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Knowing is half the battle: Seasonal forecasts, adaptive cropping systems, and the mediating role of private markets in Zambia

Giuseppe Maggio¹ & Nicholas Sitko^{1,2}

Abstract

This paper examines how smallholders living in regions where a drought is forecasted adapt their farm management in response to receiving seasonal forecast information. The article draws on a unique longitudinal dataset in Zambia, which collected information from farm households before and after a significant drought caused by the 2015/2016 El-Niño Southern Oscillation. It finds that farmers residing in areas forecasted to be drought-affected and receiving seasonal forecast information are significantly more likely to integrate drought tolerant crops into their cropping systems compared to similar households not receiving this information. Moreover, the probability that a farmer implements these adaptive farm management strategies in response to seasonal forecast information is found to increase substantially as the number of private grain buyers in the farmers' village increases. This suggests that climate change adaptation and resilience strategies that integrate the generation and dissemination of weather information with agricultural market development can achieve greater impact on farmers' adaptive response than approaches that treat these activities in isolation.

Keywords: Adaptation; agricultural practices; climate change; weather forecasts; Zambia; Sub-Saharan Africa.

JEL codes: Q02; Q17; Q18.

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1. Introduction

There is a high level of agreement within the scientific community that climate change is likely to slow down economic growth, make poverty reduction more difficult, and further erode food security (IPCC, 2014). This is particularly the case in predominantly agrarian countries in sub-Saharan Africa (SSA), where a large share of the population is reliant on rain-fed production to meet its livelihood needs (IPCC, 2014). Building the resilience of rain-fed smallholder farm systems to current and future climate conditions is, therefore, essential for countries in SSA to achieve their poverty reduction and economic growth objectives.

While there remains uncertainty about future changes in rainfall patterns and distributions in SSA, there is convergence in global climate models that large parts of southern Africa will experience increased incidences of drought (Li *et al.*, 2009; IPCC, 2014). One area of particular concern is the potential increase in frequency of extreme El Niño–Southern Oscillation (ENSO) events resulting from increased greenhouse gas concentrations in the atmosphere (Cai *et al.*, 2014). The ENSO is a cyclical warm phase of sea surface temperatures in the Pacific Ocean that is often associated with a significant shortening of the rainy season in southern Africa (Nicholson and Kim, 1997), with strong potential impacts on smallholder agricultural systems (Naylor *et al.*, 2001, Stige *et al.*, 2006). Over the last two decades, the ability of seasonal forecast (SF) models to predict the potential rainfall impact of ENSO events has improved in SSA (Manatsa *et al.*, 2017; O'Brien *et al.*, 2000). This creates new opportunities to support smallholder adaptive responses to probabilistic weather events due to ENSO and mechanisms to facilitate these responses (Patt *et al.*, 2005; Vogel and O'Brien, 2006).

Using Zambia as a case study, this article empirically examines if receiving SF information about a potential ENSO-induced drought influences smallholders' adoption of drought resilient practices and tests the extent to which market institutions mediate adaptive behavior change. In particular, this study explores two interrelated questions. First, do households living in areas forecasted to experience an ENSO-induced drought integrate more drought tolerant crops into their cropping systems when they receive SF information? Second, do market institutions help to

ease constraints associated with the adoption of drought tolerant cropping systems? This study uses a unique panel household dataset that was collected from smallholder households before and after the 2015/2016 ENSO event. The 2015/2016 ENSO was the “most widely anticipated El Niño–Southern Oscillation event ever” (L’Heureux *et al.*, 2017), with global operational forecast services predicting its effects to be comparable to the strongest ever recorded ENSO events in 1982/83 and 1997/98 (L’Heureux *et al.*, 2017). As a consequence of this event, large parts of Southern Africa received only 50-70 percent the regular quantity of rainfall during the first part of the agricultural season. This reduced crop yields and generated severe food deficit warnings (Mazvimavi *et al.*, 2017).

Availability of panel survey data that coincide with this event creates a unique opportunity to examine in detail changes in smallholder cropping systems and input use associated with receiving SF information. Unfortunately, information on households targeted with SF is only available for the last wave of the survey. As a result, the panel dimension of the survey is used to identify household-level variations in cropping systems between the agricultural seasons 2014/2015 and 2015/2016. However, the data cannot be employed to control for unobserved heterogeneity. We address this limitation using an identification strategy based on two approaches. First, we run a propensity-score matching on observable household characteristics correlated with receiving SF information. We include the resulting weights in a linear probability model and test the effect of SF on farmers’ cropping system adoption behavior. Second, to test for the causal effect of receiving SF information, we run an instrumental variable probit model. Our instrumental variables take advantage of the role of “social learning” or “learning from others” common in the social network literature on the adoption of agricultural practices (Arslan, Belotti and Lipper, 2017; Foster and Rosenzweig, 1995). The first variable is a measure of the degree of household geographic proximity to other farmers receiving SF. The second consists of a socio-institutional measure of efficiency in delivering SF and is operationalized as the leave-out share of household receiving SF in the village.

All our estimations point towards a positive effect of receiving SF on the adoption of drought tolerant cropping systems in regions forecasted to be affected by drought. This effect is evident for the extensive margin, as households receiving SF on drought are more likely, on average, to

switch their cropping systems compared to households living in the same zones but not receiving this information. Moreover, the probability that a household switches to a drought tolerant cropping system increases with the forecasted duration of the drought. Finally, we find evidence that access to private agricultural markets increases the probability that farmers adapt their cropping systems in response to receiving SF in drought forecasted regions, all else equal.

This paper makes three contributes to the literature on the role of SF in smallholder ex-ante adaptive responses to forecasted climate shocks. First, while previous studies have investigated the effect of SF on crop varietal choices and its consequences in terms of yield and income (Gunda *et al.*, 2017; Meza *et al.*, 2008; Phillips *et al.*, 2002), this is the first analysis to address crop system diversification as an adaptive response. Second, by using a unique dataset and rigorous empirical analysis with geo-located data, this paper adds novel evidence on how farmers form expectations using SF, and how they use the information in farm management decisions (see, among others, Roudier *et al.*, 2014). Finally, while literature exists on the factors limiting farmers' responses to SF information (Patt and Gwata, 2002; Orvole and Tosteson, 1999) and on factors mediating farmers' responses, such as the source of SF information (Patt *et al.*, 2005) or delivery mechanisms (e.g. Ingram, Roncoli and Kirshen 2002), this is the first analysis examining how the development of private agricultural markets may affect farmers' probability of responding to the SF information.

The paper is structured as follow. Section 2 outlines our conceptual framework for understanding how farmers respond to seasonal forecasts. Section 3 introduces the datasets used in the analysis. Section 4 describes the research design and empirical strategy. This is followed in Section 5 with the results. Section 6 presents the results of a range of robustness tests, which help to validate the robustness of the findings. Finally, Section 7 concludes with a set of policy considerations based on the results of the analysis.

2. Conceptual framework: Climate information, barriers to adaptation and market institutions

Farmers' adaptation to climate change often occurs through a two-step process (Deressa *et al.*, 2009). The first step involves a change in perception regarding climate change and an increased understanding of its potential impacts on their livelihoods and incomes. The second step involves the adoption of practices that are more resilient to these changes. SF information can play an instrumental role in this process, by providing farmers with necessary information to understand potential weather threats and to optimize their production decisions accordingly (Bryan *et al.* 2009; Patt *et al.*, 2005). Indeed, the literature on farmers' expectations about seasonal rainfall suggests that SF can reduce uncertainty over rainfall distributions, and therefore improve the choices farmers make in response (Kurukulasuriya *et al.*, 2011). However, despite its potential benefits, SF information is not widely used by farmers in developing countries (Lemos *et al.*, 2012).

The utilization or underutilization of SF information by smallholders has been explained as a function of attitudes towards risk, as well as farmers' trust in and understanding of the information provided to them (Arbuckle *et al.*, 2015; Di Falco and Perrings 2005; Gould *et al.*, 1989; Grothmann and Patt, 2005; Tanaka *et al.*, 2010; Wossen *et al.*, 2015). While these are often difficult to empirically measure, levels of education and socio-economic status are often correlated with adaptive responses to information, including SF information (Orvole and Tosteson, 1999; Rahm and Huffman, 1984; Shortle and Miranowski, 1986; Warriner and Moul, 1992). The quality and source of information is also found to be important. For example, Deressa *et al.* (2011) shows that in Ethiopia, farmers are more likely to adopt adaptive farm practices when they access information through public extension services.

In Zambia, SF information is compiled by the Zambian Meteorological Society and then disseminated to farmers via radio, mobile phone messaging, print media, and government extension services prior to the farming season. In the 2015/16 season seasonal forecasts were distributed in September. However, survey results show that prior to the 2015/2016 ENSO farming season, only 41 percent of smallholders in Zambia actually received SF information. This is likely due to

constraints within the government extension service, as well as to low levels of radio ownership, cell phone coverage, and print media distribution.

While access to reliable SF information is a clear barrier in Zambia, responding to this information represents a second challenge for farmers. Access to input and output markets are likely to be important determinants of smallholders' adaptive responses to SF information. Smallholder farmers are often financially constrained, sensitive to risk, and have few tools at their disposal to manage risk and adopt new and different farm practices (Deressa *et al.*, 2009; Markelova *et al.*, 2009). Markets may help to ease some of these constraints, and thus support better adaptive responses to information by farmers (Barrett, 2008). This can occur in a number of ways. First, access to markets can improve the availability and lower transactions costs associated with acquiring new farm technologies, including appropriate crop seeds and seed varieties for a particular region (Kassie *et al.*, 2012, Pender and Gebremedhin, 2007). Second, private output markets can be useful sources of information on market prices and demand conditions for a range of agricultural products. This information may help to lower the costs and risks to farmers of adopting new crops and technologies (Fafchamps and Minten 2002). Finally, there is emerging evidence that private markets actors in SSA are increasingly providing farmers with risk management tools, such as formal and informal delivery contracts, as well as extension advice, for a range of different crops (Sitko *et al.*, 2018). To ensure that sufficient volumes of agricultural products are produced and sold to cover fixed investment costs in regions forecasted to experience drought, private output market actors have an incentive to utilize these risk management tools to encourage adoption of more drought resilient crops and to promote the use of suitable inputs.

2.1 Identifying and modelling the impact of seasonal forecasts on the adoption of drought-tolerant practices

The conceptual framework of this article relies on the seminal work of Hilton (1981), which formalizes the economic values that agents attach to information, and which is broadly adopted in the literature on seasonal forecasts (see, for example, Meza *et al.*, 2008; Mjelde *et al.*, 1988; Letson *et al.*, 2005). The model is based on two assumptions. First, farmers are rational decision makers that face an ex-

ante optimization problem for the maximization of their utility function. Second, farmers are aware of the consequences of their management choices under the full range of potential climatic conditions.

Consider the utility function $U_i[Y_i(\mathbf{P}_i, \mathbf{C}), W_{i0}]$ of farmer i , depending on the profit Y_i and initial wealth W_{i0} . In this simplified model, profits are a function of a vector of decisions or practices, $\mathbf{P}_i$, and a vector $\mathbf{C}$ consisting in a set of weather variables for the agricultural season. Since farmers are unable to observe future weather, its distribution is uncertain, and thus the vector $\mathbf{C}$ takes the form of a random variable with a multivariate probability density function (p.d.f.) equal to $f(\mathbf{C})$. Under uncertainty, for the set of practices $\mathbf{P}_i$, the expected utility function can be expressed as:

$$E\{U_i[Y_i(\mathbf{P}_i), W_{i0}]\} = \int U_i[Y_i(\mathbf{P}_i, \mathbf{C}), W_{i0}] f(\mathbf{C}) d(\mathbf{C}) \quad (1)$$

Under conditions with no seasonal forecast information, farmers will therefore select a combination of practices $\mathbf{P}^*$ that maximize their expected utility conditional on the expected climate distribution, such that:

$$\max_{\mathbf{P}} E\{U_i[Y_i(\mathbf{P}_i), W_{i0}]\} = E\{U_i[Y_i(\mathbf{P}^*), W_{i0}]\} \quad (2)$$

Since the outcome of $\mathbf{C}$ is revealed only after the selection of $\mathbf{P}^*$, the latter does not necessarily correspond to the practices that farmers would have adopted under perfect information. Accessing seasonal weather forecasts (SF) will inform farmers' expectations on future weather distributions. This information alters the p.d.f. in their optimization problem, making the climate distribution conditional on the information contained the seasonal forecast $f(\mathbf{C}/SF)$. Receiving seasonal forecast information influences the expected utility from the adoption of each practice. Therefore, the maximization problem will have an alternative solution denoted by the vector $\mathbf{P}^{**} \neq \mathbf{P}^*$, which maximizes their new objective function:

$$\max_{\mathbf{P}} E\{U_i[Y_i(\mathbf{P}_i/SF), W_{i0}]\} = E\{U_i[Y_i(\mathbf{P}^{**}/SF), W_{i0}]\} \quad (3)$$

The baseline hypothesis of this study is that farmers receiving SF and residing in areas forecasted to be hit by ENSO-induced drought are more likely to adopt drought tolerant agricultural practices, as these ex-ante coping strategies will maximize their expected utility. To test this hypothesis, we

focus on the adoption of three drought-tolerant cropping systems $MS_i = \{MS1; MS2; MS3\}$, which are described below. The model predicts that farmers, receiving seasonal forecast information of a high probability of drought $SF = DR$ will adopt a system within MS_i against any other cropping system $CS_i \neq MS_i$ as their expected value from the drought-tolerant system will be higher, thus $E\{U_i[Y_i(MS_i/DR), W_{i0}]\} > E\{U_i[Y_i(CS_i/DR), W_{i0}]\}$.

In this framework, farmers evaluate the expected costs of adopting farming practices in response to seasonal forecast information. As discussed above, the level of private market development influences farmers' cost expectation function of responding to seasonal forecast information. As levels of market development increase, the prices associated with adopting new practices (input costs, search cost costs, information costs etc...) decrease, thus increasing the probability of adopting new practices in response to seasonal forecasts. Conversely, as market development levels decline, costs of adoption increase, thereby reducing the probability of switching practices in response to seasonal forecasts.³

The drought-tolerant cropping systems are identified within Zambia's predominantly maize-based production systems are based on combinations of seven different crops summarized in Table 1.

Table 1 Drought tolerant crops included in the maize systems

Cropping System	Crops included	Expected Resilience	Literature
MS1	Cassava; Millet; Sorghum; Sweet-potato.	High	Bidinger, Mahalakshmi, and Rao (1987); Blum and Ebercon (1976); El-Sharkawi (1993); Schlenker and Lobell (2010).
MS2	MS1+ Cow peas; Pigeon-peas	From High to Medium	Hall and Grantz (1981); Sileshi et al 2008, Snapp <i>et al.</i> , (2003)
MS3	MS2+ Cotton	From High to Medium	Rosenow <i>et al.</i> , (1983); Parida <i>et al.</i> , (2008); Cline, (2007); Morton, (2007)

³ Depending on the level of risk-aversion of farmers, they might adopt drought tolerant practices even under normal conditions. However, the simplified model adopted assumes that under normal expected weather conditions a rational farmer will not adopt these drought tolerant system because of their low expected returns relative to normal cropping systems.

The first system, MS1, includes alternative carbohydrate crops, namely cassava, millet, sorghum, and/or sweet potato. These four crops are recognized for their level of resistance to high temperatures and to low precipitations when cultivated in rain-fed agriculture. For example, literature suggests that cassava is the most drought tolerant perennial crop available to smallholder African farmers, and survives rainfall shortfalls that lead to crop failure for maize (El-Sharkawi, 1993; Schlenker and Lobell, 2010). Cropping system MS2 adds drought tolerant legumes to MS1, namely cowpeas and pigeon-peas. These legumes are unusually adaptable to drought and may also help to stabilize production under climate stress through nitrogen fixation and the improvements in soil quality (Sileshi et al 2008, Snapp *et al.*, 2003). Crop system MS3 adds cotton to the MS2 system, which historically benefitted from scientific genetic improvements in drought tolerance due to its commercial status (Rosenow *et al.*, 1983; Parida *et al.*, 2008). Some researchers predict an increase in future cotton production precisely because of its high drought tolerance (Cline, 2007; Morton, 2007).

Finally, the set of practices analysed also includes the adoption of inorganic fertilizer and the quantity applied. Evidence in the literature suggests returns to inorganic fertilizer use are strongly correlated with available soil moisture, which in rain-fed systems is driven primarily by rainfall quantity and distribution (Piha, 1993; Shapiro and Sanders, 1998). Receiving information on a potential drought is, therefore, expected to have a negative or no effect on farmers' adoption of inorganic fertilizers, as farmers may be less willing to invest in inorganic fertilizer due to the expected low returns under drought conditions. Table 2 sum up the expected impact of SF on the five dimensions considered.

Table 1 Expected impact of seasonal forecasts on adoption

Practices	Hypothesized Impact of seasonal forecasts on adoption	
	Normal seasonal forecasts	seasonal forecasts in drought forecasted regions
MS1	No effect to negative effect	Positive
MS2	No effect to negative effect	Positive
MS3	No effect to negative effect	Positive
Inorganic fertilizer	Positive	No effect to negative effect
Quantity of inorganic fertilizer	Positive	No effect to negative effect

3. Data and variable descriptions

The household data used in this study come from two sources: the El Niño Impact Assessment Survey (ENIAS) and the Rural Agricultural Livelihoods Survey (RALS) 2015. ENIAS was developed by the Agricultural Economics Development Division of the Food and Agricultural Organization of the United Nations and is comprised of a sub-sample of households included in the RALS 2015. The RALS 2015 is a national representative survey of smallholder households, conducted jointly by the Zambian Central Statistical Office, Michigan State University (MSU), the Indaba Agricultural Policy Research Institute (IAPRI), and the Ministry of Agriculture and Livestock.

ENIAS was purposely conceived to study the impact and household responses to the 2015/2016 ENSO event. The sample consists of a randomly selected sub-sample of smallholder households from RALS 2015, balanced around the probability of being exposed to ENSO-induced drought. ENIAS is comprised of two comparable set of households: a first set of households selected to be representative of households exposed to ENSO-induced drought in 2015/2016,⁴ and a second one of potentially non-exposed households, representing the control group of the analysis.

The final sample for this analysis involves a total of 1,172 farming households. This sample was derived using a propensity score matching (PSM) approach at the Standard Enumeration Area

⁴ Their geographical identification is based on Zambia Vulnerability Assessment Committee (ZVAC) Situation Report (2016). This report was published in early 2016 and thus it contains non-conclusive prediction on the potential ENSO impact.

(SEA) level using the data provided by the Zambia Vulnerability Assessment Committee Situation Report in January 2016. This methodology identifies comparable households living in areas forecasted to be adversely effected by drought in 2015/2016, with a control set of households in non-affected areas. The PSM balancing for the sample selection was implemented to account for a set of variables impacting households' ability to cope with shocks, as well as expectations based on long run rainfall variability in their ward, the smallest administrative unit in Zambia. Using the nearest neighbour matching algorithm, the sample managers selected SEAs in the common support (CS) region as treated and control to establish the sampling frame.

As consequence of this sample design, a set of households belonging to the RALS 2015 households from the north and central areas of the country were excluded from the ENIAS. Since the excluded households showed significant differences in terms of their agro-ecological conditions and cropping systems relative to households in the severely affected areas, the inclusion of these households would have biased any estimates on ENSO impact. In addition, a large share of households residing in Luapula, Northern and North-Western and most of Copperbelt and Muchinga provinces were excluded as their expected rainfall was from normal to above normal during the 2015/2016 season. The final design of the ENIAS included 22 districts out of the 35 covered in the RALS 2015 survey. In these districts, the sampling process identified 148 villages, among which 35 were expected to be severely affected (treatment) and 113 not severely affected (control).⁵ From each of these villages, a total of 9-10 households were randomly selected from the RALS 2015 roster.

ENIAS and RALS 2015 capture detailed information on household demographics, agricultural production practices, income, marketing behaviour, and other socio-economic characteristics, and can be combined to create a unique panel dataset. While RALS 2015 was the basis for the design and implementation of the ENIAS sample and questionnaire, the ENIAS included new questions capturing whether households received SF information before the agricultural season. From this question a binary variable taking the value one when a household has received SF is created.

⁵ This expectation is built using the data from the on Zambia Vulnerability Assessment Committee (ZVAC) Situation Report (2016).

Unfortunately, this information is only available for the ENIAS 2015/2016 wave, thus only these cross-sectional data are used for the present analysis. However, we take advantage of the panel nature of the data to compute the dependent variables in the analysis. These consist of three dummies that take the value of 1 when a farmer switches cropping systems between the survey years to adopt MS1, MS2, MS3. In other words, households are identified as adopting the drought tolerant cropping systems if they were not adopting them in the RALS 2015 survey year but were adopting them in the ENIAS survey year (2015/16). In contrast, the variable will take value 0 if a household does not adopt this system or had adopted the system during both the 2014/2015 and 2015/2016 seasons.⁶ More formally, for a given practice P_{it} , we estimate the probability of switching farm practices between survey years, expressed as: $\Pr(P_{it} = \frac{1}{P_{it-1}} = 0)$ ⁷. We also add a second set of dependent variables, including a dummy on the adoption of inorganic fertilizer and a continuous variable quantifying the hectares of land to which the farmer applied inorganic fertilizer.

To study the effect of receiving SF when residing in areas predicted to be severely affected by drought, we interact the dummy indicator on receiving SF with two variables. A first dummy variable captures whether the household resides in a zone predicted to be hit by ENSO-induced drought, and a second variable represents the natural logarithm of the months of drought predicted in the household's area of residence.⁸ The first interaction term, therefore, measures the extensive impact of SF in drought-affected regions, while the second interaction term measures the impact of SF on the adoption of adaptive practices, conditional on the duration of expected drought.

The variables on household residence and months of predicted drought are constructed by overlaying the monthly maps on drought forecasts, which are presented on the left-side of Figure A1 and are extracted from the *Seasonal Rainfall Forecast for 2015/2016* (Zambia Meteorological Department, 2016),⁹ to the geographical distribution of surveyed households. They show that the ENSO-induced drought was forecasted to be heterogeneous across space, with the southern region

⁶ This implies the exclusion from the estimation sample of households already adopting this system and explains the varying number of observations in the results tables.

⁷ As before, continuous and counting variables are transformed taking the natural logarithm. To include zeros observations, we add one before taking the logarithm. Unfortunately, ENIAS allow to measure the appliance of inorganic fertilizer only in hectares.

⁸ To include the zero observations, it is added one to this variable before of log-linearizing.

⁹ This document has been edited before the start of the agricultural season and published on the 19/01/2016.

expected to experience longer-lasting drought than central regions, and with districts in the north-east and north-west not forecasted to experience drought. These forecasts corresponded reasonably well with actual rainfall distributions in 2015/16. As shown on the right of Figure A1, during the period November to January 2015/16 (SPI 3 month), rainfall was below normal in areas forecasted to experience below normal rainfall. However, the forecast did not predict low rainfall in areas in northern parts of the country, some of which did experience low rainfall in the first three months of the 2015/16 season. The seasonal forecast predicted that as the season unfolded, rainfall conditions in much of the country, outside of the south, would normalize. However, as shown by the 6 month SPI in Figure 1A, low rainfall conditions persisted in much of the country in 2015/16, particularly in the east of the country. It should also be noted that the distribution of surveyed households receiving SF information prior to the 2015/2016 season was consistent for households living in areas forecasted to experience drought and for those resident in areas expecting normal rainfall levels (see Table A2 in the Appendix).¹⁰

The specification includes demographic controls such as household's head years of education and age, gender of head of the household, and number of household members. The set of controls also includes variables on wealth, such as the agricultural wealth index constructed using a principal component analysis approach¹³, the livestock owned in Tropical Livestock Units (TLU), and the size of land owned in hectares. The effect of these variables on the adoption of drought resilient practices is unclear a priori. On one hand, better socio-economic conditions may increase the likelihood of adoption as wealthier farmers may be less resource constrained, while, on the other hand, adoption may be reduced among wealthier farmers because they are more able to insure their income through other means, such as off-farm activities (Deressa *et al.*, 2009).

Government credit or input subsidy programs may serve to relax the impact of resource constraints on adaptive responses (Hassan and Nhemachena, 2008). The specification, therefore,

¹⁰ During the agricultural season 2014/2015 there was also an ENSO alert in the region, but seasonal forecasts for the year were for normal rainfall. We therefore assume this ENSO alert had no impact on farmers' cropping choices in our baseline season (See Figure A2 in Appendix).

¹³ The index is computed using the principal component analysis (PCA) on a set of count variables indicating the ownership of ploughs, harrows, cultivators, rippers, ridges, planters, tractors, carts, wheel barrows, pumps, trucks, motorbike, bikes boats, fishing nets, cattle dips, mills, rump presses, sprayers, shellers, sewing machines, home steads and water supply structure.

controls for two variables capturing the share of credit and Farmer Input Subsidy Programme (FISP) recipients at SEA level to exclude any associated form of reverse causality (Asfaw and Maggio, 2018). Two dummies on access to extension services and on cell phone use for receiving agricultural information are used to control for the possibility that the SF variable would capture an effect driven by other types/sources of agricultural information. The specification also includes a dummy capturing whether the household received information on the crops more suitable for the local agro-ecological zones during the preceding agricultural season (2014/2015). Finally, both specifications control for the likelihood of receiving a drought shock, using a drought shock probability index. This indicator captures the share of agricultural seasons with a drought shock in a given area computed across a period of eight agricultural seasons preceding the wave of the survey.¹⁴ An agricultural season is defined as drought-shocked if its 6-months SPI is equal or lower than -1.5 (Maggio, Sitko and Ignaciuk, 2018). The SPI index is constructed using location specific rainfall data measured on 10 days intervals and extracted from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). The month of reference is set to February, thus to consider the impact of drought up to two months before of the rainy season, which spans from November to April.¹⁵ This allows to test whether drought shocks before or during the first part of the rainy season has affected farmers' adoption behavior. CHIRPS delivers re-elaborated rainfall data with 0.5 degree of spatial resolution which have been matched to the household data using the centroid of households' villages. Finally, the distance from Food Reserve Agency (FRA) depots, a parastatal marketing board that buys crops from farmers, and the total number of traders buying grain within the farmers' village are included as indicators of public and private output market institutions.¹⁶

4. Empirical Strategy

Receiving climate SF and living in the predicted ENSO drought areas are two non-random events which are likely correlated with individual wealth, skills, education, access to information, and other

¹⁴ We consider a period of eight agricultural seasons to allow enough variation of this index across the villages. However we have also considered slighter longer or shorter periods and the results remain consistent.

¹⁵ We conducted some tests varying the months of reference to April. The results are consistent with what presented here and available upon request.

¹⁶ Since these variables derive from household level questions, we use the median distance and median number of traders, measured both at village level, to exclude that their computation is affected by outliers.

socio-economic characteristics. The risk of not accounting for the non-random assignment, in this case, is over-estimating the impact of SF on the probability of adoption, as part of these households may have adopted these technologies independently from the reception of the SF. While experimental works on the impact of policy actions frequently base their analysis on trials that assign randomly the treatment to the population, non-experimental researchers often rely on ex post methodologies to increase the comparability between the treated and the control groups. ENIAS has the advantage of being purposely conceived to study the impact of the 2015/2016 ENSO drought, providing a sample that is already balanced in terms of likelihood of being effected by the drought, as the design approach included the most comparable set of households across that dimension.¹⁷ In addition, focusing on the switch to a given cropping system rather than on simply its adoption reduces the exposure of our estimate to large cross-sectional differences between the households.¹⁸

For capturing the causal effect of SF on adoption of drought resilient cropping systems we follow two approaches. First, we apply a matching and reweighting strategy to increase the comparability between the two groups of households across the SF dimension. The baseline method to match treated and non-treated households is the nearest neighbor (NN) matching, which has been selected to keep consistency with the algorithm implemented in the design of the survey. The NN matching is implemented through the estimated PSM considering the three nearest observations and allowing for replacement after each match. This approach works on pairs of observations as it selects and matches an individual in the treated group with one or more individuals from the control groups with the closest propensity score value (Caliendo and Kopeinig, 2008).¹⁹

The matching between individuals is based on a set of variables likely influencing the treatment status. These variables are drawn from the survey round preceding the drought (RALS 2015), to avoid any form of endogeneity between these and the drought response. The selection of the variables has several implications for the functioning of the approach, as the exclusion of important

¹⁷ Using ENIAS data, Alfani *et al.* (2019) finds a strong and negative impact of ENSO on yield and income per capita in Zambia.

¹⁸ For example, this exclude that the estimated effect derives from households already adopting these systems while residing in zones where forecasts are better delivered.

¹⁹ As a robustness, we also match the households matching with the 2-, 5- and 1-k closest observations for the matching and the results remains consistent with the main findings of the paper.

covariates is likely to bias the estimated coefficients, while the inclusion of controls' uncorrelated dimensions reduce the likelihood of finding a CS region between the treated and the control (Bryson, Dorsett and Purdon 2002; Francesconi and Nicoletti, 2006; Heckman, Ichimura and Todd 1997). As suggested by Caliendo and Kopeinig (2008), we use economic theory and previous related findings to identify five sets of determinants affecting the likelihood of accessing to SF: market access, information access, institutional development, socio-demography characteristics, and geographical determinants. Following the extant literature, households residing closer to public markets and in villages with more traders are assumed to have more access to SF (Luseno *et al.*, 2003). Information technologies, such as mobile phones, radio, and TV, are all expected to be linked to higher access of SF information (Ingram, Roncoli and Kirshen, 2002; Luseno *et al.*, 2003). We account for this in the PSM by adding a set of dummies on TV, radio and mobile phone ownership measured at household-level. Other conventional channels for the diffusion of SF include extension services and fellow farmer networks (Blench, 1999; Patt, Suarez and Gwata, 2005). For these reasons, the PSM includes two dummies capturing whether the household had access to the extension service or self-identified as a member of a network of fellow farmers. According to Ingram, Roncoli and Kirshen (2002), to induce adaptation, SF should be delivered by credible local institutions and in an appropriate language. We proxy the local level of institutional development using variable on the share of input subsidy and credit recipients in the village. The PSM also includes dummy and count indicators capturing the gender, age and education of the head of the household and household size, as these influence households ability to access and utilize SF information. For example, female headed households are often found to have higher opportunity costs to their time, which may hinder their ability to participate in information campaigns (Meinzen-Dick and Zwarteveen, 2003), while younger households head may be more dynamic in terms of access to information and innovation (Martey, Al-Hassan and Kuwornu, 2012).

To ensure that the sample will include households with a comparable level of wealth and residing in similar zones, we add to the PSM specification an agricultural wealth index, an indicator of land ownership, measured in hectares, and the population density of the village. Finally, we balance the sample across geographic distribution and probability of shock, as stakeholders may have

disseminated SF information primarily in areas expected to be hit by the drought shocks, and across provinces, to account for unobserved heterogeneity across cultural, institutional, and geographical determinants.

Descriptive results in Table 3 show that, before applying the PSM, the two groups of households have several differences in information access, institutional development, gender and educational level, and geographical distribution. The first part of Table 3 presents the characteristics of the group of households receiving (treated) and not receiving (control) SF at national level.²⁰ The percentage of households receiving SF is stable for the national sample (41 percent) and for the subsample residing in ENSO forecasted area (42 percent). Summaries in Table 3 suggest that households receiving SF are more likely to have access to radio (+19 percent) and to television (+9 percent), which are likely to be important sources of SF information. Households accessing SF are also more likely to be in contact with extension services (+5 percent) and reside in enumeration areas with lower access to subsidy support and higher development of credit institutions, as suggested by the differences in the shares of FISP recipients (-5 percent) and higher credit recipients (+4 percent). This may indicate that the zones of residence of these households are characterized by higher economic development. Households receiving SF also more likely to be male-headed (+5 percent) and more educated, with a between groups difference of about 0.6 years of completed education. Table A1 in the annex reports similar differences between groups for the sub-sample residing in ENSO forecasted areas, thus ensuring that balancing the sample at national level will also balance the differences for the households potentially hit by droughts. Covariate similarities between the two groups increase substantially following the matching, where T-tests for all variables show no statistically significant differences between treatment and control groups (Table 3).

Table 2 Test for balance before and after matching

Market	Distance from FRA (km)	Pre-Matched		Pre-Matched Balance T-test	Matched		Matched Balance T-test
		Treated	Control		Treated	Control	
		(Seasonal Forecasts =1)	(Seasonal Forecasts =0)		(Seasonal Forecasts =1)	(Seasonal Forecasts =0)	
		6.51	6.51		6.35	7.03	

²⁰ Summary statistics for all the variables in the analysis are displayed in Table A3 in the Appendix.

	total number of traders	4.73	4.73		4.76	4.69
Information access	radio (1=yes)	0.82	0.63	***	0.82	0.8
	TV (1=yes)	0.38	0.29	***	0.38	0.4
	Cellphone (1=yes)	0.52	0.53		0.52	0.52
	Extension Service (1=yes)	0.49	0.44	*	0.5	0.48
	Fellow farmers network (1=yes)	0.43	0.46		0.43	0.47
Institutional development	Share of FISP recipient (EA's level)	0.51	0.47	***	0.51	0.51
	Share of Credit recipient (EA's level)	0.28	0.21	***	0.28	0.28
Socio-economic characteristics	Female-headed Household (1=yes)	0.17	0.22	**	0.17	0.16
	Household's age	50.04	50.71		50.1	50.72
	Head's Education (years)	6.46	5.86	**	6.4	6.48
	Household size	7.95	7.92		7.92	8.04
	Agricultural Wealth Index	0.03	-0.04		0.02	0.03
	Land owned (hectars)	7.94	6.14		7.83	8.94
	Population density (pop/km2)	31.38	30.32		31.28	31.24
Geography	Drought expected zone (1=yes)	0.84	0.82		0.84	0.84
	Copperbelt (1=yes)	0.05	0.1	***	0.05	0.05
	Eastern (1=yes)	0.63	0.4	***	0.62	0.61
	Lusaka (1=yes)	0.06	0.08		0.06	0.07
	Muchinga (1=yes)	0.02	0.01		0.02	0.01
	Southern (1=yes)	0.03	0.18	***	0.03	0.02
	Western (1=yes)	0.03	0.05	*	0.03	0.02

Notes: the table displays the matching variables for the propensity score match with 3-k neighbors and the results from the balance tests before and after the propensity score. Matching variables are dummies on radio and TV ownership, use of cellphone for gathering information on agriculture, access to extension services, reception of advice from fellow farmers. Other controls include the share of Farmer Input Subsidy Programme (FISP) and credit recipients at village level, a dummy for female-headed household, household size, a variable capturing the years of education of the head, agricultural wealth index, land-owned in hectares, population density, dummy on residence in drought expected region and on provinces, distance from Food Reserve Agency (FRA) and total number of traders.

Figure 1 confirms the existence of a common support region across the propensity score distribution, thus allowing to test the impact of the treatment with similar likelihood of being treated.

Figure 1 Common support region by treatment status

Figure Notes: the figure displays the distribution of the propensity score for the common support region by treatment status. Red histograms and blue histograms are treated and untreated observations in the common support region, respectively.

Once PSM is estimated, we test for the effect of SF running a linear probability model including: a) only for the observations in the CS region, and b) using the propensity score values as weights for each of these observations (Francesconi and Nicoletti, 2006). The first approach, therefore, takes the following form:

$$P_{ic} = \beta_0 + \gamma_1 SF_{ic} + \gamma_2 EN_c + \vartheta SF_{ic} * EN_c + \delta X_{ic} + \tau_p Prov_p + \varepsilon_{ic} \quad (2)$$

P_{ic} is a dummy taking value 1 if the household $i = 1, \dots, N$ resident in EA c switches to a drought tolerant cropping system (MS1, MS2, MS3) in ENIAS 2015/2016, or if the household adopts inorganic fertilizer. Otherwise, P_{ic} is the natural logarithm of a continuous variable measuring the quantity of inorganic fertilizer applied to the fields. In addition, β_0 denotes the intercept, SF_{ic} is a dummy activating if the household has received SF, independently of whether the forecast is for normal or below normal rainfall, EN_c can be either a dummy indicating household residence in an area predicted to be drought-affected or the natural logarithm of the expected months of drought shock in 2015/2016 agricultural season. The term $SF_{ic} * EN_c$ denotes their interaction and captures the reception of SF in drought forecasted regions, either as an intensive or extensive measure, and γ_1 , γ_2 and ϑ are their associated coefficients. Finally, the model also includes a matrix of household and the matrix of EA-level controls X_{ic} , their vector of coefficients δ , a set of province dummies $Prov_p$ and their associated coefficients τ_p , and the normally distributed error term ε_i clustered at village-level.

Following the work of Amemiya (1978) and Miranda and Rabe-Hesketh (2006), the second approach makes use of two instrumental variables in a simultaneous equation probit model (IVP) estimated

using maximum likelihood.²¹ The IVP has the advantage of accounting for the non-linear nature of the outcome variables on adoption. The model requires the inclusion of one or more instrumental variables correlated with the endogenous variable and uncorrelated to the outcome variable once controlling for the endogenous variable. Since most of the specifications include at least two endogenous variables, specifically the SF dummy and its interaction with household's zone of residence or months of expected drought, this model requires at least two instrumental variables to be exactly identified. We use two instrumental variables exploiting two different dimensions of the "learning from others" mechanisms typical of social networks (see, among others, Arslan, Belotti and Lipper, 2017; Foster and Rosenzweig, 1995). The first is a measure of household geographic centrality compared to the farmers receiving SF. The measure is operationalized as the household's median distance from other households receiving SF in the same village. To construct this indicator, we exploit the geographic position of household in the ENIAS. This instrumental variable is conceptually similar to the one employed by the works addressing the returns from schooling, which has instrumented the level of education using the distance from school (Card, 1995; Card, 2001; Maluccio, 1998). As in this literature, our assumption is that the distance satisfies the exclusion restriction if it can be considered as randomly assigned after including the other controls, indicating that we can exclude any other direct or indirect effect of the distance from SF on the likelihood of adopting the practices under consideration. The underlying hypothesis on its correlation with the endogenous variable is that, as the median distance from other households receiving SF increases, the likely that the household itself will receive SF decreases, all else equal.²²

The second instrumental variable relies on a socio-institutional measure of efficiency in delivering SF, computed as the leave-out share of household receiving SF in the village²³. Villages with higher

²¹ It is important to acknowledge that running a linear first stage on a dummy may raise issues and inconsistencies in the estimated coefficients, especially due to the non-linearity of the conditional expected function (CEF) of the first-stage (Angrist and Pischke, 2008). However, improving on this empirical issue is not straightforward. As Angrist and Pischke (2008) suggest, one solution may be to run a probit on the endogenous variable including all the controls and the instruments, and then using the non-linear predictions as instrument in a two-stage least square regression. However, as the authors stress, also this procedure has drawbacks as it uses non-linearity in the first stage as a source for identification and, according to the same authors, it is "not clear what the underlying experiment is". Following therefore what suggested by Angrist and Pischke (2008), we rely on the more straightforward approach involving a linear model in the first stage and a probit in the second stage.

²² When using the instrumental variables the number of observations slightly reduces due to the fact that the data about latitude and the longitude are missing for few households.

²³ The leave-out share for a given household excludes the household observation from the calculation, thus it varies at household level.

shares of recipients may have experienced more diffusion through official channels. This instrument is expected to be positively correlated with households' likelihood to receive SF.²⁴ Also for this instrument, we assume that it satisfies the exclusion restriction conditional on the inclusion of other controls.

The two instruments are not necessarily correlated. Indeed, a household may be located closer to another household receiving SF, but this second household can be the only one receiving SF in the village. Figure A3 in the appendix corroborates this hypothesis and shows low correlation between the two instruments, with an associated correlation coefficient equal to -0.04. In addition, Table A4 in the appendix tests whether the main controls of the specification are significantly correlated with the two instruments. To do so, we collapse the dataset at village-level, take the village-average of all the explanatory variables, and run two OLS specifications with the two instruments described above as dependent variables. As additional controls, we add province level dummies to account for institutional and other macro-level differences between groups of villages/EAs. This test further validates our instruments, as the main explanatory variables are usually non-significant, suggesting that variation in the instruments is not explainable by a rich set of village characteristics (see Table A4 in the Appendix).²⁵

For the model without the interaction term, the two equations composing the IVP model take the following form:

$$SF_i = \beta_0 + \gamma_2 EN_c + DistanceSF_i + ShareSF_{ic} + \delta X_{ic} + \omega_i \quad (3)$$

$$\Pr(P_i = 1|X) = \Phi(\beta_0 + \gamma_1 \widehat{SF}_{ic} + \gamma_2 EN_c + \delta X_{ic} + \mu_i) \quad (4)$$

Where, $DistanceSF_i$ and $ShareSF_{ic}$ are the two instruments for the equation on SF reception, Φ denotes the cumulative distribution function of the standard normal distribution, ω_i and μ_i denotes the errors terms of the endogenous and outcome equations.

²⁴ Summaries for these two instruments are displayed in Table A3 in the annex.

²⁵ The only notable exception is the average land owned in the village, which correlates with the share of households receiving seasonal forecasts (column 2 of Table A4) in the village. However, note that the main specification controls for this dimension at household level and includes an agricultural wealth index. This should insure that the instrumented variation in the adoption does not derive from household-level differences in land endowment.

5. Impacts of receiving seasonal forecasts on cropping system choices

As shown in Table 4, farmers residing in regions forecasted to be adverse affected by the ENSO-induced drought and receiving SF have a significantly higher probability of adopting cropping systems MS1, MS2, and MS3 compared to households living in same areas but not receiving the information.²⁶ In particular, for the linear model on the CS region and with IPW, receiving information on the ENSO-induced drought increases the probability of adopting the MS1 system by 11.3 percent, the MS2 system by 12.2 percent, and the MS3 system by 11.5 percent, conditional on living in areas forecasted to be affected by drought. The magnitude of this effect is consistent with other studies on the role of information in farmers' choices of agricultural practices. For example, Genius *et al.* (2006) find that active and passive information on fertilizer is correlated with an increase in the likelihood of adopting organic fertilizers of between 9.2-10.3 percent, while Deressa *et al.* (2009) finds that receiving information on climate change increases the probability of adopting crop varieties adapted to drier conditions by 17.6 percent.

The results from the IVP model show a similar effect, but smaller in magnitude. Keeping all the other variables at their mean value, receiving SF in drought forecasted regions are likely to increase the probability of shifting to a drought tolerant system by between 1 and 5 percent.²⁷

The results show that across the whole sample, including households in unaffected areas, the SF dummy variable correlates negatively with adoption of drought tolerant systems, because the variable is largely capturing the effect of SF in areas where Zambia's Meteorological Department expected rainfall to be normal (see Figure 1). The estimated decrease in probability of adoption, therefore, confirms that farmers adopt these drought-tolerant cropping systems as an ex-ante response to the expected drought shock.

²⁶ To test the validity of our instruments we run the IVP specification using only the dummy on the seasonal forecast reception as endogenous variable. The multivariate F-statistic is greater than 10 and the Kleibergen-Paap under identification test confirms that the variables are significantly correlated to the endogenous regressors. We fail to reject both the null hypothesis of the Hansen test, thus excluding over identification, and of the Anderson-Rubin Wald test, confirming the validity of the instruments (see Table A5 in Appendix).

²⁷ The Anderson-Rubin Wald test confirms the validity of the instruments (bottom of Table 5), while the Wald-test confirms that the IVP has to be preferred to a simple probit for at least MS1 and MS2 (Table A5b in the appendix).

Among the others controls, few are found to have a significant impact on the dependent variables, as expected given the matching strategy adopted. The exception is a household's agricultural wealth index, which is negatively associated with the switch toward drought tolerant cropping systems. This is likely because wealthier households have alternative means of coping with drought, such as investing in off-farm activities.

Estimates in Table 5 are derived from a specification where the dummy on household residence is replaced with a log-linear variable capturing the months of expected drought in the household location. Results from this exercise further support empirical findings on the impact of SF on cropping system choice, and show a positive and significant relationship between the probability of adopting drought tolerant cropping systems and the months of forecasted drought in a farmer's area. In terms of magnitude, the linear model suggests that an increase of 10% in the duration of the expected drought, which corresponds to roughly 4 days, increases the probability of adopting MS1 by 0.15 percent. Considering that the southern region of Zambia was predicted to receive below-normal rainfall for about 6 months, this would correspond to an increase in the likelihood of adoption by 6.75 percent, obtained only through accessing SF information.²⁸

We complements these results by showing, in Table 6, that reception of SF in drought forecasted regions negatively affects the probability of adopting inorganic fertilizer, both when considering the extensive margin (column 1) and the expected length of the drought (column 2). In addition, the coefficients of these two variables are negative, but not statistically significant, for the amount of fertilizer applied. Since inorganic fertilizer delivers increasing returns with higher rainfall, the negative effect on the probability of adoption provides support to the main hypothesis of this study.

²⁸ This value is computed considering months composed by 30 days.

Table 4 Heterogeneous effect of seasonal forecasts on the selection of climate resilient cropping systems under drought risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	To MS1	To MS1	To MS1	To MS2	To MS2	To MS2	To MS3	To MS3	To MS3
	OLS - CS Sample with IPW	IVP	Marginal effect	OLS - CS Sample with IPW	IVP	Marginal effect	OLS - CS Sample with IPW	IVP	Marginal effect
Drought-expected zone X Seasonal Forecasts	0.113** (0.056)	5.035*** (0.947)	0.01	0.122** (0.057)	5.187*** (0.768)	0.01	0.115* (0.058)	4.879*** (1.296)	0.05
Seasonal Forecasts (1=yes)	-0.134** (0.055)	-3.662*** (1.323)	-0.02	-0.141** (0.055)	-3.754*** (1.422)	-0.02	-0.142** (0.055)	-3.704*** (1.226)	-0.08
Drought expected zone (1=yes)	-0.062 (0.051)	-2.461*** (0.458)	-0.02	-0.061 (0.051)	-2.439*** (0.512)	-0.02	-0.014 (0.061)	-2.338*** (0.457)	-0.05
Agricultural Wealth Index	-0.025*** (0.008)	-0.260 (0.197)	-0.01	-0.023*** (0.007)	-0.201 (0.175)	-0.01	-0.024** (0.010)	-0.188 (0.191)	-0.02
Livestock owned (TLU)	-0.001 (0.000)	-0.018 (0.027)	0.00	-0.001* (0.000)	-0.009 (0.024)	0.00	-0.001* (0.001)	-0.009 (0.022)	0.00
Land owned (ln)	0.022** (0.011)	0.187** (0.087)	0.00	0.020* (0.011)	0.137* (0.082)	0.00	0.013 (0.013)	0.135 (0.097)	0.01
Share of Credit access (EA's level)	-0.014 (0.013)	-0.599 (0.433)	-0.02	-0.008 (0.013)	-0.504 (0.383)	-0.02	0.053* (0.031)	-0.203 (0.228)	0.01
Share of FISP recipients (EA's level)	0.013 (0.031)	-0.256 (0.276)	0.00	0.015 (0.032)	-0.320 (0.248)	0.00	0.009 (0.038)	-0.297 (0.320)	0.01
Agricultural Advice from Extension Services (1=yes)	-0.032* (0.017)	-0.280 (0.224)	-0.01	-0.028 (0.018)	-0.206 (0.191)	-0.01	-0.032 (0.021)	-0.249 (0.228)	-0.03
Drought Shock Probability	0.001 (0.001)	-0.020* (0.011)	0.00	0.001 (0.001)	-0.020* (0.011)	0.00	0.003 (0.002)	-0.013 (0.023)	0.00
Cell Phone for gathering information (1=yes)	-0.001 (0.013)	-0.147 (0.131)	0.00	-0.000 (0.013)	-0.143 (0.112)	0.00	-0.011 (0.017)	-0.167 (0.125)	0.00
Distance from FRA (ln)	-0.009 (0.007)	-0.016 (0.093)	0.00	-0.013* (0.007)	0.012 (0.078)	0.00	-0.012 (0.010)	0.029 (0.086)	0.00
Number of traders (ln)	-0.021* (0.012)	-0.106 (0.151)	0.00	-0.020* (0.011)	-0.041 (0.131)	0.00	-0.023 (0.014)	-0.021 (0.151)	-0.01
information on crop suitability (1=yes)	0.017* (0.010)	0.040 (0.130)	0.00	0.013 (0.011)	0.059 (0.100)	0.00	0.024 (0.017)	0.117 (0.136)	0.01
Other demographic controls (1=yes)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Anderson-Rubin Wald test (Chi-squared P-value)	-	3.10 (0.21)	3.10 (0.21)	-	3.99 (0.14)	3.99 (0.14)	-	3.10 (0.21)	3.10 (0.21)
R-squared	0.19	-	-	0.20	-	-	0.19	-	-
Observations	964	935	935	958	930	930	921	894	894

Notes: the table displays the estimates from a linear probability and a maximum likelihood instrumental variable probit with simultaneous estimation on the probability of switching from a non-drought resilient cropping system to drought resilient cropping systems between the agricultural seasons 2014/2015 and 2015/2016. The drought resilient systems include Maize and one or more of the following crops: MS1= Cassava, Millet, Sorghum, Sweetpotato; MS2= Cassava, Cotton, Cowpeas, Millet, Sorghum, Sweetpotato, Cowpeas, Pigeon-peas; MS3= Cassava, Millet, Pigeon-peas, Sorghum, Sweetpotato. The linear probability specifications include province dummies. The full list of controls is available in the annex (Table A6, panel A). Endogenous equations coefficients are reported in the annex (Table A6, Panel B). For the specifications' acronyms refer to Table 4. Errors are clustered at village level. Level of significances are * p<0.10; ** p<0.05; ***p<0.01.

Table 5 Effect of seasonal forecasts on adoption of drought resilient practices using a continuous measure of expected drought

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	To MS1	To MS1	To MS1	To MS2	To MS2	To MS2	To MS3	To MS3	To MS3
	OLS - CS Sample with IPW	IVP	Marginal effect	OLS - CS Sample with IPW	IVP	Marginal effect	OLS - CS Sample with IPW	IVP	Marginal effect
Months of expected drought x Seasonal Forecasts	0.015*	0.726***		0.017**	0.746***		0.016*	0.702***	
	(0.008)	(0.125)		(0.008)	(0.089)		(0.008)	(0.181)	
Seasonal Forecasts (1=yes)	-0.041***	0.405		-0.040***	0.469		-0.047***	0.285	
	(0.014)	(0.696)		(0.014)	(0.729)		(0.018)	(1.118)	
Months expected of drought (ln)	-0.008	-0.352***		-0.008	-0.348***		-0.002	-0.333***	
	(0.007)	(0.062)		(0.007)	(0.062)		(0.009)	(0.063)	
Agricultural Wealth Index	-0.025***	-0.256		-0.023***	-0.193		-0.024**	-0.182	
	(0.008)	(0.195)		(0.007)	(0.172)		(0.010)	(0.189)	
Livestock owned (TLU)	-0.001	-0.019		-0.001*	-0.009		-0.001*	-0.009	
	(0.000)	(0.027)		(0.000)	(0.024)		(0.001)	(0.022)	
Land owned (ln)	0.022*	0.189**		0.020*	0.135*		0.013	0.134	
	(0.011)	(0.086)		(0.011)	(0.079)		(0.013)	(0.097)	
Share of Credit access (EA's level)	-0.013	-0.624		-0.008	-0.528		0.053*	-0.240	
	(0.013)	(0.435)		(0.013)	(0.391)		(0.031)	(0.220)	
Share of FISP recipients (EA's level)	0.014	-0.245		0.016	-0.320		0.010	-0.298	
	(0.031)	(0.283)		(0.032)	(0.250)		(0.038)	(0.329)	
Agricultural Advice from Extension Services (1=yes)	-0.033*	-0.295		-0.029	-0.223		-0.033	-0.266	
	(0.017)	(0.224)		(0.018)	(0.194)		(0.021)	(0.231)	
Drought Shock Probability	0.001	-0.019*		0.001	-0.020**		0.003	-0.013	
	(0.001)	(0.011)		(0.001)	(0.010)		(0.002)	(0.023)	
Cell Phone for gathering information (1=yes)	-0.001	-0.157		-0.000	-0.152		-0.011	-0.175	
	(0.013)	(0.131)		(0.013)	(0.111)		(0.017)	(0.124)	
Distance from FRA (ln)	-0.009	-0.007		-0.013*	0.022		-0.012	0.038	
	(0.007)	(0.091)		(0.007)	(0.074)		(0.010)	(0.084)	
Number of traders (ln)	-0.021*	-0.100		-0.020*	-0.030		-0.023	-0.013	
	(0.012)	(0.151)		(0.011)	(0.131)		(0.014)	(0.154)	
information on crop suitability (1=yes)	0.017*	0.039		0.013	0.065		0.024	0.122	
	(0.010)	(0.133)		(0.011)	(0.100)		(0.017)	(0.137)	
Other demographic controls (1=yes)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.19			0.20			0.13		
Anderson-Rubin Wald test (Chi-squared P-value)	-	3.33 (0.18)	3.33 (0.18)	-	4.22 (0.12)	4.22 (0.12)	-	2.35 (0.31)	2.35 (0.31)
Observations	964	935	935	958	930	930	921	894	894

Notes: the table displays estimates from a linear probability and a maximum likelihood instrumental variable probit with simultaneous estimation on the probability of switching from a non-drought resilient cropping system to a drought resilient cropping system between the agricultural seasons 2014/2015 and 2015/2016. Differently from Table 4, this specification includes an intensive measure of drought consisting in the log of the expected months of drought. The drought resilient systems include Maize and one or more of the following crops: MS1= Cassava, Millet, Sorghum, Sweetpotato; MS2= Cassava, Cotton, Cowpeas, Millet, Sorghum, Sweetpotato, Cowpeas, Pigeon-peas; MS3= Cassava, Millet, Pigeon-peas, Sorghum, Sweetpotato. The full list of controls is available in the annex (Table A7). For the specifications' acronyms refer to Table 4. Endogenous equation results available upon request. Errors are clustered at village level, significance level are * p<0.10; ** p<0.05; ***p<0.01.

Table 6 Effect of seasonal forecasts on the probability of adoption and quantity adopted of inorganic fertilizer under expected drought

	(1)	(2)	(3)	(4)
	Inorganic Fertilizer	Inorganic Fertilizer	Hectares of Inorganic Fertilizer (ln)	Hectares of Inorganic Fertilizer (ln)
	IVP	IVP	2SLS-IV	2SLS- IV
Drought-expected zone X Seasonal Forecasts	-4.669***		-25.004	
	(1.137)		(26.444)	
Drought expected zone (1=yes)	1.836**		16.828	
	(0.760)		(18.911)	
Seasonal Forecasts (1=yes)	3.204**	1.827*	10.394	9.772
	(1.383)	(1.042)	(11.859)	(11.320)
Months of expected drought x SF		-1.850***		-9.974
		(0.591)		(10.564)
Months of expected drought (ln)		0.762		4.694
		(0.513)		(5.603)
Other controls	Yes	Yes	Yes	Yes
Anderson-Rubin Wald test (Chi-squared P-value)	2.45 (0.29)	1.83 (0.40)	2.42 (0.30)	1.87 (0.39)
Observations	1128	1128	1128	1128

Notes: the table displays the estimates from a maximum likelihood instrumental variable probit with simultaneous estimation on the probability of adopting inorganic fertilizer and a two-stage least square instrumental variable model (2SLS-IV) on the quantity of fertilizer adopted during the season 2015/2016. The specification considers both an extensive (dummy) and intensive (log of months expected) measure of expected drought. Dependent variables are a dummy on adoption of inorganic fertilizer, the natural logarithm of the hectares of land under inorganic fertilizer. The full list of controls is available in the annex (Table A8). For the specifications' acronyms refer to Table 4. Errors are clustered at village level, significance levels are * p<0.10; ** p<0.05; ***p<0.01.

5.1 Marginal effects at different levels of output market access

Access to competitive output markets may have a positive effect on the probability that a farmer in drought affected areas will adopt adaptive farm practices in response to SF information. To test this, we run the same linear specification as in Table 5 to compute the marginal effect of receiving SF in drought forecasted regions at different level of market access. Using the median number of traders that respondents reported come to the village to buy grains, the point estimates of Figure 2 shows that receiving SF in areas with a high probability of drought is more likely to influence adoption of MS1, MS2, and MS3, at different level of total traders' distribution. The results of this exercise have to be taken with caution, since the variation in our proxy for the market is not exogenous and may be affected by selection at village level. However, the concavity of the curves, and the confidence intervals, suggest that farmers switch cropping systems in response to SF information only once the number of traders in village reaches a threshold of five. A marginal increase in the number of traders has a stronger effect at the low tail of the distribution, when the number of trader is between 5 and 10. The estimated predicted probability of adoption is similar to the one estimated in the main part of the analysis, suggesting that both access to information and to markets are necessary conditions for adopting drought adaptive cropping systems.

In terms of magnitude, the model estimates an increase of 1.12 percent in the probability of adoption for each additional month of expected drought when the number of traders is 5 or higher and is insignificant when trader numbers are less than five. The effect of trader numbers marginally decreases, suggesting that the underlying mechanism is related to access to reasonably competitive markets, rather than to an unconditional enlargement of the market itself.

Figure 2 Seasonal forecasts, output market access, and selection of drought-resilient cropping systems

Figure notes: the figure displays the marginal effect of expecting longer spells of drought (log-linearized) on the probability of switching to resilient cropping systems at different level of output market access. The model is a linear probability model using common support observations from the propensity score method illustrated in Table 6, but includes the interaction between the market variable and the seasonal forecasts variable.

6. Robustness checks

The annex reports the results of different types of robustness tests run to check the consistency of the main findings. First, we estimate the specifications reported in Table 4 for MS1 using IPW derived from a PSM with the closest neighbor (column 1), the 5 closest neighbors (column 2) observations, kernel (column 3), and radius caliper matching strategies (column 4).²⁹ As reported in Table A9, the results remain extremely stable and consistent with the main findings. All these specifications confirm the positive impact of SF on the probability of adoption of drought-tolerant cropping systems in drought forecasted regions.

In a further test, presented Table A10, we examine whether the model is capturing a wealth effect rather than a coping strategy by testing whether households receiving SF in drought effected areas are also more likely to own technologies that are unrelated to drought coping mechanisms. The three specifications reported in Table A10 test for the ownership of agricultural sprayers, harrows, and for the level of the agricultural wealth index. The controls are the same as

²⁹ The radius of the caliper is set equal to 0.005, but the results are consistent when varying this level to 0.01. These estimates are available upon request.

the main specification with the exception of the agricultural wealth index, which is excluded to avoid collinearity. We use the IVP model for column 1 and 2, where the dependents are two dummies, and a linear 2SLS IV for the agricultural wealth index. The dependent variables are four dummies activating in case of ownership of the above tools. Since the coefficients of the interaction terms are not significant in any specification, we conclude that our specification is not capturing a wealth effect. To further test whether the instruments are correlated to the level of wealth of the household, we rerun the same exercise using two Probit models and an OLS model, excluding the SF variables and the dummy on residence, and controlling for the instruments. The remaining controls remain the same of the specification in Table A10. As shown in Table A11, we exclude any correlation with these proxies of wealth, and therefore the variation captured by these instrumental variables can be considered exogenous with respect to wealth.

Finally, in Table A12 we use the a dummy variable indicating whether the household has received weather-information using the cell phone to study whether correlation between this variable and the adoption of the above practices is consistent with what is found in the main part of the analysis. We use this variable as it is the only weather information-related determinant available at panel level and it accounts for unobserved heterogeneity using households fixed effects and time dummies, keeping only the variables available in both waves (2014/2015 and 2015/2016). This test needs to be taken with extreme caution as, among other reasons, only 2 percent of the sample declares to receive this type of information through phone. Also, weather information is different from SF, as it can relate, for example, to shorter time periods. However, as shown in Table A12, when accounting for unobserved heterogeneity, receiving weather information through phone correlates with adoption of MS1 and MS2.

7. Conclusions and Policy Considerations

Three key findings emerge from this study. First, access to information on probable adverse weather conditions positively influences the adoption of adaptive farm practices. Farmers residing

in areas forecasted to experience drought conditions as a result of the 2015/2016 ENSO event, and who received SF information, were likely to adopt drought tolerant cropping systems, while farmers in the same areas that did not receive SF information did not significantly alter their farming practices. Moreover, the predicted severity of the drought in a given region influences the probability of adopting more drought-tolerant practices.

Second, access to SF information in Zambia remains relatively low. Only 41 percent of households in the ENIAS received information regarding the probability of an ENSO-induced drought prior to the farming season. Households receiving that information are more likely to be male-headed and better educated. Also, these households are more likely to have access to sources of information for SF, such as radio and television, and reside in areas where credit market are more developed and where the community members are less in need of social assistance.

Finally, access to competitive agricultural markets is positively correlated with increased probability of adopting drought-tolerant farming practices once farmers receive the seasonal forecast information. Private markets may relax diverse constraints to farmers' adoption of the practices by reducing costs to accessing farm inputs and information on potential responses to impending droughts, providing markets for drought-tolerant crops, and generally lowering the costs and risks associated with changes in farm practices.

Three key policy considerations come out of this analysis. First, while SF information can induce adaptive responses by farmers, access to this information remains very limited. Investments in improving access to this information, particularly for households in remote areas or households with limited education or asset ownership (such as phones or radios) is critical. The marginal costs of delivering this information will vary across space. In regions where seasonal forecast information has been received by some segments of the community, but not others, the marginal cost of expanding that information through existing community groups and information systems,

such as extension services, will be relatively low. However, in remote regions where access to seasonal forecast information has not reached any community members the marginal costs of delivering the information is likely to be relatively higher, as access to this information may be hindered by significant infrastructural constraints. A detailed cost benefit analysis to assess options for delivering seasonal forecasts under different levels of geographic remoteness would be useful for guiding policies and programmes to scale up access to this information.

Second, utilizing input subsidy programs to increase private investment, particularly in drought prone regions, may offer win-win opportunities to improve farmers' adaptive capacity. Descriptive evidence presented in this study shows clear differences in terms of the socio-economic status of households that adopted drought-tolerant practices versus those that did not. Targeting poorer households in regions forecasted to receive below normal rainfall with input vouchers for drought tolerant crops that are redeemable at private sector outlets can increase the share of households that adopt these systems directly through the provision of vouchers and indirectly through improved inputs market conditions for farmers that do not receive vouchers.

Finally, policies to support private investment in agricultural output markets may be considered part of a broader climate change adaptation plan. Investments in private output markets in Zambia have historically been limited by unpredictability in agricultural trade policy and by the large role of public marketing institutions in Zambian grain markets (Sitko et al., 2017; Jayne 2012; Chapoto and Jayne 2009). Improving the predictability of trade restrictions and limiting the scope of public grain purchases can help to stimulate more private investment in output markets (Sitko and Jayne 2014).

The findings in this article suggest that by integrating the generation and dissemination of SF information with policies and investments to spur market development, policy-makers can enhance the capacity of smallholder farmers to respond effectively to adverse weather event. These approaches will become increasingly feasible as communication technologies penetrate

deeper into rural parts of SSA, and investment synergies between the public and private sectors become more common.

8. References

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9. Annex

Table A1 Summaries of seasonal forecasts determinants in drought forecasted regions

	SF=0 (N=565)	SF=1 (N=403)	
	Mean	Mean	T-test
radio (1=yes)	0.62	0.79	***
TV (1=yes)	0.26	0.36	***
Cellphone (1=yes)	0.48	0.48	
Extension Service (1=yes)	0.46	0.50	
Fellow farmers network (1=yes)	0.45	0.45	
Share of FISP recipient (EA's level)	0.44	0.50	***
Share of Credit recipient (EA's level)	0.24	0.31	***
Female-headed Household (1=yes)	0.21	0.17	*
Household's age	50.06	50.05	
Head's Education (years)	5.72	6.25	**
Household size	7.95	7.84	
Agricultural Wealth Index	0.00	0.04	
Land owned (hectars)	4.91	5.38	
Population density (pop/km2)	30.74	34.73	**
Distance from FRA (km)	6.74	6.50	
Total number of traders	4.06	4.33	

Table A2 Expected impact of seasonal forecasts on adoption

	Drought forecasted region=0	Drought forecasted region=1	
Seasonal forecasts=0	128	565	693
Seasonal forecasts=1	76	403	479
	204	968	1,172

Table A3 Summaries of variables under analysis

Variable	Mean	Std. Dev.	Min	Max
MS1	0.06	0.23	0	1
MS2	0.06	0.24	0	1
MS3	0.09	0.29	0	1
Inorganic fertilizer (1=yes)	0.81	0.38	0	1
Quantity of inorganic fertilizer applied (Kg)	1.65	2.32	0	28
Seasonal forecasts (1=yes)	0.41	0.49	0	1
Months of expected drought (ln)	1.24	0.59	0	1.79
Drought expected zone (1=yes)	0.82	0.38	0	1
Months of expected drought x Seasonal Forecasts	0.50	0.69	0	1.79
Household size (ln)	1.98	0.44	0	3.40
Age of household head (ln)	3.88	0.29	2.20	4.56
Head is female (1=yes)	0.20	0.40	0	1
Household's head year of education (ln)	1.71	0.82	0	3.00
Agricultural Wealth Index	-0.01	0.83	-0.60	4.71
Livestock owned (TLU)	6.48	11.46	0.02	160.24
Land owned (ln)	1.20	1.05	-4.83	6.41
Share of Credit access (EA's level)	0.24	0.28	0	1
Share of FISP recipients (EA's level)	0.49	0.25	0	1
Agricultural Advice from Extension Services (1=yes)	0.63	0.48	0	1
Drought Shock Probability	1.17	4.25	0	16.67
Cell Phone for gathering information (1=yes)	0.52	0.50	0	1
Distance from FRA (ln)	1.63	0.93	0	4.36
Number of traders (ln)	1.46	0.86	0	2.77
information on crops (1=yes)	0.28	0.45	0	1
Instrumental Variables				
Distance from seasonal forecasts recipients in the village	24.46	8.39	0.01	39.69
Share of seasonal forecasts recipients (EA's level)	0.34	0.22	0	1

Table A4 Validation test checking the correlation between the instruments and the main covariates

VARIABLES	(1) Distance from seasonal forecasts recipients in the village	(2) Share of seasonal forecasts recipients
Agricultural Wealth Index (EA-average)	-1.527 (2.394)	-0.022 (0.064)
Livestock owned (TLU) (EA-average)	-0.068 (0.178)	-0.003 (0.005)
Land owned (EA-average)	0.924 (1.419)	0.090** (0.038)
Share of credit access	3.778 (2.573)	-0.023 (0.069)
Share of FISP recipients (EA's level)	0.451 (2.667)	0.082 (0.070)
Share of recipients of agricultural advice from extension services	4.858 (3.302)	-0.095 (0.088)
Drought shock probability	-0.255 (0.161)	0.008* (0.004)
Share of household using cell phone for gathering information	-3.040 (2.652)	0.036 (0.071)
Distance from FRA (EA-average)	-0.787 (0.914)	0.048* (0.024)
Number of traders (EA-average)	1.163 (1.180)	-0.021 (0.031)
Share of recipients of information on crop suitability	-2.276 (3.642)	0.073 (0.097)
Demographic controls	Yes	Yes
Province dummies	Yes	Yes
Observations	148	148
R-squared	0.277	0.394

Notes: the table report a test of correlations for the two instruments with the main explanatory variables. The specification is an OLS with province dummies on a cross-section of village-level data. All the control are village-averages and include: the age, gender and years of education of household's head, agricultural wealth index, livestock owned, land owned, share of credit, FISP, and advice recipients, drought shock probability; households receiving agricultural information from the cell phone, distance from FRA, number of traders and recipients of information on crop suitability. All the village averages of dummies need to be intended as shares.

Impact of seasonal forecasts independent of forecasted weather conditions

To test the validity of the instruments we estimate the effect of receiving SF on the adoption of MS1, independent of the forecasted weather in the household's residence, using IVP. The sign of the coefficients associated with the instrumental variables and their level of significance are consistent with our expectations. In particular, the distance from SF recipients negatively correlates to the probability of receiving SF, while the leave-out share of recipients positively correlates with the probability of receiving SF. Finally, the multivariate F-statistic is greater than 10 and the Kleibergen-paap under identification test confirms that the variables are significantly correlated to the endogenous regressors. We fail to reject both the null hypothesis of the Hansen test, thus excluding over identification, and of the Anderson-Rubin Wald test, confirming the validity of the instruments. Taken together, these two tests point towards the validity of the required orthogonality conditions.

Table A5 Impact of seasonal forecasts on adoption of climate-resilient systems, outcome (panel A) and endogenous equation (panel B)

Panel A – Outcome equation

	1)
	IVP
Seasonal Forecasts (1=yes)	-0.088 (1.514)
Household size (ln)	-0.131 (0.203)
Age of household head (ln)	0.507 (0.356)
Head is female (1=yes)	-0.232 (0.178)
Household's head year of education (ln)	-0.023 (0.105)
Agricultural Wealth Index	-0.614** (0.239)
Livestock owned (TLU)	-0.067 (0.054)
Land owned (ln)	0.276*** (0.096)
Share of Credit access (EA's level)	-1.190*** (0.447)
Share of FISP recipients (EA's level)	0.094 (0.489)
Agricultural Advice from Extension Services (1=yes)	-0.388* (0.224)
Drought Shock Probability	-0.019 (0.024)
Cell Phone for gathering information (1=yes)	0.158 (0.218)
Distance from FRA (ln)	-0.088 (0.151)
Number of traders (ln)	-0.125 (0.170)
information on crop suitability (1=yes)	0.031 (0.215)

Panel B – Endogenous equation

Endogenous variable equation	
Dependent variable: Seasonal Forecasts (1=yes)	
Distance from seasonal forecasts recipients in the village	-0.008*** (0.003)
Share of seasonal forecasts recipients (EA's level)	0.233** (0.110)
Household size (ln)	0.016 (0.041)
Age of household head (ln)	0.023 (0.066)
Head is female (1=yes)	-0.034 (0.048)
Household's head year of education (ln)	0.041* (0.023)
Agricultural Wealth Index	-0.016 (0.028)
Livestock owned (TLU)	-0.001 (0.002)
Land owned (ln)	0.002 (0.021)
Share of Credit access (EA's level)	-0.014 (0.075)
Share of FISP recipients (EA's level)	0.102 (0.068)
Agricultural Advice from Extension Services (1=yes)	0.089 (0.057)
Drought Shock Probability	0.005 (0.004)
Cell Phone for gathering information (1=yes)	0.053 (0.041)
Distance from FRA (ln)	0.036 (0.025)
Number of traders (ln)	0.031 (0.027)
information on crop suitability (1=yes)	0.001 (0.051)
Kleibergen-Paap rk LM statistic (Chi-squared P-value)	12.45 (0.00)
Hansen J statistic (Chi-squared P-value)	2.417 (0.12)
F-test (Prob>F)	11.61 (0.00)
Anderson-Rubin Wald test (Chi-squared P-value)	2.60 (0.2732)
Province dummies	-
R-squared	
Observations	935

Notes: the table display estimates from a linear probability and a maximum likelihood instrumental variable probit with simultaneous estimation on the probability of switching from a non-drought resilient cropping system to a drought resilient cropping system between the agricultural seasons 2014/2015 and 2015/2016. Panel A shows the result from the outcome equation. Panel B reports the results from the endogenous equation, where the dependent variable is the seasonal forecasts dummy. The drought resilient system includes Maize and one or more of the following crops: MS1= Cassava, Millet, Sorghum, Sweetpotato. For the specifications' acronyms refer to Table 4. Errors are clustered at village level. Level of significances are * p<0.10; ** p<0.05; ***p<0.01.

Table A6 Differentiated impact of seasonal forecasts on adoption of drought-resilient systems, outcome (Panel A) and endogenous equations (panel B)
Panel A – Outcome equation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	To MS1	To MS1	To MS1	To MS2	To MS2	To MS2	To MS3	To MS3	To MS3
	OLS - CS Sample with IPW	IVP	Marginal effect	OLS - CS Sample with IPW	IVP	Marginal effect	OLS - CS Sample with IPW	IVP	Marginal effect
Drought-expected zone X Seasonal Forecasts	0.113** (0.056)	5.035*** (0.947)	0.01	0.122** (0.057)	5.187*** (0.768)	0.01	0.115* (0.058)	4.879*** (1.296)	0.05
Seasonal Forecasts (1=yes)	-0.134** (0.055)	-3.662*** (1.323)	-0.02	-0.141** (0.055)	-3.754*** (1.422)	-0.02	-0.142** (0.055)	-3.704*** (1.226)	-0.08
Drought expected zone (1=yes)	-0.062 (0.051)	-2.461*** (0.458)	-0.02	-0.061 (0.051)	-2.439*** (0.512)	-0.02	-0.014 (0.061)	-2.338*** (0.457)	-0.05
Household size (ln)	-0.014 (0.015)	-0.112 (0.120)	0.00	-0.014 (0.014)	-0.067 (0.101)	0.00	0.007 (0.020)	0.071 (0.163)	0.01
Age of household head (ln)	0.040 (0.028)	-0.072 (0.280)	0.01	0.044 (0.027)	-0.109 (0.246)	0.01	0.021 (0.031)	-0.103 (0.290)	0.02
Head is female (1=yes)	-0.026* (0.016)	-0.076 (0.143)	-0.01	-0.027** (0.013)	-0.044 (0.123)	-0.01	-0.013 (0.021)	-0.042 (0.148)	-0.01
Household's head year of education (ln)	-0.010 (0.009)	-0.081 (0.062)	0.00	-0.010 (0.009)	-0.068 (0.059)	0.00	-0.004 (0.010)	-0.046 (0.056)	0.00
Agricultural Wealth Index	-0.025*** (0.008)	-0.260 (0.197)	-0.01	-0.023*** (0.007)	-0.201 (0.175)	-0.01	-0.024** (0.010)	-0.188 (0.191)	-0.02
Livestock owned (TLU)	-0.001 (0.000)	-0.018 (0.027)	0.00	-0.001* (0.000)	-0.009 (0.024)	0.00	-0.001* (0.001)	-0.009 (0.022)	0.00
Land owned (ln)	0.022** (0.011)	0.187** (0.087)	0.00	0.020* (0.011)	0.137* (0.082)	0.00	0.013 (0.013)	0.135 (0.097)	0.01
Share of Credit access (EA's level)	-0.014 (0.013)	-0.599 (0.433)	-0.02	-0.008 (0.013)	-0.504 (0.383)	-0.02	0.053* (0.031)	-0.203 (0.228)	0.01
Share of FISP recipients (EA's level)	0.013 (0.031)	-0.256 (0.276)	0.00	0.015 (0.032)	-0.320 (0.248)	0.00	0.009 (0.038)	-0.297 (0.320)	0.01
Agricultural Advice from Extension Services (1=yes)	-0.032* (0.017)	-0.280 (0.224)	-0.01	-0.028 (0.018)	-0.206 (0.191)	-0.01	-0.032 (0.021)	-0.249 (0.228)	-0.03
Drought Shock Probability	0.001 (0.001)	-0.020* (0.011)	0.00	0.001 (0.001)	-0.020* (0.011)	0.00	0.003 (0.002)	-0.013 (0.023)	0.00
Cell Phone for gathering information (1=yes)	-0.001 (0.013)	-0.147 (0.131)	0.00	-0.000 (0.013)	-0.143 (0.112)	0.00	-0.011 (0.017)	-0.167 (0.125)	0.00
Distance from FRA (ln)	-0.009 (0.007)	-0.016 (0.093)	0.00	-0.013* (0.007)	0.012 (0.078)	0.00	-0.012 (0.010)	0.029 (0.086)	0.00
Number of traders (ln)	-0.021* (0.012)	-0.106 (0.151)	0.00	-0.020* (0.011)	-0.041 (0.131)	0.00	-0.023 (0.014)	-0.021 (0.151)	-0.01
information on crop suitability (1=yes)	0.017* (0.010)	0.040 (0.130)	0.00	0.013 (0.011)	0.059 (0.100)	0.00	0.024 (0.017)	0.117 (0.136)	0.01
Anderson-Rubin Wald test (Chi-squared P-value)	-	3.10 (0.21)	3.10 (0.21)	-	3.99 (0.14)	3.99 (0.14)	-	3.10 (0.21)	3.10 (0.21)
R-squared	0.19	-	-	0.20	-	-	0.19	-	-
Observations	964	935	935	958	930	930	921	894	894

Panel B – Endogenous equation

	(1) To MS1 IVP	(2) To MS1 IVP	(3) To MS2 IVP	(4) To MS2 IVP	(5) To MS3 IVP	(6) To MS3 IVP
	Dependent variable: Seasonal Forecasts (1=yes)	Dependent variable: Drought- expected zone X Seasonal Forecasts	Dependent variable: Seasonal Forecasts (1=yes)	Dependent variable: Drought- expected zone X Seasonal Forecasts	Dependent variable: Seasonal Forecasts (1=yes)	Dependent variable: Drought- expected zone X Seasonal Forecasts
Distance from seasonal forecasts recipients in the village	-0.008*** (0.003)	-0.007** (0.003)	-0.006** (0.003)	-0.005* (0.003)	-0.006* (0.003)	-0.005 (0.003)
Share of seasonal forecasts recipients (EA's level)	0.239** (0.095)	0.131 (0.093)	0.261*** (0.096)	0.153 (0.097)	0.277*** (0.096)	0.162* (0.093)
Drought expected zone (1=yes)	0.392*** (0.039)	-0.078 (0.051)	-0.089* (0.053)	0.381*** (0.040)	-0.092* (0.054)	0.379*** (0.041)
Household size (ln)	0.019 (0.037)	0.015 (0.041)	0.005 (0.041)	0.009 (0.037)	0.003 (0.042)	0.005 (0.038)
Age of household head (ln)	0.064 (0.060)	0.019 (0.065)	0.002 (0.065)	0.047 (0.060)	-0.011 (0.068)	0.036 (0.063)
Head is female (1=yes)	-0.036 (0.041)	-0.039 (0.048)	-0.026 (0.049)	-0.022 (0.042)	-0.026 (0.050)	-0.022 (0.043)
Household's head year of education (ln)	0.036 (0.023)	0.039* (0.023)	0.036 (0.023)	0.034 (0.023)	0.034 (0.024)	0.032 (0.023)
Agricultural Wealth Index	0.002 (0.024)	-0.012 (0.028)	-0.004 (0.030)	0.010 (0.025)	-0.008 (0.031)	0.005 (0.026)
Livestock owned (TLU)	-0.002 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.003** (0.001)	-0.002 (0.002)	-0.003* (0.001)
Land owned (ln)	-0.020 (0.018)	-0.003 (0.021)	0.007 (0.020)	-0.010 (0.017)	0.012 (0.020)	-0.004 (0.018)
Share of Credit access (EA's level)	0.044 (0.076)	0.002 (0.073)	0.034 (0.069)	0.076 (0.073)	0.040 (0.071)	0.082 (0.075)
Share of FISP recipients (EA's level)	0.127* (0.067)	0.087 (0.067)	0.114* (0.065)	0.154** (0.065)	0.112* (0.066)	0.154** (0.065)
Agricultural Advice from Extension Services (1=yes)	0.084 (0.054)	0.088 (0.057)	0.085 (0.056)	0.081 (0.054)	0.082 (0.056)	0.080 (0.054)
Drought Shock Probability	0.008* (0.004)	0.005 (0.004)	0.006 (0.004)	0.008* (0.004)	0.006 (0.004)	0.009** (0.004)
Cell Phone for gathering information (1=yes)	0.069* (0.038)	0.046 (0.042)	0.034 (0.043)	0.056 (0.039)	0.028 (0.043)	0.053 (0.039)
Distance from FRA (ln)	0.016 (0.024)	0.030 (0.025)	0.022 (0.024)	0.008 (0.023)	0.026 (0.025)	0.010 (0.024)
Number of traders (ln)	0.012 (0.028)	0.016 (0.029)	0.001 (0.030)	-0.004 (0.029)	-0.013 (0.031)	-0.018 (0.030)
information on crop suitability (1=yes)	-0.000 (0.049)	0.001 (0.052)	-0.028 (0.045)	-0.031 (0.042)	-0.026 (0.046)	-0.031 (0.043)
Anderson-Rubin Wald test (Chi-squared P-value)	3.10 (0.21)	3.10 (0.21)	3.99 (0.14)	3.99 (0.14)	3.10 (0.21)	3.10 (0.21)
Wald-test of exogeneity chi2 (P-value)	12.46 (0.00)	12.46 (0.00)	21.45 (0.00)	21.45 (0.00)	2.62 (0.26)	2.62 (0.26)
Observations	935	935	930	930	894	894

Notes: the table displays estimates from a maximum likelihood instrumental variable probit with simultaneous estimation on the probability of switching from a non-drought resilient cropping system to a drought resilient cropping system between the agricultural seasons 2014/2015 and 2015/2016. The drought resilient systems include Maize and one or more of the following crops: MS1= Cassava, Millet, Sorghum, Sweetpotato; MS2= Cassava, Cotton, Cowpeas, Millet, Sorghum, Sweetpotato, Cowpeas, Pigeon-peas; MS3= Cassava, Millet, Pigeon-peas, Sorghum, Sweetpotato. For the specifications' acronyms refer to Table 4. Errors are clustered at village level. Level of significances are * p<0.10; ** p<0.05; ***p<0.01.

Table A7 Effect of seasonal forecasts on adoption of drought resilient practices using a continuous measure of expected drought

	(1) To MS1 OLS - CS Sample	(2) To MS1 IVP with IPW	(3) To MS1 Marginal effect	(4) To MS2 OLS - CS Sample	(5) To MS2 IVP	(6) To MS2 Marginal effect	(7) To MS3 OLS - CS Sample	(8) To MS3 IVP	(9) To MS3 Marginal effect
Months of expected drought x Seasonal Forecasts	0.015* (0.008)	0.726*** (0.125)	0.001	0.017** (0.008)	0.746*** (0.089)	0.002	0.016* (0.008)	0.702*** (0.181)	0.007
Seasonal Forecasts (1=yes)	-0.041*** (0.014)	0.405 (0.696)	-0.009	-0.040*** (0.014)	0.469 (0.729)	-0.011	-0.047*** (0.018)	0.285 (1.118)	-0.038
Months of expected drought (ln)	-0.008 (0.007)	-0.352*** (0.062)	-0.002	-0.008 (0.007)	-0.348*** (0.062)	-0.002	-0.002 (0.009)	-0.333*** (0.063)	-0.007
Household size (ln)	-0.015 (0.015)	-0.112 (0.119)	-0.003	-0.015 (0.014)	-0.065 (0.101)	-0.003	0.007 (0.020)	0.067 (0.163)	0.015
Age of household head (ln)	0.040 (0.028)	-0.065 (0.278)	0.008	0.044 (0.027)	-0.103 (0.246)	0.009	0.022 (0.031)	-0.095 (0.291)	0.018
Head is female (1=yes)	-0.026* (0.016)	-0.079 (0.141)	-0.005	-0.028** (0.013)	-0.048 (0.123)	-0.005	-0.013 (0.021)	-0.048 (0.146)	-0.010
Household's head year of education (ln)	-0.010 (0.009)	-0.074 (0.062)	-0.001	-0.010 (0.009)	-0.062 (0.057)	-0.002	-0.005 (0.010)	-0.042 (0.055)	-0.001
Agricultural Wealth Index	-0.025*** (0.008)	-0.256 (0.195)	-0.010	-0.023*** (0.007)	-0.193 (0.172)	-0.011	-0.024** (0.010)	-0.182 (0.189)	-0.024
Livestock owned (TLU)	-0.001 (0.000)	-0.019 (0.027)	-0.001	-0.001* (0.000)	-0.009 (0.024)	-0.001	-0.001* (0.001)	-0.009 (0.022)	-0.003
Land owned (ln)	0.022* (0.011)	0.189** (0.086)	0.005	0.020* (0.011)	0.135* (0.079)	0.005	0.013 (0.013)	0.134 (0.097)	0.014
Share of Credit access (EA's level)	-0.013 (0.013)	-0.624 (0.435)	-0.018	-0.008 (0.013)	-0.528 (0.391)	-0.019	0.053* (0.031)	-0.240 (0.220)	0.006
Share of FISP recipients (EA's level)	0.014 (0.031)	-0.245 (0.283)	0.004	0.016 (0.032)	-0.320 (0.250)	0.005	0.010 (0.038)	-0.298 (0.329)	0.009
Agricultural Advice from Extension Services (1=yes)	-0.033* (0.017)	-0.295 (0.224)	-0.007	-0.029 (0.018)	-0.223 (0.194)	-0.007	-0.033 (0.021)	-0.266 (0.231)	-0.026
Drought Shock Probability	0.001 (0.001)	-0.019* (0.011)	0.000	0.001 (0.001)	-0.020** (0.010)	0.000	0.003 (0.002)	-0.013 (0.023)	0.001
Cell Phone for gathering information (1=yes)	-0.001 (0.013)	-0.157 (0.131)	0.001	-0.000 (0.013)	-0.152 (0.111)	0.002	-0.011 (0.017)	-0.175 (0.124)	-0.002
Distance from FRA (ln)	-0.009 (0.007)	-0.007 (0.091)	-0.002	-0.013* (0.007)	0.022 (0.074)	-0.002	-0.012 (0.010)	0.038 (0.084)	-0.001
Number of traders (ln)	-0.021* (0.012)	-0.100 (0.151)	-0.005	-0.020* (0.011)	-0.030 (0.131)	-0.005	-0.023 (0.014)	-0.013 (0.154)	-0.010
information on crop suitability (1=yes)	0.017* (0.010)	0.039 (0.133)	0.001	0.013 (0.011)	0.065 (0.100)	0.000	0.024 (0.017)	0.122 (0.137)	0.010
R-Squared	0.19			0.20			0.13		
Anderson-Rubin Wald test (Chi-squared P-value)	-	3.33 (0.18)	3.33 (0.18)	-	4.22 (0.12)	4.22 (0.12)	-	2.35 (0.31)	2.35 (0.31)
Observations	964	935	935	958	930	930	921	894	894

Notes: the table displays estimates from a linear probability and a maximum likelihood instrumental variable probit with simultaneous estimation on the probability of switching from a non-drought resilient cropping system to a drought resilient cropping systems between the agricultural seasons 2014/2015 and 2015/2016. Differently from Table 4, this specification includes an intensive measure of drought consisting in the log of the expected months of drought. Dependent variables are dummies on switching from a non-drought resilient cropping system to a drought resilient cropping system between the agricultural seasons 2014/2015 and 2015/2016. For the specifications' acronyms refer to Table 4. Errors are clustered at village level, significance level are * p<0.10; ** p<0.05; ***p<0.01. Endogenous equation results available upon request.

Table A8 Effect of seasonal forecasts on probability of adoption and quantity adopted of inorganic fertilizer in drought forecasted regions

	(1) Inorganic Fertilizer	(2) Inorganic Fertilizer	(3) Hectares of Inorganic Fertilizer	(4) Hectares of Inorganic Fertilizer
	IVP	IVP	2SLS-IV	2SLS-IV
Drought-expected zone X Seasonal Forecasts	-4.669*** (1.137)		-25.004 (26.444)	
Drought expected zone (1=yes)	1.836** (0.760)		16.828 (18.911)	
Seasonal Forecasts (1=yes)	3.204** (1.383)	1.827* (1.042)	10.394 (11.859)	9.772 (11.320)
Months of expected drought x Seasonal Forecasts		-1.850*** (0.591)		-9.974 (10.564)
Months of expected drought (ln)		0.762 (0.513)		4.694 (5.603)
Household size (ln)	0.173 (0.178)	0.172 (0.215)	0.896* (0.463)	0.717 (0.500)
Age of household head (ln)	0.148 (0.150)	0.190 (0.159)	0.486 (1.278)	0.723 (1.388)
Head is female (1=yes)	-0.039 (0.105)	-0.026 (0.117)	-0.200 (0.617)	-0.120 (0.599)
Household's head year of education (ln)	0.068 (0.066)	0.012 (0.092)	0.406 (0.256)	0.036 (0.415)
Agricultural Wealth Index	0.099 (0.083)	0.113 (0.092)	0.630 (0.409)	0.648 (0.400)
Livestock owned (TLU)	-0.004 (0.003)	-0.002 (0.004)	-0.016 (0.019)	-0.003 (0.017)
Land owned (ln)	0.005 (0.113)	0.064 (0.129)	0.367 (0.575)	0.580 (0.402)
Share of Credit access (EA's level)	0.338 (0.306)	0.423 (0.297)	1.942** (0.804)	2.234** (1.118)
Share of FISP recipients (EA's level)	0.923* (0.536)	0.859 (0.682)	4.603** (1.822)	3.599*** (1.166)
Agricultural Advice from Extension Services (1=yes)	0.164 (0.121)	0.134 (0.143)	0.930 (0.668)	0.730 (0.721)
Drought Shock Probability	0.023** (0.010)	-0.004 (0.012)	0.113 (0.124)	-0.036 (0.066)
Cell Phone for gathering information (1=yes)	0.095 (0.106)	-0.054 (0.111)	0.578 (0.892)	-0.217 (0.488)
Distance from FRA (ln)	-0.106 (0.072)	-0.173*** (0.063)	-0.545* (0.328)	-0.851 (0.627)
Number of traders (ln)	-0.062 (0.082)	0.009 (0.118)	-0.187 (0.421)	0.269 (0.636)
Information on crop suitability (1=yes)	0.000 (0.103)	0.082 (0.117)	-0.172 (0.537)	0.258 (0.793)
Anderson-Rubin Wald test (Chi-squared P-value)	2.45 (0.29)	1.83 (0.40)	2.42 (0.30)	1.87 (0.39)
Observations	1128	1128	1128	1128

Notes: the table displays the estimates from a maximum likelihood instrumental variable probit with simultaneous estimation on the probability of adopting inorganic fertilizer and a two-stage least square instrumental variable model on the quantity of fertilizer adopted during the season 2015/2016. For the specifications' acronyms refer to Table 4. Errors are clustered at village level, significance level are * p<0.10; ** p<0.05; ***p<0.01.

Table A9 Impact of seasonal forecasts on probability of shifting to MS1 system using the closest neighbor, the 5 closest neighbor, kernel and caliper matching approaches

	(1)	(2)	(3)	(4)
	To MS1	To MS1	To MS1	To MS1
	OLS - CS Sample with IPW on 1 neighbor	OLS - CS Sample with IPW on 5 neighbors	OLS - CS Sample with IPW using Kernel	OLS - CS Sample with IPW using Caliper
Drought-expected zone X Seasonal Forecasts	0.113** (0.056)	0.113** (0.056)	0.114** (0.055)	0.114** (0.055)
Seasonal Forecasts (1=yes)	-0.134** (0.055)	-0.134** (0.055)	-0.131** (0.055)	-0.131** (0.055)
Drought expected zone (1=yes)	-0.062 (0.051)	-0.062 (0.051)	-0.067 (0.051)	-0.067 (0.052)
Household size (ln)	-0.014 (0.015)	-0.014 (0.015)	-0.017 (0.014)	-0.017 (0.014)
Age of household head (ln)	0.040 (0.028)	0.040 (0.028)	0.023 (0.026)	0.023 (0.026)
Head is female (1=yes)	-0.026* (0.016)	-0.026* (0.016)	-0.014 (0.015)	-0.014 (0.015)
Household's head year of education (ln)	-0.010 (0.009)	-0.010 (0.009)	0.000 (0.006)	0.000 (0.006)
Agricultural Wealth Index	-0.025*** (0.008)	-0.025*** (0.008)	-0.018*** (0.007)	-0.018*** (0.007)
Livestock owned (TLU)	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Land owned (ln)	0.022** (0.011)	0.022** (0.011)	0.014 (0.009)	0.014 (0.009)
Share of Credit access (EA's level)	-0.014 (0.013)	-0.014 (0.013)	-0.011 (0.013)	-0.011 (0.013)
Share of FISP recipients (EA's level)	0.013 (0.031)	0.013 (0.031)	-0.005 (0.026)	-0.005 (0.026)
Agricultural Advice from Extension Services (1=yes)	-0.032* (0.017)	-0.032* (0.017)	-0.029** (0.014)	-0.029** (0.014)
Drought Shock Probability	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Cell Phone for gathering information (1=yes)	-0.001 (0.013)	-0.001 (0.013)	0.003 (0.009)	0.003 (0.009)
Distance from FRA (ln)	-0.009 (0.007)	-0.009 (0.007)	-0.010 (0.007)	-0.010 (0.007)
Number of traders (ln)	-0.021* (0.012)	-0.021* (0.012)	-0.027*** (0.010)	-0.028*** (0.010)
information on crop suitability (1=yes)	0.017* (0.010)	0.017* (0.010)	0.015 (0.010)	0.015 (0.010)
Observations	964	964	968	965

Notes: the table displays estimates from a linear probability on the probability of switching from a non-drought resilient cropping system to a drought resilient cropping system between the agricultural seasons 2014/2015 and 2015/2016. Compared to the baseline strategy, here the weighting (IPW) from the propensity score matching (PSM) are obtained matching the closest neighbor (column 1) the 5 closest neighbor (column 2), kernel (column 3) and caliper (column 4) equal to 0.005 matching techniques. The drought resilient system include Maize and one or more of the following crops: MS1= Cassava, Millet, Sorghum, Sweetpotato. The linear probability models include province dummies. For the specifications' acronyms refer to Table 4. Errors are clustered at village level. Level of significances are * p<0.10; ** p<0.05; ***p<0.01.

Table A10 Impact of seasonal forecasts on probability of ownership of climate unrelated assets

	(1)	(2)	(3)
	Sprayer	Harrow	Agricultural Wealth index
	IVP	IVP	2SLS IV
Drought-expected zone X Seasonal Forecasts	-1.302	2.921	-0.187
	(4.917)	(3.242)	(2.461)
Seasonal Forecasts (1=yes)	1.120	-3.107	0.126
	(3.441)	(2.217)	(1.856)
Drought-expected zone (1=yes)	0.780	-1.367	0.273
	(2.151)	(1.495)	(1.080)
Other controls	Yes	Yes	Yes
Observations	935	859	1,041

Notes: the table displays estimates from an instrumental variable probit (column 1 and 2) and 2SLS OLS (column 3) on the probability of owning Sprayer, Harrow, and on the level of agricultural wealth index. Controls are the same of the ones included in the main specification with the exception of the agricultural wealth index, which is excluded to avoid collinearity. The weighting strategy is based on a 3-k nearest neighbor matching. For the specifications' acronyms refer to Table 4. Errors are clustered at village level. Level of significances are * p<0.10; ** p<0.05; ***p<0.01. Full list of results for the controls is available upon request.

Table A11 Impact of seasonal forecasts on probability of ownership of climate unrelated assets

	(1)	(2)	(3)
	Sprayer	Harrow	Agricultural Wealth index
	Probit	Probit	OLS
Distance from Seasonal Forecasts recipients in the village	-0.002	0.001	-0.002
	(0.006)	(0.008)	(0.003)
Share of Seasonal Forecasts recipients (EA's level)	0.057	-0.707*	-0.042
	(0.206)	(0.401)	(0.118)
Other controls	Yes	Yes	Yes
Observations	1,133	1,054	1,133
Pseudo R-squared/R-squared	0.16	0.34	0.423

Notes: the table displays estimates from a probit (column 1 and 2) and OLS (column 3) on how the instruments affect the probability of owning Sprayer, Harrow, and on the level of agricultural wealth index. Controls are the same of the ones included in the main specification with the exception of the agricultural wealth index, which is excluded to avoid collinearity. The weighting strategy is based on a 3-k nearest neighbors matching. For the specifications' acronyms refer to Table 4. Errors are clustered at village level. Level of significances are * p<0.10; ** p<0.05; ***p<0.01.

Table A12 Impact of weather information received through cell phone on drought-related adoption using the panel sample

VARIABLES	(1) MS1	(2) MS2	(3) MS3
Weather information through phone	0.105*	0.144**	0.109
	(0.0589)	(0.0662)	(0.0787)
Household size (ln)	-0.0680***	-0.0738***	-0.0709**
	(0.0245)	(0.0260)	(0.0296)
Age of household head (ln)	-0.0391	-0.0237	0.0467
	(0.0398)	(0.0413)	(0.0661)
Head is female (1=yes)	-0.409**	-0.416**	-0.409**
	(0.197)	(0.199)	(0.200)
Household's head year of education (ln)	-0.0502	-0.0489	-0.0394
	(0.0558)	(0.0559)	(0.0555)
Agricultural Wealth Index	-0.0176	-0.0180	-0.0110
	(0.0117)	(0.0120)	(0.0152)
Livestock owned (TLU)	0.00626	0.00725	-0.00402
	(0.00819)	(0.00922)	(0.0155)
Land owned (ln)	-0.00104**	-0.00128**	-0.000743
	(0.000487)	(0.000551)	(0.00143)
Share of Credit access (EA's level)	0.0127	0.0201*	0.0224*
	(0.0111)	(0.0112)	(0.0134)
Share of FISP recipients (EA's level)	0.00470	-0.00360	0.0234
	(0.0362)	(0.0382)	(0.0521)
Agricultural Advice from Extension Services (1=yes)	0.000710	0.00722	-0.00720
	(0.0492)	(0.0499)	(0.0569)
Drought Shock Probability	0.0628	0.00977	-0.0241
	(0.102)	(0.108)	(0.124)
Household Fixed Effects	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Observations	2,008	2,008	2,008
R-squared	0.043	0.047	0.024

Notes: the table displays results from a linear probability OLS model with fixed effects on households and time dummies, applied to the panel sample. The model focuses on the impact of receiving weather information through cell phone on the adoption of drought related practices. The drought resilient systems include Maize and one or more of the following crops: MS1= Cassava, Millet, Sorghum, Sweetpotato; MS2= Cassava, Cotton, Cowpeas, Millet, Sorghum, Sweetpotato, Cowpeas, Pigeon-peas; MS3= Cassava, Millet, Pigeon-peas, Sorghum, Sweetpotato. For the specifications' acronyms refer to Table 4. Errors are clustered at village level. Level of significances are * p<0.10; ** p<0.05; ***p<0.01.

Figure A1 Areas with seasonal forecasts predicting normal to below normal rainfall for the period October 2015 – March 2016 (on the left) and and rainfall SPI3 and SPI6 indexes for the same period.

Figure Notes: The figure displays, on the left, the 2015/2016 rainfall SF in Zambia (Source: Zambia Meteorological Department, 2016), and on the right SPI3 and SPI6 index for the same period.

Figure A2 Seasonal rainfall forecasts for the period October 2014-January 2015 (Source: SARCOF, 2018).

Figure A3 Correlation between centrality of the households to seasonal forecasts information and share of households receiving seasonal forecasts

Figure Notes: the figure displays a scatter plot and the linear correlation between the variable measuring the distance of the household with respect to SF recipients, and the leave-out share of households receiving SF in the village. Leave out share is computed excluding the household observation from the computation. The correlation coefficient between these two dimensions is equal to -0.04.