only at the household-level. Given that we only have five different crops, and a large set of parameters to estimate, we are unable to directly cluster standard errors at just the crop level. Clustering at the household-level provides results qualitatively equivalent to those when we cluster at the household-crop level.[11]

5 Results

We estimate the yield function in equation (14) by regressing yields for each crop on crop-specific inputs, CA, deviations from average rainfall, and their interaction. We present the results from a large complement of estimates in Tables 5 - 8. All models are estimated using the log of yield as

[11] To address the issue of too few crops for clustering, we estimated crop-specific yield functions with household fixed effects as a system of equations. This approach allows for correlation among crop-specific error terms, though it implicitly imposes the assumption that observations are independent if they are in the same household (Greene, 2011). We also estimated our preferred specification but clustered errors at just the household level. Results from all of these regressions are available from the authors upon request.

the dependent variable and log values of measured inputs as independent variables. Hence, point estimates can be read directly as elasticities.[12] For brevity, we only report coefficients on CA, the rainfall deviations, and the interaction terms. Estimated coefficients on measured inputs are presented in the Appendix.

5.1 Main Results

We first focus on the results presented in Table 5 in which CA is treated as exogenous. While it is unlikely that the decision to adopt CA is uncorrelated with the time-varying error term, these results are informative as they allow us to directly compare our estimates with previous literature on the correlation between CA and yields. Column (1) presents a simple yield function that lacks both our rainfall variable and household fixed effects. Results in column (2) come from the same regression but with fixed effects to control for time-invariant household unobservables. In all other crop cases CA has no statistically significant association with yields.

Adding deviations from average rainfall and its interaction with CA tells a very different story. Columns (3) and (4) present point estimates of the more flexible yield function with and without household fixed effects. Focusing on the fixed effects results in column (4), CA by itself no longer increases yields for any crop and appears to be correlated with lower yields for sorghum. Exposure to a rainfall shock decreases yields for all crops. When we examine the interaction terms, we find that CA is correlated with higher yields for maize and sorghum during periods of rainfall stress. For millet, groundnut, and cowpea CA has no statistically significant association with yields, regardless of rainfall levels.

The results in columns (1) and (2) of a positive correlation between maize yields and CA are similar to the results presented in much of the previous literature (Kassie et al., 2009; Mazvimavi and Twomlow, 2009; Kassie et al., 2010; Teklewold et al., 2013; Brouder and Gomez-Macpherson, 2014; Ndlovu et al., 2014; Abdulai, 2016; Manda et al., 2016). These positive and statistically significant correlations are often interpreted as demonstrating that CA increases yields compared to traditional cultivation practices and are used to justify the continued promotion of CA (Giller

[12] Given the prevalence of zero values in the input data, and to a lesser extent in the output data, we use the inverse hyperbolic sine transformation to convert levels into logarithmic values.

et al., 2009). However, similar to Arslan et al. (2015), we find that this result is not robust to the inclusion of rainfall measures. Additionally, we expect this result to be biased due to correlation between the decision to adopt and the error term.

Table 6 presents first stage results from the IV regression. For all four specifications our instrument is positive and significantly correlated with the choice to adopt CA. In Table 7 we present results similar to those in Table 5 but controlling for the endogeneity of CA. Our preferred specification is column (4) because it simultaneously controls for unobserved shocks through the IV and unobserved heterogeneity through household fixed effects. We find that CA, by itself, decreases yields on maize and provides no significant advantage over traditional cultivation practices for the other crops. Similar to the results in column (4) of Table 5, we find that rainfall deviations reduce yields on all crops.

While the lack of impact of CA on yields is discouraging, it is not the full story.[13] When we examine the interaction between CA and rainfall we find that CA increases yields in times of rainfall stress for maize and groundnut. For all crops, except sorghum, the coefficients on our instrumented variables are of a larger magnitude then the un-instrumented variables. Once we control for the endogeneity of the adoption decision, the coefficients on CA tend to be more negative while the coefficients on the interaction terms tend to be more positive. The bias generated from not controlling for the endogeneity of CA appears to underestimate the impact, either positive or negative, of CA on yields. Having controlled for the bias, we conclude that smallholder farmers in Zimbabwe who cultivate their crops using CA practices receive higher yields compared to conventional farmers but only in times of rainfall stress.

5.2 Alternative Rainfall Measures

While our main results provide evidence that CA cultivation during deviations from average rainfall helps mitigate crop loss, our measure of rainfall deviation is agnostic to whether or not the shock is from surplus rainfall or a shortage of rainfall. While proponents of CA claim that CA will have

[13]It is prudent to remember that in many cases the positive yield impacts of CA only appear after ten to fifteen years of CA cultivation (Giller et al., 2009, 2011). Given that our panel only covers four years, it may be that households have yet to reap the benefits of CA practices.

a positive impact on yields in both abnormally wet and abnormally dry conditions, there is reason to believe that CA may be more effective in one situation compared to the other, depending on the crop in question.

The first three columns in Table 8 present results from regressions which treat CA as endogenous and include household fixed effects. Column (1) shows results from the regression with the rainfall shock measured as a shortage as in equation (17). Column (2) replaces the rainfall shortage with a rainfall surplus as in equation (18). Column (3) uses both rainfall shortage and surplus measures. This last specification is our preferred one because it includes the full range of data and allows the impact of CA to vary based on the type of rainfall event and what crop is being cultivated.

Focusing on column (3), rainfall shortages have a negative and significant impact on yields for all crops, while rainfall surpluses have a negative and significant impact on yields for all crops, except groundnut. In average rainfall periods, the use of CA does not have a significant impact on any crop. Examining the interaction terms, the use of CA improves maize yields both when rainfall is above average and during times of drought. For sorghum and cowpea, CA improves yields during times of drought but not surplus rainfall. CA has no specific impact in mitigating losses from either surpluses or shortfalls of rain for millet and groundnut.

In summary, we find that during periods of average rainfall, CA typically has no impact on yields compared to traditional cultivation practices. Furthermore, the coefficient on CA is generally negative, suggesting that if CA has any impact on yields it is to reduce them compared to traditional cultivation methods. This is in marked contrast to much of the previous literature, which finds a positive correlation between CA and yields. We believe this difference is due to previous studies failing to control for the multiple sources of endogeneity in the CA adoption decision. Second, during seasons that experience above or below average rainfall, CA mitigates yield losses due to these deviations. Maize and groundnut yields are more resilient under CA.[14] Third, when we allow for rainfall shortages to impact yields differently from surplus rainfall we find that only maize yields

[14] We test the robustness of this conclusion by generating two new measures of rainfall shock. In the first we replace any deviation in rainfall that is within $\pm$ one standard deviation of the mean (0.476) with a zero. Thus, any realized value that is $0.202 \leq \mathrm{R}_{jt} \leq 0.749$ is set to zero. In the second we replace any deviation in rainfall that is within $\pm$ one half of a standard deviation of the mean (0.476) with a zero. Thus, any realized value that is $0.339 \leq \mathrm{R}_{jt} \leq 0.612$ is set to zero. These changes to our rainfall shock term do not have a material effect on our results. See Table A6 in the Appendix.

are consistently more resilient under CA than under traditional cultivation methods.[15] Where CA does not have a positive impact on yields in times of stress it has no impact at all. In none of our regressions do we find that CA reduces yields in times of rainfall stress when compared to traditional cultivation practices. Thus we conclude that while CA may not improve yields during average seasons, and may even decrease yields, production using CA practices is more resilient, especially for maize, when rainfall shocks occur.

5.3 Plot Level Controls

One potential concern with our previous results is that the choice to adopt CA may not be driven by unobserved household characteristics but instead by unobserved plot-level characteristics. Given that CA is promoted as a technology to halt and reverse land degradation, households may apply CA on plots where they know soil quality is poor. If this is the case, we would expect yields on CA plots to be systematically lower than yields on other plots. Alternatively, though the reasoning is less clear, households might apply CA on plots where they know soil quality is good.

Our panel covers only four seasons with households initially adopting CA in one to four years prior to data collection. Since it takes anywhere between ten and fifteen seasons for CA to significantly increase soil organic matter (Giller et al., 2009), we assume that plot characteristics, such as soil quality, are time-invariant in our data. We employ panel data methods to control for the correlation between the decision to adopt and unobserved plot characteristics. However, there might also be time-variant shocks that influence the decision to put a specific plot under CA instead of influencing the household-level decision to adopt. To control for potential time-invariant shocks we again use instrumental variables.

Columns (4) in Table 8 presents results from a regressions designed to control for different sources of plot-level endogeneity. We restrict the sample to plots that we observe more than once over the study period. This reduces our sample size to $5,004$ but allows us to directly control for unobserved heterogeneity at the plot-level. However, due to issues of collinearity we are unable to

[15] To check the robustness of this finding, we replace our first stage probit with the Mundlak-Chamberlain device with a first stage Tobit with fixed effects. Results are consistent regardless of how we specify the first stage adoption devision. See Tables A7 and A8 in the Appendix.

use plot-level fixed effects and instead implement the Mundlak-Chamberlain device in both the first and second stage regressions. We find that our results for all crops, when controlling for endogeneity at the household-level (column (3)), are robust in our plot-level endogenous CA regression. CA by itself has no impact on yields and CA continues to build resilience for maize, sorghum, and cowpea. Similar to our previous results, we find that CA has no specific impact in mitigating losses from either surplus or shortfalls of rain for millet and groundnut.

5.4 Returns to CA

To provide some intuition on the size of impact CA has on yields we calculate predicted returns to adoption at various levels of rainfall. Using the results in column (3) of Table 8, we multiply the coefficient on the CA-rainfall interaction terms by the realized values of the shortage or surplus. We then sum these values along with the coefficient on the CA-only term. We calculate predicted returns for each crop as well as for an average across crops.

Figure 6 graphs the returns to CA across the realized values of rainfall surpluses and shortages.[16] For maize, the returns to CA are positive only when rainfall is one standard deviation above the average. In seasons where cumulative rainfall is below one standard deviation, the returns to CA practices are negative. The returns to using CA to cultivate sorghum are positive for almost any shortage in rainfall while they are close to zero for above average rainfall. For millet, the returns to CA are rarely ever positive, though unlike sorghum, returns are positive when rainfall is well above average. The returns to CA cultivation of groundnut are near zero, regardless of rainfall. Finally, for cowpea, returns to CA are similar to sorghum, though the negative effect of CA is more pronounced.

Taking a weighted average across crops, where the weights are the number of observations for each crop in the data, we can describe the returns to CA for a typical smallholder household in the multi-cropping environment of Zimbabwe. Households would need to experience rainfall shortages greater than one and a half standard deviations away from the mean or rainfall surpluses greater than one standard deviation away from the mean before the returns to CA became positive.

[16] Vertical lines are drawn at ± half, one, one and a half, and two standard deviations from the mean value, which is 0.065.

During seasons where rainfall was within this range, the average returns to CA would be negative and households would be better off using traditional cultivation practices. Examining seasonal rainfall data from 1997 - 2015 across the 45 wards in our sample, 65 percent of seasons have fallen within this 'normal' range, making the returns to CA negative. Thirty-four percent of the time was rainfall either low enough or high enough that the returns to CA would have been positive. Overall, we find that the mean predicted returns to CA for the past 15 years would have been positive but that the median returns would have been negative. This is because in some wards, rainfall events are extremely variable so that the returns to CA would be positive half of the time, while in most wards rainfall is less variable, making returns to CA positive only about 20 percent of the time. We conclude that CA may not be an appropriate technology for all of Zimbabwe, or any region of Sub-Saharan Africa where rainfall is not highly variable. Rather, policy should target CA for households living in areas prone to frequent severe drought or flooding.

6 Conclusions and Policy Implications

Conservation Agriculture has been widely promoted as a way for smallholder farmers in Sub-Saharan Africa to increase yields while also making yields more resilient to changing climate conditions. Using four years of panel data from Zimbabwe, we find evidence that contradicts the first claim but supports the later claim. We estimate a large compliment of yield functions that include rainfall shocks, household fixed effects, and controls for the endogeneity of the choice to adopt CA practices. In all these cases we find that, where CA has a significant impact on yields, it is always to reduce yields compared to traditional cultivation practices during periods of average rainfall. When we consider yields during rainfall shocks, we find that yields tend to be more resilient under CA cultivation then under traditional cultivation practices. Overall, returns to CA are only positive for those households that experience high variability in rainfall patterns. We conclude that previous econometric analysis that found a positive correlation between CA and yields was most likely due to a failure to control for unobserved heterogeneity among households and selection bias in the choice to adopt CA. This conclusion comes with the caveat that our data covers only four years. In the long run, CA may indeed have a positive impact on yield. To our knowledge, no long run observational data set exists on which this hypothesis can be tested.

Two policy recommendations can be drawn from our analysis. First, our results help address the empirical puzzle of low CA adoption rates in Sub-Saharan Africa. We find that, over the four year study period, CA had either a negative impact or no impact at all on yields during periods of average rainfall. Smallholder farmers tend to be risk averse, and CA is often associated with increased labor demand and the need for purchased fertilizer inputs. Given that returns to CA can be negative, especially for maize, it makes sense that smallholders have been hesitant to undertake the added risk and cost of CA practices. We find no evidence at the plot-level that CA is associated with yield increases and therefore conclude that households' decision to not adopt, or dis-adopt as in the case of Zimbabwe, is most likely rational in the short term. Policy to promote CA among smallholders should acknowledge this point and take steps to manage expectations regarding the short term and long term benefits of CA.

Second, CA can be effective in mitigating yield loss in environments with increased weather risk. Climate change threatens to disrupt normal rainfall patterns by reducing the duration and frequency of rainfall (prolonged droughts) but also by increasing the intensity of rainfall. We find that in both cases (abnormally high and abnormally low rainfall) yields are often more resilient under CA then under traditional cultivation. This insight provides a way forward for the promotion of CA practices among smallholders. Policy should be designed to focus on CA's potential benefits in mitigating risk due to changing rainfall patterns.

We conclude that CA is indeed an example of 'climate smart' agriculture to the extent that a changing climate will result in more abnormal rainfall patterns and CA appears effective in mitigating yield loss due to deviations in rainfall. Such a conclusion does not imply that CA is a sustainable approach to agriculture for all farmers, or even for most farmers, living in Sub-Saharan Africa. This is because in periods of normal rainfall the returns to CA are negative, at least in the short run. In order to test the long term benefits of CA on yields through improved soil fertility, future research should focus on establishing long run observational datasets on CA practices. The challenge here is to convince enough farmers to consistently adopt costly agricultural practices that may in the short term cost them, absent the realization of extreme rainfall events.

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Table 1: Descriptive Statistics by Crop

	Maize	Sorghum	Millet	Groundnut	Cowpea	Total
Yield (kg/ha)	1,217	827.7	641.0	1,065	662.4	1,040
	(1,366)	(1,137)	(946.7)	(1,251)	(1,137)	(1,284)
CA (= 1)	0.350	0.263	0.137	0.193	0.313	0.290
	(0.477)	(0.440)	(0.345)	(0.395)	(0.464)	(0.454)
Basal applied fertilizer (kg)	13.41	2.281	0.923	1.429	3.457	7.716
	(30.39)	(10.35)	(5.952)	(7.653)	(12.19)	(23.21)
Top applied fertilizer (kg)	17.58	3.366	1.636	1.843	4.112	10.16
	(32.56)	(10.69)	(8.786)	(9.264)	(13.11)	(25.32)
Seed (kg)	8.143	4.896	5.974	10.96	3.099	7.543
	(9.169)	(6.460)	(11.40)	(14.80)	(4.047)	(10.20)
Area (m^2)	3,466	3,225	3,978	2,060	1,553	3,035
	(3,782)	(3,697)	(4,138)	(2,100)	(1,894)	(3,486)
Rainfall shock	0.469	0.482	0.551	0.469	0.463	0.476
	(0.274)	(0.267)	(0.301)	(0.273)	(0.258)	(0.274)
HH in ward with NGO support	20.62	22.01	24.75	21.77	23.29	21.56
	(13.09)	(15.51)	(17.62)	(14.12)	(15.15)	(14.25)
number of observations	3,827	1,264	488	1,397	667	7,643
number of plots	2,643	1,007	405	1,220	615	4,171
number of households	715	415	177	598	388	728
number of wards	45	41	26	45	43	45

Note: The first five columns of the table display means of the data by crop with standard deviations in parenthesis. The final column displays means and standard deviations for the pooled data.

Table 2: Descriptive Statistics by Year

	2008	2009	2010	2011
Yield (kg/ha)	760.6	1,278	1,151	936.0
	(1,210)	(1,355)	(1,415)	(1,094)
CA (= 1)	0.435	0.385	0.247	0.170
	(0.496)	(0.487)	(0.431)	(0.376)
Basal applied fertilizer (kg)	7.044	3.898	4.335	14.00
	(20.92)	(14.73)	(15.26)	(32.48)
Top applied fertilizer (kg)	8.679	6.776	7.331	16.14
	(20.16)	(16.82)	(20.15)	(34.80)
Seed (kg)	7.961	6.399	7.133	8.499
	(10.02)	(7.737)	(12.29)	(9.729)
Area planted (m^2)	3,473	2,870	2,891	3,015
	(4,172)	(3,896)	(3,348)	(2,714)
Rainfall shock	0.682	0.487	0.351	0.453
	(0.289)	(0.267)	(0.225)	(0.231)
HH in ward with NGO support	27.87	18.00	21.63	20.21
	(19.20)	(10.38)	(13.34)	(12.58)
number of observations	1,452	1,732	2,116	2,343
number of plots	1,403	1,677	2,015	2,312
number of households	388	401	432	584
number of wards	29	30	31	43

Note: Columns in the table display means of the data by year with standard deviations in parenthesis.

Table 3: Descriptive Statistics by Crop and Cultivation Method

	Maize			Sorghum			Millet			Groundnut			Cowpea		
	TC	CA	MW-test	TC	CA	MW-test	TC	CA	MW-test	TC	CA	MW-test	TC	CA	MW-test
Yield(kg/ha)	932.6	1,745	***	736.8	1,082	***	627.7	724.1	**	978.4	1,428	***	626.5	740.9	***
	(1,127)	(1,595)		(1,073)	(1,267)		(979.8)	(703.2)		(1,117)	(1,665)		(1,153)	(1,101)	
Basal applied fertilizer (kg)	11.46	17.03	***	1.149	5.457	***	0.705	2.291	***	0.547	5.106	***	1.417	7.925	***
	(31.01)	(28.86)		(8.582)	(13.73)		(6.151)	(4.284)		(4.424)	(14.32)		(7.236)	(18.22)	
Top applied fertilizer (kg)	15.11	22.18	***	0.996	10.01	***	0.724	7.365	***	0.591	7.065	***	1.298	10.27	***
	(32.24)	(32.65)		(4.346)	(17.96)		(5.712)	(17.98)		(4.137)	(18.43)		(6.539)	(20.01)	
Seed planted (kg)	9.287	6.021	***	5.206	4.023	***	6.477	2.812	***	12.38	5.027	***	2.957	3.408	***
	(10.61)	(4.931)		(5.776)	(8.023)		(12.15)	(2.750)		(16.01)	(4.570)		(4.432)	(3.023	
Area planted (m^2)	3,988	2,496	***	3,809	1,582	***	4,465	915.1	***	2,260	1,223	***	1,782	1,051	***
	(4,299)	(2,257)		(4,038)	(1,619)		(4,227)	(1,249)		(2,191)	(1,386)		(2,119)	(1,116)	
Rainfall shock	0.465	0.473		0.473	0.503		0.547	0.568		0.455	0.527	***	0.466	0.453	
	(0.273)	(0.275)		(0.262)	(0.275)		(0.309)	(0.241)		(0.266)	(0.293)		(0.260)	(0.252)	
HH in ward with NGO support	19.50	22.68	***	21.23	24.18	**	23.26	34.13	***	20.41	27.40	***	21.54	27.11	***
	(12.85)	(13.26)		(14.69)	(17.42)		(17.01)	(18.52)		(13.32)	(15.88)		(14.31)	(16.21)	
number of observations	2,486	1,341		932	332		421	67		1,127	270		458	209	
number of plots	2,001	966		792	277		357	58		1,015	254		437	198	
number of households	670	537		369	206		168	44		562	188		306	153	
number of wards	45	44		40	30		26	10		45	24		43	30	

Note: Columns in the table display means of the data by crop with standard deviations in parenthesis. Columns headed TC are output and inputs used under traditional cultivation practices while columns headed CA are output and inputs used under conservation agriculture. The final column for each crop presents the results of Mann-Whitney two-sample tests for differences in distribution. Results are similar if a Kolmogorov-Smirnov test is used. Significance of MW-tests are reported as $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 4: Input Change Over Time Conditional on Ward

	2008			2011		
	Always adopter	Future dis-adopter	MW-test	Always adopter	Future dis-adopter	MW-test
ln(Yield) (kg/ha)	0.469	0.386		0.512	-0.028	***
	(1.190)	(1.270)		(0.939)	(1.113)	
ln(Seed) (kg/ha)	0.089	0.206	*	0.029	-0.054	*
	(0.802)	(0.883)		(0.717)	(0.674)	
ln(Basal fertilizer) (kg/ha)	0.122	0.009		0.188	-0.312	***
	(0.799)	(0.851)		(0.912)	(0.835)	
ln(Top fertilizer) (kg/ha)	0.201	0.052		0.363	-0.242	***
	(0.846)	(0.857)		(0.974)	(0.940)	
Observations	162	299		86	346	

	Never adopter	Future adopter	MW-test	Never adopter	Future adopter	MW-test
ln(Yield) (kg/ha)	-0.394	-0.239		-0.154	0.455	***
	(1.281)	(1.366)		(1.188)	(1.064)	
ln(Seed) (kg/ha)	-0.172	-0.001		0.012	0.132	*
	(0.944)	(0.831)		(0.769)	(0.857)	
ln(Basal fertilizer) (kg/ha)	-0.298	0.054		-0.127	0.125	
	(1.198)	(0.597)		(0.813)	(1.109)	
ln(Top fertilizer) (kg/ha)	-0.415	0.068	**	-0.190	0.285	***
	(1.057)	(0.778)		(0.873)	(1.157)	
Observations	446	84		656	75	

Note: Table displays the mean residuals of inputs by adoption type and year. Residuals are calculated from a regression of the input variable on ward indicators. In the upper panel, "Always adopters" are those who in every year adopt CA. They are compared to "Future dis-adopters," those households who adopt CA in 2008 but dis-adopt subsequent years. In the lower panel, "Never adopters" are those who in every year do not adopt CA. They are compared to "Future adopters," those households who do not adopt in 2008 but adopt in subsequent years. The final column for each year presents the results of Mann-Whitney two-sample tests for differences in distribution. Results are similar if a Kolmogorov-Smirnov test is used. Significance of MW-tests are reported as *p<0.1; **p<0.05; ***p<0.01.

Table 5: Yield Function with CA as Exogenous

	(1)	(2)	(3)	(4)
Maize				
CA (= 1)	0.631***	0.573***	0.222	0.207
	(0.081)	(0.081)	(0.139)	(0.137)
rainfall shock			−0.667***	−0.904***
			(0.215)	(0.227)
CA × rainfall shock			0.872***	0.744***
			(0.247)	(0.237)
Sorghum				
CA (= 1)	0.041	−0.051	−0.756***	−0.596**
	(0.180)	(0.190)	(0.271)	(0.288)
rainfall shock			−1.285***	−1.432***
			(0.303)	(0.317)
CA × rainfall shock			1.652***	1.130**
			(0.458)	(0.499)
Millet				
CA (= 1)	−0.145	0.118	−0.994	−0.711
	(0.359)	(0.374)	(0.709)	(0.736)
rainfall shock			−1.094***	−1.521***
			(0.306)	(0.319)
CA × rainfall shock			1.492	1.475
			(0.940)	(1.171)
Groundnut				
CA (= 1)	0.299**	0.323**	−0.326	0.130
	(0.142)	(0.144)	(0.287)	(0.279)
rainfall shock			−0.403*	−0.489**
			(0.208)	(0.228)
CA × rainfall shock			1.106**	0.331
			(0.493)	(0.456)
Cowpea				
CA (= 1)	−0.035	0.194	−0.844*	−0.362
	(0.241)	(0.250)	(0.466)	(0.460)
rainfall shock			−1.053**	−1.216***
			(0.452)	(0.448)
CA × rainfall shock			1.688*	1.114
			(0.905)	(0.878)
Household FE	No	Yes	No	Yes
Observations	7,643	7,643	7,643	7,643
R^2	0.899	0.922	0.900	0.923

Note: Dependent variable is log of yield. Though not reported, all specifications include crop-specific inputs and intercept terms, and year dummies. See Table A2 in the Appendix for coefficient estimates of crop-specific inputs. Column (1) excludes the rainfall variable as well as household fixed effects. Column (2) excludes the rainfall variable but includes household fixed effects. Column (3) includes the rainfall variable and its interaction with CA but excludes household fixed effects. Column (4) includes both the rainfall variable, its interaction with CA, and household fixed effects. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table 6: First Stage IV Probit

	(1)	(2)	(3)	(4)
HH in ward with NGO support	0.010***	0.009***	0.010***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Household MCD	No	Yes	No	Yes
Observations	7,643	7,643	7,643	7,643
Log Likelihood	-3,153	-3,110	-3,143	-3,100

Note: Dependent variable is an indicator for whether or not CA was used on the plot. Regressions are probits that include the IV, the rainfall variable, crop-specific inputs and intercept terms, and year dummies. The instrument is the number of households in the ward that receive NGO support. Column (1) excludes the rainfall variable as well as the Mundlak-Chamberlain device (MCD). Column (2) excludes the rainfall variable but includes the MCD. Column (3) includes the rainfall variable and its interaction with CA but excludes the MCD. Column (4) includes both the rainfall variable, its interaction with CA, and the MCD. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table 7: Yield Function with CA as Endogenous

	(1)	(2)	(3)	(4)
Maize				
CA (= 1)	13.404	−1.939*	15.697	−2.853**
	(10.916)	(1.122)	(18.025)	(1.141)
rainfall shock			0.569	−1.675***
			(2.198)	(0.353)
CA × rainfall shock			1.335	2.628***
			(2.896)	(0.704)
Sorghum				
CA (= 1)	19.230	−0.275	24.937	−0.171
	(13.886)	(1.498)	(24.052)	(1.603)
rainfall shock			−0.940	−1.476***
			(0.823)	(0.353)
CA × rainfall shock			−2.555	0.899
			(4.717)	(0.904)
Millet				
CA (= 1)	32.388	−4.551	49.502	−3.784
	(30.713)	(3.402)	(64.115)	(3.808)
rainfall shock			0.654	−1.715***
			(2.163)	(0.341)
CA × rainfall shock			−12.938	3.357
			(30.199)	(2.279)
Groundnut				
CA (= 1)	14.997	0.050	16.999	−0.272
	(10.282)	(1.199)	(16.357)	(1.324)
rainfall shock			−1.659*	−0.950***
			(0.886)	(0.265)
CA × rainfall shock			2.423	1.433*
			(2.895)	(0.832)
Cowpea				
CA (= 1)	10.530	−0.938	12.451	−1.564
	(8.312)	(1.147)	(14.121)	(1.349)
rainfall shock			−0.061	−1.606***
			(1.643)	(0.485)
CA × rainfall shock			0.775	2.123
			(3.789)	(1.404)
Household FE	No	Yes	No	Yes
Kleibergen-Paap LM	1.773	26.89***	1.028	33.86***
Observations	7,643	7,643	7,643	7,643
Log Likelihood	-24,462	-16,378	-25,914	-16,192

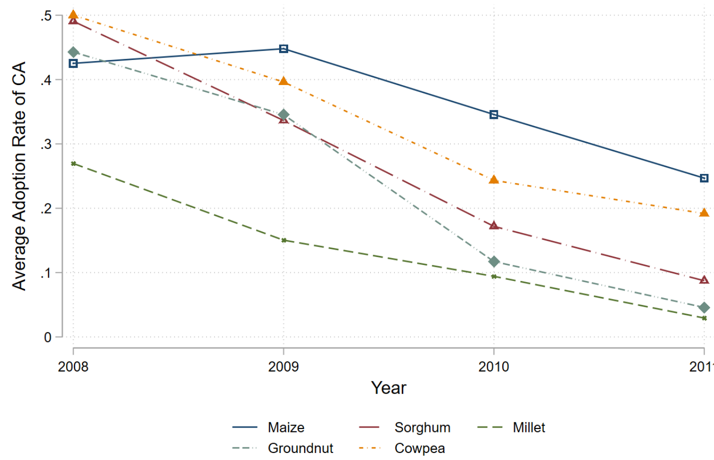
Note: Dependent variable is log of yield. Though not reported, all specifications include crop-specific inputs and intercept terms, and year dummies. See Table A3 in the Appendix for coefficient estimates of crop-specific inputs. In each regression the adoption of CA is treated as endogenous and is instrumented with the Inverse Mills Ratio (IMR) calculated from the predicted values of the first stage regressions reported in Table 6. The CA × rainfall shock term is also treated as endogenous and instrumented using the interaction of the IMR and the rainfall shock term. The underindentification test uses the Kleibergen-Paap LM statistic. Column (1) excludes the rainfall variable as well as household fixed effects. Column (2) excludes the rainfall variable but includes household fixed effects. Column (3) includes the rainfall variable and its interaction with CA but excludes household fixed effects. Column (4) includes both the rainfall variable, its interaction with CA, and household fixed effects. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table 8: Yield Function with Rain Shortage or Surplus

	(1)	(2)	(3)	(4)
Maize				
CA (= 1)	−0.466	−2.657*	−1.893	3.393
	(1.379)	(1.378)	(1.472)	(3.156)
rainfall shortage	0.089		−1.076**	−1.411**
	(0.400)		(0.481)	(0.695)
CA × rainfall shortage	0.147		2.098**	3.522**
	(0.744)		(0.987)	(1.597)
rainfall surplus		−1.619***	−1.884***	−0.444
		(0.304)	(0.358)	(0.637)
CA × rainfall surplus		2.012***	2.931***	1.953**
		(0.513)	(0.657)	(0.845)
Sorghum				
CA (= 1)	−0.262	−1.211	−0.512	5.808
	(1.464)	(2.042)	(1.780)	(4.791)
rainfall shortage	−1.079***		−1.702***	−2.235***
	(0.389)		(0.454)	(0.769)
CA × rainfall shortage	2.437*		2.356*	3.654*
	(1.263)		(1.326)	(1.977)
rainfall surplus		−0.550	−1.214***	−0.531
		(0.342)	(0.377)	(0.533)
CA × rainfall surplus		−0.369	0.464	−0.144
		(1.008)	(0.987)	(1.507)
Millet				
CA (= 1)	−2.913	−3.914	−2.671	12.779
	(2.890)	(3.404)	(3.293)	(12.606)
rainfall shortage	−0.508		−1.604**	−1.438
	(0.610)		(0.658)	(0.927)
CA × rainfall shortage	−0.136		1.930	−4.318
	(1.576)		(2.344)	(8.524)
rainfall surplus		−1.287***	−1.689***	−0.427
		(0.356)	(0.320)	(0.584)
CA × rainfall surplus		2.726*	3.170	−0.775
		(1.548)	(2.202)	(7.605)
Groundnut				
CA (= 1)	0.359	−1.519	−0.266	4.764
	(1.159)	(1.550)	(1.499)	(3.664)
rainfall shortage	−1.125***		−1.229***	−2.298**
	(0.318)		(0.338)	(0.934)
CA × rainfall shortage	0.240		0.405	1.499
	(0.772)		(0.984)	(1.570)
rainfall surplus		0.036	−0.170	0.506
		(0.297)	(0.281)	(0.465)
CA × rainfall surplus		0.056	−0.205	−0.607
		(0.899)	(0.985)	(1.422)
Cowpea				
CA (= 1)	−0.742	−0.929	−1.188	1.829
	(1.141)	(1.415)	(1.439)	(3.818)
rainfall shortage	−0.628		−1.493***	−2.468**
	(0.477)		(0.553)	(1.221)
CA × rainfall shortage	3.171***		3.763***	6.006**
	(1.008)		(1.272)	(2.558)
rainfall surplus		−1.103**	−1.492***	−0.970
		(0.482)	(0.557)	(1.002)
CA × rainfall surplus		−0.286	1.234	3.148
		(1.309)	(1.624)	(2.543)
Type of Effect	Household FE	Household FE	Household FE	Plot MCD
Observations	7,643	7,643	7,643	5,004
Kleibergen-Paap LM	22.96***	23.02***	25.23***	3.790*
Log Likelihood	-15,908	-16,406	-15,902	-12,268

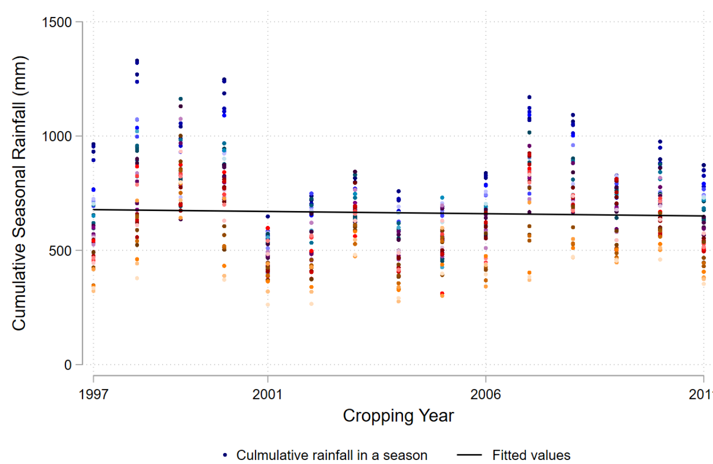
Note: Dependent variable is log of yield. Though not reported, all specifications include crop-specific inputs and intercept terms, and year dummies. See Table A5 in the Appendix for coefficient estimates of crop-specific inputs. In each regression the adoption of CA is treated as endogenous and is instrumented with the Inverse Mills Ratio (IMR) calculated from the predicted values of first stage regressions which are presented in the Appendix, Table A4. The CA × rainfall shortage and CA × rainfall surplus terms are also treated as endogenous and instrumented using the interaction of the IMR and the rainfall terms. The underindentification test uses the Kleibergen-Paap LM statistic. Column (1) includes a rainfall shortage and its interaction with the instrumented CA term. Column (2) includes a rainfall surplus and its interaction with the instrumented CA term. Column (3) includes both a rainfall shortage and a rainfall surplus and their interactions with the instrumented CA term. Column (4) restricts the sample to plots with more than one observation and where CA is either always used or never used. It presents results that include a plot-level Mundlak-Chamberlain device (MCD) where CA is treated as endogenous and is instrumented as described previously. Standard errors in columns (1) - (3) are clustered by household and crop while standard errors in column (4) are clustered at the plot-level. All standard errors are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Figure 1: Average Annual Level of CA Adoption by Crop



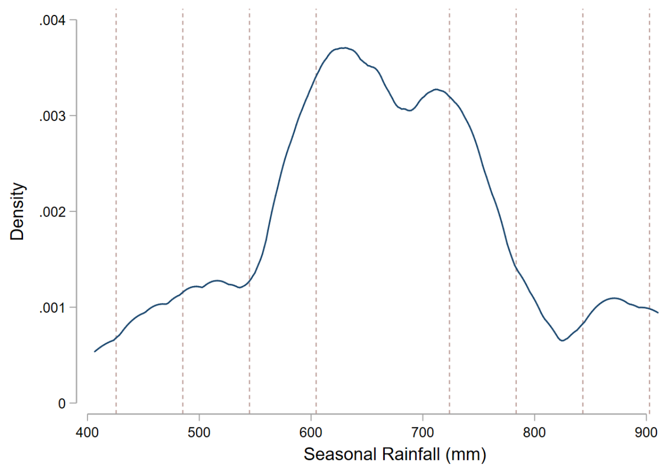
Note: Figure displays the average number of plots on which CA techniques are used by crop per year.

Figure 2: Historic Seasonal Rainfall by Ward



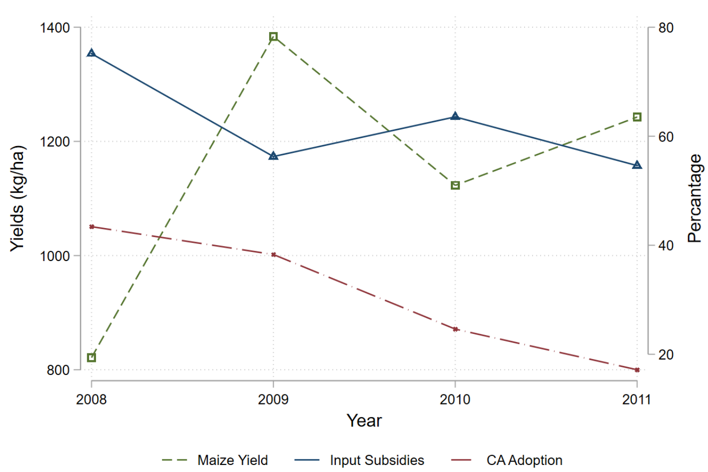
Note: Figure displays the cumulative rainfall for each cropping season in each ward for the 15 year period from 1997-2011. A linear trendline is fitted to the data with a slope of -3.71 which is significantly different from zero at the 99 percent level. Data comes from the CHIRPS database (Funk et al., 2015).

Figure 3: Distribution of Seasonal Rainfall by Ward



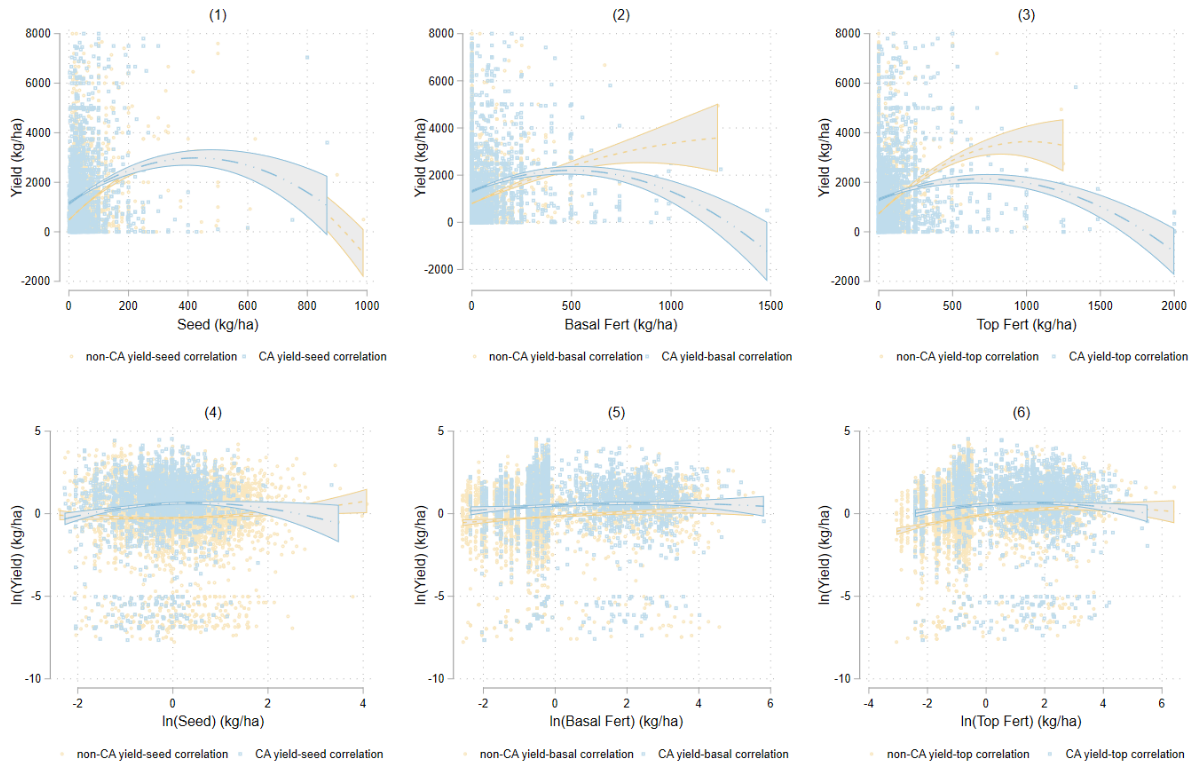
Note: Figure displays the kernel density of cumulative seasonal rainfall in each ward for the four year study period (2008-2011). Vertical lines are drawn at ± half, one, one half, and two standard deviations from the mean, which is 664mm. Data comes from the CHIRPS database (Funk et al., 2015).

Figure 4: Maize Yields, Rates of CA Adoption, and Input Subsidies



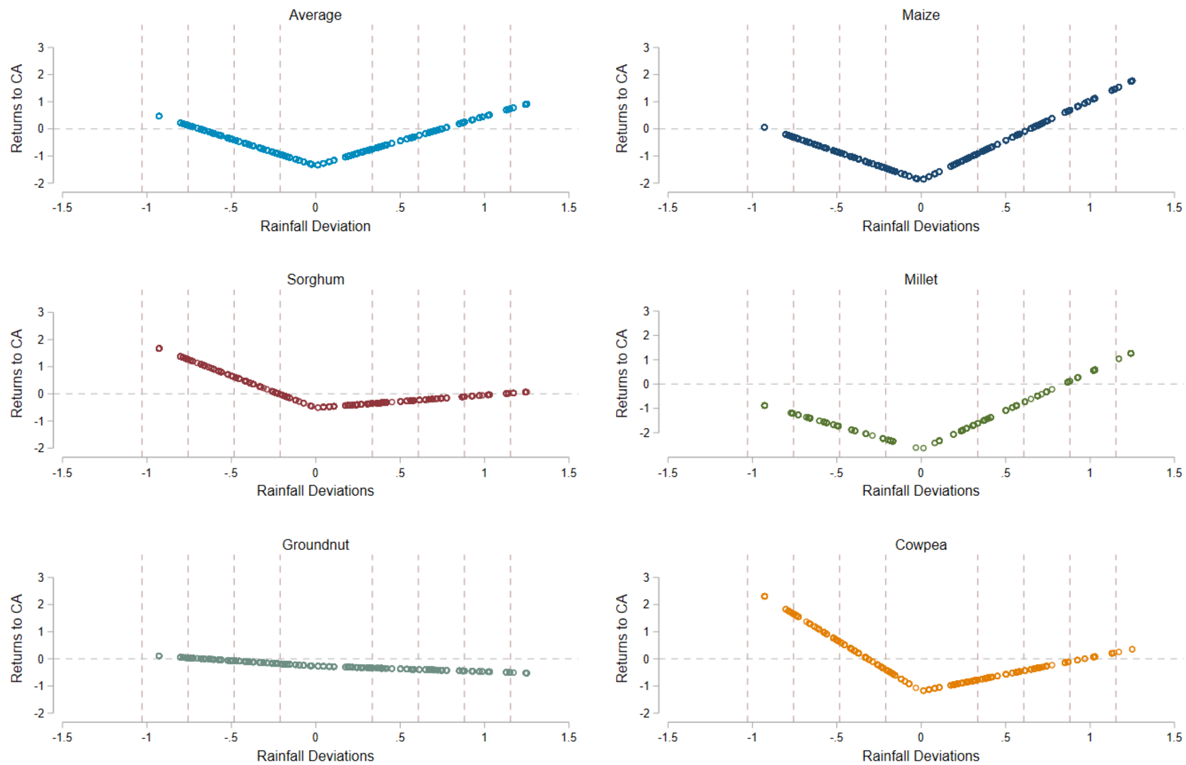
Note: Figure displays average maize yield on the left axis. On the right axis is the average rate of CA adoption at the plot-level along with the average percentage of households receiving input subsidies within a ward.

Figure 5: Yield Response to Inputs by CA Adoption



Note: Graphs in the top row display scatter plots of the correlation between yields and inputs (seeds, basal applied fertilizer, and top applied fertilizer). Graphs in the bottom row display scatter plots using residuals from a regression of output and inputs on ward indicators. Added to the scatter plots are quadratic lines of best fit with 90% confidence intervals. Across all four graphs, yellow represents data from conventional plots while blue represents data from CA plots. Note that all zeros in the data have been removed.

Figure 6: Predicted Returns to CA by Crop



Note: Figure displays the predicted returns to CA averaged over all crops and also by crop. Returns are calculated using the coefficients from column (3) in Table 8. By crop, we multiple the coefficient on the CA × rainfall shortage by realized shortages and multiple the coefficient on the CA × rainfall surplus by realized surpluses. We then sum these values along with the coefficient on the CA term. For the average return we take a weighted average of the crop specific returns where the weights are the number of observations for each crop in the data. The x-axis marks the realizations of rainfall surpluses and shortages where shortages are the to left of zero. Dots represent individual predicted returns where a lower density of dots represents fewer observations, and thus less confidence. Vertical lines are drawn at ± half, one, one half, and two standard deviations from the mean, which is 0.062.

A Appendix For Online Publication: Full Results from Yield Functions

This appendix contains evidence on the impact of seasonal versus monthly rainfall deviations on yields. It also contains full specifications and first stage regression results for the models presented in an abbreviated form in the paper. In all specifications we include controls for crop-specific inputs. These inputs include logged amounts of basal fertilizer application, top application of fertilizer, seeds, and land area. Since our primary focus is the impact of CA and rainfall shocks on yields, we treated these variables as exogenous controls and refrained from reporting the relevant point estimates in the paper. For those interested in the full specifications, the following tables will be of interest.

Table A1: Yield Function with Rainfall Deviations

	Maize (1)	Sorghum (2)	Millet (3)	Groundnut (4)	Cowpea (5)
Panel A: Deviation in Seasonal Rainfall					
Seasonal deviation	−0.631***	−1.125***	−1.389***	−0.407*	−0.913**
	(0.192)	(0.269)	(0.312)	(0.212)	(0.399)
Panel B: Deviation in Monthly Rainfall					
Oct deviation	0.324*	−0.262	0.023	0.534***	0.129
	(0.196)	(0.212)	(0.302)	(0.199)	(0.314)
Nov deviation	−0.213*	−0.056	−0.076	0.154	−0.028
	(0.111)	(0.176)	(0.194)	(0.127)	(0.238)
Dec deviation	−0.199*	−0.122	−0.535*	0.226*	0.338
	(0.114)	(0.222)	(0.309)	(0.136)	(0.265)
Jan deviation	−0.571***	0.119	−0.267	0.251	0.418*
	(0.167)	(0.176)	(0.261)	(0.153)	(0.235)
Feb deviation	−1.054***	−0.320	−0.254	−0.683***	−2.011***
	(0.213)	(0.274)	(0.358)	(0.259)	(0.443)
Mar deviation	−1.001***	−0.701**	−0.587	−0.764***	0.112
	(0.187)	(0.322)	(0.506)	(0.242)	(0.386)
Apr deviation	−0.295***	0.104	−0.372***	−0.154	−0.015
	(0.092)	(0.108)	(0.140)	(0.105)	(0.155)

Note: Coefficients are presented in columns based on crop type in order to minimize space. Panel A reports results from a single regression with log yield as the dependent variable and deviations in cumulative seasonal rainfall as the variable of interest (Observations = $7,643$; $R^2 = 0.923$). Panel B reports results from a single regression with log yield as the dependent variable and deviations in cumulative monthly rainfall as the variables of interest (Observations = $7,643$; $R^2 = 0.926$). Though not reported, both specifications include crop-specific CA adoption term, crop-specific inputs, crop-specific intercept terms, year dummies, and household fixed effects. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A2: Yield Function with CA as Exogenous

	(1)	(2)	(3)	(4)
Maize				
CA (= 1)	0.631***	0.573***	0.222	0.207
	(0.081)	(0.081)	(0.139)	(0.137)
rainfall shock			−0.667***	−0.904***
			(0.215)	(0.227)
CA × rainfall shock			0.872***	0.744***
			(0.247)	(0.237)
ln(basal)	0.118***	0.079***	0.120***	0.085***
	(0.025)	(0.024)	(0.025)	(0.023)
ln(top)	0.321***	0.270***	0.312***	0.261***
	(0.028)	(0.026)	(0.028)	(0.025)
ln(seed)	0.250***	0.248***	0.236***	0.233***
	(0.075)	(0.074)	(0.075)	(0.073)
ln(area)	−0.449***	−0.496***	−0.442***	−0.483***
	(0.061)	(0.064)	(0.061)	(0.063)
Sorghum				
CA (= 1)	0.041	−0.051	−0.756***	−0.596**
	(0.180)	(0.190)	(0.271)	(0.288)
rainfall shock			−1.285***	−1.432***
			(0.303)	(0.317)
CA × rainfall shock			1.652***	1.130**
			(0.458)	(0.499)
ln(basal)	0.038	0.015	0.037	0.020
	(0.089)	(0.070)	(0.091)	(0.070)
ln(top)	0.107	0.130**	0.106	0.124**
	(0.066)	(0.060)	(0.065)	(0.059)
ln(seed)	0.395***	0.428***	0.396***	0.426***
	(0.112)	(0.119)	(0.111)	(0.118)
ln(area)	−0.527***	−0.560***	−0.500***	−0.530***
	(0.085)	(0.098)	(0.085)	(0.098)
Millet				
CA (= 1)	−0.145	0.118	−0.994	−0.711
	(0.359)	(0.374)	(0.709)	(0.736)
rainfall shock			−1.094***	−1.521***
			(0.306)	(0.319)
CA × rainfall shock			1.492	1.475
			(0.940)	(1.171)
ln(basal)	0.230**	0.180	0.191*	0.136
	(0.105)	(0.127)	(0.102)	(0.127)
ln(top)	−0.233*	−0.126	−0.216*	−0.109
	(0.123)	(0.130)	(0.122)	(0.125)
ln(seed)	0.221	0.264*	0.258*	0.298**
	(0.156)	(0.148)	(0.153)	(0.144)
ln(area)	−0.451***	−0.584***	−0.465***	−0.601***
	(0.135)	(0.129)	(0.134)	(0.127)
Groundnut				
CA (= 1)	0.299**	0.323**	−0.326	0.130
	(0.142)	(0.144)	(0.287)	(0.279)
rainfall shock			−0.403*	−0.489**
			(0.208)	(0.228)
CA × rainfall shock			1.106**	0.331
			(0.493)	(0.456)
ln(basal)	0.075	−0.007	0.081	−0.008
	(0.076)	(0.067)	(0.075)	(0.067)
ln(top)	−0.085	−0.039	−0.052	−0.030
	(0.076)	(0.065)	(0.075)	(0.066)
ln(seed)	0.560***	0.470***	0.558***	0.470***
	(0.076)	(0.076)	(0.076)	(0.076)
ln(area)	−0.490***	−0.614***	−0.487***	−0.608***
	(0.077)	(0.074)	(0.077)	(0.074)

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Table A2 – Continued

	(1)	(2)	(3)	(4)
Cowpea				
CA (= 1)	−0.035	0.194	−0.844*	−0.362
	(0.241)	(0.250)	(0.466)	(0.460)
rainfall shock			−1.053**	−1.216***
			(0.452)	(0.448)
CA × rainfall shock			1.688*	1.114
			(0.905)	(0.878)
ln(basal)	0.306***	0.106	0.298***	0.108
	(0.112)	(0.095)	(0.112)	(0.095)
ln(top)	−0.134	−0.085	−0.127	−0.082
	(0.112)	(0.099)	(0.115)	(0.102)
ln(seed)	0.440***	0.385**	0.459***	0.395**
	(0.164)	(0.163)	(0.165)	(0.163)
ln(area)	−0.541***	−0.652***	−0.550***	−0.660***
	(0.108)	(0.114)	(0.109)	(0.115)
Household FE	No	Yes	No	Yes
Observations	7,643	7,643	7,643	7,643
R^2	0.899	0.922	0.900	0.923

Note: Dependent variable is log of yield. All specifications include crop-specific intercept terms and year dummies. Column (1) excludes rainfall variables as well as household fixed effects. Column (2) excludes rainfall variables but includes household fixed effects. Column (3) includes the rainfall shock and its interaction with CA but excludes household fixed effects. Column (4) includes both the rainfall shock, its interaction with CA, and household fixed effects. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A3: Yield Function with CA as Endogenous

	(1)	(2)	(3)	(4)
Maize				
CA (= 1)	13.404	−1.939*	15.697	−2.853**
	(10.916)	(1.122)	(18.025)	(1.141)
rainfall shock			0.569	−1.675***
			(2.198)	(0.353)
CA × rainfall shock			1.335	2.628***
			(2.896)	(0.704)
ln(basal)	−0.632	0.219***	−0.789	0.219***
	(0.639)	(0.069)	(0.993)	(0.063)
ln(top)	−0.283	0.404***	−0.433	0.360***
	(0.527)	(0.065)	(0.795)	(0.057)
ln(seed)	1.819	−0.052	2.189	−0.017
	(1.347)	(0.164)	(2.105)	(0.150)
ln(area)	−0.006	−0.608***	0.101	−0.568***
	(0.429)	(0.090)	(0.630)	(0.082)
Sorghum				
CA (= 1)	19.230	−0.275	24.937	−0.171
	(13.886)	(1.498)	(24.052)	(1.603)
rainfall shock			−0.940	−1.476***
			(0.823)	(0.353)
CA × rainfall shock			−2.555	0.899
			(4.717)	(0.904)
ln(basal)	−0.840	0.043	−0.978	0.023
	(0.678)	(0.106)	(1.006)	(0.096)
ln(top)	−3.028	0.150	−3.788	0.060
	(2.260)	(0.236)	(3.640)	(0.220)
ln(seed)	0.246	0.395***	0.236	0.400***
	(0.317)	(0.113)	(0.387)	(0.113)
ln(area)	1.480	−0.551***	1.936	−0.467***
	(1.453)	(0.180)	(2.290)	(0.166)
Millet				
CA (= 1)	32.388	−4.551	49.502	−3.784
	(30.713)	(3.402)	(64.115)	(3.808)
rainfall shock			0.654	−1.715***
			(2.163)	(0.341)
CA × rainfall shock			−12.938	3.357
			(30.199)	(2.279)
ln(basal)	−1.721	0.453*	−2.112	0.228
	(2.080)	(0.237)	(2.943)	(0.196)
ln(top)	−4.778	0.547	−6.297	0.209
	(4.456)	(0.530)	(7.398)	(0.482)
ln(seed)	−1.215	0.424*	−1.737	0.371*
	(1.547)	(0.225)	(2.612)	(0.198)
ln(area)	3.501	−1.163***	4.771	−0.858**
	(3.877)	(0.437)	(6.379)	(0.402)
Groundnut				
CA (= 1)	14.997	0.050	16.999	−0.272
	(10.282)	(1.199)	(16.357)	(1.324)
rainfall shock			−1.659*	−0.950***
			(0.886)	(0.265)
CA × rainfall shock			2.423	1.433*
			(2.895)	(0.832)
ln(basal)	−1.137	0.001	−1.370	−0.036
	(0.893)	(0.114)	(1.369)	(0.106)
ln(top)	−1.966	−0.008	−2.362	−0.031
	(1.336)	(0.159)	(2.133)	(0.158)
ln(seed)	1.090***	0.566***	1.197**	0.561***
	(0.398)	(0.084)	(0.591)	(0.086)
ln(area)	0.405	−0.654***	0.603	−0.610***
	(0.676)	(0.103)	(1.040)	(0.096)

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Table A3 – Continued

	(1)	(2)	(3)	(4)
Cowpea				
CA (= 1)	10.530	−0.938	12.451	−1.564
	(8.312)	(1.147)	(14.121)	(1.349)
rainfall shock			−0.061	−1.606***
			(1.643)	(0.485)
CA × rainfall shock			0.775	2.123
			(3.789)	(1.404)
ln(basal)	0.049	0.146	−0.014	0.134
	(0.296)	(0.099)	(0.399)	(0.096)
ln(top)	−1.999	0.100	−2.385	0.047
	(1.477)	(0.205)	(2.297)	(0.197)
ln(seed)	−0.231	0.433***	−0.362	0.446***
	(0.592)	(0.167)	(0.901)	(0.168)
ln(area)	0.517	−0.776***	0.745	−0.741***
	(0.852)	(0.163)	(1.319)	(0.159)
Household FE	No	Yes	No	Yes
Kleibergen-Paap LM	1.773	26.89***	1.028	33.86***
Observations	7,643	7,643	7,643	7,643
Log Likelihood	-24,462	-16,378	-25,914	-16,192

Note: Dependent variable is log of yield. All specifications include crop-specific intercept terms and year dummies. In each regression the adoption of CA is treated as endogenous and is instrumented with the Inverse Mills Ratio (IMR) calculated from the predicted values of the first stage regressions reported in Table 6. The CA × rainfall shock term is also treated as endogenous and instrumented using the interaction of the IMR and the rainfall shock term. The underindentification test uses the Kleibergen-Paap LM statistic. Column (1) excludes rainfall variables as well as household fixed effects. Column (2) excludes rainfall variables but includes household fixed effects. Column (3) includes the rainfall shock and its interaction with CA but excludes household fixed effects. Column (4) includes both the rainfall shock, its interaction with CA, and household fixed effects. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A4: First Stage IV Probit with Rain Shortage or Surplus

	(1)	(2)	(3)	(4)
HH in ward with NGO support	0.009***	0.009***	0.009***	0.010***
	(0.001)	(0.001)	(0.001)	(0.002)
Type of Effect	Household MCD	Household MCD	Household MCD	Plot MCD
Observations	7,643	7,643	7,643	5,004
Log Likelihood	-3,107	-3,102	-3,096	-2,102

Note: Regressions are probits that include the IV, crop-specific inputs and intercept terms, and year dummies. The instrument is the number of households in the ward that receive NGO support. Column (1) includes rainfall shortage as well as the Mundlak-Chamberlain device (MCD). Column (2) includes rainfall surplus and the MCD. Column (3) includes both rainfall shortage and surplus and the MCD. Column (4) includes both the rainfall variable and the MCD calculated at the plot-level. Standard errors in columns (1) - (3) are clustered by household and crop while standard errors in column (4) are clustered at the plot-level. All standard errors are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A5: Yield Function with Rain Shortage or Surplus

	(1)	(2)	(3)	(4)
Maize				
CA (= 1)	−0.466	−2.657*	−1.893	3.393
	(1.379)	(1.378)	(1.472)	(3.156)
rainfall shortage	0.089		−1.076**	−1.411**
	(0.400)		(0.481)	(0.695)
CA × rainfall shortage	0.147		2.098**	3.522**
	(0.744)		(0.987)	(1.597)
rainfall surplus		−1.619***	−1.884***	−0.444
		(0.304)	(0.358)	(0.637)
CA × rainfall surplus		2.012***	2.931***	1.953**
		(0.513)	(0.657)	(0.845)
ln(basal)	0.131	0.248***	0.166**	−0.115
	(0.080)	(0.084)	(0.081)	(0.172)
ln(top)	0.319***	0.397***	0.305***	0.138
	(0.074)	(0.078)	(0.073)	(0.108)
ln(seed)	0.122	−0.053	0.100	0.699**
	(0.187)	(0.193)	(0.185)	(0.342)
ln(area)	−0.532***	−0.595***	−0.518***	−0.462***
	(0.091)	(0.096)	(0.089)	(0.150)
Sorghum				
CA (= 1)	−0.262	−1.211	−0.512	5.808
	(1.464)	(2.042)	(1.780)	(4.791)
rainfall shortage	−1.079***		−1.702***	−2.235***
	(0.389)		(0.454)	(0.769)
CA × rainfall shortage	2.437*		2.356*	3.654*
	(1.263)		(1.326)	(1.977)
rainfall surplus		−0.550	−1.214***	−0.531
		(0.342)	(0.377)	(0.533)
CA × rainfall surplus		−0.369	0.464	−0.144
		(1.008)	(0.987)	(1.507)
ln(basal)	0.018	0.114	0.037	−0.190
	(0.107)	(0.108)	(0.101)	(0.264)
ln(top)	0.079	0.311	0.093	−0.671
	(0.249)	(0.289)	(0.257)	(0.553)
ln(seed)	0.396***	0.407***	0.405***	0.508***
	(0.113)	(0.112)	(0.112)	(0.194)
ln(area)	−0.518***	−0.663***	−0.510***	−0.008
	(0.182)	(0.195)	(0.179)	(0.420)
Millet				
CA (= 1)	−2.913	−3.914	−2.671	12.779
	(2.890)	(3.404)	(3.293)	(12.606)
rainfall shortage	−0.508		−1.604**	−1.438
	(0.610)		(0.658)	(0.927)
CA × rainfall shortage	−0.136		1.930	−4.318
	(1.576)		(2.344)	(8.524)
rainfall surplus		−1.287***	−1.689***	−0.427
		(0.356)	(0.320)	(0.584)
CA × rainfall surplus		2.726*	3.170	−0.775
		(1.548)	(2.202)	(7.605)
ln(basal)	0.342*	0.275	0.161	−0.524
	(0.207)	(0.198)	(0.177)	(0.671)
ln(top)	0.312	0.364	0.098	−1.148
	(0.455)	(0.483)	(0.424)	(1.090)
ln(seed)	0.358*	0.380*	0.325*	0.022
	(0.208)	(0.198)	(0.186)	(0.360)
ln(area)	−0.957**	−0.935**	−0.738**	0.809
	(0.383)	(0.391)	(0.353)	(1.229)

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Table A5 – Continued

	(1)	(2)	(3)	(4)
Groundnut				
CA (= 1)	0.359	−1.519	−0.266	4.764
	(1.159)	(1.550)	(1.499)	(3.664)
rainfall shortage	−1.125***		−1.229***	−2.298**
	(0.318)		(0.338)	(0.934)
CA × rainfall shortage	0.240		0.405	1.499
	(0.772)		(0.984)	(1.570)
rainfall surplus		0.036	−0.170	0.506
		(0.297)	(0.281)	(0.465)
CA × rainfall surplus		0.056	−0.205	−0.607
		(0.899)	(0.985)	(1.422)
ln(basal)	−0.012	0.119	0.027	−0.256
	(0.110)	(0.128)	(0.110)	(0.291)
ln(top)	−0.072	0.191	0.014	−0.551
	(0.158)	(0.182)	(0.172)	(0.435)
ln(seed)	0.563***	0.516***	0.543***	0.891***
	(0.083)	(0.092)	(0.086)	(0.252)
ln(area)	−0.646***	−0.751***	−0.689***	−0.600***
	(0.100)	(0.101)	(0.093)	(0.161)
Cowpea				
CA (= 1)	−0.742	−0.929	−1.188	1.829
	(1.141)	(1.415)	(1.439)	(3.818)
rainfall shortage	−0.628		−1.493***	−2.468**
	(0.477)		(0.553)	(1.221)
CA × rainfall shortage	3.171***		3.763***	6.006**
	(1.008)		(1.272)	(2.558)
rainfall surplus		−1.103**	−1.492***	−0.970
		(0.482)	(0.557)	(1.002)
CA × rainfall surplus		−0.286	1.234	3.148
		(1.309)	(1.624)	(2.543)
ln(basal)	0.073	0.168	0.090	−0.162
	(0.098)	(0.104)	(0.098)	(0.276)
ln(top)	0.003	0.092	−0.008	−0.650
	(0.205)	(0.218)	(0.207)	(0.569)
ln(seed)	0.451***	0.454***	0.463***	0.659**
	(0.168)	(0.171)	(0.170)	(0.287)
ln(area)	−0.720***	−0.799***	−0.723***	−0.491*
	(0.162)	(0.169)	(0.162)	(0.291)
Type of Effect	Household FE	Household FE	Household FE	Plot MCD
Observations	7,643	7,643	7,643	5,004
Kleibergen-Paap LM	22.96***	23.02***	25.23***	3.790*
Log Likelihood	-15,908	-16,406	-15,902	-12,268

Note: Dependent variable is log of yield. All specifications include crop-specific intercept terms and year dummies. In each regression the adoption of CA is treated as endogenous and is instrumented with the Inverse Mills Ratio (IMR) calculated from the predicted values of first stage regressions which are presented in Table A4. The CA × rainfall shortage and CA × rainfall surplus terms are also treated as endogenous and instrumented using the interaction of the IMR and the rainfall terms. The underindentification test uses the Kleibergen-Paap LM statistic. Column (1) includes a rainfall shortage and its interaction with the instrumented CA term. Column (2) includes a rainfall surplus and its interaction with the instrumented CA term. Column (3) includes both a rainfall shortage and a rainfall surplus and their interactions with the instrumented CA term. Column (4) restricts the sample to plots with more than one observation and where CA is either always used or never used. It presents results that include a plot-level Mundlak-Chamberlain device (MCD) where CA is treated as endogenous and is instrumented as described previously. Standard errors in columns (1) - (3) are clustered by household and crop while standard errors in column (4) are clustered at the plot-level. All standard errors are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A6: Yield Function with Alternative Rainfall Measures

	(1)	(2)
Maize		
CA (= 1)	−2.411**	−3.587***
	(1.130)	(1.240)
rainfall shock	−1.050***	−0.879***
	(0.309)	(0.279)
CA × rainfall shock	2.095***	2.153***
	(0.546)	(0.544)
Sorghum		
CA (= 1)	−0.538	−1.511
	(1.480)	(1.628)
rainfall shock	−0.735**	−0.753***
	(0.286)	(0.286)
CA × rainfall shock	0.874	0.546
	(0.601)	(0.605)
Millet		
CA (= 1)	−3.088	−4.552
	(2.841)	(3.115)
rainfall shock	−0.602*	−0.764**
	(0.311)	(0.316)
CA × rainfall shock	−1.687	−1.063
	(2.346)	(1.663)
Groundnut		
CA (= 1)	−0.178	−1.283
	(1.194)	(1.270)
rainfall shock	−0.498**	−0.487**
	(0.245)	(0.219)
CA × rainfall shock	1.095*	1.276**
	(0.631)	(0.608)
Cowpea		
CA (= 1)	−1.024	−1.969
	(1.145)	(1.281)
rainfall shock	−0.798*	−1.207***
	(0.433)	(0.419)
CA × rainfall shock	0.411	1.847*
	(1.339)	(1.094)
Household FE	Yes	Yes
Kleibergen-Paap rk LM statistic	30.05***	26.68***
Observations	7643	7643
Log Likelihood	-16417	-16800

Note: Dependent variable is log of yield. All specifications include crop-specific intercept terms and year dummies. In each regression the adoption of CA is treated as endogenous and is instrumented as previously discussed. Column (1) replaces any deviation in rainfall that is with ± one standard deviation with a zero. Thus, any realized value that is $0.202 \leq \mathrm{R}_{jt} \leq 0.749$ is set to zero. Column (2) replaces any deviation in rainfall that is with ± one half of a standard deviation with a zero. Thus, any realized value that is $0.339 \leq \mathrm{R}_{jt} \leq 0.612$ is set to zero. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A7: First Stage IV Tobit with Rain Shortage and Surplus

	(1)	(2)
HH in ward with NGO support	0.005**	0.007***
	(0.002)	(0.001)
Household Control	FE	MCD
Observations	7,643	7,643
Log Likelihood	-4,310	-4,870

Note: Regressions are first stage Tobits with CA adoption as the dependent variable and includes the IV, rainfall shortages and surpluses, crop-specific inputs and intercept terms, and year dummies. The instrument is the number of households in the ward that receive NGO support. Column (1) includes household fixed effects, column (2) includes the Mundlak-Chamberlain device. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A8: Yield Function using First Stage Tobit

	(1)	(2)
Maize		
CA (= 1)	−0.141	−0.611
	(0.448)	(0.736)
rainfall shortage	−0.366	−0.639
	(0.365)	(0.440)
CA × rainfall shortage	0.216	0.958
	(0.684)	(0.927)
rainfall surplus	−1.329***	−1.659***
	(0.313)	(0.321)
CA × rainfall surplus	1.544***	2.450***
	(0.533)	(0.613)
Sorghum		
CA (= 1)	−0.185	−0.099
	(0.763)	(1.002)
rainfall shortage	−1.770***	−1.929***
	(0.417)	(0.434)
CA × rainfall shortage	2.460**	3.335***
	(1.105)	(1.243)
rainfall surplus	−1.207***	−1.410***
	(0.365)	(0.364)
CA × rainfall surplus	0.579	1.141
	(0.787)	(0.838)
Millet		
CA (= 1)	−1.942	−1.352
	(1.749)	(1.767)
rainfall shortage	−1.859***	−1.866***
	(0.629)	(0.637)
CA × rainfall shortage	3.248	3.356
	(2.573)	(2.629)
rainfall surplus	−1.595***	−1.699***
	(0.308)	(0.299)
CA × rainfall surplus	2.778	3.663*
	(1.819)	(2.030)
Groundnut		
CA (= 1)	0.177	0.333
	(0.535)	(0.627)
rainfall shortage	−1.258***	−1.368***
	(0.318)	(0.321)
CA × rainfall shortage	0.555	1.049
	(0.731)	(0.808)
rainfall surplus	−0.061	−0.088
	(0.248)	(0.246)
CA × rainfall surplus	−0.321	−0.339
	(0.601)	(0.673)
Cowpea		
CA (= 1)	−0.800	−0.606
	(0.734)	(0.992)
rainfall shortage	−1.430***	−1.500***
	(0.533)	(0.550)
CA × rainfall shortage	3.558***	3.802***
	(1.027)	(1.189)
rainfall surplus	−1.572***	−1.440***
	(0.536)	(0.537)
CA × rainfall surplus	1.733	1.234
	(1.421)	(1.604)
Household FE	Yes	Yes
Observations	7,643	7,643
Kleibergen-Paap LM	279.51***	182.71***
Log Likelihood	-15,737	-15,770

Note: Dependent variable is log of yield. Though not reported, all specifications include crop-specific inputs and intercept terms, and year dummies. Column (1) uses the predicted value and the Inverse Mills Ratio from the first stage Tobit with household fixed effects as presented in column (1) of Table A7. Column (2) uses the predicted value and the Inverse Mills Ratio from the first stage Tobit with household a Mundlak-Chamberlain device as presented in column (2) of Table A7. The underindentification test uses the Kleibergen-Paap LM statistic. All standard errors are clustered by household and crop and are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).