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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. Farmers who practice CA tend to receive higher yields compared to conventional farmers 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.

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1 Introduction

Conservation agriculture (CA) is a cropping system based on three principles promoted as a means for sustainable agricultural intensification. These practices include 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, in combination with mulching, which increases water infiltration and moisture conservation (Thierfelder and Wall, 2009), while, in the case of excess rainfall, through the retention of crop residue, which reduces erosion rates (Schuller et al., 2007). As a result, CA has become a prominent component of global agricultural development policy to sustainably increase crop productivity, and a fixture in the promotion of 'climate smart' agriculture (FAO, 2011).[1] Yet little evidence exists regarding CA's 'climate smart' properties (Andersson and D'Souza, 2014). A few studies explore the effect of CA on yields during normal rainfall years, but these studies either use agronomic analysis of field station trials, missing potential effects of farmer behavior, or use observational data that fail to control for the selection bias in the adoption decision (Pannell et al., 2014).

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. Additionally, the resilience of yields under CA may differ depending on if farmers experience rainfall shortages or rainfall surpluses. We follow Di Falco and Chavas (2008) in defining resilience in terms of a set of agricultural practices that retain their productivity when challenged by climatic events. To test the resilience of yields on fields where farmers practice CA we use four years of plot level panel data covering $4,217$ plots from 730 households across Zimbabwe. The data include plot level inputs and outputs for five different crops: maize, sorghum, millet, groundnut,

[1] FAO (2013) broadly defines climate smart agriculture (CSA) as an approach to agriculture designed to help farmers effectively respond to climate change. More narrowly, the role of CA as a 'climate smart' technology is through its proposed ability to build resilience to climate change and reduce greenhouse gas emissions through carbon sequestration.

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 household heterogeneity that influences both adoption and yields but is otherwise unobserved. We employ household fixed effects to control for correlation between time-invariant unobservables and the choice to adopt CA. Second is the possible presence of unobserved time-varying shocks captured in the error term that might affect a household's access to and use of CA. We use the intensity of nearby CA promotion to instrument for household adoption of CA. In addition to these two primary concerns, we test for other potential factors that could confound the causal identification of CA on yields. Because farmers 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 plot level fixed effects regressions.

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. CA results in yields that are more resilient to these rainfall shocks than yields using conventional farming methods for maize and cowpea. The climate resilience of crops under CA is robust to the disaggregation of rainfall shocks into shortages and surpluses and to the inclusion of plot level effects. We then use the estimated coefficients on the CA terms to predict the returns to CA at various values for rainfall. Just over a half standard deviation decrease or increase in rainfall is required before the returns to CA become positive. Under average rainfall conditions, overall returns to CA are 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 research on the economics of CA at the farm or plot level. 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, in the first two seasons (2008 and 2009) households simply identified the plots on which they practiced CA. Only in the final two seasons (2010 and 2011) were households asked to specify which practices they implemented when using 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 operate with a practical definition of CA as, at the very least, use of no-till, the original and central principle of CA. We then define conventional or traditional cultivation practices as everything other than self-identified CA adoption, which for the majority of plots amounts to tillage by ox-drawn or tractor plows. 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 ability to mitigate yield loss from rainfall shocks has been a key proposed benefit of CA (Giller et al., 2009) and evidence exists that farmers who adopt CA do so with the expectation that CA will provide resilient yields (Arslan et al., 2014). Yet, the only evidence of the resilience of yields under CA comes from station or on-farm field trial data.[3] We use realizations of on-farm yields over four years and control for several sources of endogeneity. Thus we provide the first rigorous evidence about CA's 'climate smart' properties.

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 (Brouder and Gomez-Macpherson, 2014). 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 production function that allows coefficients on inputs to vary across crops. This approach accommodates heterogeneity in

[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.

[3]Recent examples include Thierfelder et al. (2013) and Thierfelder et al. (2015). See Corbeels et al. (2014) for a review of this literature.

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 a stochastic production function:

$$y_{kit} = f(\mathbf{x}_{kit}; \mathbf{c})e^{\epsilon_{kit}}, \tag{1}$$

where y_{kit} is yield for crop k cultivated by household i at time t, $\mathbf{x}_{kit}$ is a vector of measured inputs used on the k^{th} crop by household i at time t, and $\mathbf{c}$ is a vector of other factors that include CA, rainfall, and their interaction. The disturbance term is composed of two elements: $\epsilon_{kit} = \mu_i + u_{kit}$. We assume both μ_i and u_{kit} are independently distributed. The μ_i reflects unobserved household level effects that impact the production technology while $u_{kit} \sim \mathcal{N}(0, \sigma^2_{u_{kit}})$.

We consider the following specification:

$$\ln(y_{kit}) = \alpha_k + \ln(\mathbf{x}_{kit})\beta_k + \phi_{k0}\mathrm{C}_{kit} + \phi_{k1}\mathrm{R}_{kjt} + \phi_{k2}\mathrm{C}_{kit} \cdot \mathrm{R}_{kjt} + \mu_i + u_{kit}, \tag{2}$$

where α_k is a crop-specific intercept term and β_k is a vector of crop-specific coefficients to be estimated for the input vector $\mathbf{x}_{kit}$. Our variables of interest are the indicator variable C_{kit} for whether or not CA methods were used by household i in cultivating crop k at time t, along with our measure of rainfall deviations, R_{jt}, calculated for ward j at time t, and the interaction term, $\mathrm{C}_{kit} \cdot \mathrm{R}_{kjt}$. The ϕ terms are estimated coefficients which will allow us to test the impact of CA on yields both during times of average rainfall (ϕ_{k0}) and during periods of deviation from the average (ϕ_{k2}). In our empirical implementation we instrument for the likely endogeneity of the C term using an approach outlined by Wooldridge (2003). We discuss this approach more fully in Section 4.

Note that the specification in equation (2) reduces to a Cobb-Douglas function when $\phi_{k0} = \phi_{k1} = \phi_{k2} = 0$. 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). To allow for some flexibility in production we relax the assumption of constant returns to measured inputs and allow the input-response curves to vary by crop. We also include both the levels and the interaction of CA and the rainfall measures and allow these coefficients to vary by crop. Since these interactions are our variables of interest, this estimation approach gives us a flexible specification where we believe it matters most, while maintaining a degree of parsimony in our equation of estimation.

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.[4] The wards come from 20 different districts which were purposefully selected to provide coverage of high rainfall, medium rainfall, semi-arid, and arid regions (see Figure 1). 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 730 randomly selected households. The 53 excluded households come from the 2007 round, which we

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

drop completely, because in that year the survey only targeted households who had received NGO support that was designed to stimulate CA adoption.

3.1 Household Data

Our subset provides us with detailed cultivation data for five crops on $4,217$ unique plots (see Table 1). Maize, the staple grain of Zimbabwe, is the most commonly cultivated crop. Nearly 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.

In Table 2 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. Turning to inputs, we find that CA maize production uses more fertilizer but less seed and the area under CA is less than the area under traditional cultivation. This same pattern of input use is repeated for all the other crops. The higher yields for most crops under CA is correlated with more intensive fertilizer use and, once having controlled for fertilizer use, CA might not have an effect on yields. We more fully explore these relationships in our econometric analysis below.

Figure 2 shows the distribution of yields over the period 2008-2011 by cultivation method and by rainfall. In seasons when rainfall is normal, mean yields are larger under CA compared to traditional cultivation.[6] Using the Kolmogorov-Smirnov test we reject the equality of yield distributions for CA and traditional cultivation under normal conditions with 99 percent confidence.[7] When we examine

[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-Wilcoxon (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.

[6]We define normal as cumulative seasonal rainfall that is within one standard deviation of mean seasonal rainfall. The mean and standard deviation of seasonal rainfall is calculated using rainfall data from the last 15 years. We define abnormal as cumulative seasonal rainfall that is more than one standard deviation away from the mean.

[7]In the context of marginal distributions we prefer the KS test to the MW test since the KS test is sensitive to

yields during periods of abnormal rainfall, mean yields are again larger under CA. Additionally, the variance in CA yields is lower than the variance of yields under traditional cultivation. Using the Kolmogorov-Smirnov test, these differences are significant at the 99 percent level. Focusing just on CA yields, we observe only a small difference in mean yields during normal and abnormal rainfall seasons, although we still reject the equality of these distributions at the 90 percent level. Conversely, we observe a much larger difference in mean yields from traditional cultivation for periods of normal rainfall compared to abnormal rainfall (we reject the null of equality with 99 percent confidence). This descriptive evidence suggests that CA may contribute to yield resilience during periods of rainfall shock. Note that these graphs do not imply a causal relation between cultivation methods and yields since they fail to account for potential selection bias in households that adopt CA.

Examining the production data by year reveals a high degree of annual variability (see Table 3). Yields in 2009 and 2010 were about 50 percent higher than yields in 2008 or in 2011, despite the much higher levels of fertilizer and seed use in the low yield years. CA practices vary both by crop and over time (see Figure 3). In 2008, adoption of CA was at over 50 percent for those cultivating sorghum, groundnut, and cowpea and it was 45 percent for those cultivating maize. 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 of households. Previous literature has hypothesized that this abandonment of CA by farmers in Zimbabwe is due to the withdrawal of NGO input support subsequent to the 2008 economic crisis (Ndlovu et al., 2014; Pedzisa et al., 2015). 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. CHIRPS incorporates 0.05° resolution satellite imagery with in-situ station data to create a gridded rainfall time series. More details are available in Funk

any differences in the two distributions (shape) and not just to differences in location. We also test for differences using the MW test. Results are equivalent to those obtained from the KS test.

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, where the growing season in Zimbabwe lasts from October until April the following year.

Figure 4 shows historic seasonal rainfall distribution by ward over the 15 year period 1997-2011. We observe a large seasonal fluctuation 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 realization, we fit a linear trendline to the data.[8] 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 5). 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:

$$\mathrm{R}_{jt} = \left| \frac{r_{jt} - \bar{r}_j}{\sigma_{r_j}} \right|. \tag{3}$$

Here shocks are calculated for each ward j in year t where r_{jt} is the observed amount of rainfall for the season, $\bar{r}_j$ is the average seasonal rainfall for the ward over the period, and σ_{r_j} 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). To understand the validity of these claims we also calculate a measure of rainfall shortage as:

[8]The slope of this line is -3.71 and is significantly different from zero at the 99 percent level.

$$
\underline{\mathrm{R}}_{jt} = \begin{cases} \left| \frac{r_{jt} - \bar{r}_j}{\sigma_{r_j}} \right| & \text{if } r_{jt} < \bar{r}_j \\ 0 & \text{otherwise} \end{cases}, \tag{4}
$$

as well as a measure of rainfall surplus:

$$
\overline{\mathrm{R}}_{jt} = \begin{cases} \left| \frac{r_{jt} - \bar{r}_j}{\sigma_{r_j}} \right| & \text{if } r_{jt} > \bar{r}_j \\ 0 & \text{otherwise} \end{cases}. \tag{5}
$$

These measures can 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 deviations in meteorological data which are designed to proxy for agricultural drought or overabundance of rainfall. In Zimbabwe, agricultural drought frequently 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. For all five crops, deviations in seasonal rainfall have a significant and negative impact on crop yields. By contrast, we find little empirical evidence that late onset of rainfall decreases crop yields and only minor evidence that mid-season dry spells reduce yields. Results from these regressions are presented in the Online 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

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 u_{kit} may simultaneously affect the adoption decision and crop yields.

The first source of endogeneity may arise because some households have greater skill at farming or are less risk averse and therefore more likely to adopt CA. We address this issue by incorporating household fixed effects in our estimation of equation (2). Fixed effects remove any unobserved time-invariant household effects that may be correlated with both the μ_i term, the decision to adopt, and yields.

We next deal with the presence of unobserved shocks that simultaneously affect the idiosyncratic error term, the decision to adopt, and yields. Because adoption of CA is not random, it is likely to be correlated with unobserved time-varying factors, such as external promotion of CA, that may simultaneously influence yields. In the particular case of Zimbabwe, CA was heavily promoted by agricultural research stations, extension agents, and NGOs. This promotion often took the form of direct support for input purchases or technical training (Mazvimavi et al., 2008). Thus, adoption of CA is strongly correlated with having received external support (Mazvimavi and Twomlow, 2009; Ndlovu et al., 2014; Pedzisa et al., 2015). 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 implement an instrumental variables approach. An appropriate instrument for this model must be correlated with a household's decision to adopt CA but be uncorrelated with plot yields except through the treatment. As Mazvimavi and Twomlow (2009) and Ndlovu et al. (2014) demonstrate, there is a strong correlation between the probability that a household adopts CA and their receiving assistance from an NGO in the form of input subsidies. While having received NGO support is plausibly exogenous at the household level, it could be that NGOs target individual households based on some time-varying unobservable.[9] We take an added precaution and instead use as the instrument the number of households in a ward in a given year that receive input support from an NGO, excluding the household under consideration. The level of support that other 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 local conditions.[10] Thus, the number of households in the ward that receive NGO support satisfies the

[9]Note that if NGOs target based on time-invariant characteristics, such as wealth or ability, our use of fixed effects control for this, making the use of household level NGO support a valid instrument.

[10]One may be concerned with potential spillover effects, in that a farmer who 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.

exclusion restriction.

Given that the problematic term, C_{it}, is interacted with either crop type (to give C_{kit}) or with crop type and the exogenous rainfall shock (to give $\mathrm{C}_{kit} \cdot \mathrm{R}_{kjt}$), we follow Wooldridge (2003) in instrumenting for only the potentially endogenous term. We estimate a version of equation (2) 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 $\hat{\mathrm{C}}_{it}$ from the following equation:

$$\mathrm{C}_{it} = 1\left[\alpha_k + \ln(\mathbf{x}_{kit})\beta_k + \gamma \mathrm{G}_{jt} + \delta_{k1}\mathrm{R}_{kjt} + \mu_i + v_{it} \geq 0\right], \tag{6}$$

where G_{jt} is the number of other households in ward j that received NGO support at time t, γ is the associated coefficient, and $v_{it} \sim \mathcal{N}(0, \sigma^2_{v_{it}})$ and is independent of u_{it} and μ_i. Since our first stage reduced form equation is nonlinear, we use correlated random effects to control for household unobservables instead of the fixed effects used in the second stage structural equation.[11] This amounts to replacing μ_i with its linear projection onto the time averages of observable choice variables $\mu_i = \bar{\mathbf{x}}_i\lambda + a_i$, where $a_i \sim \mathcal{N}(0, \sigma^2_{a_i})$ (Mundlak, 1978; Chamberlain, 1984). Using correlated random effects 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 μ_i, identification of C_{it} still fully relies on our instrumental variable G_{jt}. 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 C_{it}.

We then calculate the Inverse Mills Ratio (IMR) and instrument C_{kit} with the IMR interacted with crop type and instrument $\mathrm{C}_{kit} \cdot \mathrm{R}_{kjt}$ with the IMR interacted with crop type and the exogenous

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 farmer are not contiguous with neighboring farmers.

[11] In the Online Appendix, Tables A8 and A9, we present results from a robustness check using a Tobit and household fixed effects for the first stage.

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 household level or cluster only at the crop level. Clustering at the household level provides results qualitatively equivalent to those when we cluster at the household-crop level.[12] 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. Instead, in a robustness check, we estimate a system of crop-specific production functions and allow for correlation across crops.

5 Results

We estimate the production function in equation (2) 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 4 - 9. All models are estimated using the log of yield as the dependent variable and log values of measured inputs as independent variables. Hence, point estimates can be read directly as elasticities. 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. For brevity, we only report coefficients on CA, the rainfall deviations, and the interaction terms. Estimated coefficients on measured inputs are presented in the Online Appendix.

5.1 Main Results

We first focus on the results presented in Table 4 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

[12]Results from these regressions are available from the authors upon request.

on the correlation between CA and yields. Column (1) presents a simple production 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. The correlation between CA and yields is positive and significant for maize both with and without household fixed effects. CA is positively correlated with groundnut yields but only when we include household fixed effects. 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 production function with and without fixed effects. Focusing on the fixed effects results in column (4), CA by itself no longer increases yields for maize or groundnut. CA is now 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.

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 (Mazvimavi and Twomlow, 2009; Brouder and Gomez-Macpherson, 2014; Ndlovu et al., 2014; Abdulai, 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 et al., 2009). However, 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 5 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 6 we present results similar to those in Table 4 but with the endogeneity of CA controlled for with our instrument. Our preferred specification is column (4) because it simultaneously controls for unobserved shocks through the IV and unobserved heterogeneity through 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 4, 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 cowpea. The use of CA during periods of rainfall stress appears to have no benefit for sorghum, millet, and groundnut yields. For all crops, except sorghum, the coefficients on our instrumented variables are of a larger magnitude then the un-instrumented variables. Once we have controlled 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 deviations 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 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.

Table 7 presents results from three regressions all of 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 (4). Column (2) replaces the rainfall shortage with a rainfall surplus as in equation (5). 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

[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 farmers have yet to reap the benefits of CA practices.

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 has no significant impact on yields for 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 impact in mitigating losses from either surplus or shortfalls of rain for both millet and groundnut.

Synthesizing these results and comparing them to our main results leads to several conclusions. First, during periods of average rainfall, CA 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 would 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 generally mitigates yield losses due to these deviations. Maize and cowpea yields are more resilient under CA.[14] Third, when we allow for rainfall shortages to impact yields differently from surplus rainfall we find that maize, sorghum, and cowpea yields are all 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 when rainfall shocks

[14]We test the robustness of this conclusion by generate two new measures of rainfall shock. In the first we replace any deviation in rainfall that is within ± one standard deviation of the mean (0.476) with a zero. Thus, any realized value that is $0.202 \leq \mathrm{R}_{jt} \leq 0.748$ is set to zero. In the second we replace any deviation in rainfall that is within ± one half of a standard deviation of the mean (0.476) with a zero. Thus, any realized value that is $0.338 \leq \mathrm{R}_{jt} \leq 0.612$ 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 Online Appendix.

[15]To check the robustness of this finding, we replace our first stage probit with correlated random effects with a first stage Tobit with fixed effects. Results are consistent regardless of how we specify the first stage adoption devision. See Tables A8 and A9 in the Online Appendix.

occurs.

5.3 Crop-Specific Production Functions

Our preferred specification estimates the production function for all crops and accommodates heterogeneity in the input-response curves by allowing slopes and intercepts to vary across crops. This allows us to relax the assumption that input parameters are the same for all crops without splitting the random sample based on a non-random criteria. We have allowed for the variance structure of the error term to vary across households and crops by cluster our standard errors at the household-crop level. However, this approach implicitly imposes the assumption that observations are independent if they are in the same household but are from a different crop (Bertrand et al., 2004; Cameron and Miller, 2015). To address this issue, we estimate crop-specific production functions with household fixed effects as a system of equations. This approach allows for correlation between crop-specific error terms, though it implicitly imposes the assumption that observations are independent if they are in the same household (Greene, 2011). First stage instrumental variables regressions utilize seemingly unrelated regression to predict CA adoption.[16] We then use predicted values as instruments for adoption in a three-stage least squares (3SLS) framework. Our goal in doing so is to provide a robustness check on our main results.[17]

We first compare the results in Panel A of Table 8 from the crop system of regressions when we instrument for the endogenous CA term with our main results in column (4) of Table 6. In general, the 3SLS results are not as significant as those from the main production function. CA by itself is never significant, rainfall shocks, where significant, reduce yields, and the interactions of CA with rainfall, where significant, increase yields. We next compare results when we use both rainfall shortage and surplus measures instead of the single rainfall term (see Panel B of Table 8 and column (4) in Table 7). Similar to above, none of our significant coefficients of interest change

[16]We report first stage IV results for the crop production system in Table A7 of the Online Appendix.

[17]We also estimate production using five separate crop-specific sub-samples of the data. Note that this approach implicitly assumes observations across crops are i.i.d. both within and across households. Using this approach is similar to but less efficient then using a system and coefficient estimates tend to be less significant but do not change in sign. An additional alternative approach to dealing with correlated errors, the one suggested by Bertrand et al. (2004), is to return to our preferred specification and cluster at just the household level (instead of the household-crop level). None of the results presented in Sections 5.1 and 5.2 change in a material way when we use any of these alternatives. Results from these alternative regressions are available from the authors upon request.

in sign between the two sets of regressions. However, many of the coefficients in the crop system of regressions are no longer statistically significant.

In general, coefficient estimates in the system of equations are measured with less precision than in our main results. We do not believe that this is indicative of any underlying change in the relationship between CA and yields. Rather, we believe it is due to a mis-specification in the variance estimates. While the systems approach allows for correlation of errors across crops, it imposes independence within equations. The result is that if we believe errors are correlated within a household, the systems approach mis-specifies the variance-covariance matrix, which results in inaccurate hypothesis testing. Despite this limitation, the results from the system of crop-specific production functions provide a useful robustness check of our main results. In all cases where coefficients are significant, the point estimates share the same sign across the different specifications.

5.4 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, it is likely that households 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. The direction of this bias would mean that our previous results are underestimates and that CA has an even stronger impact on yields during times of rainfall stress than we have estimated. Alternatively, though the reasoning is less clear, households might apply CA on plots where they know soil quality is good. If this is the case, our previous results will be overestimates of the true impact of CA on yields.

Our panel covers only four seasons with households initially adopting CA in the 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.

Table 9 presents results from two different regressions designed to control for different sources of plot level endogeneity. In column (1) we restrict the sample to plots with more than one observation and where CA is either always used or never used. This restriction reduces our sample size by about half ($3,343$) but, by focusing on plots where the use of CA does not change over time, we can focus solely on time-invariant unobservables. We use both rainfall shortage and surplus measures along with plot level fixed effects and treat CA, conditional on controlling for time-invariant unobservables, as exogenous. Similar to our previous results, we find that CA by itself tends to have no impact on yields. We find that our results for maize and sorghum, when controlling for endogeneity at the household level (column (3), Table 7), prove not to be robust in our plot level fixed effects regression. This may be due to a lack of variation in the data as well as insufficient power given our sample size. However, our results for millet, groundnut, and cowpea are consistent across specifications.

In column (2) of Table 9 we add back in plots where the use of CA changes over time. This increases our sample size to $5,167$ but also re-introduces the concern that time-variant shocks might impact the decision to apply CA to a specific plot. To control for this, we use instrumental variables as previously discussed. However, due to issues of collinearity we are unable to use plot level fixed effects and instead implement correlated random effects in both the first and second stage regressions. Results from the IV regression with correlated random effects are very similar to those presented in column (3) of Table 7. CA by itself has no impact on yields while CA increases yield resilience during periods of rainfall shortage for maize, sorghum, and cowpea. Maize yields during periods of excess rainfall continue to be resilient under CA.

5.5 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 7, we multiple 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.[18] For maize, the returns to CA are positive only when rainfall is one standard deviation below the average or half a standard deviation above the average. In seasons where cumulative rainfall is within this range, 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. Similarly, the returns to millet are rarely ever negative, though unlike sorghum, returns are positive when rainfall is both below and above average. The returns to CA cultivation of groundnut are almost always positive, regardless of rainfall. Only in extremely rainy seasons, where rainfall is one standard deviation above the average, do the returns to CA become negative for groundnuts. Finally, for cowpea, returns to CA are similar to maize, though the negative effect of CA is less 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 a half standard deviation away from the mean before the returns to CA became positive. 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, 30 percent of seasons have fallen within this 'normal' range. Seventy percent of the time rainfall is either low enough or high enough that, on average, the returns to CA should be positive. In some wards, rainfall events tend to be so extreme that the returns to CA would be positive 89 percent of the time, while in other wards rainfall is less variable and returns to CA are positive only about 42 percent of the time. We conclude that CA may not be an appropriate technology for regions of Sub-Saharan Africa where rainfall is consistent. Rather, policy should target CA for households living in areas prone to several drought or flooding.

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

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 production 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. 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. Thus, the empirical puzzle of low adoption rates despite the apparent benefits of CA is only really a puzzle in policy circles. 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)	1,428	1,049	734.5	1,257	926.4	1,245
	(2,345)	(2,348)	(1,593)	(1,994)	(2,622)	(2,281)
CA (= 1)	0.357	0.264	0.140	0.198	0.313	0.295
	(0.479)	(0.441)	(0.347)	(0.398)	(0.464)	(0.456)
basal applied fertilizer (kg)	14.283	2.355	0.921	1.684	3.479	8.185
	(52.05)	(11.02)	(5.896)	(11.21)	(12.20)	(38.02)
top applied fertilizer (kg)	18.36	3.345	1.637	2.158	4.723	10.62
	(40.08)	(10.58)	(8.693)	(12.43)	(17.59)	(30.65)
seed planted (kg)	8.096	5.203	6.615	11.32	3.691	7.722
	(9.302)	(12.05)	(19.45)	(19.60)	(14.56)	(13.62)
area planted (m^2)	3,412	3,187	3,925	2,022	1,520	2,984
	(3,766)	(3,683)	(4,133)	(2,102)	(1,895)	(3,470)
Rainfall shock	0.470	0.480	0.548	0.470	0.461	0.476
	(0.274)	(0.266)	(0.299)	(0.273)	(0.257)	(0.273)
HH in ward with NGO support	20.68	22.10	24.78	21.87	23.36	21.63
	(13.10)	(15.56)	(17.58)	(14.20)	(15.09)	(14.28)
number of observations	3,906	1,297	500	1,437	697	7,837
number of plots	2,674	1,026	413	1,250	637	4,217
number of households	716	417	178	605	394	730
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 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)	1,016	2,168	***	954.9	1,311	***	734.6	733.2	**	1,130	1,772	***	867.5	1,055	***
	(1,549)	(3,198)		(2,381)	(2,235)		(1,694)	(705.8)		(1,696)	(2,850)		(2,567)	(2,737)	
Basal applied fertilizer (kg)	12.82	16.90	***	1.125	5.775	***	0.690	2.335	***	0.795	5.288	***	1.368	8.116	***
	(61.18)	(28.93)		(8.485)	(15.62)		(6.087)	(4.309)		(9.844)	(15.08)		(7.081)	(18.32)	
Top applied fertilizer (kg)	16.13	22.37	***	1.010	9.838	***	0.727	7.223	***	0.864	7.408	***	1.919	10.88	***
	(43.29)	(33.15)		(4.370)	(17.72)		(5.659)	(17.62)		(9.758)	(19.03)		(15.09)	(20.86)	
Seed planted (kg)	9.236	6.042	***	5.640	3.986	***	7.230	2.835	***	12.86	5.051	***	3.809	3.429	***
	(10.58)	(5.836)		(13.20)	(7.904)		(20.88)	(2.698)		(21.49)	(4.510)		(17.45)	(3.014)	
Area planted (m^2)	3,959	2,425	***	3,766	1,577	***	4,418	893.1	**	2,230	1,175	***	1,744	1,024	***
	(4,290)	(2,252)		(4,030)	(1,618)		(4,228)	(1,226)		(2,196)	(1,368)		(2,124)	(1,103)	
Rainfall shock	0.464	0.479		0.471	0.503	*	0.544	0.570		0.454	0.530	***	0.464	0.453	
	(0.273)	(0.274)		(0.262)	(0.273)		(0.308)	(0.236)		(0.265)	(0.292)		(0.259)	(0.251)	
HH in ward with NGO support	19.49	22.79	***	21.28	24.37	**	23.22	34.32	***	20.50	27.42	***	21.63	27.14	***
	(12.85)	(13.25)		(14.75)	(17.41)		(16.94)	(18.46)		(13.45)	(15.75)		(14.19)	(16.30)	
number of observations	2,511	1,395		954	343		430	70		1,153	284		479	218	
number of plots	2,019	995		806	286		363	60		1,036	265		455	204	
number of households	672	538		307	210		169	45		570	195		315	156	
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-Wilcoxon 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 3: Descriptive Statistics by Year

	2008	2009	2010	2011
Yield(kg/ha)	998.1	1,473	1,519	973.2
	(2,276)	(2,316)	(2,944)	(1,277)
CA (= 1)	0.442	0.388	0.251	0.174
	(0.497)	(0.487)	(0.434)	(0.379)
Basal applied fertilizer (kg)	7.115	3.853	4.848	15.214
	(21.06)	(14.60)	(25.09)	(60.70)
Top applied fertilizer (kg)	8.704	6.712	8.990	16.28
	(20.04)	(16.68)	(38.38)	(34.97)
Seed planted (kg)	7.902	6.577	6.985	9.231
	(9.938)	(9.653)	(12.22)	(18.83)
Area planted (m^2)	3,410	2,830	2,796	3,008
	(4,148)	(3,879)	(3,312)	(2,724)
Rainfall shock	0.683	0.487	0.351	0.453
	(0.287)	(0.266)	(0.225)	(0.231)
HH in ward with NGO support	28.02	18.07	21.65	20.26
	(19.22)	(10.39)	(13.37)	(12.57)
number of observations	1,485	1,765	2,219	2,368
number of plots	1,732	1,707	2,107	2,334
number of households	390	404	434	586
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 4: Production Function with CA as Exogenous

	(1)	(2)	(3)	(4)
Maize				
CA (= 1)	0.645***	0.577***	0.198	0.197
	(0.083)	(0.081)	(0.139)	(0.136)
rainfall shock			−0.690***	−0.943***
			(0.217)	(0.230)
CA × rainfall shock			0.958***	0.776***
			(0.251)	(0.238)
Sorghum				
CA (= 1)	−0.033	−0.067	−0.783***	−0.576**
	(0.181)	(0.191)	(0.272)	(0.286)
rainfall shock			−1.305***	−1.467***
			(0.301)	(0.313)
CA × rainfall shock			1.572***	1.060**
			(0.464)	(0.501)
Millet				
CA (= 1)	−0.167	0.180	−1.066	−0.731
	(0.357)	(0.374)	(0.711)	(0.733)
rainfall shock			−1.094***	−1.563***
			(0.303)	(0.316)
CA × rainfall shock			1.596*	1.637
			(0.945)	(1.165)
Groundnut				
CA (= 1)	0.218	0.286**	−0.575**	−0.029
	(0.143)	(0.144)	(0.288)	(0.281)
rainfall shock			−0.462**	−0.538**
			(0.208)	(0.228)
CA × rainfall shock			1.419***	0.553
			(0.488)	(0.454)
Cowpea				
CA (= 1)	−0.059	0.232	−0.983**	−0.429
	(0.242)	(0.252)	(0.455)	(0.447)
rainfall shock			−1.058**	−1.216***
			(0.444)	(0.435)
CA × rainfall shock			1.924**	1.321
			(0.895)	(0.874)
Household FE	No	Yes	No	Yes
Observations	7,837	7,837	7,837	7,837
R^2	0.898	0.922	0.899	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 Online 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 5: First Stage IV Probit

	(1)	(2)	(3)	(4)
Num HH in ward with NGO support	0.010***	0.009***	0.010***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Household CRE	No	Yes	No	Yes
Observations	7,837	7,837	7,837	7,837
Log Likelihood	-3,274	-3,230	-3,263	-3,219

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) excludesthe rainfall variable as well as household correlated random effects. Column (2) excludes the rainfall variable but includes household correlated random effects. Column (3) includes the rainfall variable and its interaction with CA but excludes household correlated random effects. Column (4) includes both tthe rainfall variable, its interaction with CA, and household correlated random effects. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table 6: Production Function with CA as Endogenous

	(1)	(2)	(3)	(4)
Maize				
CA (= 1)	7.233*	−1.289	6.659	−2.413*
	(4.255)	(1.286)	(5.359)	(1.378)
rainfall shock			−0.440	−1.656***
			(0.791)	(0.377)
CA × rainfall shock			2.009	2.690***
			(1.470)	(0.736)
Sorghum				
CA (= 1)	10.882**	0.202	11.961*	0.185
	(5.383)	(1.678)	(6.868)	(1.862)
rainfall shock			−1.155**	−1.494***
			(0.488)	(0.358)
CA × rainfall shock			−0.437	0.806
			(1.987)	(0.955)
Millet				
CA (= 1)	16.373	−1.926	21.906	−1.133
	(11.625)	(3.323)	(20.303)	(3.897)
rainfall shock			−0.422	−1.693***
			(0.702)	(0.337)
CA × rainfall shock			−4.889	2.449
			(12.602)	(2.250)
Groundnut				
CA (= 1)	8.800**	0.586	8.726*	0.257
	(3.939)	(1.321)	(4.938)	(1.554)
rainfall shock			−1.122***	−0.893***
			(0.394)	(0.269)
CA × rainfall shock			1.492	1.140
			(1.733)	(0.892)
Cowpea				
CA (= 1)	5.985*	−0.069	4.840	−1.017
	(3.256)	(1.231)	(4.068)	(1.439)
rainfall shock			−1.004	−1.659***
			(0.720)	(0.471)
CA × rainfall shock			2.962	2.481*
			(2.067)	(1.413)
Household FE	No	Yes	No	Yes
Kleibergen-Paap LM	4.875**	21.38***	3.865**	25.17***
Observations	7,837	7,837	7,837	7,837
Log Likelihood	-21,406	-16,587	-21,798	-16,527

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 Online 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 5. 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 7: Production Function with Rain Shortage or Surplus

	(1)	(2)	(3)
Maize			
CA (= 1)	0.470	−2.052	−1.145
	(1.590)	(1.656)	(1.802)
rainfall shortage	0.293		−0.918*
	(0.412)		(0.519)
CA × rainfall shortage	−0.099		1.984*
	(0.752)		(1.049)
rainfall surplus		−1.683***	−1.884***
		(0.306)	(0.386)
CA × rainfall surplus		2.147***	2.964***
		(0.493)	(0.701)
Sorghum			
CA (= 1)	0.197	−0.574	−0.021
	(1.652)	(2.367)	(2.080)
rainfall shortage	−1.144***		−1.736***
	(0.391)		(0.455)
CA × rainfall shortage	3.139**		2.749**
	(1.305)		(1.332)
rainfall surplus		−0.465	−1.166***
		(0.356)	(0.390)
CA × rainfall surplus		−0.880	0.176
		(1.111)	(1.067)
Millet			
CA (= 1)	−0.418	−1.914	−0.163
	(2.826)	(3.570)	(3.455)
rainfall shortage	−0.599		−1.637**
	(0.592)		(0.638)
CA × rainfall shortage	−0.005		1.222
	(1.401)		(2.299)
rainfall surplus		−1.184***	−1.619***
		(0.376)	(0.328)
CA × rainfall surplus		2.168	2.188
		(1.509)	(2.242)
Groundnut			
CA (= 1)	0.997	−0.957	0.390
	(1.298)	(1.764)	(1.769)
rainfall shortage	−1.121***		−1.186***
	(0.320)		(0.334)
CA × rainfall shortage	0.177		0.136
	(0.723)		(1.033)
rainfall surplus		0.111	−0.081
		(0.324)	(0.310)
CA × rainfall surplus		−0.147	−0.537
		(0.951)	(1.120)
Cowpea			
CA (= 1)	0.232	−0.022	−0.411
	(1.237)	(1.559)	(1.581)
rainfall shortage	−0.507		−1.434***
	(0.479)		(0.546)
CA × rainfall shortage	3.314***		4.067***
	(1.047)		(1.331)
rainfall surplus		−1.170**	−1.558***
		(0.477)	(0.547)
CA × rainfall surplus		−0.329	1.463
		(1.307)	(1.668)
Household FE	Yes	Yes	Yes
Observations	7,837	7,837	7,837
Kleibergen-Paap LM	18.32***	15.75***	17.67***
Log Likelihood	-16,282	-16,607	-16,272

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 Online 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 Online 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. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table 8: Production Functions by Crop Type with CA as Endogenous

	Maize (1)	Sorghum (2)	Millet (3)	Groundnut (4)	Cowpea (5)
Panel A: Rainfall Shock					
CA (= 1)	−2.376	6.880	1.400	5.581	4.270
	(4.090)	(4.886)	(1.970)	(4.318)	(2.986)
rainfall shock	−0.811***	−0.409	0.191	−0.141	0.130
	(0.270)	(0.322)	(0.130)	(0.285)	(0.197)
CA × rainfall shock	−0.322	1.947*	−0.061	1.238	0.354
	(0.841)	(1.005)	(0.405)	(0.888)	(0.614)
R^2	0.391	−1.030	0.125	−0.324	−0.902
Panel B: Rainfall Shortage and Surplus					
CA (= 1)	−2.673	7.091	1.347	5.430	4.305
	(4.134)	(4.940)	(1.950)	(4.259)	(2.996)
rainfall shortage	−0.076	−0.472	0.188	−0.268	−0.097
	(0.394)	(0.471)	(0.186)	(0.406)	(0.286)
CA × rainfall shortage	−0.991	1.624	0.051	1.742	0.669
	(1.033)	(1.234)	(0.487)	(1.064)	(0.748)
rainfall surplus	−0.960***	−0.430	0.193	−0.121	0.172
	(0.284)	(0.340)	(0.134)	(0.293)	(0.206)
CA × rainfall surplus	−0.284	2.116**	−0.081	1.182	0.338
	(0.892)	(1.066)	(0.421)	(0.919)	(0.646)
R^2	0.370	−1.101	0.132	−0.305	−0.940

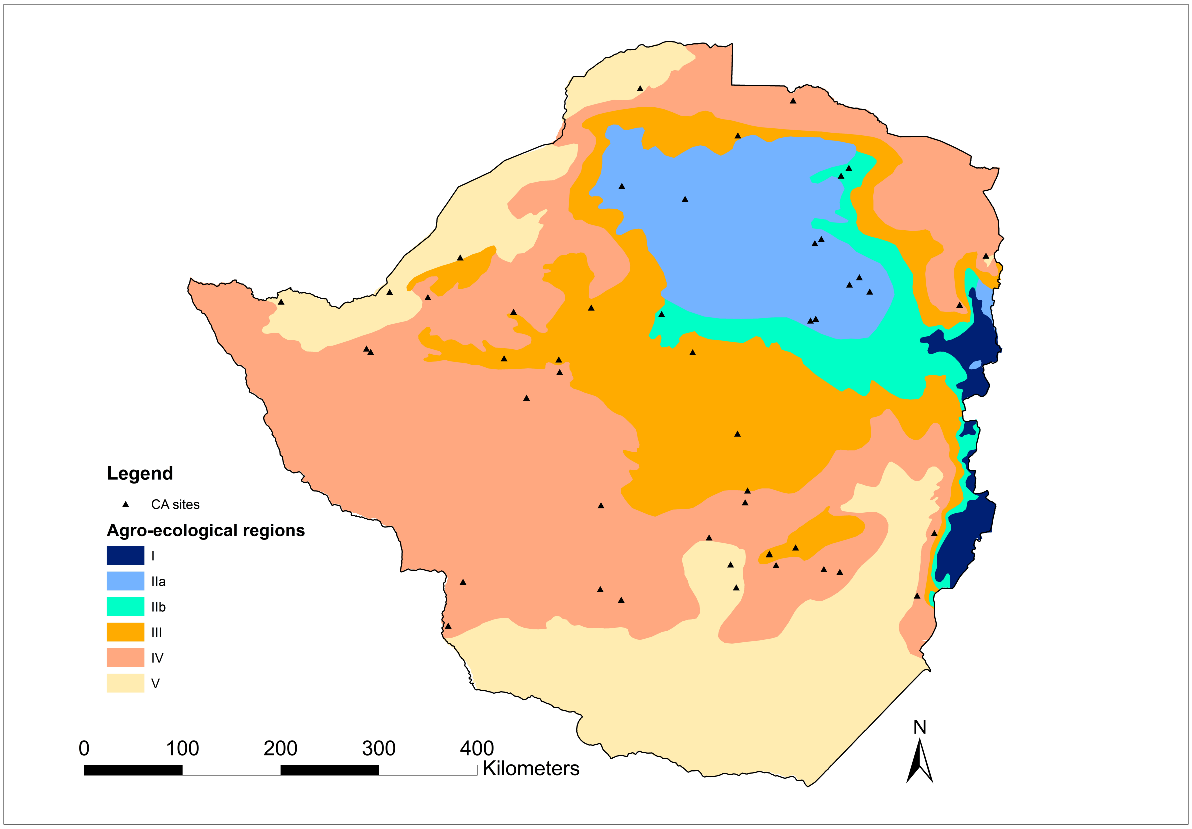
Note: Dependent variable is log of yield. Crop specific production functions are estimated as a system of equations using 3SLS to allow for correlation in the error terms across crop type. Panel A presents results using rainfall shocks and, though not reported, includes inputs, year dummies, and household fixed effects (Observations = $7,083$; Log Likelihood = $-78,662$). Panel B presents results using rainfall shortages and surpluses and, though not reported, includes inputs, year dummies, and household fixed effects (Observations = $7,083$; Log Likelihood = $-78,622$). In each regression the adoption of CA is treated as endogenous and is instrumented using the predicted values from the first stage seemingly unrelated regression which are presented in the Online Appendix, Table A7. The CA × rainfall terms are also treated as endogenous and instrumented using the interaction of the predicted values and the rainfall shock terms. Standard errors are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table 9: Production Function with Plot Level Effects

	(1)	(2)
Maize		
CA (= 1)	0.385	1.958
	(0.322)	(1.892)
rainfall shortage	−0.388	−1.220**
	(0.464)	(0.596)
CA × rainfall shortage	−0.875	3.054**
	(0.616)	(1.307)
rainfall surplus	−0.673**	−0.617
	(0.340)	(0.486)
CA × rainfall surplus	0.425	1.916**
	(0.404)	(0.789)
Sorghum		
CA (= 1)	−0.047	3.328
	(0.647)	(2.835)
rainfall shortage	−1.389**	−1.964***
	(0.595)	(0.566)
CA × rainfall shortage	1.895	3.978**
	(1.507)	(1.793)
rainfall surplus	−1.677***	−0.598
	(0.513)	(0.448)
CA × rainfall surplus	1.126	0.287
	(1.023)	(1.193)
Millet		
CA (= 1)	1.410	7.739
	(1.195)	(7.046)
rainfall shortage	−1.079	−1.085
	(0.695)	(0.711)
CA × rainfall shortage	−2.383	−3.238
	(1.657)	(5.807)
rainfall surplus	−1.319***	−0.572
	(0.462)	(0.425)
CA × rainfall surplus	−0.703	0.265
	(1.096)	(5.322)
Groundnut		
CA (= 1)	−0.580	2.897
	(0.707)	(2.173)
rainfall shortage	−1.618***	−1.831***
	(0.525)	(0.611)
CA × rainfall shortage	0.689	0.795
	(1.038)	(1.218)
rainfall surplus	−0.208	0.409
	(0.387)	(0.386)
CA × rainfall surplus	0.018	−0.484
	(1.056)	(1.176)
Cowpea		
CA (= 1)	−0.282	0.691
	(1.027)	(2.235)
rainfall shortage	−0.150	−2.147*
	(1.082)	(1.148)
CA × rainfall shortage	4.379**	6.127***
	(1.865)	(2.184)
rainfall surplus	−1.733*	−0.931
	(0.902)	(0.873)
CA × rainfall surplus	2.901*	2.730
	(1.682)	(2.173)
Plot Controls	FE	CRE
Observations	3,344	5,168
Kleibergen-Paap LM		9.520***
Log Likelihood	-6,210	-11,914

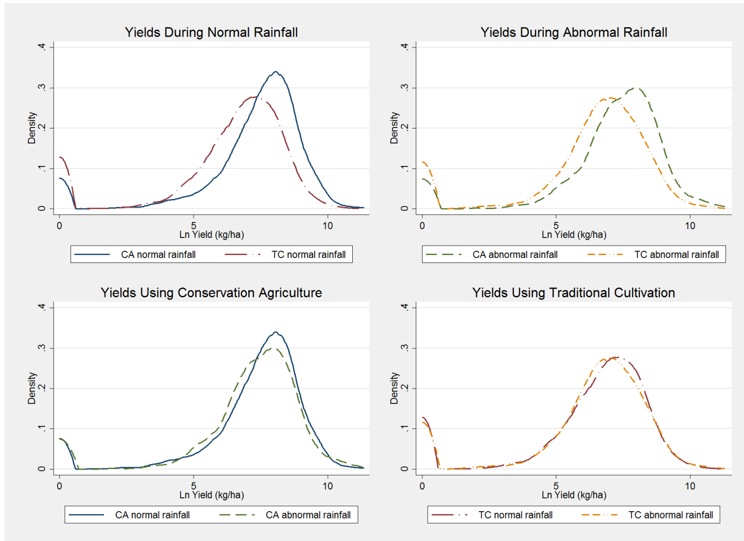
Note: Dependent variable is log of yield. Though not reported, all specifications include crop-specific inputs and intercept terms, and year dummies. Column (1) restricts the sample to plots with more than one observation and where CA is either always used or never used. It presents results from a plot level fixed effects regression where CA is exogenous. Column (2) restricts the sample to plots with more than one observation but includes plots where CA status changes over time. It presents results from a plot level CRE regression where CA is treated as endogenous and is instrumented as described previously. The underindentification test uses the Kleibergen-Paap LM statistic. All standard errors are clustered at the plot level and are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Figure 1: Location of Surveyed Wards in Zimbabwe



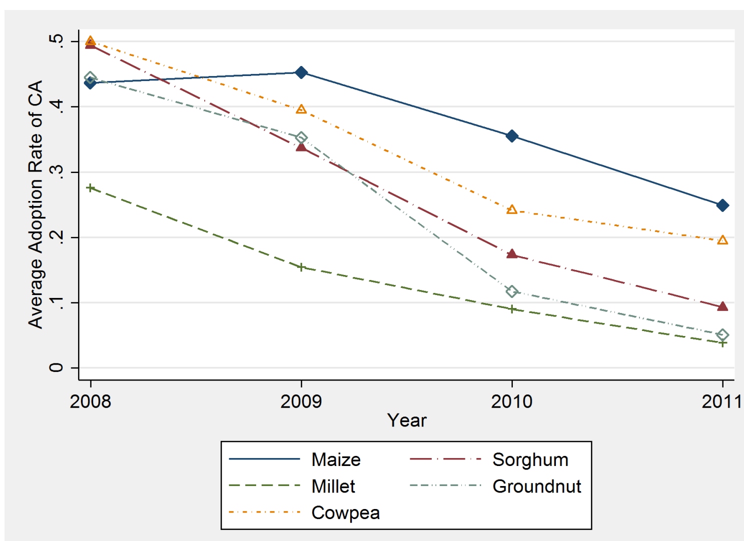
Note: Figure displays the locations of wards in the survey. Shading represents the agro-ecological regions of Zimbabwe. Regions III, IV, and V are all considered semi-arid and subject to frequent seasonal droughts.

Figure 2: Marginal Distributions of Yields by Cultivation Method and Rainfall



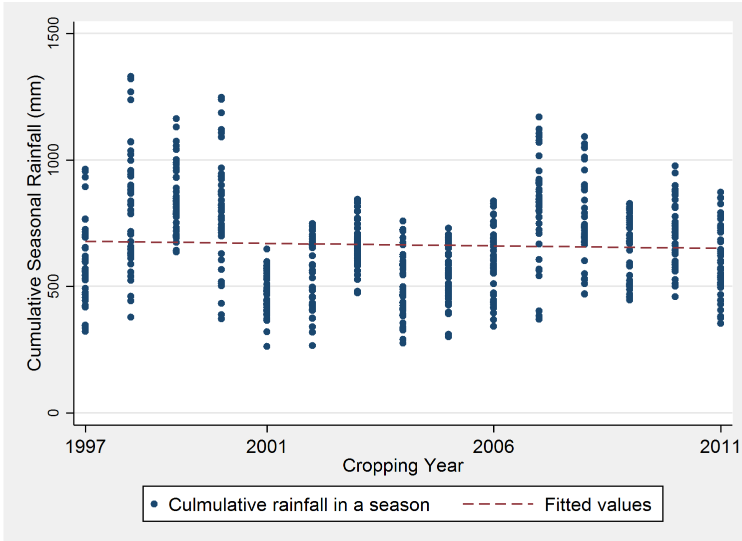
Note: Figure displays the kernel density plots of log of yields by either conservation agriculture (CA) or by traditional cultivation (TC) under normal and abnormal rainfall.

Figure 3: Average Annual Level of CA Adoption by Crop



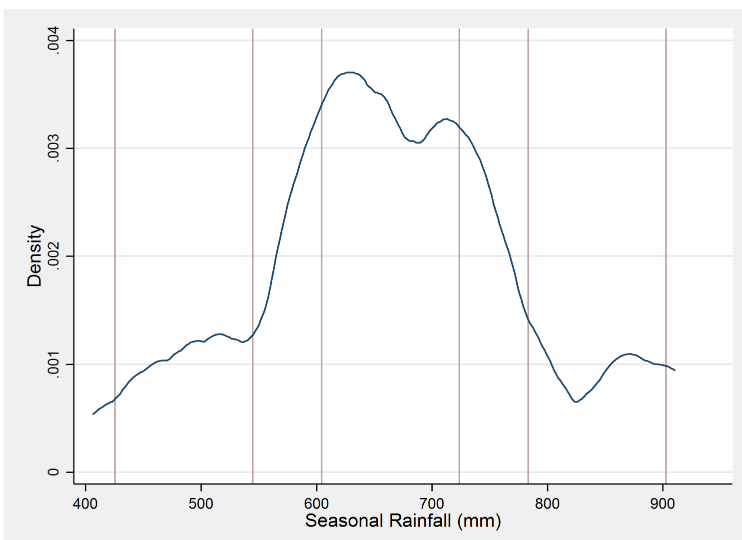
Note: Figure displays the average number of plots on which CA techniques are used by crop per year.

Figure 4: Historic Seasonal Rainfall by Ward



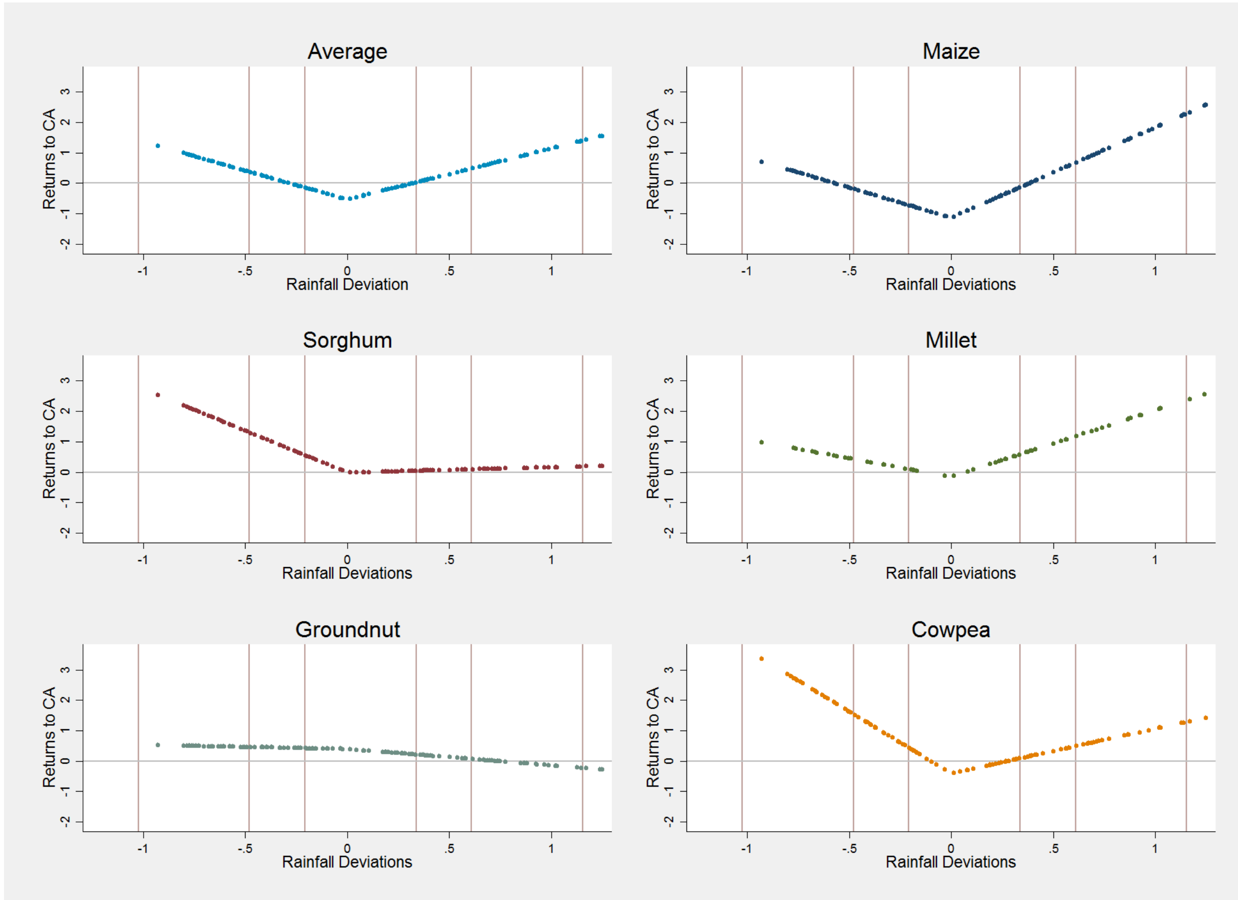
Note: Figure displays the cumulative rainfall for each cropping season in each ward for the 15 year period from 1997-2011. A linear trendline is fitted to the data with a slope of -3.71 which is significantly different from zero at the 99 percent level. Data comes from the CHIRPS database (Funk et al.,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

Figure 5: 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 $\pm$ half, one, and two standard deviations from the mean, which is 664mm. Data comes from the CHIRPS database (Funk et al., 2015).

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 7. By crop, we multiple the coefficient on the CA $\times$ rainfall shortage by realized shortages and multiple the coefficient on the CA $\times$ 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 $\pm$ half, one, and two standard deviations from the mean, which is 0.065.

A Appendix For Online Publication: Full Results from Production 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: Production Function with Rainfall Deviations

	Maize (1)	Sorghum (2)	Millet (3)	Groundnut (4)	Cowpea (5)
Panel A: Deviation in Seasonal Rainfall					
Seasonal deviation	−0.653***	−1.177***	−1.418***	−0.403*	−0.853**
	(0.195)	(0.267)	(0.308)	(0.214)	(0.394)
Panel B: Deviation in Monthly Rainfall					
Oct deviation	0.294	−0.298	0.024	0.511***	0.030
	(0.193)	(0.210)	(0.308)	(0.197)	(0.304)
Nov deviation	−0.196*	0.001	−0.070	0.084	−0.070
	(0.111)	(0.175)	(0.192)	(0.128)	(0.237)
Dec deviation	−0.186	−0.122	−0.448	0.223*	0.293
	(0.115)	(0.219)	(0.305)	(0.134)	(0.265)
Jan deviation	−0.585***	0.118	−0.273	0.218	0.386*
	(0.166)	(0.174)	(0.255)	(0.152)	(0.233)
Feb deviation	−1.103***	−0.361	−0.343	−0.682***	−2.155***
	(0.215)	(0.270)	(0.355)	(0.256)	(0.441)
Mar deviation	−1.045**	−0.807**	−0.605	−0.788***	0.100
	(0.186)	(0.320)	(0.503)	(0.241)	(0.379)
Apr deviation	−0.284***	0.104	−0.323**	−0.116	0.023
	(0.091)	(0.106)	(0.135)	(0.104)	(0.154)

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 = $7,837$; 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 = $7,837$; 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: Production Function with CA as Exogenous

	(1)	(2)	(3)	(4)
Maize				
CA (= 1)	0.645***	0.577***	0.198	0.197
	(0.083)	(0.081)	(0.139)	(0.136)
rainfall shock			−0.690***	−0.943***
			(0.217)	(0.230)
CA × rainfall shock			0.958***	0.776***
			(0.251)	(0.238)
ln(basal)	0.117***	0.072***	0.119***	0.078***
	(0.025)	(0.024)	(0.025)	(0.024)
ln(top)	0.324***	0.276***	0.314***	0.267***
	(0.028)	(0.026)	(0.028)	(0.026)
ln(seed)	0.286***	0.267***	0.273***	0.254***
	(0.078)	(0.073)	(0.078)	(0.073)
ln(area)	−0.514***	−0.536***	−0.506***	−0.525***
	(0.067)	(0.067)	(0.066)	(0.066)
Sorghum				
CA (= 1)	−0.033	−0.067	−0.783***	−0.576**
	(0.181)	(0.191)	(0.272)	(0.286)
rainfall shock			−1.305***	−1.467***
			(0.301)	(0.313)
CA × rainfall shock			1.572***	1.060**
			(0.464)	(0.501)
ln(basal)	0.029	−0.001	0.031	0.006
	(0.085)	(0.068)	(0.088)	(0.068)
ln(top)	0.125*	0.145**	0.122*	0.138**
	(0.066)	(0.059)	(0.065)	(0.058)
ln(seed)	0.390***	0.407***	0.390***	0.406***
	(0.109)	(0.111)	(0.108)	(0.110)
ln(area)	−0.601***	−0.620***	−0.572***	−0.590***
	(0.083)	(0.091)	(0.083)	(0.091)
Millet				
CA (= 1)	−0.167	0.180	−1.066	−0.731
	(0.357)	(0.374)	(0.711)	(0.733)
rainfall shock			−1.094***	−1.563***
			(0.303)	(0.316)
CA × rainfall shock			1.596*	1.637
			(0.945)	(1.165)
ln(basal)	0.209*	0.143	0.170	0.097
	(0.107)	(0.130)	(0.104)	(0.130)
ln(top)	−0.260**	−0.134	−0.242**	−0.114
	(0.121)	(0.126)	(0.120)	(0.121)
ln(seed)	0.153	0.203	0.190	0.239*
	(0.159)	(0.144)	(0.158)	(0.140)
ln(area)	−0.464***	−0.594***	−0.474***	−0.604***
	(0.130)	(0.128)	(0.128)	(0.124)
Groundnut				
CA (= 1)	0.218	0.286**	−0.575**	−0.029
	(0.143)	(0.144)	(0.288)	(0.281)
rainfall shock			−0.462**	−0.538**
			(0.208)	(0.228)
CA × rainfall shock			1.419***	0.553
			(0.488)	(0.454)
ln(basal)	0.067	−0.026	0.074	−0.026
	(0.071)	(0.062)	(0.069)	(0.062)
ln(top)	−0.068	−0.019	−0.028	−0.004
	(0.070)	(0.060)	(0.068)	(0.060)
ln(seed)	0.483***	0.396***	0.481***	0.392***
	(0.088)	(0.083)	(0.087)	(0.083)
ln(area)	−0.523***	−0.623***	−0.518***	−0.612***
	(0.079)	(0.073)	(0.079)	(0.074)

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Table A2 – Continued

	(1)	(2)	(3)	(4)
Cowpea				
CA (= 1)	−0.059	0.232	−0.983**	−0.429
	(0.242)	(0.252)	(0.455)	(0.447)
rainfall shock			−1.058**	−1.216***
			(0.444)	(0.435)
CA × rainfall shock			1.924**	1.321
			(0.895)	(0.874)
ln(basal)	0.336***	0.129	0.327***	0.129
	(0.106)	(0.088)	(0.105)	(0.088)
ln(top)	−0.164	−0.137	−0.147	−0.125
	(0.109)	(0.097)	(0.110)	(0.098)
ln(seed)	0.370***	0.412***	0.389***	0.422***
	(0.138)	(0.139)	(0.139)	(0.139)
ln(area)	−0.588***	−0.716***	−0.596***	−0.720***
	(0.102)	(0.106)	(0.103)	(0.108)
Household FE	No	Yes	No	Yes
Observations	7,837	7,837	7,837	7,837
R^2	0.898	0.922	0.899	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: Production Function with CA as Endogenous

	(1)	(2)	(3)	(4)
Maize				
CA (= 1)	7.233*	−1.289	6.659	−2.413*
	(4.255)	(1.286)	(5.359)	(1.378)
rainfall shock			−0.440	−1.656***
			(0.791)	(0.377)
CA × rainfall shock			2.009	2.690***
			(1.470)	(0.736)
ln(basal)	−0.270	0.174**	−0.281	0.184**
	(0.247)	(0.078)	(0.285)	(0.074)
ln(top)	0.013	0.375***	−0.022	0.340***
	(0.210)	(0.073)	(0.229)	(0.065)
ln(seed)	1.015**	0.078	1.052*	0.089
	(0.475)	(0.162)	(0.543)	(0.153)
ln(area)	−0.211	−0.636***	−0.180	−0.601***
	(0.232)	(0.101)	(0.253)	(0.093)
Sorghum				
CA (= 1)	10.882**	0.202	11.961*	0.185
	(5.383)	(1.678)	(6.868)	(1.862)
rainfall shock			−1.155**	−1.494***
			(0.488)	(0.358)
CA × rainfall shock			−0.437	0.806
			(1.987)	(0.955)
ln(basal)	−0.487*	−0.009	−0.491	−0.018
	(0.288)	(0.119)	(0.317)	(0.108)
ln(top)	−1.654*	0.096	−1.811*	0.032
	(0.887)	(0.258)	(1.044)	(0.247)
ln(seed)	0.368**	0.388***	0.376*	0.396***
	(0.184)	(0.106)	(0.193)	(0.106)
ln(area)	0.421	−0.572***	0.515	−0.509***
	(0.513)	(0.181)	(0.591)	(0.169)
Millet				
CA (= 1)	16.373	−1.926	21.906	−1.133
	(11.625)	(3.323)	(20.303)	(3.897)
rainfall shock			−0.422	−1.693***
			(0.702)	(0.337)
CA × rainfall shock			−4.889	2.449
			(12.602)	(2.250)
ln(basal)	−0.831	0.274	−0.938	0.090
	(0.874)	(0.224)	(0.976)	(0.199)
ln(top)	−2.562	0.173	−3.006	−0.103
	(1.737)	(0.493)	(2.261)	(0.471)
ln(seed)	−0.617	0.278	−0.761	0.234
	(0.657)	(0.198)	(0.864)	(0.188)
ln(area)	1.513	−0.854**	1.872	−0.603
	(1.475)	(0.408)	(1.891)	(0.392)
Groundnut				
CA (= 1)	8.800**	0.586	8.726*	0.257
	(3.939)	(1.321)	(4.938)	(1.554)
rainfall shock			−1.122***	−0.893***
			(0.394)	(0.269)
CA × rainfall shock			1.492	1.140
			(1.733)	(0.892)
ln(basal)	−0.653*	−0.064	−0.690	−0.087
	(0.371)	(0.121)	(0.422)	(0.115)
ln(top)	−1.131**	−0.055	−1.207*	−0.065
	(0.518)	(0.166)	(0.620)	(0.173)
ln(seed)	0.720***	0.477***	0.745***	0.468***
	(0.204)	(0.089)	(0.224)	(0.091)
ln(area)	0.035	−0.614***	0.077	−0.580***
	(0.298)	(0.115)	(0.336)	(0.107)

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Table A3 – Continued

	(1)	(2)	(3)	(4)
Cowpea				
CA (= 1)	5.985*	−0.069	4.840	−1.017
	(3.256)	(1.231)	(4.068)	(1.439)
rainfall shock			−1.004	−1.659***
			(0.720)	(0.471)
CA × rainfall shock			2.962	2.481*
			(2.067)	(1.413)
ln(basal)	0.148	0.147	0.124	0.133
	(0.179)	(0.100)	(0.185)	(0.098)
ln(top)	−1.154**	−0.092	−1.158*	−0.104
	(0.563)	(0.198)	(0.634)	(0.193)
ln(seed)	−0.036	0.432***	−0.020	0.448***
	(0.281)	(0.147)	(0.311)	(0.148)
ln(area)	−0.029	−0.747***	−0.013	−0.727***
	(0.321)	(0.152)	(0.362)	(0.150)
Household FE	No	Yes	No	Yes
Kleibergen-Paap LM	4.875**	21.38***	3.865**	25.17***
Observations	7,837	7,837	7,837	7,837
Log Likelihood	-21,406	-16,587	-21,798	-16,527

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 5. 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)
Num HH in ward with NGO support	0.010***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)
Household CRE	Yes	Yes	Yes
Observations	7,837	7,837	7,837
Log Likelihood	-3,226	-3,223	-3,217

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 a rainfall shortage, column (2) includes a rainfall surplus, and column (3) includes both a rainfall shortage and a rainfall surplus. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A5: Production Function with Rain Shortage or Surplus

	(1)	(2)	(3)
Maize			
CA (= 1)	0.470	−2.052	−1.145
	(1.590)	(1.656)	(1.802)
rainfall shortage	0.293		−0.918*
	(0.412)		(0.519)
CA × rainfall shortage	−0.099		1.984*
	(0.752)		(1.049)
rainfall surplus		−1.683***	−1.884***
		(0.306)	(0.386)
CA × rainfall surplus		2.147***	2.964***
		(0.493)	(0.701)
ln(basal)	0.074	0.204**	0.116
	(0.091)	(0.099)	(0.097)
ln(top)	0.279***	0.366***	0.271***
	(0.084)	(0.091)	(0.085)
ln(seed)	0.262	0.077	0.222
	(0.186)	(0.198)	(0.192)
ln(area)	−0.535***	−0.621***	−0.529***
	(0.113)	(0.115)	(0.111)
Sorghum			
CA (= 1)	0.197	−0.574	−0.021
	(1.652)	(2.367)	(2.080)
rainfall shortage	−1.144***		−1.736***
	(0.391)		(0.455)
CA × rainfall shortage	3.139**		2.749**
	(1.305)		(1.332)
rainfall surplus		−0.465	−1.166***
		(0.356)	(0.390)
CA × rainfall surplus		−0.880	0.176
		(1.111)	(1.067)
ln(basal)	−0.037	0.077	−0.006
	(0.120)	(0.124)	(0.116)
ln(top)	0.011	0.248	0.040
	(0.275)	(0.327)	(0.293)
ln(seed)	0.398***	0.398***	0.406***
	(0.107)	(0.106)	(0.106)
ln(area)	−0.536***	−0.680***	−0.540***
	(0.183)	(0.200)	(0.184)
Millet			
CA (= 1)	−0.418	−1.914	−0.163
	(2.826)	(3.570)	(3.455)
rainfall shortage	−0.599		−1.637**
	(0.592)		(0.638)
CA × rainfall shortage	−0.005		1.222
	(1.401)		(2.299)
rainfall surplus		−1.184***	−1.619***
		(0.376)	(0.328)
CA × rainfall surplus		2.168	2.188
		(1.509)	(2.242)
ln(basal)	0.163	0.168	0.033
	(0.203)	(0.198)	(0.185)
ln(top)	−0.043	0.098	−0.196
	(0.429)	(0.483)	(0.427)
ln(seed)	0.220	0.263	0.198
	(0.188)	(0.186)	(0.179)
ln(area)	−0.670*	−0.737*	−0.510
	(0.361)	(0.387)	(0.351)

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Table A5 – Continued

	(1)	(2)	(3)
Groundnut			
CA (= 1)	0.997	−0.957	0.390
	(1.298)	(1.764)	(1.769)
rainfall shortage	−1.121***		−1.186***
	(0.320)		(0.334)
CA × rainfall shortage	0.177		0.136
	(0.723)		(1.033)
rainfall surplus		0.111	−0.081
		(0.324)	(0.310)
CA × rainfall surplus		−0.147	−0.537
		(0.951)	(1.120)
ln(basal)	−0.083	0.058	−0.033
	(0.117)	(0.140)	(0.121)
ln(top)	−0.129	0.142	−0.035
	(0.167)	(0.196)	(0.190)
ln(seed)	0.472***	0.446***	0.456***
	(0.091)	(0.083)	(0.089)
ln(area)	−0.600***	−0.721***	−0.653***
	(0.113)	(0.110)	(0.104)
Cowpea			
CA (= 1)	0.232	−0.022	−0.411
	(1.237)	(1.559)	(1.581)
rainfall shortage	−0.507		−1.434***
	(0.479)		(0.546)
CA × rainfall shortage	3.314***		4.067***
	(1.047)		(1.331)
rainfall surplus		−1.170**	−1.558***
		(0.477)	(0.547)
CA × rainfall surplus		−0.329	1.463
		(1.307)	(1.668)
ln(basal)	0.058	0.166	0.076
	(0.101)	(0.111)	(0.104)
ln(top)	−0.197	−0.099	−0.182
	(0.199)	(0.218)	(0.207)
ln(seed)	0.431***	0.440***	0.442***
	(0.149)	(0.150)	(0.152)
ln(area)	−0.681***	−0.760***	−0.690***
	(0.154)	(0.163)	(0.157)
Household FE	Yes	Yes	Yes
Observations	7,837	7,837	7,837
Kleibergen-Paap LM	18.32***	15.75***	17.67***
Log Likelihood	-16,282	-16,607	-16,272

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. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A6: Production Function with Alternative Rainfall Measures

	(1)	(2)
Maize		
CA (= 1)	−1.849	−3.143**
	(1.322)	(1.446)
rainfall shock	−0.975***	−0.843***
	(0.322)	(0.282)
CA × rainfall shock	2.120***	2.156***
	(0.530)	(0.526)
Sorghum		
CA (= 1)	−0.131	−1.167
	(1.693)	(1.853)
rainfall shock	−0.664**	−0.718**
	(0.301)	(0.292)
CA × rainfall shock	0.711	0.408
	(0.617)	(0.617)
Millet		
CA (= 1)	−1.161	−2.725
	(2.889)	(3.139)
rainfall shock	−0.534*	−0.724**
	(0.307)	(0.307)
CA × rainfall shock	−0.848	−0.507
	(2.074)	(1.413)
Groundnut		
CA (= 1)	0.335	−0.847
	(1.353)	(1.433)
rainfall shock	−0.367	−0.432**
	(0.249)	(0.218)
CA × rainfall shock	0.809	1.152**
	(0.612)	(0.574)
Cowpea		
CA (= 1)	−0.172	−1.204
	(1.248)	(1.385)
rainfall shock	−0.744*	−1.199***
	(0.431)	(0.418)
CA × rainfall shock	0.044	1.803*
	(1.293)	(1.081)
Household FE	Yes	Yes
Kleibergen-Paap rk LM statistic	23.04***	20.35***
Observations	7,837	7,837
Log Likelihood	-16,661	-17,022

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 $0.202 \leq R_{jt} \leq 0.748$ 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 $0.338 \leq R_{jt} \leq 0.612$ 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 by Crop Type

	Maize (1)	Sorghum (2)	Millet (3)	Groundnut (4)	Cowpea (5)
			Panel A: Rainfall Shock		
Num HH with NGO support	-0.001^{**}	0.001^{***}	-0.000	0.001^{**}	0.001^{***}
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.327	0.167	0.112	0.135	0.139
			Panel B: Rainfall Shortage and Surplus		
Num HH with NGO support	-0.001^{**}	0.001^{***}	-0.000	0.001^{**}	0.001^{***}
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.327	0.168	0.112	0.136	0.139

Note: Panel A reports results from a first stage seemingly unrelated regression with CA adoption as the dependent variable and includes the IV, rainfall shock, inputs, year dummies, and household fixed effects (Observations $= 7,837$; Log Likelihood $= 13,700$). Panel B reports results from a first stage seemingly unrelated regression with CA adoption as the dependent variable and includes the IV, rainfall shortages and surplus, inputs, year dummies, and household fixed effects (Observations $= 7,837$; Log Likelihood $= 13,713$). Standard errors are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A8: First Stage IV Tobit with Rain Shortage and Surplus

	(1)	(2)
Num HH in ward with NGO support	0.005**	0.007***
	(0.002)	(0.001)
Household Control	FE	CRE
Observations	7,837	7,837
Log Likelihood	-4,483	-5,060

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 household correlated random effects. Standard errors clustered by household and crop are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

Table A9: Production Function using First Stage Tobit

	(1)	(2)
Maize		
CA (= 1)	−0.037	−0.998
	(0.472)	(0.809)
rainfall shortage	−0.358	−0.710
	(0.368)	(0.450)
CA × rainfall shortage	0.394	1.226
	(0.695)	(0.954)
rainfall surplus	−1.471***	−1.823***
	(0.321)	(0.334)
CA × rainfall surplus	1.842***	2.751***
	(0.544)	(0.631)
Sorghum		
CA (= 1)	0.154	−0.303
	(0.774)	(1.027)
rainfall shortage	−1.753***	−1.935***
	(0.423)	(0.444)
CA × rainfall shortage	2.725**	3.674***
	(1.105)	(1.229)
rainfall surplus	−1.273***	−1.456***
	(0.363)	(0.364)
CA × rainfall surplus	0.512	1.103
	(0.762)	(0.830)
Millet		
CA (= 1)	−1.580	−1.291
	(1.716)	(1.755)
rainfall shortage	−1.798***	−1.763***
	(0.612)	(0.618)
CA × rainfall shortage	2.814	2.713
	(2.495)	(2.543)
rainfall surplus	−1.574***	−1.723***
	(0.303)	(0.297)
CA × rainfall surplus	2.698	3.515*
	(1.799)	(2.008)
Groundnut		
CA (= 1)	0.306	0.385
	(0.541)	(0.675)
rainfall shortage	−1.208***	−1.257***
	(0.320)	(0.322)
CA × rainfall shortage	0.362	0.585
	(0.720)	(0.807)
rainfall surplus	−0.110	−0.113
	(0.250)	(0.251)
CA × rainfall surplus	−0.207	−0.436
	(0.597)	(0.677)
Cowpea		
CA (= 1)	−1.118	−0.931
	(0.768)	(1.064)
rainfall shortage	−1.533***	−1.552***
	(0.532)	(0.554)
CA × rainfall shortage	4.461***	4.488***
	(1.167)	(1.387)
rainfall surplus	−1.835***	−1.714***
	(0.513)	(0.533)
CA × rainfall surplus	2.785**	2.148
	(1.406)	(1.718)
Household FE	Yes	Yes
Observations	7,837	7,837
Kleibergen-Paap LM	256.2***	164.8***
Log Likelihood	-16,223	-16,273

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 A8. Column (2) uses the predicted value and the Inverse Mills Ratio from the first stage Tobit with household correlated random effects as presented in column (2) of Table A8. 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).