Adaptation to climate change in Sub-Saharan agriculture: assessing the evidence and rethinking the drivers

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Abstract

In this paper, after a review of the evolution of the literature on climate change economics in agriculture, I present some evidence of the impact of different moments of the distribution of rainfall on farmers risk aversion. It is found that while more rainfall is negatively associated with the probability of observing risk aversion, rainfall variability is positively correlated. This result highlights an important behavioural dimension of climatic factors.

1. Introduction

Climate change is a fundamental threat to agricultural productivity, food security and development prospects in Sub-Saharan Africa (SSA). In this part of the world, production conditions can be particularly challenging. Millions of small-scale subsistence farmers, generally with less than 1 hectare of land, produce food crops facing a combination of low land productivity, missing markets, low technology adoption and harsh weather conditions (e.g. high average temperature, erratic rainfall). These result in very low yields and food insecurity (Di Falco and Chavas, 2009). Given the reliance on rainfall and the limited opportunities for economic diversification, SSA's development prospects have been closely associated with climate. Climate change is projected to further reduce food security (Rosenzweig and Parry, 1994; Parry, Rosenzweig and Livermore, 2005; Cline, 2007; Lobell *et al*., 2008; McIntyre *et al.*, 2009; Schlenker and Lobell, 2010). As indicated in the fourth Intergovernmental Panel on Climate Change (IPCC), at lower latitudes, crop productivity is

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expected to decrease 'for even small local temperature increases $(1-2°C)$' (IPCC, 2007). In many African countries access to food will be severely affected, 'yields from rain-fed agriculture could be reduced by up to 50% by 2020' (IPCC, 2007, p. 10). Scientists tell us that future warming is not preventable. As a matter of fact, even if agreements to limit emissions would be achieved and implemented, farmers will thus still face a warmer production environment and agriculture will be more vulnerable.

The agricultural sector is more crucial where economic development is most needed. Christiansen *et al.* (2011) showed the important contribution of agriculture to poverty reduction among the poorest and most vulnerable populations. Diao, Hazell and Thurlow (2010), using an economy-wide model, stressed the key role that agriculture still plays in Africa. This is because of the job opportunities provided to the poorest compared with industrial growth. They conclude that there is little evidence showing that 'African countries can bypass a broad-based agricultural revolution to successfully launch their economic transformations'. Climate change poses a serious risk to reverse progress towards achieving the Millennium Development Goals. Climate change is both a development and an environmental challenge. Given these premises, there is no question that achieving successful adaptation processes in agriculture is of paramount importance. This entails the understanding of barriers and drivers to adaptation and the identification of its implications in terms of welfare.

This paper contribution is two-fold. First, it provides a brief review the evolution of the literature on climate change economics in agriculture over the last 20 years. The focus is mostly on micro-studies in east Africa. I highlight some of the main findings and underscore how the literature on impact of climate change on agriculture as developed separately from the adaptation literature. I argue that adaptation and impact need to be modelled jointly. I, therefore, present an econometric procedure that allows analysing adaptation and its effect on a given outcome (e.g. productivity, food security, revenues). Second, it provides some preliminary evidence on the behavioural dimension of climate change. I examine the causal effect of climate change on risk preferences. How do climatic events affect some behavioural parameters? Are people who are exposed to more or less rainfall, for instance, more likely to be risk averse? I provide empirical evidence on the role of climatic factors in determining farmers risk aversion. The paper proceeds as follows. The next section provides some background on climate change in SSA. In Section 3, a structural model that can be used for estimating both adaptation and its implications is presented. Section 4 provides the empirical analysis of the role of climate on risk aversion and rate of time preferences. Section 5 offers some reflections on future research. Section 6 concludes the paper.

2. Agriculture and climate change in SSA

SSA is the part of Africa extended below the Sahara Desert. Its surface is equal to an area of 2.4×10^9 ha. It is rich in natural resources (although not

uniformly distributed) and presents different climatic and geological features (IAASTD, 2009).

SSA's economy is mostly driven by the agriculture sector in spite of the issue of land degradation and desertification and poor land management systems (UNEP, 2002a, in IAASTD, 2009). Over 60 per cent of the population rely on agriculture for their livelihood, but only 8 per cent of the land is suitable for staple production (IAASTD, 2009). Characterised by crop production and traditional livestock, it is the sector where the majority of the labour force is employed and contributes to a considerable part of the GDP, about 40 per cent (Barrios *et al.*, 2008). However, SSA countries are different one to another. For instance, Ethiopia and Rwanda are land-locked countries, highly populated; agriculture is the main economic activity and about four-fifth of inhabitant live in rural areas. Nevertheless, Rwanda, with high altitude, has geological features that represent a hurdle to its agriculture development compared with the costal countries such as Ghana and Kenya which present settled agro-processing and industrial sectors. In contrast, Uganda is a land-locked country but together with Ghana shows agriculture growth and a stable GDP (Diao *et al.*, 2010). Yet, in Tanzania, over 70 per cent of population rely on subsistence rain-fed agriculture. It accounts for 50 per cent of Gross Net Product and 66 per cent of export earnings (Mary and Majule, 2009). In Kenya, agriculture contributes to about 24 per cent of GDP and employment with about 70 per cent of household living in rural areas. The main output is crop production which depends on soils, hydrological and climate characteristics. The majority of the land is classified as arid or semi-arid, therefore dedicated for extensive livestock production and only 12 per cent of the land is positively used for farming or intense livestock production (Kabubo-Mariara and Karanja, 2007). In Ethiopia 85 per cent of the population based its livelihood on agriculture which does account for more than 40 per cent of national GDP, 90 per cent of exports and provides basic needs and income for more than 90 per cent of the poor (Diao *et al.*, IFPRI, 2010, p. 5). Cereals are the main product and source of Ethiopians' daily calorie intake (62 per cent). About 70 per cent of land is used for cereal production which is chiefly concentrated in the western regions (Diao *et al.*, 2010). Generally, in SSA it is possible to distinguish four different kinds of farming systems:

- The maize-mixed system, which is based primarily on maize, cotton, cattle and goats.
- Cereal/root crop-mixed system, which is based on maize, sorghum, millet, cassava, yams and cattle.
- Irrigated system, based on maize, sorghum, millet, cassava yams and cattle.
- The tree crop-based system, anchored in cocoa, coffee, oil palm and rubber, mixed with yams and maize (IAASTD, 2009)

They are mainly subsistence oriented and the use of technology is almost absent. The farms are small-scaled and the average size decreased from 1.5 hectares in 1970 to 0.5 hectares in 1990 (IAASTD, 2009) in part due to the '*exhaustion of land frontiers*' (IAASTD, 2009).

The diverse topography that characterises SSA is reflected in farm house-holds operating areas.[1] In Kenya, for example, there are seven agro-climate zones identified following the moisture index.[2] When the index is greater than 50 per cent, it is favourable to crop production but those areas (zone I, II, III) account for 18 per cent of the land. Generally, they are situated above 1,200 m of altitude with mean annual temperature lower than 18°C. On the other hand, the majority of the country, almost 80 per cent, presents the moisture index less than 50 per cent, annual mean temperature between 22 and 40°C, mean annual rainfall less than 1,100 mm and is situated below 1,260 m. As a result, they are semi-humid to arid regions (zones IV, V, VI and VII) hence, low potential farming zone (Kabubo-Mariara and Karanja, 2007). According to Hurni's studies (1998), Ethiopia is divided into five major agro-ecological zones that are dissimilar in altitude, soil and consequently in food production. Those are Bereha (hot, arid lowlands), Kolla (warm, semi-arid lowlands), Woina Dega (temperate, cool sub-humid highlands), Dega (cool, humid highlands) and Wurch (cold highlands). Zones are largely based on altitude and climate dictates the crop types grown in each zone. The highland zones contain much of Ethiopia's crop production, while the lowland zones are dominated by pastoral production systems. Precipitation and temperature changes will not be consistent across these agro-ecological zones which each support differing livelihoods. For example, the lowlands are more reliant on livestock grazing (Hurni, 1998). Yet, although Ethiopia has 3.5 million hectares of irrigable land, only 160,000 hectares (accounting for 3 per cent of the land available) is irrigated. There are two main agriculture seasons that correspond to the rain season Belg and Kirmet. Meher is the name of agriculture season during Kirmet. It is extended between June and September, the period that registers the highest quantity of output, 90–95 per cent of the national production.

It is clearly apparent a dependence of agriculture on the effect of weather and climate. In fact, the occurrence of drought during the grown season, for instance, it will generate a decrease of production and, consequently, a negative influence on food security (Giorgis, Tadege and Tibebe, 2006). Climate variability in Ethiopia is well documented and closely linked with the country's economic growth (Figure 1; Diao and Pratt, 2007; World Bank, 2010).

Climate extremes are not a novelty to Ethiopia but studies underline that drought has occurred more often during the last few decades particularly in the lowlands (Lautze *et al*., 2003). A study undertaken by the national meteorological service (published in 2007) highlights that annual minimum temperature has been increasing by about 0.37°C every 10 years over the past 55 years. Rainfall has been more erratic with some areas becoming drier while others relatively wetter. These findings point out that climatic variations have already happened. Further climate change can exacerbate this very difficult situation. Most climate

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1 The ecological and agricultural characteristics (agro-climatic condition, livestock raising condition, land resource conditions) by which the landscape is classified.

2 Index based on annual rainfall expressed as a percentage of potential evaporation.
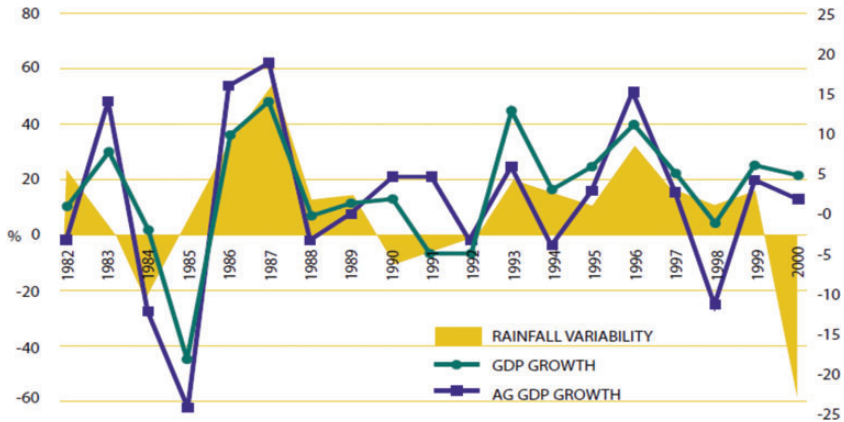
Fig. 1. Ethiopia's economic growth and climate variability. *Source:* World Bank, 2010 using De Jong, 2005

models converge in forecasting gloomy scenarios of increased temperatures for most of Ethiopia (Dinar *et al.*, 2008).

SSA is the most vulnerable region in the world to climate change although its contribution to the global GHGs emission is equal only at 2–3 per cent (IAASTD, 2009). Its vulnerability depends on poverty and the limited capacity to adapt (IPCC, 2007). Adaptation measures in agriculture might include water conservation and irrigation Mendelsohn and Dinar (2003), crop species switching, improved seed varieties, improved on-farm technology, climate and weather forecasting, application of fertilisers and soil nutrient which is the lowest in the world, access to extension services, consideration of topographical heterogeneity and investments in research and development.

3. The economics of climate change: impact and adaptation as two separate issues

Until recently, most of the literature on the economics of climate change developed two independent streams. One focused on the study of the impact of climate change on agriculture, and the other focused on the estimation of the barriers and drivers to adaptation. In this section, I provide a review of these two areas of research. Let me begin with the former. I highlight micro-studies undertaken in SSA.

3.1. Impact of climate change on agriculture

Since the pioneering work by Mendelsohn, Nordhaus and Shaw (1994), the so-called Ricardian approach represents the workhorse within the economic analysis of the impact of climate change. It has been very frequently used to estimate the impact of climatic variables on agriculture. In its traditional

application, it is a cross-sectional analysis that measures the long-term impact of climate and other variables on agricultural performance (e.g. land value and farm revenues). This approach has the advantage to consider either of the consequences of climate on productivity and how farmers adapt to it. Therefore, it overcomes the main critique to the use of production functions in the context of impact of climate change. Notably, Mendelsohn *et al.* (1994) claimed that the production function approach consistently overestimates production damage by omitting the variety of adaptations that farmers customarily make in response to changing economic or environmental conditions.[3] It is the so-called dumb-farm scenario (Mendelsohn *et al.*, 1994). In particular, the authors highlighted the role of adaptation actions in which new activities displace activities no longer (or less) profitable due to changes in climate variables.

Kurukulasuriya *et al.* (2006) used a Ricardian model to study how climate variables influence farmers' revenues in 11 African countries: Burkina Faso, Cameron, Egypt, Ethiopia, Ghana, Kenya, Niger, Senegal, South Africa, Zambia and Zimbabwe. In this case, the total net farm revenues resulted from the incomes generated by dryland crops which are rain-fed, irrigated crops and livestock. Separate regressions were estimated to highlight the response of the three activities. Using data from a survey of about 9,000 farmers, the study confirms that African crop production is sensitive to climate and the hotter and drier regions are likely to be affected most. Temperature rises and decreases in precipitations have a negative impact on the net revenue. Similarly but to smaller extend will be the effect on the revenues generated by irrigated land because less vulnerable to warming. To the contrary, an increase of rainfall brings an overall beneficial effect.

Revenues show a quadratic relationship with both temperature and precipitation. As a result, the marginal impact of climate change varies according to the temperature and rainfall levels presented across different farms. In fact, although Africa is overall hot and dry, the impacts of climate change are not uniform across the country. For instance, dry land through SSA is under risk; cropland with irrigation support located around the Nile or highlands of Kenya have some benefits from warming; drier countries such as Egypt, Niger or Senegal benefit for the livestock from rainfall increase (Kurukulasuriya *et al.*, 2006). With an increase of 1°C, the African net revenues in dryland and livestock showed a decrement of about $27 and $379 per hectare, respectively, while the irrigated resulted in a rise (an average of $30 per hectare). This effect is due to the fact that crops benefit from the irrigation when rainfall shortage occur and also because they are generally located in cool areas. Similarly, the marginal effect of precipitations varies among the activities. One millimetre/month increase in rainfall generates an aggregate enhancement on net revenues of $67 per farm.

Also, the elasticities confirm that the sensitivity of crop and livestock to temperature is greater than the effect of precipitation. The figures support this interpretation. The temperature elasticity is $-1.9, 0.5$ and -5.4 compared with the

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3 Mendelsohn *et al.* (1994, p. 754).

elasticity of precipitation which are equal to 0.1, 0.4 and 0.8 for dryland, irrigated crops and livestock respectively (Kurukulasuriya *et al.*, 2006).

Deressa and Hassan (2010) provided an application of this method in Ethiopia.[4] In their paper net crop revenue per hectare was regressed on climate, household and soil variables. The results showed that these variables have a significant impact on the net crop revenue per hectare. The seasonal marginal impact analysis indicated that marginally increasing temperature during summer and winter would significantly reduce crop net revenue per hectare whereas marginally increasing precipitation during spring would considerably increase net crop revenue per hectare.

Another example of the application of the Ricardian is offered by Kabubo-Mariara and Karanja (2007) to measure the impact of climate on net crop revenues. Using a sample of 816 households, they underlined the negative influence of climate change on productivity.

A slightly different approach was offered by Benhin (2008) who utilised the revised Ricardian approach to assess the impact of climate change on crop production in South Africa. Including hydrological variables (river flow and water resources) which are particularly affected by climate change, he extended the earlier study proposed by Deressa and Hassan (2010). The mean annual estimates indicated that if the temperature rises by 1 per cent the net crop revenue will increase about $80.00 whereas rainfall decreases of 1 mm/month revenue produces a revenues fall $2.00. However, the impacts are different according to the season. The study also predicts a 90 per cent decrease of crop net revenue by 2100 (Benhin, 2008).

The Ricardian model has been criticised from different point view.[5] It does not take into account transaction costs, for instance the costs generated by the decision of changing production abruptly. Secondly, it can suffer from an omitted variable problem – as it does not take into account time-independent location-specific factors such as unobservable skills of farmers and soil quality (Barnwal and Kotani, 2010). Another drawback is the fact that does not consider variables invariant respect to the space, for example, carbon fertilisation effect (Cline, 1996). This is a weak point in climate change studies conducted at small level, especially in low-income countries where each meteorological station controls a large portion of the territory (Di Falco, Veronesi and Yesuf, 2011). Yet, assuming constant prices leads to error measurements of loss and benefits (Cline, 1996; Kurukulasuriya and Mendelsohn, 2006).

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4 The first economic studies on the impact of climate change in developing countries, using this approach came from India and Brazil (Mendelsohn and Dinar, 1999; Kumar and Parikh, 2001). These studies confirm earlier predictions that even a modest level of warming would affect agricultural productivity in these countries, although the impact may not be uniform in all areas, some regions benefiting while the vast majority being affected adversely.

5 Schlenker and Roberts (2009) dealt with the omitted variables issue in a production function set up. They combine historical crop production and weather data in SSA into a panel analysis. This approach can take care of the omitted variable problem by using fixed effects capturing all time-invariant effects for which data are not available (e.g. soil texture). Similar approach to deal with unobservables is presented by Fisher *et al.* (2012).

Further, despite its successful application over 27 countries (Mendelsohn and Dinar, 2009), apart from a few exceptions, it normally refers to a single year. Deschenes and Greenstone (2007) argued that in order to obtain stable results over time on climate change impacts we should refer to intertemporal variations of the weather instead of cross sections. Nevertheless, Massetti and Mendelshon (2011) claimed that weather changes are not useful to explain climate change effects because farmers do not have a chance to adapt in the short run. Using weather data may provide a biased evaluation of the long-term effect of climate change (Massetti and Mendelsohn, 2011).

3.2. Estimating drivers of adaptation

SSA is the most vulnerable area to climate change due to the fact that warming will be greater than the predicted average and agriculture, mainly rain-fed and managed in small scale, represents the main source of subsistence for African rural communities. Hence, climate change is a threat and adaptation has primary importance in reducing vulnerability and, thus, ensuring livelihood, achieving food and water security and biodiversity (Bryan *et al.*, 2009).

In order to design specific and effective adaptation policies, it is crucial to identify what factors influence farmers' adaptation to climate variations and how to measure them (Bryan *et al.*, 2009; Below *et al.*, 2012).

In this sub-section, we will provide a review of the evidence on the barriers and drivers of adaptation capacity. Most of the literature has focused on the micro level of the issue where the process of adaptation is independently implemented by farmers or private firms in the field. This is what is it called *autonomous adaptation* distinguished from the *planned adaptation* decided by the government. During the last few decades, the Ricardian method has been the main tool in forecasting autonomous adaptation to climate change providing, therefore, useful information to policymakers in order to develop and promote well-targeted policies (Stage, 2010). A number of micro-econometric studies are focused on adaptation and agriculture productivity (Kurukulasuriya *et al.*, 2006; Seo and Mendelsohn, 2008; Di Falco *et al.*, 2011, 2012; Bryan *et al.*, 2013) and others on the determinants of using adaptation methods (Maddison, 2007; Hassan and Nhemachena, 2008; Bryan *et al.*, 2009; Deressa *et al.*, 2009; Gbetibouo, 2009). It is crucial to understand how the social, economic, institutional and ecological context mediates the climate impacts and influences the adaptation response (Bryan *et al.*, 2009).

According to Maddison (2007), there are two important components of adaptation: perception and adoption of strategies. Adaptation can, thus, be thought as a two-step process. The first step requires that the farmers perceive a change in the climatic conditions. In the second step, farmers implement a set of strategies to deal with the different conditions (Maddison, 2007).

Based on Heckman's probit model, the analysis conducted by Maddison (2007) on a sample of selected households in 11 Africa countries reveals that experience increases the likelihood of perception of climate change but education seems to be the main determinant in using at least one adaptation strategy.

In addition, agriculturists who have easier access to the market where they sell their products and have access to free extension advise show higher willingness to adapt. Changing in crop variety (particularly when temperature varies) and changing dates of planting (following rainfall variations) are, overall, the most common ways to adaptation (Maddison, 2007).

Bryan *et al*. (2009) studied the adaptation strategies adopted by farmers in Ethiopia and South Africa and the drivers that contributed to choice adaptation. Based on a sample of 1,800 farm households, it emerges that farmers generally use the following methods of adaptation: use of different crops or crop varieties, planting trees, soil conservation, changing planting dates and irrigation (Bryan *et al*., 2009). Nevertheless, in spite of the awareness of climate variability, it is not easy to implement them. Access to credit, extension services and wealth are obstacles to adaptation for the farmers of both countries. Farmers in Ethiopia also indicated that lack of access to land and information about climate change was a barrier to adaptation. Policymakers should pay attention on small-scale subsistence farmer and enhance adaptation providing access to information, credit and markets (Bryan *et al*., 2009).

Deressa *et al*. (2009) undertook a micro-analysis using data from cross-sectional household survey data collected from 1,000 households during 2004/2005 production season in the Nile basin of Ethiopia. This survey was the first one to explicitly address climate change. One section of this survey did indeed ask farmers about their perception on climate change and their adaptation strategies. More specifically, farm households were asked questions about their observations in the patterns of temperature and rainfall over the past 20 years. The results indicate that 50.6 per cent of the surveyed farmers have observed increasing temperature over the past 20 years whereas 53 per cent of them have observed decreasing rainfall over the past 20 years. The perception of the farmers in this part of Africa is matched with the climatic observation of temperature. Less unequivocal is the evidence on rainfall. In microeconomic studies undertaken by Bryan *et al*. in 2009 and 2013, first in Ethiopia and South Africa and then on Kenya, by, farmers perceive changes in precipitation and temperature but just a small portion of them made management adjustments to tackle climate change. For instance, in Ethiopia 83 per cent of farmers perceive variation in temperature but 56 per cent of them do not use adaptation strategies. Among those who chose adaptation, the most frequent method is using different crops or different varieties, planting trees, irrigation, changes in planting period. Less frequent is the use of new technologies or migration to urban areas.

Similar conclusions describe South Africa's situation. Because the percentage of farmers who decide to undertake adaptation strategy is low, this means that not only long-term changes in climate influence farmers decisions-making: extreme weather events; timing, duration and frequency of precipitation, socio economic status, household characteristics and distance from the market determine the outcome. The study reveals that, in South Africa, farmers are more educated than in Ethiopia, on average of 7 years against 2; in both the countries family are quite large, on average six members; farmers in South Africa are

better off than in Ethiopia and income are higher, receive farm support input such as seeds, tools, machinery, subsidies instead of food aid. In term of farm characteristics Ethiopia has more access to formal and informal credit even though farmers in South Africa borrow more money; farmers are more closer to markets and are less affected by extreme events (Bryan *et al*., 2009).

The study on Kenya is an extension of the previous study conducted in 2009 that underlines the differences in adaptation choices across agro-ecological zones. Farmers' perceptions of climate change and climate risk is a decisive variable in adaptation decision-making. Varying by district, farmers confirmed that they perceived an average increase in temperature and decrease in rainfall and also a variation in variability during the last 20 years. Generally, farmers from the humid zone are more sensitive to a decrease of precipitation than those who live in arid zone. Generally, farmer with more experience and with more access to extension services are more likely to perceive climate changes (Bryan *et al*., 2013).

Deressa *et al*. (2009) defined adaptation as crop switching, late planting, soil and tree planting. They showed that the level of education, gender, age and wealth of the head of household; access to extension and credit; information on climate, social capital, agro-ecological settings, and temperature all influence farmers' choices. The main barriers include lack of information on adaptation methods and financial constraints.

Changing crop mix has been found as key strategy in a number of studies on adaptation to climate in Africa. Studies were undertaken across different scales. For instance, Maddison (2007), Kurukulasuriya and Mendelsohn (2008a), Seo and Mendelsohn (2008) and Hassan and Nhemachena (2008) provide evidence at the aggregate level that changing crops is the most likely adaptation strategy. Aggregate studies, however, can mask spatial heterogeneity. Changing the crop mix, or crop switching, is a strategy that farmers have implemented for long time. Farmers, in fact, match crops to soils and environmental conditions – including climate. Moreover, greater use of different crop could be associated with lower expense and ease of access by farmers (Deressa *et al*., 2009). Implementing more structural adaptation measures (i.e. irrigation) requires more resources and public investment.

Di Falco and Chavas (2009) documented that growing a combination of different barley landraces (e.g. crop genetic diversity) was associated with less production risk exposure in the highlands of Ethiopia. These results showed that maintaining a higher biodiversity regime can be an important asset for sub-Saharan agriculture. In this case, a study of the highlands of Ethiopia conserving landraces in the field delivered important productive services and allowed farmers to mitigate some of the negative effects of harsh weather and agro-ecological conditions. Therefore, *in situ* conservation of crop biological diversity is one of the strategies that can help improve Ethiopia's poor agricultural performance and alleviate food insecurity. The analysis also showed that the beneficial effects of this diversity become of greater value in degraded land. When the land is less fertile, the contribution of crop biodiversity towards reducing crop failure becomes stronger. This underlines the potential

role that crop genetic diversification can play as adaptation strategy. It can also be considered to be one of the cheapest adaptation strategies, when compared with more labour intensive activities such as building soil conservation measures or water harvesting methods. It also highlights the importance of the genetic traits of African crops. This can be extremely valuable to provide raw material for future genetic improvement of existing crops. Crop mix or crop switching implies taking advantage of the fact that different crop species have different genetic traits. Genetic variability within and between species confers the potential to resist biotic and abiotic stresses, both in the short and the long term (Giller *et al.*, 1997). Growing more crop species enhances the possibility of producing in years where rainfall regimes or environmental conditions are more challenging. Thus, having functionally similar plants that respond differently to weather and temperature randomness contributes to resilience (Holling, 1973) and ensures that 'whatever the environmental conditions there will be plants of given functional types that thrive under those conditions' (Heal, 2000). In the African context, for instance, it has been found that more diverse cropping systems provide a wider range of productive responses to weather and climatic shocks.

Besides diversification of crop, farm activities and household income diversification are relevant. In principle, obtaining income from non-farm (less climate sensitive) sources is seen as crucial. Screening the literature, the evidence supporting this as an adaptation strategy is very thin. Moreover, Deressa *et al.* (2009) found that non-farm income also significantly increases the likelihood of planting trees, changing planting dates and using irrigation as adaptation options. In other words, the extra amount of resources is actually reinvested in the farm.

Moving into a mixed crop livestock system is also related to diversification and adaptation (e.g. Hassan and Nhemachena, 2008; Kurukulasuriya and Mendelsohn, 2008a; Seo and Mendelsohn, 2008). Livestock choice is also climate sensitive. Farmers are more likely to raise sheep and goats as temperatures rise and less likely to raise dairy and beef cattle (Seo and Mendelsohn, 2008). Whether they increase or decrease their reliance on chickens depends on their current climate.

4. Modelling adaptation and its implications: a structural approach

From a policy perspective understanding adaptation to climate change is of paramount importance. Besides determining the impact of climatic variables on welfare, it is necessary to understand how the set of strategies implemented in the field by farmers (e.g. changing crops, adopting new technologies or soil conservation measures) in response to long-term changes in environmental conditions are chosen and how they affect productivity or revenues (Di Falco *et al.*, 2011).[6] The standard Ricardian approach assumes optimal adaptation to climate

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6 It should be noted that the original Ricardian approach assumes that markets function properly. Access to inputs, credit or technology may however be 'imperfect'.

by the farmers in the past; the regression coefficients estimate the marginal impact on outputs of future temperature or rainfall changes incorporating farmers' adaptive response. It thus does not provide any insight into how farmers adapt (Seo and Mendelsohn, 2008b). To overcome this issue, Seo and Mendelsohn (2008a, 2008b), Kurukulasuriya and Mendelsohn (2008b) and Di Falco and Veronesi (2013) developed the so-called structural Ricardian model, which explicitly models the underlying endogenous decisions by farmers.

The climate change adaptation decision and its implications in terms of an outcome of interest (e.g. productivity, food security, revenue) can be modelled in the setting of a two-stages framework. In the first stage, I use a selection model for climate change adaptation where a representative risk averse farm household chooses to implement climate change adaptation strategies if it generates net benefits.[7] Let A^* be the latent variable that captures the expected benefits from the adaptation choice with respect to not adapting. We specify the latent variable as

$$A_i^* = \mathbf{Z_i}\alpha + \eta_i \quad \text{with } A_i = \begin{cases} 1 & \text{if } A_i^* > 0 \\ 0 & \text{otherwise} \end{cases}, \tag{1}$$

that is farm household i will choose to adapt ($A_i = 1$), through the implementation of some strategies in response to long-term changes in mean temperature and rainfall, if $A^* > 0$, and 0 otherwise.

The vector $\mathbf{Z}$ represents variable that affects the expected benefits of adaptation. These factors can be classified into different groups. First, we consider characteristics of the operating farm (e.g. soil fertility and erosion). For instance, farms characterised by more fertile soil might be less affected by climate change and therefore relatively less likely to implement adaptation strategies. Then, climatic factors (e.g. rainfall and temperature) as well as the experience of previous extreme events such as droughts and flood can also play a role in determining the probability of adaptation. To account for selection biases, I adopt an endogenous switching regression model where farmers face two regimes (1) to adapt, and (2) not to adapt defined as follows:

$$\text{Regime 1:} \quad y_{1i} = \mathbf{X_{1i}}\beta_1 + \varepsilon_{1i} \quad \text{if } A_i = 1 \tag{2a}$$

$$\text{Regime 2:} \quad y_{2i} = \mathbf{X_{2i}}\beta_2 + \varepsilon_{2i} \quad \text{if } A_i = 0 \tag{2b}$$

where y_i is the quantity produced or revenues per hectare in regimes 1 and 2, and $\mathbf{X_i}$ represents, for instance, a vector of inputs (e.g. seeds, fertilisers, manure and labour), farm household's characteristics, soil characteristics, assets and the climatic factors included in $\mathbf{Z}$. Finally, the error terms in equations (1), (2a) and

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7 A more comprehensive model of climate change adaptation is provided by Mendelsohn (2000).

(2b) are assumed to have a trivariate normal distribution, with zero mean and covariance matrix Σ, i.e. $(\eta, \epsilon_1, \epsilon_2)' \sim N(\mathbf{0}, \Sigma)$

$$\text{with } \Sigma = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & \cdot \\ \sigma_{2\eta} & \cdot & \sigma_2^2 \end{bmatrix},$$

where σ_η^2 is the variance of the error term in the selection equation (1), which can be assumed to be equal to 1 since the coefficients are estimable only up to a scale factor (Maddala, 1983, p. 223), σ_1^2 and σ_2^2 are the variances of the error terms in the productivity functions (2a) and (2b), and $\sigma_{1\eta}$ and $\sigma_{2\eta}$ represent the covariance of η_i and ε_{1i} and ε_{2i}.[8] Since y_{1i} and y_{2i} are not observed simultaneously, the covariance between ε_{1i} and ε_{2i} is not defined (reported as dots in the covariance matrix Σ, Maddala, 1983, p. 224). An important implication of the error structure is that because the error term of the selection equation (1) η_i is correlated with the error terms of the productivity functions (2a) and (2b) (ε_{1i} and ε_{2i}), the expected values of ε_{1i} and ε_{2i} conditional on the sample selection are non-zero:

$E[\varepsilon_{1i}|A_i = 1] = \sigma_{1\eta}(\phi(\mathbf{Z_i}\alpha)/\Phi(\mathbf{Z_i}\alpha)) = \sigma_{1\eta}\lambda_{1i}$, and $E[\varepsilon_{2i}|A_i = 0] = -\sigma_{2\eta}$ $(\phi(\mathbf{Z_i\alpha})/1 - \Phi(\mathbf{Z_i\alpha})) = \sigma_{2\eta}\lambda_{2i}$, where $\phi(\cdot)$ is the standard normal probability density function, $\Phi(\cdot)$ the standard normal cumulative density function, and $\lambda_{1i} = \phi(\mathbf{Z_i}\alpha)/\Phi(\mathbf{Z_i}\alpha)$, and $\lambda_{2i} = -\phi(\mathbf{Z_i}\alpha)/(1 - \Phi(\mathbf{Z_i}\alpha))$. If the estimated covariances $\hat{\sigma}_{1\eta}$ and $\hat{\sigma}_{2\eta}$ are statistically significant, then the decision to adapt and the quantity produced per hectare are correlated, that is one finds evidence of endogenous switching then we can reject the null hypothesis of the absence of sample selectivity bias. This model is defined as a 'switching regression model with endogenous switching' (Maddala and Nelson, 1975). An efficient method to estimate endogenous switching regression models is full information maximum likelihood estimation (Lee and Trost, 1978).[9] The logarithmic likelihood function, given the previous assumptions regarding the distribution of the error terms, is:

$$\ln L_i = \sum_{i=1}^{N} A_i \left[\ln \phi\left(\frac{\varepsilon_{1i}}{\sigma_1}\right) - \ln \sigma_1 + \ln \Phi(\theta_{1i}) \right]$$
$$+ (1 - A_i)\left[\ln \phi\left(\frac{\varepsilon_{2i}}{\sigma_2}\right) - \ln \sigma_2 + \ln(1 - \Phi(\theta_{2i})) \right], \quad (3)$$

where $\theta_{ji} = (\mathbf{Z_i}\alpha + \rho_j \varepsilon_{ji}/\sigma_j)/\sqrt{1 - \rho_j^2}, \quad j = 1, 2$, with ρ_j denoting the correlation coefficient between the error term η_i of the selection equation (1) and

8 For notational simplicity, the covariance matrix Σ does not reflect the clustering implemented in the empirical analysis. In addition, constraining the variance term in a single equation to equal one is not the same as deriving the proper form of the posterior or even the sampling distribution of the cross-equation correlation matrix.

9 An alternative estimation method is the two-step procedure (see Maddala, 1983, p. 224 for details).

the error term ϵ_{ji} of equations (2a) and (2b), respectively.[10] The model can easily be expanded in the context of multiple adaptation strategies and multiple outcomes.

Stage I – Selection Model of Multiple Climate Change Adaptation Strategies

In the first stage, let $A*$ be the latent variable that captures the expected net revenues from implementing strategy j ($j = 1 \ldots M$) with respect to implementing any other strategy k. We specify the latent variable as

$$A_{ij}^* = \bar{V}_{ij} + \eta_{ij} = \mathbf{Z_i}\boldsymbol{\alpha_j} + \eta_{ij}$$

$$\text{with} \quad A_i = \begin{cases} 1 & \text{iff} \quad A_{i1}^* > \max_{k \neq 1}(A_{ik}^*) & \text{or } \varepsilon_{i1} < 0 \\ \vdots & \quad \vdots & \vdots \\ M & \text{iff} \quad A_{iM}^* > \max_{k \neq M}(A_{ik}^*) & \text{or } \varepsilon_{iM} < 0 \end{cases}, \quad (4)$$

that is farm household i will choose strategy j in response to long-term changes in mean temperature and rainfall if strategy j provides expected net revenues greater than any other strategy $k \neq j$, i.e. if $\varepsilon_{ij} = \max_{k \neq j}(A_{ik}^* - A_{ij}^*) < 0$. Equation (4) includes a deterministic component ($\bar{V}_{ij} = \mathbf{Z_i}\boldsymbol{\alpha_j}$), and an idiosyncratic unobserved stochastic component η_{ij}. Equation (1) includes a deterministic component ($\bar{V}_{ij} = \mathbf{Z_i}\boldsymbol{\alpha_j}$), and an idiosyncratic unobserved stochastic component η_{ij}. The latter captures all the variables that are relevant to the farm household's decisionmaker but are unknown to the researcher such as skills or motivation. It can be interpreted as the unobserved individual propensity to adapt.

The deterministic component $\bar{V}_{ij}$ depends on factors $\mathbf{Z_i}$, as defined above, that affect the likelihood of choosing strategy j. It is assumed that the covariate vector $\mathbf{Z_i}$ is uncorrelated with the idiosyncratic unobserved stochastic component η_{ij}, i.e. $E(\eta_{ij}|\mathbf{Z_i}) = 0$. Under the assumption that η_{ij} are independent and identically Gumbel distributed, that is under the Independence of Irrelevant Alternatives (IIA) hypothesis, selection model (1) leads to a multinomial logit model (McFadden, 1973) where the probability of choosing strategy j (P_{ij}) is

$$P_{ij} = P(\varepsilon_{ij} < 0|\mathbf{Z_i}) = \frac{\exp(\mathbf{Z_i}\boldsymbol{\alpha_j})}{\sum_{k=1}^{M} \exp(\mathbf{Z_i}\boldsymbol{\alpha_k})} \quad (5)$$

Stage II – Multinomial Endogenous Switching Regression Model

In the second stage a multinomial endogenous switching regression model to investigate the impact of each strategy on net revenues can be estimated by applying Bourguignon, Fournier and Gurgand (2007) selection bias correction model. The model implies that farm households face a total of M regimes (one regime per strategy, where $j = 1$ is the reference category 'non-adapting').

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10 Assuming a normal distribution.

A net revenue equation corresponding to each possible j strategy is defined as m regime:

$$(3a) \quad \text{Regime 1:} \quad y_{i1} = \mathbf{X_i}\boldsymbol{\beta_1} + u_{i1} \quad \text{if } A_i = 1$$

$$\vdots \qquad \vdots \qquad\qquad \vdots$$

$$(3m) \quad \text{Regime M:} \quad y_{iM} = \mathbf{X_i}\boldsymbol{\beta_M} + u_{iM} \quad \text{if } A_i = M$$

where y_{ji} is the net revenue per hectare of farm household i in regime j, ($j = 1 \ldots M$), and $\mathbf{X_i}$ represents a vector of inputs (e.g. seeds, fertilisers, manure and labour), farmer head's and farm household's characteristics, soil's characteristics and the past climatic factors included in $\mathbf{Z_i}$; u_{ij} represents the unobserved stochastic component, which verifies $E(u_{ij}|\mathbf{X_i}, \mathbf{Z_i}) = 0$ and $V(u_{ij}|\mathbf{X_i}, \mathbf{Z_i}) = \sigma_j^2$. For each sample observation, only one among the M dependent variables net revenues is observed.[11] To correct for the potential inconsistency one can take into account the correlation between the error terms η_{ij} from the multinomial logit model estimated in the first stage and the error terms from each net revenue equation u_{ij}. I refer to this model as a 'multinomial endogenous switching regression model'.

Bourguignon *et al.* (2007, p. 179) show that consistent estimates of $\boldsymbol{\beta_j}$ in the outcome equations $(3a)$–$(3m)$ can be obtained by estimating the following selection bias-corrected net revenues equations,

$$(4a) \; \text{Regime 1:} \; y_{i1} = \mathbf{X_i}\boldsymbol{\beta_1} + \sigma_1\left[\rho_1 m(P_{i1}) + \sum_j \rho_j m(P_{ij})\frac{P_{ij}}{(P_{ij}-1)}\right] + v_{i1} \text{ if } A_i = 1$$

$$\vdots \qquad \vdots \qquad\qquad\qquad \vdots$$

$$(4m) \; \text{Regime M:} \; y_{iM} = \mathbf{X_i}\boldsymbol{\beta_M} + \sigma_M\left[\rho_M m(P_{iM}) + \sum_j \rho_j m(P_{ij})\frac{P_{ij}}{(P_{ij}-1)}\right]$$
$$+ v_{iM} \text{ if } A_i = M$$

where P_{ij} represents the probability that farm household i chooses strategy j as defined in (2), ρ_j is the correlation between u_{ij} and η_{ij} and $m(P_{ij}) = \int J(v - \log P_j)g(v)dv$ with $J(\cdot)$ being the inverse transformation for the normal distribution function, $g(\cdot)$ the unconditional density for the Gumbel distribution and $v_{ij} = \eta_{ij} + \log P_j$. This implies that the number of bias correction terms in each equation is equal to the number of multinomial logit choices M.[12]

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11 When estimating an OLS model, the net revenues equations (3a)–(3m) are estimated separately. However, if the error terms of the selection model (1) η_{ij} are correlated with the error terms u_{ij} of the net revenues functions (3a)–(3m), the expected values of u_{ij} conditional on the sample selection are nonzero, and the OLS estimates will be inconsistent.

12 A crucial assumption of the Bourguignon *et al.* (2007)'s model is that IIA holds. However, Bourguignon *et al.* (2007) show that 'selection bias correction based on the multinomial logit model can provide fairly good correction for the outcome equation, even when the IIA hypothesis is violated' (p. 199).

If panel data are at hand, one can specify a fixed effect version of the above models. Di Falco and Veronesi (2013) exploit plot-level information to deal with the issue of farmers' unobservable characteristics such as their skills. Plot-level information can be used to construct panel data and control for farm specific effects (Udry, 1996). I follow Mundlak (1978) and Wooldridge (2002) to control for unobservable characteristics. We exploit the plot-level information, and insert in the net revenues equations (4a)–(4m) the average of plot-variant variables $\bar{\mathbf{S}}_i$, for instance the inputs used (seeds, manure, fertiliser and labour). This approach relies on the assumption that the unobservable characteristics v_i are a linear function of the averages of the plot-variant explanatory variables $\bar{S}_i$ that is $v_i = \bar{S}_i \pi + \psi_i$ with $\psi_i \tilde{I}IN(0, \sigma^2_{\psi})$ and $E(\psi_i/\bar{S}_i) = 0$, where π is the corresponding vector of coefficients, and ψ_i is a normal error term uncorrelated with $\bar{S}_i$.

4.1. Building up a counterfactual analysis

Switching regression models allows estimating counterfactuals. One can estimate the treatment effects (Heckman, Tobias and Vytlacil, 2001) thus the effect of the treatment 'adoption of strategy j' on the net revenues of the farm households that adopted strategy j. In the absence of a self-selection problem, it would be appropriate to assign to farm households that adapted a counterfactual net revenue equal to the average net revenue of non-adapters with the same observable characteristics. Unobserved heterogeneity in the propensity to choose an adaptation strategy also affects net revenues and creates a selection bias in the net revenue equation that cannot be ignored. The multinomial endogenous switching regression model can be applied to produce selection-corrected predictions of counterfactual net revenues.

In particular, one can follow Bourguignon *et al.* (2007, p. 179 and pp. 201–203), and derive the expected net revenues or land values of farm households who adapted, that in our study means $j = 2 \ldots M$ ($j = 1$ is the reference category 'non-adapting'), as

$$(5a) \quad E(y_{i2}|A_i = 2) = \mathbf{X_i \beta_2} + \sigma_2 \left[\rho_2 m(P_{i2}) + \sum_{k \neq 2}^{M} \rho_k m(P_{ik}) \frac{P_{ik}}{(P_{ik} - 1)} \right]$$

$$\vdots$$

$$(5m) \quad E(y_{iM}|A_i = M) = \mathbf{X_i \beta_M} + \sigma_M \left[\rho_M m(P_{iM}) + \sum_{k = 1 \ldots M-1} \rho_k m(P_{ik}) \frac{P_{ik}}{(P_{ik} - 1)} \right]$$

Then, one can obtain the expected net revenues or land values of farm households that adopted strategy j in the counterfactual hypothetical case that they did not adapt ($j = 1$) as

(6*a*) $E(y_{i1}|A_i=2)=\mathbf{X_i}\boldsymbol{\beta_1}+\sigma_1$

$$\left[\rho_1 m(P_{i2})+\rho_2 m(P_{i1})\frac{P_{i1}}{(P_{i1}-1)}+\sum_{k=3\ldots M}\rho_k m(P_{ik})\frac{P_{ik}}{(P_{ik}-1)}\right]$$

$$\vdots$$

(6*m*) $E(y_{i1}|A_i=M)=\mathbf{X_i}\boldsymbol{\beta_1}+\sigma_1\left[\rho_1 m(P_{iM})+\sum_{k=2\ldots M}\rho_k m(P_{i,k-1})\frac{P_{i,k-1}}{(P_{i,k-1}-1)}\right]$

This allows us calculating the treatment effects (TT), for example, as the difference between equations (5*a*) and (6*a*) or (5*m*) and (6*m*).

4.2. What have we learned from the structural approach?

Di Falco and Veronesi (2013) used the above multinomial framework to answer the following questions. What are the factors affecting the adoption of strategies in isolation or in combination? What are the 'best' strategies that can be implemented to deal with climatic change in the field? In particular, what are the economic implications of different strategies? They used plot-level farm data and found that the choice of what adaptation strategy to adopt is crucial to support farm revenues. They found that strategies adopted in combination with other strategies rather than in isolation are more effective. Adaptation is, therefore, more effective when it is composed by a portfolio of actions rather than one single action. More specifically, it is found that the positive impact of changing crop is significant when is coupled with water and soil conservation strategies. This highlights the importance of not implementing water or soil conservation programs in isolation.

With regard to the drivers of adaptation, the first-stage analysis highlighted the role of tenure security. The estimated coefficient is positively correlated with all the strategies. The dissemination of information on changing crops and implementing soil conservation strategies are also found to be important. Extension services are, for instance, significant in determining the implementation of adaptation strategies, which could result in more food security for all farmers irrespective of their unobservable characteristics. Moreover, the availability of information on climate change may raise farmers' awareness of the threats posed by the changing climatic conditions. This is consistent with the finding of Deressa *et al.* (2009).

5. The behavioural dimension of adaptation to climate change: risk aversion

From the results reported above, a set of different institutional drivers (e.g. tenure security, extension services), market drivers (e.g. missing credit markets) have been identified in connection with the issue of lack of adaptation. Lately, attention on climatic effects on different outcomes has been increasing. A large body of literature has used the exogenous variation in climatic factors to

identify the causal effect of climate on different outcome. For instance, some researchers focused on economic outcomes such as land values, income and growth (e.g., Mendelsohn *et al*., 1994; Deschenes and Greenstone, 2007, 2011; Dell *et al*., 2009, 2012; Schlenker and Roberts, 2009; Graff-Zivin and Neidell, 2010; Hsiang, 2010; Fischer *et al*., 2012; Graff-Zivin, Hsiang and Neidell, 2013). Others have paid attention on other crucial impacts of climatic variables such as conflicts (Hsiang, Meng and Cane, 2011), education, health, migration (Barrios *et al*., 2006) and social norms (Miguel, 2005).

In this section I examine the causal effect of climatic conditions on behavioural parameters that can have a crucial implication for the choice of adaptation strategies: specifically farmers risk aversion. If farmers are averse to risk, they may also be more reluctant of undertaking potentially profitable investments if these entails some more risk. In this case, a higher variability leads to higher risk premium and lower investment. This finding is well established in the risk literature (e.g. Just and Pope, 1978; Binswanger and Rosenzweig, 1993; Chavas, 2004; Dercon and Christiansen, 2011). We address this issue directly and analyse how the first and the second moment of the long-run distribution of rainfall affects risk preferences. More specifically, I ask the following research question: are people that are exposed to more variable rainfall more likely to display higher risk aversion? To my knowledge, the estimation of the role of climatic factors on behavioural parameters is a novel.

I use a series of economic experiments where payoffs vary both in terms of riskiness. The experiments were carried out in the highland of Ethiopia in 2007. In order to elicit each participant's risk preference, the respondents were presented with a hypothetical farming scenario involving alternative levels of output depending on the weather. The hypothetical agricultural scenario consisted of two plots the productivity of which differs depending on if the rains are good or bad each at 50 per cent probability. As can be seen in Table A1 in the appendix, a series of six choices were presented to the respondents with each choice consisting of a payment with higher spread and higher payoff versus a choice with lower spread and lower payoff (see Yesuf and Bluffstone, 2009, for a full description of the experiment). I consider if farmers choose scenarios that qualify them as risk averse. We therefore assign a dummy that takes the value of 1 if yes and 0 otherwise. We regress this against the first two moments of the long-run distribution of rainfall. These are calculated over a 30 years period. Table 2 reports the results. We find that the probability of being classified as risk averse is determined by these climatic factors. More specifically, higher rainfall is negatively correlated with the probability of being a risk averse. The second moment of the distribution of rainfall (captured by the coefficient of variation) is instead positively correlated with the probability of being a risk averter. We extend the analysis with different controls. Results (reported in table 2) are consistent both from a qualitative and quantitative point of view. Table 1 provides the summary statistics.

Increasing long-term rainfall variability is therefore associated with higher risk aversion. The result underscores the potential importance of behavioural parameters in climate change adaptation. These parameters are crucially

Table 1. Summary statistics

Variable	Description	Mean	Std. Dev.	Min	Max
Risk averter	HH head classified as risk averter (see Table A1)	33%		0	1
Rainfall	Rainfall average (1970–2004) in mm/year	1173.6	89.4	269.76	1550.2
Rainfall CV	Rainfall coefficient of variation (1970–2004)	0.27	0.052	0.22	1.039
Distance to plots	Average walking distance from the homestead to the plots in minutes	6.25	12.5	0	150
Distance to town	Average walking distance to the nearest market town in minutes	63.39	42.3	0	240
Tenure insecurity	Expect no changes in land holdings (1 = yes; 0 = otherwise)	41%		0	1
Household size	Number of members of the households	6.495	2.38	1	19
Livestock	Livestock units	4.367	3.207	0	18.6
Gender	Gender of HH head (1 = female; 0 = male)	17%		0	1
Age	Age of the HH head	52.31	15.06	18	105
Illiterate	Household head unable to write or read (1 = yes; 0 = otherwise)	60%	0.489	0	1
Temperature	Lon run temperature average in degrees celsius	10.38	4.734	2.78	19.64

Table 2. Risk aversion and Climate change

Dependent variable: Risk averter

	(1)	(2)	(3)	(4)
Rainfall	−0.000815*** (0.000119)	−0.000652*** (0.000110)	−0.000550*** (0.000106)	−0.000564*** (0.000105)
Rainfall CV	0.940*** (0.355)	1.007*** (0.366)	1.114*** (0.313)	1.115*** (0.312)
Distance to the plots		−0.00312*** (0.000338)	−0.00326*** (0.000251)	−0.00310*** (0.000281)
Distance to town		−0.0000175 (0.000306)	−0.000171 (0.000324)	−0.000171 (0.000319)
Tenure insecurity		0.202*** (0.0237)	0.209*** (0.0188)	0.208*** (0.0183)
HH size			0.0357*** (0.00955)	0.0356*** (0.00968)
Livestock			0.00780** (0.00341)	0.00865** (0.00348)
Gender			0.161*** (0.0319)	0.165*** (0.0323)
Age			0.000706* (0.000405)	0.000633 (0.000422)
Illiterate			−0.0368 (0.0390)	−0.0341 (0.0386)
Temperature				0.00427*** (0.000900)
N	763	626	626	626

Probit marginal effects.
Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; constant not reported.

affected by climate. This may uncover a mechanism through which climate may also affect investment decisions that are central in the adaptation process.

6. Concluding remarks

In this paper, I reviewed some of the existing evidence on the impact and adaptation to climate change with a focus on the SSA. Research published to date highlights that adaptation based on a portfolio of strategies significantly increases farm net revenues. Changing crop varieties has a positive and significant impact on net revenues when coupled with water conservation strategies or soil conservation strategies but not when implemented in isolation. It is also found that tenure security and access to extension services are key determinants of the decision to adapt. Finally, I combined climatic data and experimentally elicited risk preferences to analyse the impact of climatic factors on behaviour. More rainfall variability is associated with less risk aversion. This may uncover an important behavioural dimension of the impact of climate change in agriculture. More variable rainfall may make farmers more risk averse. This could also imply a lower propensity to undertake investment. Future research on the behavioural dimension of climate change is necessary to uncover mechanisms and psychological impacts.

  At this stage of the paper other considerations are appropriate. Most of the results published and reported in this paper rely on cross-sectional and plot-level data. More and better data (e.g. panel data with long-time dimension) should be made available to provide more robust evidence on both the role of adaptation and its implications for agriculture. The dynamic of the problem should be also explicated. Some adaptation strategies can be effective in the short run while others may be delivering a pay-off in the long term.

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Appendix

Table A1. Choice sets for the risk preference experiment

	Bad harvest	Good harvest	Expected mean	Spread	CPRA* coefficient	Risk classification
Choice set 1	100	100	100	0	∞–7.5	Extreme
Choice set 2	90	180	105	90	7.5–2.0	Severe
Choice set 3	80	240	160	160	2.0–0.812	Intermediate
Choice set 4	60	300	180	240	0.812–0.316	Moderate
Choice set 5	20	360	190	360	0.316–0.0	Slight
Choice set 6	0	400	200	400	0.0–∞	Neutral

*Constant partial risk aversion.
Note: Numbers represent kilogram output.