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Food and Agriculture
Organization of the
United Nations

Smallholder adaptive responses to seasonal weather forecasts

**A case study of the 2015/16 El Niño
Southern Oscillation in Zambia**

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**Food and Agriculture Organization of the United Nations
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Smallholder adaptive responses to seasonal weather forecasts

A case study of the 2015/16 El Niño Southern Oscillation in Zambia

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Abstract

Does receiving information on potential adverse weather conditions induce adaptive responses by smallholders? Do market institutions ease constraints to adaptation of these practices? This report examines these questions using a unique panel dataset of Zambian smallholder households collected before and after 2015/16 El Niño Southern Oscillation event. The analysis finds that farmers receiving drought-related seasonal forecasts are more likely to integrate drought tolerant crops into their cropping systems and to acquire improved maize seed varieties. These farmers, on average, are found to apply double the quantity of improved maize seeds than farmers residing in the same zones but not receiving weather information. Larger and more competitive private output markets function as enablers of smallholder adaptive responses to seasonal forecast information, as farmers with improved market access are more likely to shift toward drought resilient technologies than farmers with low output market access. Three policy recommendations emerge from the findings. First, while seasonal forecast information can induce adaptive responses by farmers, there is the need of improving access to this information, particularly for households in remote areas or limited asset ownership. Second, targeting voucher-based farmer input support programs based on seasonal forecast information can enable the crowding in of private investments in these regions and increase the adaptive responses of farmers, particularly resource constrained farmers. Finally, this analysis suggests that policies that incentivize private investment in agricultural markets should be considered within the broader framework of smallholder climate adaptation and resilience in Zambia. This includes strategies to improve agricultural trade predictability and structured trading platforms.

Keywords: adoption, agricultural practices, El Niño, weather forecasts, Zambia.

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 (Intergovernmental Panel on Climate Change (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 production 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 the 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 in this regard 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 models to predict the potential rainfall impact of ENSO events has improved in SSA (Manatsa, Mushore and Lebouo, 2017; O'Brien *et al.*, 2000). This creates new opportunities to support smallholder adaptive responses to probabilistic weather events due to ENSO. Receiving information on potential adverse weather conditions can enable farmers to adopt production practices that moderate the adverse impact of these weather conditions (Patt, Suarez and Gwata, 2005; Vogel and O'Brien, 2006). However, access to weather information is likely to be necessary, but insufficient to induce widespread changes in production practices in the context of probable adverse weather condition. Smallholder producers operate under a diverse range of resource, market access, and socio-cultural condition that shape their tolerance for risk and influence their willingness and capacity to change production practices (Barret, 2008; Komicha, 2007). Understanding how access to information on probable adverse weather conditions associated with ENSO influences smallholder production practices and the factors that may facilitate these changes is important for developing appropriate policies to enhance adaptation to these events.

Using Zambia as a case study, this article empirically examines if receiving seasonal forecast information on the potential occurrence of an ENSO-related drought influences smallholders' adoption of drought resilient practices and technologies 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-related drought integrate more drought tolerant crops into their cropping systems or increase the adoption of improved seed varieties when they receive seasonal forecast information? Second, do market institutions help to ease constraints associated with the adoption of more drought tolerant cropping systems and improved seed varieties? Through its analysis, this study contributes to the empirical evidence base on smallholder adaptation to climate change in southern Africa.

This study examines these questions using a unique panel household dataset that was collected from smallholder households before and after the 2015/16 ENSO event. The 2015/16 ENSO was the "most widely anticipated El Niño Southern Oscillation (ENSO) event ever" (L'Heureux

et al., 2017), with global operational forecast services around the globe 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 of its regular quantity of rainfall during the first part of the agricultural season. This reduced crop yields and generated severe food deficit warnings (Mazvimavi, Murendo and Chivenge, 2017). Availability of panel survey data that coincides with this event creates a unique opportunity to examine in detail changes in smallholder cropping systems and input use associated with receiving forecast information.

The paper introduces its findings as follow. Section 2 outlines the conceptual framework where the literature evidence on information and farmers' behavior is study in the light of how seasonal forecast service can shape farmers adoption in the presence of market institutions. Section 3 introduces ENIAS and the other data sources under study. Section 4 proposes the research design. Section 5 show summary statistics and discuss the results. Finally, Section 6 concludes.

2 Conceptual framework

2.1 Climate information, barriers to adaptation and market institutions

Farmers' adaptation to climate change often occurs through 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 active action to adopt practices that are more resilient to these changes. Seasonal forecast 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, Suarez and Gwata, 2005). However, despite this beneficial potential, climate forecast information is still underused by farmers in developing countries (Lemos, Kirchhoff and Ramprasad, 2012).

The utilization or underutilization of climate forecast 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, Morton and Hobbs, 2015; Di Falco and Perrings 2005; Gould, Saupe and Klemme, 1989; Grothmann and Patt, 2005; Tanaka *et al.*, 2010; Wossen, Berger and Di Falco, 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 seasonal forecast information (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, Hassan and Ringler (2011) shows that in Ethiopia, farmers are more likely to adopt adaptive farm practices when farmers access information through public extension services. In Zambia, seasonal weather forecast information is compiled by the Zambian Meteorological Society and then disseminated to farmers via radio, mobile phone messaging, print media, and government extension services. In Section 5.1, the effects of receiving this information on cropping system choice and hybrid seed utilization is tested.

However, survey results show that only 41 percent of smallholders in Zambia actually received seasonal forecast information that year. This is likely due constraints within the government extension service, as well as low levels of radio ownership, cell phone coverage, and print media distribution.

While access to reliable seasonal forecast information is a clear barrier in Zambia, responding to this information represents a second important challenge for farmers. Access to input and output markets are likely to be important determinants of smallholders' adaptive responses to seasonal forecast 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 input markets can improve the availability and transactions costs associated with acquiring a diverse range of farm technologies, including appropriate crop seeds and seed varieties for a particular region (Kassie *et al.*, 2012, Pender and Gebremedhin, 2007). Second, there is emerging evidence that competitive output markets that are developing in Zambia, and elsewhere in southern and eastern Africa, are increasingly providing farmers with risk management tools such as formal and informal delivery contracts, as well as extension advice (Sitko *et al.*, 2018). To ensure sufficient production volumes in regions forecasted to experience drought, private output market

actors may encourage diversification to more drought resilient crops, if downstream markets for these crops exit. The effects of market access on farmer's cropping and input behavior in the context of seasonal forecast information is examined in Section 5.2.

2.2 Identifying drought-resilient practices

The baseline hypothesis of this study is that farmers receiving seasonal forecasts and residing in areas hit by ENSO-induced drought will be more likely to switch toward climate-resilient agricultural practices as an ex-ante coping strategy. To test this argument, we focus on two different set of practices: drought-tolerant cropping systems, and changes in the intensity of hybrid maize seed use and fertilizer application.

Three drought-tolerant cropping systems are identified within Zambia's predominantly maize-based production systems. These drought tolerant cropping systems are based on combinations of seven different crops summarized in Table 1. The first system, MS1, includes alternative carbohydrate crops, namely cassava, millet, sorghum, and/or sweetpotato. 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 resistant perennial crop available to smallholder African farmers, as it survives to rainfall shortfalls that often distress maize production (El-Sharkawi, 1993; Schlenker and Lobell, 2010). Cropping system MS2 adds drought tolerant legumes, namely cowpeas and pigeon-peas, to the previous system. These legumes are unusually adaptable to drought and may be able to stabilize production under climate stress through nitrogen fixation and the improvements of 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 resistance (Cline, 2007; Morton, 2007).

Table 1. Drought resistant 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+ cowpeas; pigeon-peas	From high to medium	Hall and Grantz, 1981; Sileshi <i>et al.</i> , 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.

Source: Authors' own elaboration.

The adoption of hybrid maize seeds offers a second potential ex-ante strategy to cope with the ENSO-induced drought in Zambia. Most hybrid seeds available in Zambia are adapted to shorter growing season lengths than traditional, non-hybrid varieties (Kalinda *et al.*, 2014). In the context of the 2015/16 ENSO event in Zambia, many areas of the country were forecasted to receive below normal rainfall, particularly in the first half of the rainy season (Zambia Meteorological Department, 2016). It is hypothesized, therefore, that residing in a region forecasted to be effected by the ENSO-drought and receiving seasonal forecast information will be associated with an increase in adoption of hybrid maize seeds and an increased use rate of these seeds, all else equal.

Finally, the set of practices includes also the adoption and the quantity of inorganic fertilizer. Evidence in the literature suggests returns to inorganic fertilizer use are strongly correlated with available soil moisture, which in rain-fed systems is driven primary by rainfall quantity and distribution (Piha, 1993; Shapiro and Sanders, 1998). Receiving information on a potential drought is, therefore, expected to have from a negative to a neutral effect on farmers' adoption of inorganic fertilizers.

Table 2. Expected impact of seasonal forecasts on adoption

Practices	Hypothesized Impact of seasonal forecasts on adoption	
	Normal seasonal forecasts	Drought-related seasonal forecasts
MS1	Negative	Positive
MS2	Negative	Positive
MS3	Negative	Positive
Hybrid seeds	Neutral to negative	Positive
Quantity of maize-hybrid seeds	Neutral to negative	Positive
Inorganic fertilizer	Positive	Neutral to negative
Quantity of inorganic fertilizer	Positive	Neutral to negative

Source: Authors' own elaboration.

3 Data

3.1 Data description

The household data used in this study comes 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 has been purposely conceived to study the impact and household responses to the 2015/16 El Niño. It 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 2015/16,¹ and a second one of potentially non-exposed households, representing the control group of the analysis, for a total of 1 311 household observations. This sample was derived using a propensity score matching (PSM) approach at the Standard Enumeration Area (SEA) level. This methodology identifies comparable households living in potentially severely affected areas with a control set of households in non-affected areas.

As consequence of this sample design, a large number of RALS 2015 households from the north and central areas of the country were excluded from the ENIAS. Since these households showed significant differences in terms of their agro-ecological conditions and cropping systems than the households in the severely affected areas, the inclusion of these households would have unbalanced any estimates on ENSO impact. In addition, a large part 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 2015/16 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 149 SEAs, among which 60 were expected to be severely affected (treatment) and 89 not severely affected (control). From each of these SEAs, 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 with to create a unique panel dataset. While RALS 2015 represented the basis for the design and implementation of the ENIAS sample and questionnaire, the ENIAS included new questions capturing whether households received seasonal forecast information before the agricultural season. From this question derives the binary variable assuming value one when a household has received seasonal. Unfortunately, this information is only available for the ENIAS 2015/16 wave, thus only these cross-sectional data are used for the present analysis. However, the panel dimension of the surveys is used identify changes in household production behaviours, namely cropping system and input use changes.

¹ 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 impact of El Niño.

To study the effect of receiving seasonal forecast when residing in the predicted severely affected area, we interact the indicator on receiving seasonal forecast with a second variable representing the natural logarithm of the months of drought predicted in the household's area of residence.² This indicator is constructed by overlaying the monthly maps on drought forecasts in Figure A1 in the Annex, extracted from the *Seasonal Rainfall Forecast 2015/16* (Zambia Meteorological Department, 2016),³ to the geographical distribution of surveyed households.

The first set of dependent variables consist in three dummies indicating the switching to cropping systems MS1, MS2, MS3. The panel dimension of the data allows to determine whether these systems were already adopted during the preceding agricultural seasons. Dummies on adoption take value 1 if a household was not adopting one of the three drought tolerant cropping systems during the RALS 2015 survey year but had switched to one of these systems in the ENIAS survey. In contrast, the variable will take value 0 if a household does not switch.⁴ The second set of dependent variables involves two dummies on switching to the adoption of hybrid seed and inorganic fertilizer, computed as above. In addition to these, two further dependent variables include change in the kilograms of maize seeds applied, and a second one quantifying changes in the hectares of land that the farmer applied inorganic fertilizer to.⁵

The specification involves demographic controls such as household's head years of education and age, gender of head of household, and number of household members (Dolisca *et al.*, 2006; Hassan, Nhemachena, 2008; Nyangena, 2007). The set of controls also include variables on wealth, such as the agricultural wealth index constructed using a principal component analysis approach, the livestock owned in Total Livestock Units (TLU), and the size of land owned in hectares. The effect of these variables on adoption 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-constraints, 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, controls for two variables capturing the share of credit and input subsidy (FISP) recipients at enumeration area level to exclude any form of reverse causality in reception (Asfaw and Maggio, 2018). Two dummies on the access to extension services and on cell phone use for receiving agricultural information are used to control for the possibility that the seasonal forecast variable would capture an effect driven by other types/sources of agricultural information. 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. An agricultural season is defined as drought-shocked if its 6-months Standardized Precipitation Index (SPI) is equal or lower than -1.5 (Maggio, Sitko and Ignaciuk, 2018; Scognamiglio, Asfaw and Ignaciuk, forthcoming). The SPI index is constructed using location specific rainfall data measured on 10 days interval and extracted from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). CHIRPS delivers re-elaborated rainfall data with 0.5 degree of spatial resolution which have

² To include the zero observations, it is added one to this variable before of log-linearizing.

³ This document has been edited before the start of the agricultural season and published on the 19/01/2016.

⁴ 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.

⁵ As before, continuous and counting variables are transformed taking the natural logarithm. To include zeros observations, we add one before taking the logarithm. Unfortunately, EINAS allow to measure the appliance of inorganic fertilizer only in hectares.

been matched to the household data using the centroid of households' villages. To control whether input market mechanisms are influencing the selection of a given cropping system, the specification for the first set of dependent variables includes as controls the average seed prices for legumes, staples, and cash-crops. Finally, the distance from Food Reserve Agency depots, a parastatal marketing board that buys crops from farmers, and the total number of traders buying grain within the farmers' village as indicators of public and private output market institutions.⁶

⁶ Since these variables derive from household level questions, we use the median distance and number of traders to exclude that their computation is affected by outliers.

4 Research design

The adoption of climate-resilient cropping strategies and practices is modelled using a random utility framework, where farmers take the adoption's decision while maximizing their utility function subject to input, ecological, demographic, and institutional constraints (Di Falco and Veronesi, 2013; Feder, 1982; Manda *et al.*, 2016). The background of this framework can be adapted to a non-separable household model where adoption of MS1, MS2, MS3, and hybrid seeds can be simultaneously influenced by exogenous determinants (De Janvry, Fafchamps and Sadoulet, 1991; Wouterse and Taylor, 2008). Household's indirect utility V subject to the adoption of a practice Y and a set of observable determinants X_i can take the following form:

$$V_{ip} = f[P_i(SF_i, K_i); X_i] \quad (1)$$

Where the adoption of practice P_i is a function of receiving seasonal forecasts (SF_i) a vector of natural, physical, human, financial, and social capital X_i . The assumption is that household i will maximize the expected indirect utility V_{ip} by comparing the expected utility derived from the adoption of practice p against the one derived from any alternative of practice k , selecting practice p if and only if $V_{ip} > V_{ik}$.

4.1 Empirical strategy

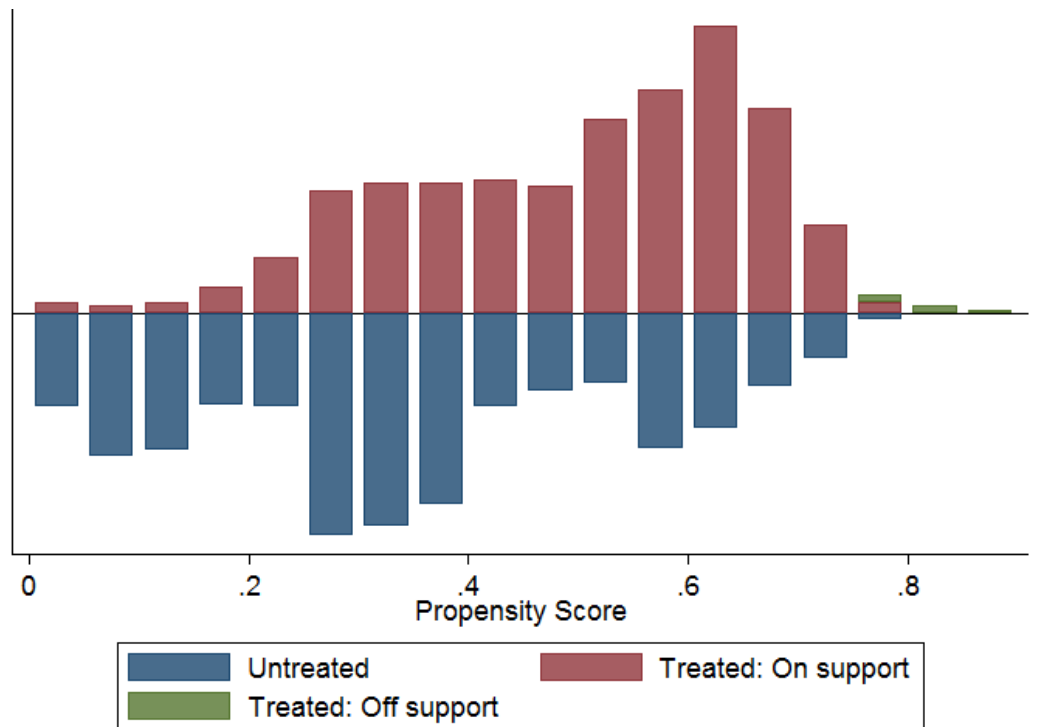
Receiving climate seasonal forecasts and living in the predicted ENSO drought area are two non-random events which are likely correlated with individual wealth, skills, education, access to information, and other socio-economic characteristics. For example, compared to an illiterate individual living in ENSO drought area, a literate one may be able to read seasonal forecasts on the newspaper, and therefore decide to adopt the practices under study. The risk of not accounting for the non-random assignment, in this case, is over-estimating the impact of seasonal forecasts on the probability of adoption, as part of these households may have however adopted these technologies independently from the reception of the seasonal forecasts. While experimental works on the impact of policy actions frequently base their analysis on trials that assign randomly the treatment on a treated and control group, non-experimental researches have often focused on methodologies to increase the comparability between the treated and the control groups. ENIAS has the advantage of being purposely conceived for studying the impact of El Niño shocks and therefore the sample is already balanced in terms of likelihood of receiving a shock, as the design approach has included the most comparable set of households across that dimension.⁷ However, the sample remains unbalanced on the reception of seasonal forecasts. For the purpose of our analysis, therefore, we apply a matching and reweighting strategy to increase the comparability between the two groups of households across the seasonal forecast dimension. The baseline method to match treated and non-treated households is the nearest neighbor (NN) matching, implemented through the estimated propensity scores (PSM) considering the three nearest observations and allowing for replacement after each match. This approach works on pairs of observations as it selects and match 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).⁸ The matching between individuals is based on a set of variables likely influencing the treatment status. The selection of the variables has several implications for the functioning of the approach, as the

⁷ Using ENIAS data, Alfani *et al.* (2019) finds a strong and negative impact of ENSO on yield and income per capita in Zambia.

⁸ 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.

exclusion of important covariates is likely to bias the estimated coefficients, while the inclusion of controls' uncorrelated dimensions reduce the likelihood of finding a common support 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 four sets of determinants affecting the likelihood of accessing to seasonal forecast: information access, institutional and non-institutional networks, socio-demography characteristics, geographical and market access determinants. Descriptive results in Table 3 show that the two groups of households have several differences in access to information, institutional and non-institutional network, and geographical distribution. In contrast, pre-match samples are similar in terms of socio-demography as a consequence of the original PSM sample design. Covariates similarities between the two groups sharply increase as shown by the post-match summaries, where the test conducted does not report any statistically significant difference. 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



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 regions, respectively.

Source: Authors' own elaboration.

Unfortunately, given that the question on weather forecasts is only included in ENIAS sample, it is not possible to control for unobserved heterogeneity. We deal with this issue by adding the province dummies included in the geographical determinants, whose balancing ensure that households are exposed to a similar set of unobserved cultural, institutional, and geographical unobserved determinants. Finally, as further check we run the same linear probability model using weights computed by the propensity score values (Francesconi and Nicoletti, 2006).

Table 3. Test for balance before and after matching

	Pre-Matched		Pre-matched balance T-test	Matched		Matched balance T-test
	Treated (seasonal forecast=1)	Control (seasonal forecast=0)		Treated (seasonal forecast=1)	Control (seasonal forecast=0)	
Distance from FRA (km)	6.51	6.51		6.35	7.03	
Total number of traders	4.73	4.73		4.76	4.69	
Radio (1=yes)	0.82	0.63	***	0.82	0.80	
Tv (1=yes)	0.38	0.29	***	0.38	0.40	
Cellphone (1=yes)	0.52	0.53		0.52	0.52	
Extension service (1=yes)	0.49	0.44	*	0.50	0.48	
Fellow farmers network (1=yes)	0.43	0.46		0.43	0.47	
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	
Female-headed household (1=yes)	0.17	0.22	**	0.17	0.16	
Household's age	50.04	50.71		50.10	50.72	
Head's education (years)	6.46	5.86	**	6.40	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 (hectares)	7.94	6.14		7.83	8.94	
Residence in El Niño area (1=yes)	0.84	0.82		0.84	0.84	
Population density (pop/km ²)	31.38	30.32		31.28	31.24	
Copperbelt (1=yes)	0.05	0.10	***	0.05	0.05	
Eastern (1=yes)	0.63	0.40	***	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 display the control variables for the propensity score match with 3-k neighbors and the results from the balance tests before and after the propensity score. Control variables are dummies on radio and tv ownership, use of cellphone for gathering information on agriculture, access to extension service, reception of advice from fellow farmers. Other controls include the share of FISP and credit recipients at village level, dummy for female-headed household, household size, years of education of the head, agricultural wealth index, land-owned in hectares, population density, dummy on residence in El Niño area and on provinces, distance from Food Reserve agency and total number of traders.

Source: Authors' own elaboration.

We adopt two empirical approaches using the resulting sample of the matching and weight strategy. The first approach relies on a simple OLS linear probability model for the common support region, taking the following form:

$$P_i = \beta_0 + \gamma_1 SF_{ic} + \gamma_2 EN_c + \vartheta SF_{ic} * EN_c + \delta X_{ic} + \varepsilon_i \quad (2)$$

P_i is a dummy taking value 1 if the household $i=1, \dots, N$ resident in EA c switch from a non-climate resilient in RALS 2014/15 to a climate-resilient cropping system (MS1, MS2, MS3) in ENIAS 2015/16, or if the households adopt hybrid seeds or inorganic fertilizer. Otherwise, P_{ic} is a continuous variable for the amount of hybrid maize-seeds planted or for 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 seasonal forecasts, EN_c is the natural logarithm of the expected months of drought shock in 2015/16 agricultural season, $SF_{ic} * EN_c$ denotes their interaction term and captures the reception of drought-related seasonal forecasts, 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 , and the normally distributed error term ε_i clustered at village level.

The second approach relies on a Seemingly Unrelated Regression (SUR) equation, which addresses the possibility of farmers implementing the combination of climate-resilient practices while accounting for interdependences in adoption (Zellner, 1962; Zellner, 1963). Since practices MS1, MS2 and MS3 are mutually exclusive, the simultaneity derives from the adoption of each of these practices and hybrid seeds. This model focus on adoption rather than shifting to new practices, this because it requires the employment of the full sample and the expansion of the first model across the climate resilient practices j , as follow:

$$P_{ij} = \beta_{0j} + \gamma_{1j} SF_{icj} + \gamma_{2j} EN_{cj} + \vartheta SF_{icj} * EN_{cj} + \delta_j X_{ij} + \varepsilon_{ij} \quad (3)$$

Where, differently from (2), j denotes the practice adopted and ε is assumed to be correlated across the cropping and the hybrid seeds adoption equations, where errors ε are characterized the following overall variance-covariance matrix:

$$\Omega = (\varepsilon \varepsilon') = \Sigma \otimes I_N \quad (4)$$

5 Results

5.1 Statistics on seasonal forecast receivers

The first part of Table 3 presents the characteristics of the group of households receiving (treated) and not receiving (control) seasonal forecasts at national level. The percentage of households receiving seasonal forecasts 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 seasonal forecast are more likely to have access to radio (+19 percent) and to television (+9 percent), which are likely to be important sources of seasonal forecast information. Households accessing seasonal forecasts are also more likely to be in contact with extension services (+5 percent) and reside in enumeration areas with lower access to social security 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 seasonal forecast 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 insuring that balancing the sample at national level will also balance the differences for the households potentially hit by droughts. A preliminary unconditional analysis suggests that households receiving seasonal forecasts have a significantly higher maize yield, both in the overall sample and in the subsample located in the expected severely affected areas. The average maize yield is generally lower in the groups residing in the ENSO affected areas, indicating that these variables are likely capturing the shock that occurred during the 2015/16 season. Crop income follows a similar pattern, although in this case the difference between the two groups is not significant (Figures A2 and A3 in the Annex).

Taken together, this descriptive evidence suggests that seasonal forecast information on the ENSO-induced drought did not reach the majority of smallholders in Zambia, even among those in areas predicted to be effected, and that those that received information were on average better-off farmers. Expanding the reach of seasonal forecast information to poorer households in more marginal areas is therefore an important priority to increase climate adaptation among smallholders.

5.2 Average impact of drought-related forecasts

Drought-related seasonal forecasts are an important determinant for farmers switching to climate resilient cropping systems. For all the three drought tolerant cropping systems, farmers residing in forecast region of the ENSO-related drought and receiving seasonal forecasts significantly increase their probability of adoption of MS1, MS2 and MS3 compared to households living in same areas but not receiving the information (Table 4). Receiving seasonal forecast information in affected regions have a comparable impact for the adoption of these three cropping systems. In particular, receiving information on the ENSO-induced drought increases the probability of adopting the MS1 system by 6.6–7 percent, the MS2 system by 7.3–8.2 percent, and the MS3 system by 5.5–7.7 percent,⁹ conditional on living in effected area.

The results show that across the whole sample, including households in unaffected areas, the seasonal forecast dummy variable correlates negatively with adoption of these systems

⁹ We are referring to the probability of adoption computed as $\exp(P_{ij}=E[SF_{icj}=1/EN_{cj} = 1] - E[SF_{icj}=0/EN_{cj} = 1]) - 1$.

because the variable is capturing the effect of seasonal forecasts 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. Households not receiving seasonal forecasts but residing in El Niño forecasted areas are not likely to change their adoption behavior.

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 a climate-resilient cropping system. This is likely because wealthier households have alternative means of coping with drought, such as investing in off-farm activities.

Estimates show that farmers receiving drought-related seasonal forecast are likely to apply double the quantity of hybrid seeds than farmers residing in the same zones but not receiving weather information, all else equal. In contrast, the seasonal weather forecasts has no effect on households residing in unaffected areas. Estimates exclude any correlational evidence between both the probability and amount of inorganic fertilizer applied, and the prediction of lower than normal rainfall. Since inorganic fertilizer delivers increasing returns with higher rainfall, the absence of an effect on adoption provides support to the main hypothesis of this study. In terms of controls, adoption of hybrid seeds is more likely to occur in younger and more educated households, characterized by more wealth and agricultural assets, such as land (see Table A3 in the Annex). A similar result applies for adopters of inorganic fertilizers, whose adoption is negatively correlated with the number of livestock owned, as possibly these farmers substitute inorganic fertilizer with manure. Among the remaining controls, households residing in areas with more access to FISP significantly increases the amount of seeds and fertilizer applied.

Table 4. Seasonal forecasts and selection of climate resilient cropping systems under drought risk

	(1) To MS1	(2) To MS1	(3) To MS1	(4) To MS2	(5) To MS2	(6) To MS2	(7) To MS3	(8) To MS3	(9) To MS3
	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR
Months expected drought x seasonal forecasts	0.070** (0.034)	0.073** (0.036)	0.066*** (0.023)	0.080** (0.034)	0.082** (0.036)	0.073*** (0.024)	0.072** (0.035)	0.077** (0.036)	0.055* (0.030)
Months expected drought (ln)	-0.044 (0.039)	-0.039 (0.034)	-0.037 (0.024)	-0.042 (0.039)	-0.040 (0.034)	-0.033 (0.024)	-0.003 (0.049)	-0.007 (0.042)	0.031 (0.031)
Seasonal forecasts (1=yes)	-0.118** (0.048)	-0.121** (0.052)	- 0.119*** (0.031)	- 0.127*** (0.048)	-0.131** (0.052)	- 0.126*** (0.032)	- 0.132*** (0.048)	-0.137*** (0.052)	- 0.130*** (0.041)
Agricultural Wealth Index	- 0.023*** (0.008)	-0.026*** (0.008)	- 0.030*** (0.010)	- 0.022*** (0.008)	-0.024*** (0.008)	- 0.029*** (0.010)	-0.023** (0.010)	-0.024** (0.011)	-0.020 (0.013)
Livestock owned (TLU)	-0.001* (0.000)	-0.001 (0.000)	-0.001 (0.001)	-0.001* (0.000)	-0.001* (0.000)	-0.001 (0.001)	-0.001** (0.000)	-0.001* (0.001)	-0.001 (0.001)
Land owned (ln)	0.013 (0.010)	0.022* (0.011)	0.013* (0.007)	0.011 (0.010)	0.020* (0.011)	0.012 (0.007)	0.005 (0.011)	0.013 (0.013)	0.001 (0.009)
Share of credit access (EA's level)	-0.012 (0.017)	-0.014 (0.013)	-0.054** (0.027)	-0.004 (0.017)	-0.009 (0.013)	-0.051* (0.027)	0.055 (0.033)	0.052* (0.030)	0.085** (0.035)
Share of FISP recipients (EA's level)	0.018 (0.032)	0.013 (0.030)	0.018 (0.027)	0.018 (0.031)	0.014 (0.031)	0.025 (0.028)	0.016 (0.037)	0.008 (0.037)	0.005 (0.036)
Agricultural advice from extension services (1=yes)	-0.020 (0.016)	-0.035* (0.019)	-0.015 (0.016)	-0.015 (0.016)	-0.030 (0.019)	-0.007 (0.017)	-0.021 (0.019)	-0.034 (0.023)	-0.003 (0.021)
Drought shock probability	0.001 (0.001)	0.001 (0.001)	0.001 (0.002)	0.001 (0.001)	0.001 (0.001)	0.001 (0.002)	0.002 (0.002)	0.002 (0.002)	0.001 (0.002)
Cell phone for gathering information (1=yes)	0.006 (0.012)	-0.003 (0.013)	0.012 (0.013)	0.005 (0.012)	-0.002 (0.014)	0.009 (0.014)	-0.008 (0.015)	-0.014 (0.018)	-0.016 (0.017)
Distance from FRA (ln)	-0.008 (0.010)	-0.010 (0.007)	0.014* (0.008)	-0.014 (0.009)	-0.014** (0.007)	0.011 (0.008)	-0.012 (0.012)	-0.014 (0.010)	-0.004 (0.010)
Number of traders (ln)	- 0.035*** (0.013)	-0.021* (0.012)	- 0.037*** (0.010)	-0.031** (0.012)	-0.018 (0.012)	- 0.036*** (0.010)	-0.032** (0.014)	-0.022 (0.015)	- 0.048*** (0.013)
information on crop and weather	0.010 (0.012)	0.016* (0.010)	0.014 (0.015)	0.005 (0.014)	0.013 (0.011)	0.011 (0.015)	0.021 (0.019)	0.024 (0.017)	0.019 (0.020)
Other demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.14	0.18	0.21	0.15	0.19	0.21	0.11	0.13	0.28
Chi-Squared	-	-	229.1	-	-	237.39	-	-	149.3
Observations	967	967	967	961	961	961	924	924	924

Notes: The table display estimates from a linear probability and a SUR model 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. The full list of controls is available in the Annex (Table A2). Errors are clustered at village level. Level of significances are *p<0.10; **p<0.05; ***p<0.01.

Source: Authors' own elaboration.

Table 5. Seasonal forecasts and selection of other agricultural practices under drought risk

	(1) Hybrid seed (1=yes)	(2) Hybrid seed (1=yes)	(3) Hybrid seed (1=yes)	(4) Kg of hybrid seed maize (ln)	(5) Kg of hybrid seed maize (ln)	(6) Kg of hybrid seed maize (ln)	(7) inorganic fertilizer applied at hh	(8) inorganic fertilizer applied at hh	(9) hectares of inorganic fertilizer use at hh	(10) hectares of inorganic fertilizer use at hh
	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	OLS - CS sample	OLS - CS sample with IPW
Months expected drought x seasonal forecasts	0.316***	0.322***	0.068*	0.922***	1.056***	0.230	0.192	0.211	0.051	0.087
	(0.113)	(0.111)	(0.041)	(0.315)	(0.308)	(0.156)	(0.264)	(0.216)	(0.611)	(0.532)
Months expected drought (ln)	-0.219*	-0.172	-0.040	-0.560	-0.553	-0.202	-0.298*	-0.150	-1.973***	-1.812***
	(0.125)	(0.126)	(0.042)	(0.344)	(0.338)	(0.160)	(0.174)	(0.194)	(0.310)	(0.293)
Seasonal forecasts (1=yes)	-0.292*	-0.325**	-0.015	-0.675	-0.944**	0.092	-0.343	-0.366	-0.039	-0.181
	(0.155)	(0.158)	(0.055)	(0.426)	(0.439)	(0.209)	(0.383)	(0.316)	(0.895)	(0.764)
Agricultural Wealth Index	0.119**	0.140**	0.045**	0.556***	0.556***	0.391***	0.221**	0.151	0.450*	0.358
	(0.054)	(0.053)	(0.018)	(0.188)	(0.186)	(0.067)	(0.101)	(0.111)	(0.243)	(0.220)
Livestock owned (TLU)	0.003	0.001	0.000	0.030**	0.026*	0.015***	-0.018***	-0.024***	-0.014	-0.023
	(0.004)	(0.004)	(0.001)	(0.014)	(0.014)	(0.005)	(0.006)	(0.007)	(0.015)	(0.015)
Land owned (ln)	0.050*	0.064**	0.045***	0.283***	0.353***	0.371***	-0.027	0.025	0.198	0.279**
	(0.026)	(0.031)	(0.013)	(0.097)	(0.104)	(0.049)	(0.051)	(0.051)	(0.122)	(0.111)
Share of credit access (EA's level)	0.421***	0.442***	0.267***	-0.239	-0.100	-0.344*	0.280**	0.287	0.091	0.119
	(0.104)	(0.115)	(0.048)	(0.365)	(0.390)	(0.182)	(0.139)	(0.172)	(0.223)	(0.254)
Share of FISP recipients (EA's level)	0.104	0.129	0.242***	0.648	0.611	0.930***	0.204	0.437	-0.197	-0.022
	(0.103)	(0.124)	(0.049)	(0.459)	(0.520)	(0.184)	(0.266)	(0.283)	(0.372)	(0.341)
Agricultural advice from extension services (1=yes)	0.066	0.055	0.022	0.283	0.204	0.004	-0.008	-0.042	0.064	-0.016
	(0.082)	(0.093)	(0.029)	(0.228)	(0.266)	(0.109)	(0.096)	(0.102)	(0.109)	(0.139)
Drought shock probability	0.009	0.009	0.003	0.003	0.005	-0.019*	-0.003	-0.006	-0.008	-0.009
	(0.010)	(0.009)	(0.003)	(0.023)	(0.024)	(0.011)	(0.010)	(0.009)	(0.017)	(0.014)
Cell phone for gathering information (1=yes)	0.089*	0.093	0.034	0.169	0.234	0.127	-0.029	-0.060	-0.061	-0.098
	(0.051)	(0.065)	(0.024)	(0.198)	(0.229)	(0.090)	(0.077)	(0.082)	(0.147)	(0.172)
Distance from FRA (ln)	-0.054	-0.078*	0.003	-0.209	-0.299**	-0.037	-0.044	-0.100	-0.066	-0.119
	(0.040)	(0.046)	(0.014)	(0.127)	(0.131)	(0.053)	(0.059)	(0.063)	(0.103)	(0.096)
Number of traders (ln)	-0.090*	-0.058	-0.028	-0.220	-0.090	0.067	-0.043	-0.079	0.122	0.063
	(0.047)	(0.056)	(0.017)	(0.136)	(0.168)	(0.066)	(0.062)	(0.066)	(0.103)	(0.090)
Information on crop and weather (1=yes)	-0.035	-0.076	-0.004	0.006	-0.110	-0.026	0.217**	0.180	0.428	0.344
	(0.069)	(0.078)	(0.027)	(0.217)	(0.222)	(0.102)	(0.092)	(0.112)	(0.273)	(0.277)
Constant	1.043**	0.826*	0.900***	1.685	1.189	2.418***	0.663	0.487	2.966***	3.352***
	(0.407)	(0.465)	(0.183)	(1.180)	(1.406)	(0.694)	(0.807)	(0.860)	(1.076)	(1.073)
Other demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	(1) Hybrid seed (1=yes)	(2) Hybrid seed (1=yes)	(3) Hybrid seed (1=yes)	(4) Kg of hybrid seed maize (ln)	(5) Kg of hybrid seed maize (ln)	(6) Kg of hybrid seed maize (ln)	(7) inorganic fertilizer applied at hh	(8) inorganic fertilizer applied at hh	(9) hectares of inorganic fertilizer use at hh	(10) hectares of inorganic fertilizer use at hh
	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	OLS - CS sample	OLS - CS sample with IPW
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.28	0.31	0.38	0.36	0.41	0.34	0.27	0.33	0.26	0.26
Observations	308	308	1,172	308	308	1,172	168	168	168	168

Notes: The table display estimates from a linear probability and a SUR model on the adoption different practices during the agricultural season 2015/16. Dependent variables are a dummy on adoption of hybrid seed and inorganic fertilizer, the natural logarithm kg of maize hybrid seed planted and of the hectares of land under inorganic fertilizer. The full list of controls is available in the Annex (Table A3). Errors are clustered at village level, significance level are *p<0.10; **p<0.05; ***p<0.01.

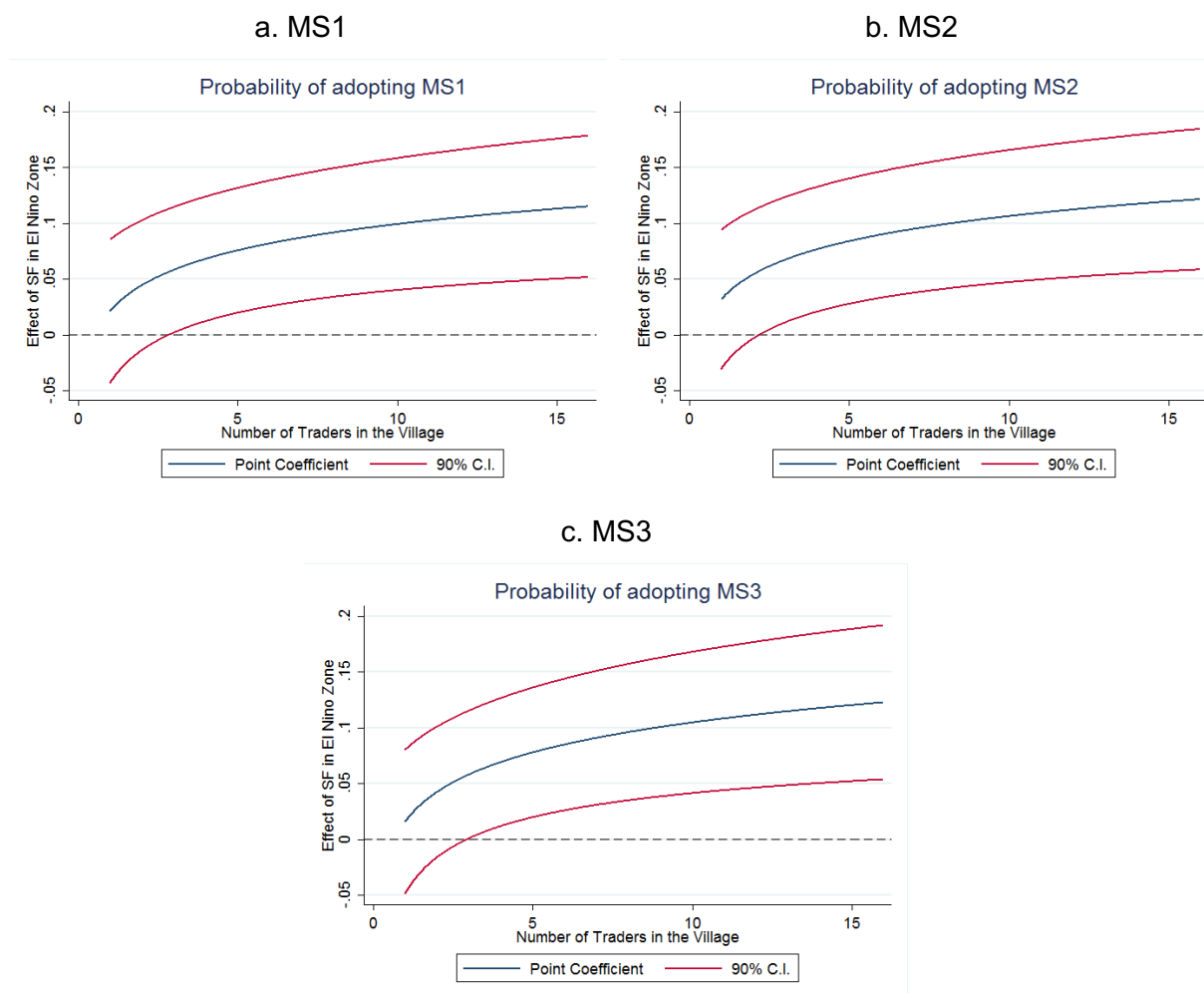
Source: Authors' own elaboration.

5.3 Marginal effects at different level of output market access

Access to competitive output markets has a positive and significant effect on the probability that a farmer will adopt adaptive farm practices in response to seasonal forecast information. Using the number of traders that come to the village to buy grains, the point estimates of Figure 2 shows that receiving seasonal forecast in areas with a high probability of drought is more likely to influence adoption of MS1, MS2 and MS3, than hybrid seeds at different level of total traders' distribution. Households receiving drought seasonal forecasts increase their likelihood of adopting drought tolerant systems from zero when there are no private traders to 7 percent when the number of agricultural traders in their village is five. The concavity of the curves suggests that a marginal increase in the number of traders has a strong and significant 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 between 5–10 percent when the magnitude (i.e. the time spell) of the predicted drought increases by 1 percent. This effect is positive but marginally decreasing, indicating that at higher levels of trader density, further expansions of the market would not have any further significant impact on adoption. This also suggests that the underlying mechanism is related to access to reasonably competitive markets, rather than to an unconditional enlargement of the market itself.

Figure 3 show a similar pattern for the adoption of hybrid seeds, which appear more linear, and for the amount of hybrid seeds adopted. In terms of magnitude, receiving seasonal forecast increase the likelihood of hybrid seeds adoption by about 5 percent. These results suggest the need to support private investment in output markets as a strategy to encourage adaptive responses by smallholders to seasonal forecast information.

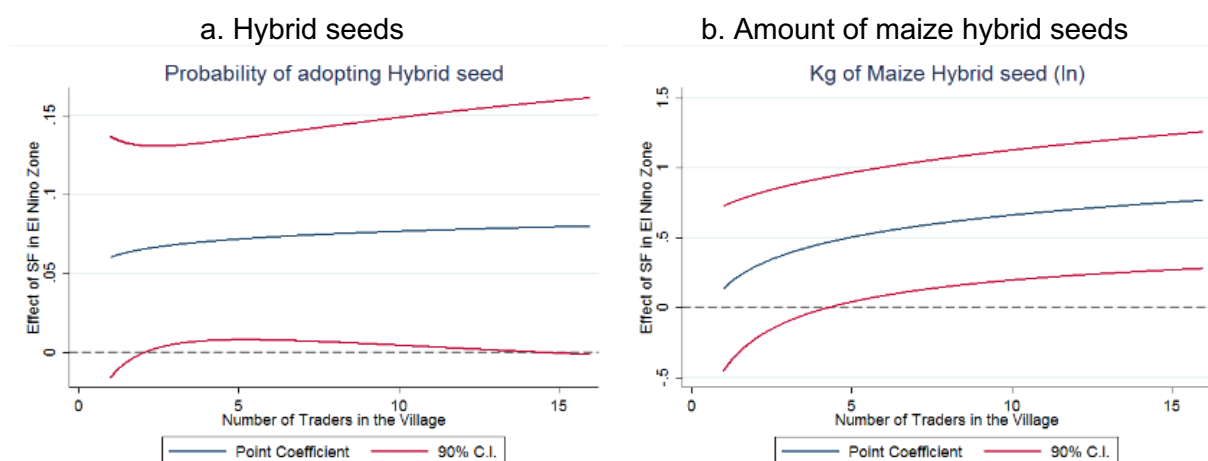
Figure 2. Seasonal forecasts, output market and selection of drought-resilient cropping systems



Notes: The figure displays the marginal effect of receiving weather forecast on the probability of switching to resilient cropping systems at different level of output market access.

Source: Authors' own elaboration.

Figure 3. Seasonal forecasts, output market and selection of hybrid seeds



Notes: The figure displays the marginal effect of receiving weather forecast on the probability of adopting hybrid seeds and on the quantity of maize hybrid adopted at different level of output market access.

Source: Authors' own elaboration.

The Annex reports the results of four types of robustness tests run to check the consistency of the main findings. First, we estimate the specifications reported in Table 5 using only the closest neighbor observation for the matching strategy. As reported in Table A4, the result is stable and consistent with the main findings. Secondly, in Table A5 we report the impact of seasonal forecast on the probability of shifting to MS1 using the following set of matching strategies: two and five closest matches, radius with caliber equal to 0.03 and kernel match. All these specifications confirm the positive impact of drought-related seasonal forecasts on the propensity of adoption of drought-resilient technologies and practices. Thirdly, we exclude that the model is capturing a wealth effect rather than a coping strategy by testing whether households receiving seasonal forecasts in El Niño areas are also more likely to own drought-unrelated technologies. The four specifications reported in Table A6 test for ownership of plough, harrow, sprayer and tractor. The dependent variables are four dummies activating in case of ownership of the above tools. Since coefficient of the interaction terms is not significant in any specification, we exclude that farmers receiving drought-related forecasts are more likely to be own those tools (see Table A6 in the Annex).¹⁰ Finally, since linear probability models are likely to report estimated coefficients out of the 0-1 bound, we test the consistency of the results when correcting for the heteroscedasticity of the observations $h_i = (x_i' \beta (1 - x_i' \beta))$. This involves a two-step procedure, where the weight $\hat{h}^{-1/2}$, computed using the first step coefficients, is multiplied to the dependent variable and regressors included in the second step. The second step coefficient reported in Table A7 confirms the consistency of the estimated coefficients for the drought-related forecasts.

¹⁰ As alternative model, we also test a probit specification on the adoption of MS1, MS2 and MS3 (results available upon request). The results are positive and significant for MS2 and MS3 and consistent with the findings of the papers, whereas MS1 report a positive but slightly insignificant coefficient ($P > |z| = 0.13$).

6 Conclusions

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 2015/16 ENSO event, and who received seasonal forecast information, were likely to adopt drought tolerant cropping systems and/or apply improved maize seed varieties, while farmers in the same areas that did not receive seasonal forecast 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 seasonal forecast information in Zambia remains relatively low. Only 41 percent of households in the ENIAS received information regarding the probability of an ENSO related 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 access to sources of information for seasonal forecasts, 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 input and output markets have positive effects on the probability of adopting drought-tolerant farming practices. This is likely because private markets may relax diverse constraints to farmers' adoption of the practices by increasing the availability of diverse farm inputs, increasing access to information on potential responses to impending droughts, and lowering the costs and risks associated with changes in farm practices.

Three key policy recommendations come out of this analysis. First, while seasonal forecast 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. 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 markets needs to be considered as part of a broader climate change adaptation plan. Several areas to consider in this regard, include: i) improved predictability in agricultural trade policy, such as the use of transparent price triggers for export restrictions or waivers on import tariffs (Jayne, 2012; Chapoto and Jayne, 2009); ii) promote the diversification of commodities purchased by the Food Reserve Agency in Zambia and the use of local private buyers to purchase crops from farmers, including in remote regions, in order to foster private investment in output markets in these regions and for alternative crops; iii) support the development of structured trading systems, including the Zambian Agricultural Commodity Exchange, by utilizing the platform to acquire and manage Zambia's grain reserve (Sitko and Jayne, 2014).

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Annex

Table A1. Summaries of seasonal forecast determinants in El Niño area

	Seasonal forecasts=0 (N=565)	Seasonal forecasts=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 (hectares)	4.91	5.38	
Population density (pop/km ²)	30.74	34.73	**
Distance from FRA (km)	6.74	6.50	
Total number of traders	4.06	4.33	

Source: Authors' own elaboration.

Table A2. Impact of seasonal forecasts on adoption of climate-resilient systems, full specification

	(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	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR
Months expected drought x seasonal forecasts	0.070**	0.073**	0.066***	0.080**	0.082**	0.073***	0.072**	0.077**	0.055*
	(0.034)	(0.036)	(0.023)	(0.034)	(0.036)	(0.024)	(0.035)	(0.036)	(0.030)
Months expected drought (ln)	-0.044	-0.039	-0.037	-0.042	-0.040	-0.033	-0.003	-0.007	0.031
	(0.039)	(0.034)	(0.024)	(0.039)	(0.034)	(0.024)	(0.049)	(0.042)	(0.031)
Seasonal Forecasts (1=yes)	-0.118**	-0.121**	-0.119***	-0.127***	-0.131**	-0.126***	-0.132***	-0.137***	-0.130***
	(0.048)	(0.052)	(0.031)	(0.048)	(0.052)	(0.032)	(0.048)	(0.052)	(0.041)
HH size (ln)	-0.009	-0.017	0.016	-0.010	-0.017	0.017	0.006	0.005	0.013
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.019)	(0.020)	(0.020)
Age of household head (ln)	0.035	0.042	0.040*	0.039	0.046*	0.042*	0.017	0.024	-0.031
	(0.026)	(0.027)	(0.023)	(0.026)	(0.027)	(0.023)	(0.030)	(0.031)	(0.030)
Head is female (1=yes)	-0.018	-0.026	-0.010	-0.023	-0.027**	-0.004	-0.017	-0.012	0.000
	(0.019)	(0.016)	(0.016)	(0.015)	(0.014)	(0.017)	(0.020)	(0.021)	(0.021)
HH's head year of education (ln)	-0.005	-0.011	0.001	-0.007	-0.011	0.001	-0.002	-0.006	-0.006
	(0.007)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.011)	(0.011)
Agricultural Wealth Index	-0.023***	-0.026***	-0.030***	-0.022***	-0.024***	-0.029***	-0.023**	-0.024**	-0.020
	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)	(0.010)	(0.010)	(0.011)	(0.013)
Livestock owned (TLU)	-0.001*	-0.001	-0.001	-0.001*	-0.001*	-0.001	-0.001**	-0.001*	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Land owned (ln)	0.013	0.022*	0.013*	0.011	0.020*	0.012	0.005	0.013	0.001
	(0.010)	(0.011)	(0.007)	(0.010)	(0.011)	(0.007)	(0.011)	(0.013)	(0.009)
Share of Credit access (EA's level)	-0.012	-0.014	-0.054**	-0.004	-0.009	-0.051*	0.055	0.052*	0.085**
	(0.017)	(0.013)	(0.027)	(0.017)	(0.013)	(0.027)	(0.033)	(0.030)	(0.035)
Share of FISP recipients (EA's level)	0.018	0.013	0.018	0.018	0.014	0.025	0.016	0.008	0.005
	(0.032)	(0.030)	(0.027)	(0.031)	(0.031)	(0.028)	(0.037)	(0.037)	(0.036)
Agricultural advice from extension services (1=yes)	-0.020	-0.035*	-0.015	-0.015	-0.030	-0.007	-0.021	-0.034	-0.003
	(0.016)	(0.019)	(0.016)	(0.016)	(0.019)	(0.017)	(0.019)	(0.023)	(0.021)
Drought shock probability	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Cell phone for gathering information (1=yes)	0.006	-0.003	0.012	0.005	-0.002	0.009	-0.008	-0.014	-0.016
	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)	(0.014)	(0.015)	(0.018)	(0.017)
Distance from FRA (ln)	-0.008	-0.010	0.014*	-0.014	-0.014**	0.011	-0.012	-0.014	-0.004
	(0.010)	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.012)	(0.010)	(0.010)

	(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	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR
Number of traders (ln)	-0.035***	-0.021*	-0.037***	-0.031**	-0.018	-0.036***	-0.032**	-0.022	-0.048***
	(0.013)	(0.012)	(0.010)	(0.012)	(0.012)	(0.010)	(0.014)	(0.015)	(0.013)
information on crop and weather	0.010	0.016*	0.014	0.005	0.013	0.011	0.021	0.024	0.019
	(0.012)	(0.010)	(0.015)	(0.014)	(0.011)	(0.015)	(0.019)	(0.017)	(0.020)
Constant	0.083	0.059	-0.024	0.085	0.050	-0.036	0.141	0.105	0.348***
	(0.109)	(0.110)	(0.102)	(0.103)	(0.106)	(0.105)	(0.123)	(0.128)	(0.134)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.14	0.18	0.21	0.15	0.19	0.21	0.11	0.13	0.28
Chi-Squared	-	-	229.1	-	-	237.39	-	-	149.3
Observations	967	967	967	961	961	961	924	924	924

Notes: The table display estimates from a linear probability model on the probability of switching from a non-drought resilient cropping system to a drought resilient cropping system between the agricultural seasons 2014/15 and 2015/16. The drought resilient systems include Maize and one or more of the following crops: MS1 = sorghum, millet, cassava, sweetpotato, rice; MS2 = sorghum, millet, cassava, sweetpotato; MS3 = sorghum millet, cassava, sweetpotato, and cotton. Errors are clustered at village level. Level of significances are *p<0.10; **p<0.05; ***p<0.01.

Source: Authors' own elaboration.

Table A3. Impact of seasonal forecasts on adoption of drought-resilient and non- drought resilient technology, full specification

	(1) Hybrid seed (1=yes)	(2) Hybrid seed (1=yes)	(3) Hybrid seed (1=yes)	(4) Kg of hybrid seed maize (ln)	(5) Kg of hybrid seed maize (ln)	(6) Kg of hybrid seed maize (ln)	(7) inorganic fertilizer applied at hh	(8) inorganic fertilizer applied at hh	(9) hectares of inorganic fertilizer use at hh	(10) hectares of inorganic fertilizer use at hh
	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	OLS - CS sample	OLS - CS sample with IPW
Months expected drought x seasonal forecasts	0.316***	0.322***	0.068*	0.922***	1.056***	0.230	0.192	0.211	0.051	0.087
	(0.113)	(0.111)	(0.041)	(0.315)	(0.308)	(0.156)	(0.264)	(0.216)	(0.611)	(0.532)
Months expected drought (ln)	-0.219*	-0.172	-0.040	-0.560	-0.553	-0.202	-0.298*	-0.150	-1.973***	-1.812***
	(0.125)	(0.126)	(0.042)	(0.344)	(0.338)	(0.160)	(0.174)	(0.194)	(0.310)	(0.293)
Seasonal forecasts (1=yes)	-0.292*	-0.325**	-0.015	-0.675	-0.944**	0.092	-0.343	-0.366	-0.039	-0.181
	(0.155)	(0.158)	(0.055)	(0.426)	(0.439)	(0.209)	(0.383)	(0.316)	(0.895)	(0.764)
Household size (ln)	0.024	0.007	0.041	0.188	0.125	0.177*	0.207**	0.255**	0.215	0.164
	(0.062)	(0.064)	(0.027)	(0.158)	(0.176)	(0.104)	(0.084)	(0.101)	(0.143)	(0.169)
Age of household head (ln)	-0.078	-0.021	-0.096**	0.019	0.167	-0.334**	0.017	0.002	-0.084	-0.167
	(0.090)	(0.100)	(0.041)	(0.247)	(0.287)	(0.153)	(0.138)	(0.154)	(0.177)	(0.199)
Head is female (1=yes)	-0.031	-0.022	-0.022	-0.165	-0.188	-0.057	-0.169*	-0.197*	-0.236*	-0.241*
	(0.062)	(0.072)	(0.029)	(0.185)	(0.197)	(0.111)	(0.099)	(0.117)	(0.142)	(0.141)
Household 's head year of education (ln)	0.040	0.055	0.041***	0.140*	0.203**	0.176***	0.037	0.030	-0.004	-0.035
	(0.034)	(0.037)	(0.015)	(0.078)	(0.084)	(0.056)	(0.062)	(0.068)	(0.121)	(0.110)
Agricultural Wealth Index	0.119**	0.140**	0.045**	0.556***	0.556***	0.391***	0.221**	0.151	0.450*	0.358
	(0.054)	(0.053)	(0.018)	(0.188)	(0.186)	(0.067)	(0.101)	(0.111)	(0.243)	(0.220)
Livestock owned (TLU)	0.003	0.001	0.000	0.030**	0.026*	0.015***	-0.018***	-0.024***	-0.014	-0.023
	(0.004)	(0.004)	(0.001)	(0.014)	(0.014)	(0.005)	(0.006)	(0.007)	(0.015)	(0.015)
Land owned (ln)	0.050*	0.064**	0.045***	0.283***	0.353***	0.371***	-0.027	0.025	0.198	0.279**
	(0.026)	(0.031)	(0.013)	(0.097)	(0.104)	(0.049)	(0.051)	(0.051)	(0.122)	(0.111)
Share of credit access (EA's level)	0.421***	0.442***	0.267***	-0.239	-0.100	-0.344*	0.280**	0.287	0.091	0.119
	(0.104)	(0.115)	(0.048)	(0.365)	(0.390)	(0.182)	(0.139)	(0.172)	(0.223)	(0.254)
Share of FISP recipients (EA's level)	0.104	0.129	0.242***	0.648	0.611	0.930***	0.204	0.437	-0.197	-0.022
	(0.103)	(0.124)	(0.049)	(0.459)	(0.520)	(0.184)	(0.266)	(0.283)	(0.372)	(0.341)
Agricultural advice from extension services (1=yes)	0.066	0.055	0.022	0.283	0.204	0.004	-0.008	-0.042	0.064	-0.016
	(0.082)	(0.093)	(0.029)	(0.228)	(0.266)	(0.109)	(0.096)	(0.102)	(0.109)	(0.139)
Drought shock probability	0.009	0.009	0.003	0.003	0.005	-0.019*	-0.003	-0.006	-0.008	-0.009

	(1) Hybrid seed (1=yes)	(2) Hybrid seed (1=yes)	(3) Hybrid seed (1=yes)	(4) Kg of hybrid seed maize (ln)	(5) Kg of hybrid seed maize (ln)	(6) Kg of hybrid seed maize (ln)	(7) inorganic fertilizer applied at hh	(8) inorganic fertilizer applied at hh	(9) hectares of inorganic fertilizer use at hh	(10) hectares of inorganic fertilizer use at hh
	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	OLS - CS sample	OLS - CS sample with IPW
	(0.010)	(0.009)	(0.003)	(0.023)	(0.024)	(0.011)	(0.010)	(0.009)	(0.017)	(0.014)
Cell phone for gathering information (1=yes)	0.089*	0.093	0.034	0.169	0.234	0.127	-0.029	-0.060	-0.061	-0.098
	(0.051)	(0.065)	(0.024)	(0.198)	(0.229)	(0.090)	(0.077)	(0.082)	(0.147)	(0.172)
Distance from FRA (ln)	-0.054	-0.078*	0.003	-0.209	-0.299**	-0.037	-0.044	-0.100	-0.066	-0.119
	(0.040)	(0.046)	(0.014)	(0.127)	(0.131)	(0.053)	(0.059)	(0.063)	(0.103)	(0.096)
Number of traders (ln)	-0.090*	-0.058	-0.028	-0.220	-0.090	0.067	-0.043	-0.079	0.122	0.063
	(0.047)	(0.056)	(0.017)	(0.136)	(0.168)	(0.066)	(0.062)	(0.066)	(0.103)	(0.090)
information on crop and weather (1=yes)	-0.035	-0.076	-0.004	0.006	-0.110	-0.026	0.217**	0.180	0.428	0.344
	(0.069)	(0.078)	(0.027)	(0.217)	(0.222)	(0.102)	(0.092)	(0.112)	(0.273)	(0.277)
Constant	1.043**	0.826*	0.900***	1.685	1.189	2.418***	0.663	0.487	2.966***	3.352***
	(0.407)	(0.465)	(0.183)	(1.180)	(1.406)	(0.694)	(0.807)	(0.860)	(1.076)	(1.073)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.28	0.31	0.38	0.36	0.41	0.34	0.27	0.33	0.26	0.26
Observations	308	308	1,172	308	308	1,172	168	168	168	168

Notes: The table display estimates from a linear probability model (column 1–4) on the adoption different practices during the agricultural season 2015/2016. Dependent variables are a dummy on adoption of hybrid seed and inorganic fertilizer (column 1 and 3), the natural logarithm kg of maize hybrid seed planted (column 2), the hectares of land under inorganic fertilizer (column 4). Errors are clustered at village level, significance level are *p<0.10; **p<0.05; ***p<0.01.

Source: Authors' own elaboration.

Table A4. Impact of seasonal forecasts on probability of shifting to climate-resilient systems using the closest neighbor

	(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	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR
Months expected drought x seasonal forecasts	0.070**	0.073**	0.066***	0.080**	0.082**	0.073***	0.072**	0.077**	0.055*
	(0.034)	(0.036)	(0.023)	(0.034)	(0.036)	(0.024)	(0.035)	(0.036)	(0.030)
Months expected drought (ln)	-0.044	-0.039	-0.037	-0.042	-0.040	-0.033	-0.003	-0.007	0.031
	(0.039)	(0.034)	(0.024)	(0.039)	(0.034)	(0.024)	(0.049)	(0.042)	(0.031)
Seasonal Forecasts (1=yes)	-0.118**	-0.121**	-0.119***	-0.127***	-0.131**	-0.126***	-0.132***	-0.137***	-0.130***
	(0.048)	(0.052)	(0.031)	(0.048)	(0.052)	(0.032)	(0.048)	(0.052)	(0.041)
HH size (ln)	-0.009	-0.017	0.016	-0.010	-0.017	0.017	0.006	0.005	0.013
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.019)	(0.020)	(0.020)
Age of household head (ln)	0.035	0.042	0.040*	0.039	0.046*	0.042*	0.017	0.024	-0.031
	(0.026)	(0.027)	(0.023)	(0.026)	(0.027)	(0.023)	(0.030)	(0.031)	(0.030)
Head is female (1=yes)	-0.018	-0.026	-0.010	-0.023	-0.027**	-0.004	-0.017	-0.012	0.000
	(0.019)	(0.016)	(0.016)	(0.015)	(0.014)	(0.017)	(0.020)	(0.021)	(0.021)
HH's head year of education (ln)	-0.005	-0.011	0.001	-0.007	-0.011	0.001	-0.002	-0.006	-0.006
	(0.007)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.011)	(0.011)
Agricultural Wealth Index	-0.023***	-0.026***	-0.030***	-0.022***	-0.024***	-0.029***	-0.023**	-0.024**	-0.020
	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)	(0.010)	(0.010)	(0.011)	(0.013)
Livestock owned (TLU)	-0.001*	-0.001	-0.001	-0.001*	-0.001*	-0.001	-0.001**	-0.001*	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Land owned (ln)	0.013	0.022*	0.013*	0.011	0.020*	0.012	0.005	0.013	0.001
	(0.010)	(0.011)	(0.007)	(0.010)	(0.011)	(0.007)	(0.011)	(0.013)	(0.009)
Share of Credit access (EA's level)	-0.012	-0.014	-0.054**	-0.004	-0.009	-0.051*	0.055	0.052*	0.085**
	(0.017)	(0.013)	(0.027)	(0.017)	(0.013)	(0.027)	(0.033)	(0.030)	(0.035)
Share of FISP recipients (EA's level)	0.018	0.013	0.018	0.018	0.014	0.025	0.016	0.008	0.005
	(0.032)	(0.030)	(0.027)	(0.031)	(0.031)	(0.028)	(0.037)	(0.037)	(0.036)
Agricultural advice from extension services (1=yes)	-0.020	-0.035*	-0.015	-0.015	-0.030	-0.007	-0.021	-0.034	-0.003
	(0.016)	(0.019)	(0.016)	(0.016)	(0.019)	(0.017)	(0.019)	(0.023)	(0.021)
Drought shock probability	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Cell phone for gathering information (1=yes)	0.006	-0.003	0.012	0.005	-0.002	0.009	-0.008	-0.014	-0.016
	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)	(0.014)	(0.015)	(0.018)	(0.017)
Distance from FRA (ln)	-0.008	-0.010	0.014*	-0.014	-0.014**	0.011	-0.012	-0.014	-0.004
	(0.010)	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.012)	(0.010)	(0.010)

	(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	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR	OLS - CS sample	OLS - CS sample with IPW	SUR
Number of traders (ln)	-0.035***	-0.021*	-0.037***	-0.031**	-0.018	-0.036***	-0.032**	-0.022	-0.048***
	(0.013)	(0.012)	(0.010)	(0.012)	(0.012)	(0.010)	(0.014)	(0.015)	(0.013)
information on crop and weather	0.010	0.016*	0.014	0.005	0.013	0.011	0.021	0.024	0.019
	(0.012)	(0.010)	(0.015)	(0.014)	(0.011)	(0.015)	(0.019)	(0.017)	(0.020)
Constant	0.083	0.059	-0.024	0.085	0.050	-0.036	0.141	0.105	0.348***
	(0.109)	(0.110)	(0.102)	(0.103)	(0.106)	(0.105)	(0.123)	(0.128)	(0.134)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.14	0.18	0.21	0.15	0.19	0.21	0.11	0.13	0.28
Chi-Squared	-	-	229.1	-	-	237.39	-	-	149.3
Observations	967	967	967	961	961	961	924	924	924

Notes: The table display estimates from a linear probability model on the probability of switching from a non-drought resilient cropping system to a drought resilient cropping system between the agricultural seasons 2014/15 and 2015/16. The propensity score matching is done using the closest neighbor method. The drought resilient systems include Maize and one or more of the following crops: MS1 = sorghum, millet, cassava, sweetpotato, rice; MS2 = sorghum, millet, cassava, sweetpotato; MS3 = sorghum millet, cassava, sweetpotato, and cotton. Errors are clustered at village level. Level of significances are *p<0.10; **p<0.05; ***p<0.01.

Source: Authors' own elaboration.

Table A5. Impact of seasonal forecasts on probability of shifting to MS1 using alternative weighting strategies

PSM type	(1) To MS1 2 closest neighbors OLS - CS sample with IPW	(2) To MS1 5 closest neighbors OLS - CS sample with IPW	(3) To MS1 Radius (caliper=0.03) OLS - CS sample with IPW	(4) To MS1 Kernel OLS - CS sample with IPW
Months expected drought x seasonal forecasts	0.073**	0.073**	0.073**	0.073**
	(0.036)	(0.036)	(0.036)	(0.036)
Months expected drought (ln)	-0.039	-0.039	-0.039	-0.039
	(0.034)	(0.034)	(0.034)	(0.034)
Seasonal forecasts (1=yes)	-0.121**	-0.121**	-0.121**	-0.121**
	(0.052)	(0.052)	(0.052)	(0.052)
Household size (ln)	-0.017	-0.017	-0.017	-0.017
	(0.015)	(0.015)	(0.015)	(0.015)
Age of household head (ln)	0.042	0.042	0.042	0.042
	(0.027)	(0.027)	(0.027)	(0.027)
Head is female (1=yes)	-0.026	-0.026	-0.026	-0.026
	(0.016)	(0.016)	(0.016)	(0.016)
Household's head year of education (ln)	-0.011	-0.011	-0.011	-0.011
	(0.009)	(0.009)	(0.009)	(0.009)
Agricultural Wealth Index	-0.026***	-0.026***	-0.025***	-0.025***
	(0.008)	(0.008)	(0.008)	(0.008)
Livestock owned (TLU)	-0.001	-0.001	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Land owned (ln)	0.022*	0.022*	0.022*	0.022*
	(0.011)	(0.011)	(0.011)	(0.011)
Share of credit access (EA's level)	-0.014	-0.014	-0.014	-0.014
	(0.013)	(0.013)	(0.013)	(0.013)
Share of FISP recipients (EA's level)	0.013	0.013	0.013	0.013
	(0.030)	(0.030)	(0.030)	(0.030)
Agricultural advice from extension services (1=yes)	-0.035*	-0.035*	-0.035*	-0.035*
	(0.019)	(0.019)	(0.019)	(0.019)
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)	-0.003	-0.003	-0.003	-0.003
	(0.013)	(0.013)	(0.013)	(0.013)
Distance from FRA (ln)	-0.010	-0.010	-0.011	-0.011
	(0.007)	(0.007)	(0.007)	(0.007)
Number of traders (ln)	-0.021*	-0.021*	-0.021*	-0.021*
	(0.012)	(0.012)	(0.012)	(0.012)

	(1) To MS1	(2) To MS1	(3) To MS1	(4) To MS1
PSM type	2 closest neighbors	5 closest neighbors	Radius (caliper=0.03)	Kernel
	OLS - CS sample with IPW	OLS - CS sample with IPW	OLS - CS sample with IPW	OLS - CS sample with IPW
information on crop and weather	0.016*	0.016*	0.016	0.016
	(0.010)	(0.010)	(0.010)	(0.010)
Constant	0.059	0.059	0.059	0.059
	(0.110)	(0.110)	(0.110)	(0.110)
Province dummies	Yes	Yes	Yes	Yes
R-squared	0.18	0.18	0.18	0.18
Observations	967	967	968	968

Notes: The table display estimates from a linear probability model on the probability of switching from a non-drought resilient cropping system to a drought resilient cropping system between the agricultural seasons 2014/15 and 2015/16. The drought resilient systems include Maize and one or more of the following crops: MS1 = sorghum, millet, cassava, sweetpotato, rice. Level of significances are *p<0.10; **p<0.05; ***p<0.01.

Source: Authors' own elaboration.

Table A6. Impact of seasonal forecasts on probability of ownership of climate unrelated assets

	(1) Plough	(2) Harrow	(3) Sprayer	(4) Tractor
	OLS - CS sample with IPW	OLS - CS sample with IPW	OLS - CS sample with IPW	OLS - CS sample with IPW
Months expected drought x seasonal forecasts	-0.010	-0.016	-0.065	0.004
	(0.045)	(0.018)	(0.053)	(0.015)
Months expected drought (ln)	0.075	0.043	0.143**	-0.038
	(0.055)	(0.031)	(0.059)	(0.025)
Seasonal forecasts (1=yes)	-0.015	0.005	0.144**	-0.002
	(0.058)	(0.021)	(0.061)	(0.021)
Household size (ln)	0.060**	-0.018	0.121***	-0.022*
	(0.027)	(0.012)	(0.033)	(0.011)
Age of household head (ln)	-0.018	-0.025	-0.019	0.012
	(0.042)	(0.018)	(0.046)	(0.011)
Head is female (1=yes)	-0.060**	0.037***	-0.092***	0.010
	(0.030)	(0.012)	(0.030)	(0.007)
Household 's head year of education (ln)	-0.043**	0.001	0.001	0.006*
	(0.017)	(0.006)	(0.019)	(0.003)
Agricultural Wealth Index	0.342***	0.233***	0.195***	0.064***
	(0.024)	(0.017)	(0.027)	(0.020)
Livestock owned (TLU)	0.001	-0.000	-0.001	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Land owned (ln)	0.041***	-0.009	0.041**	-0.003
	(0.015)	(0.007)	(0.019)	(0.003)
Share of credit access (EA's level)	-0.089	0.050**	0.294***	-0.003
	(0.064)	(0.021)	(0.061)	(0.010)
Share of FISP recipients (EA's level)	0.116*	-0.035	0.092	-0.016
	(0.070)	(0.027)	(0.064)	(0.015)
Agricultural advice from extension services (1=yes)	0.041	0.017	0.009	-0.012
	(0.036)	(0.015)	(0.041)	(0.010)
Drought shock probability	-0.009**	0.001	0.006**	0.000
	(0.004)	(0.001)	(0.003)	(0.000)
Cell phone for gathering information (1=yes)	0.020	-0.033***	-0.022	0.008
	(0.024)	(0.012)	(0.030)	(0.005)
Distance from FRA (ln)	0.001	-0.013*	0.015	0.001
	(0.018)	(0.007)	(0.019)	(0.005)
Number of traders (ln)	0.052**	-0.007	-0.031	-0.003
	(0.021)	(0.011)	(0.021)	(0.006)

	(1) Plough	(2) Harrow	(3) Sprayer	(4) Tractor
	OLS - CS sample with IPW	OLS - CS sample with IPW	OLS - CS sample with IPW	OLS - CS sample with IPW
information on crop and weather	-0.032	-0.002	-0.039	0.005
	(0.028)	(0.016)	(0.039)	(0.008)
Constant	0.114	0.344***	-0.116	0.052
	(0.191)	(0.085)	(0.221)	(0.055)
Province dummies	Yes	Yes	Yes	Yes
R-squared	0.52	0.57	0.25	0.19
Observations	1.167	1.167	1.167	1.167

Notes: The table display estimates from a linear probability model on the probability of switching from a non-drought resilient cropping system to a drought resilient cropping system between the agricultural seasons 2014/15 and 2015/16. The weighting strategy is based on a 2-k nearest neighbor matching. Errors are clustered at village level. Level of significances are *p<0.10; **p<0.05; ***p<0.01.

Source: Authors' own elaboration.

Table A7. Impact of seasonal forecasts on probability of ownership of climate unrelated assets

	(1) To MS1	(2) To MS3	(3) To MS2	(4) Inorganic fertilizer	(5) To MS3
	Corrected OLS - CS sample	Corrected OLS - CS sample	Corrected OLS - CS sample	Corrected OLS - CS sample	Corrected OLS - CS sample
Months expected drought x seasonal forecasts	0.082***	0.111***	0.072**	0.210***	0.055
	(0.026)	(0.033)	(0.030)	(0.049)	(0.246)
Months expected drought (ln)	-0.030	-0.038	0.029	-0.160*	-0.221
	(0.019)	(0.026)	(0.033)	(0.092)	(0.625)
Seasonal forecasts (1=yes)	-0.149***	-0.189***	-0.150***	-0.424**	-0.161
	(0.041)	(0.051)	(0.051)	(0.211)	(0.360)
Household size (ln)	-0.011*	-0.003	0.025**	0.028	0.286***
	(0.006)	(0.007)	(0.012)	(0.068)	(0.092)
Age of household head (ln)	0.078***	0.092***	0.051***	0.148***	0.121
	(0.019)	(0.023)	(0.017)	(0.053)	(0.159)
Head is female (1=yes)	-0.034***	-0.041***	-0.020	-0.022	-0.145
	(0.008)	(0.011)	(0.012)	(0.063)	(0.096)
Household's head year of education (ln)	-0.006***	-0.014***	0.002	0.067***	0.029
	(0.002)	(0.004)	(0.003)	(0.022)	(0.064)
Agricultural Wealth Index	-0.044***	-0.047***	-0.035**	0.141***	0.296**
	(0.010)	(0.012)	(0.014)	(0.048)	(0.115)
Livestock owned (TLU)	-0.001*	-0.002**	-0.001	0.006	-0.026***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.008)
Land owned (ln)	0.021***	0.019***	0.001	0.021	-0.071
	(0.006)	(0.006)	(0.005)	(0.026)	(0.057)
Share of credit access (EA's level)	-0.021***	-0.020**	0.098***	0.360***	0.165
	(0.006)	(0.009)	(0.032)	(0.096)	(0.135)
Share of FISP recipients (EA's level)	0.040***	0.042**	0.027	0.113	0.436
	(0.012)	(0.017)	(0.017)	(0.081)	(0.263)
Agricultural advice from extension services (1=yes)	-0.034***	-0.027***	-0.025*	0.052	0.064
	(0.008)	(0.010)	(0.013)	(0.099)	(0.108)
Drought shock probability	0.002***	0.002***	0.004**	0.009*	-0.004
	(0.001)	(0.001)	(0.002)	(0.005)	(0.010)
Cell phone for gathering information (1=yes)	0.013**	0.012	-0.009	0.106**	-0.012
	(0.005)	(0.008)	(0.007)	(0.043)	(0.076)
Distance from FRA (ln)	-0.012***	-0.027***	-0.020**	-0.066*	0.004
	(0.004)	(0.007)	(0.008)	(0.039)	(0.072)
Number of traders (ln)	-0.062***	-0.057***	-0.040***	-0.071	-0.032
	(0.016)	(0.016)	(0.014)	(0.052)	(0.067)
information on crop and weather	0.018***	0.015***	0.029**	-0.060	0.208**
	(0.006)	(0.006)	(0.013)	(0.054)	(0.088)

	(1) To MS1	(2) To MS3	(3) To MS2	(4) Inorganic fertilizer	(5) To MS3
	Corrected OLS - CS sample	Corrected OLS - CS sample	Corrected OLS - CS sample	Corrected OLS - CS sample	Corrected OLS - CS sample
Constant	0.083	0.059	-0.024	0.085	0.05
	-0.109	-0.11	-0.102	-0.103	-0.106
Province dummies	Yes	Yes	Yes	Yes	Yes
R-squared	0.07	0.08	0.04	0.88	0.40

Notes: The table display estimates from the two step linear probability model corrected by multiplying the dependent and explanatory variables by the heteroskedasticity weights. Errors are clustered at village level. Level of significances are *p<0.10; **p<0.05; ***p<0.01.

Source: Authors' own elaboration.

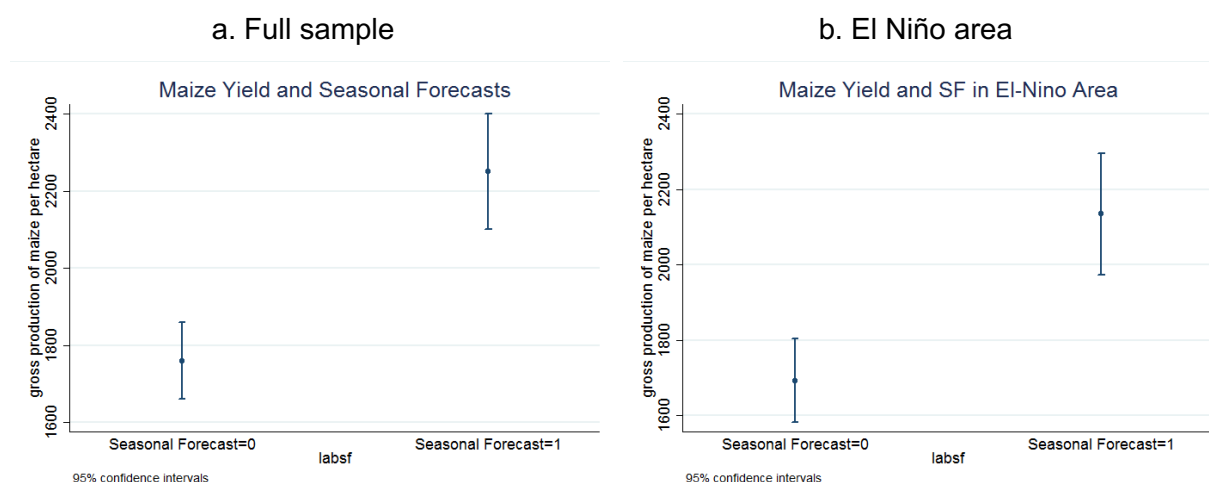
Figure A1. Areas with normal to below normal rainfall in seasonal forecast



Notes: 2015/16 rainfall seasonal forecast in Zambia.

Source: Zambia Meteorological Department, 2016.

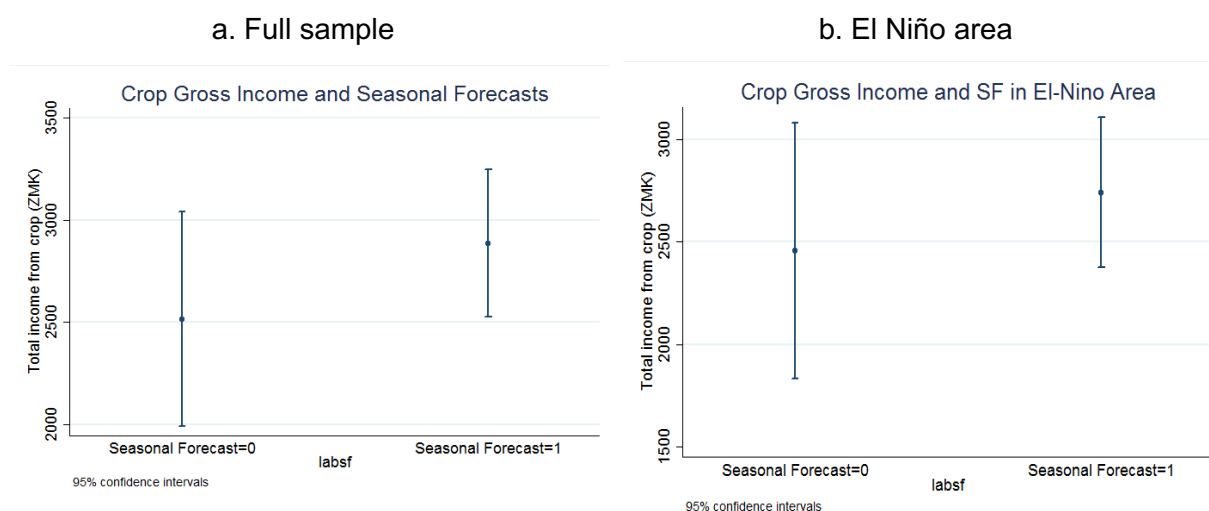
Figure A2. Seasonal forecast and maize yield in full sample and El Niño area



Notes: Figure A2a displays maize yield by seasonal forecast status in Zambia Sample during 2015/16, Figure A2b focus on El Niño area subsample

Source: Authors' own elaboration.

Figure A3. Seasonal forecast and crop gross income in the full sample and El Niño area



Notes: Figure A3a shows the crop gross income by seasonal forecast status in Zambia Sample during 2015/16, Figure A3b focus on the El Niño area subsample.

Source: Authors' own elaboration.

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