Land tenure, climate and risk management

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1. Introduction

Farmers in developing countries are exposed to substantial amounts of risk. Dercon (2002) documents a range of risk sources and shows that harvest failure is by far the most important among them. 78% of households report being "severely affected" by harvest failure while less than half of all households report the same for other risks including policy shocks, labor problems and problems with livestock. Accordingly, farmers have developed a range of strategies to deal with the risk of harvest failure. In this paper we analyze to what extent climate conditions affect the prevalence of specific land tenure regimes in Africa, in particular sharecropping, as a form of insurance against climate risks. We investigate how sharecropping tenure interacts with fertilizer use and livestock ownership that both influence production risk.

The important role of harvest risk for farmers in Africa thus indicates a significant potential to improve welfare if improved strategies for addressing production risks are used. One potential is that better ways of addressing risk can replace harmful risk management strategies and allow for a more efficient use of resources and more investment. There is also a certain urgency to find better ways of addressing risk. Climate change alters weather patterns in Africa and is expected to increase variability (Dunning et al., 2018; Nicholson, 2017). This can have drastic consequences as an increase in rainfall variability has been observed to cause an increase in violent conflicts in Africa (Hendrix and Salehyan, 2012; Martin-Shields and Stojetz, 2019; Raleigh and Kniveton, 2012).

Alderman and Paxson (1994) propose classifying risk strategies into risk management, defined as "actions to reduce the variability of income", and risk coping, defined as strategies "that smooth consumption intertemporally…and those that smooth consumption across households". In a sharecropping contract, the tenant farmer compensates the land owner in the form of a share of the harvest. This arrangement provides a form of insurance for the farmer since he does not have to pay for the land when the harvest fails. Like other forms of insurance, sharecropping is thus a risk coping strategy, because the risk of a failed harvest is shared with the land owner. Reducing fertilizer input is a risk management strategy as fertilizer allows larger harvests in good years, but causes costs without benefits in bad years. Keeping livestock also works as a risk management strategy. Selling livestock in years of poor harvests smooths income, but binds productive means and thus reduces average harvests. A farmer able to reduce risk in one of these ways can

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thus be expected to have less need for the others.

The substitution between risk coping and risk management is highly relevant from a social perspective. From the individual perspective, sacrificing some average yield can increase welfare when it increases profits in years with adverse climatic events. From a social perspective, however, risks at an individual or local level cancel out (at least to a large extent) so that risk coping strategies are preferred to risk management strategies. Taking into account the risk coping aspects of sharecropping can thus allow governments to improve adaptation to climate risks. This might become increasingly important when climate change increases climate variability.

We develop a stylized theoretical model to analyze farmers' choice between sharecropping and non-sharecropping land tenure regimes. Additionally, we study the implications of tenure regime and production risk for investments into production. For the empirical analysis of the predicted behavior, we employ a comprehensive cross-sectional household survey coordinated by the Centre for Environmental Economics and Policy for Africa (CEEPA) in eleven African countries (Dinar et al., 2008; Waha et al., 2016). For climate variables we use the Climate Research Unit's (CRU) TS 3.10 gridded data set on monthly climatology 1901–2009 (Harris et al., 2014).

In a first step, we identify which factors contribute to the use of risk coping and management. As the main indicators of risk in agriculture, variability of temperature and precipitation during the growing season have been identified (Auffhammer et al., 2012; McCarl et al., 2008; Rowhani et al., 2011). As annual temperature is rather stable among surveyed districts in our dataset, we consider low precipitation levels and interannual variability in precipitation as the major indicator for production risk.[1] We find that, consistent with our theoretical model, tenure regime is endogenous to climate: farmers in areas with low precipitation are more likely to be sharecroppers. Climate conditions therefore can explain the prevalence of specific traditional forms of land tenure. Climate driven production risk also influences the use of fertilizer and the ownership of livestock: Livestock ownership has been identified as a risk management strategy in Dercon (1996), while Dercon and Christiaensen (2011) find that farmers react to higher risk with lower fertilizer input. In a second step, we therefore analyze how fertilizer use and livestock ownership are influenced by climate. While we confirm the positive impact of drought risk on livestock ownership we reject the negative impact on fertilizer application.

As risk management and risk coping decisions interact, we consider in a third step the correlation of risk adaptation strategies, by conducting bivariate probit regressions. We find that sharecropping is negatively correlated with livestock ownership. Farmers under a sharecropping contract are thus less likely to own livestock. Sharecropping is positively correlated with fertilizer use. These findings are thus in line with the hypothesis that all three risk adaptation strategies are to some extent substitutes. They further indicate that sharecropping does not necessarily reduce fertilizer application compared to a renting or ownership tenure.

Similarly to our paper, Srinivasan (1972) and Barrett (1996) consider the effect of uncertainty on the purchase of inputs. Bardhan and Srinivasan (1971) and Stiglitz (1974) explain the variation in incidence of sharecropping with uncertainty, pointing out that the sharing of risk makes it attractive for regions with high risk. We combine these ideas and show how the choice of inputs and of tenancy interact and are related to climate. The beneficial role of insurance for farming has recently gained attention, in particular in the form of index based insurance (Chantarat et al., 2013; Karlan et al., 2014; Patt et al., 2009). We show that sharecropping functions in a similar way, albeit at a lower level of technology. Additionally, our work differs by using a unique data set covering eleven African countries, thereby exploiting larger heterogeneity in climate conditions than ever studied before in this context.

Studies on the success of consumption smoothing during droughts (Kazianga and Udry, 2006) and the effectiveness of insurance when available (Karlan et al., 2014) indicate that agricultural households in Africa face considerable uninsured risk. Keeping livestock functions as a way of saving and thus to achieve intertemporal consumption smoothing, but achieves this only very imperfectly (Fafchamps et al., 1998; Hoddinott, 2006). Further options include the use of drought tolerant crops and non-farm activities (Lyimo and Kangalawe, 2010) as well as migration (Kubik and Maurel, 2016). All of these are risk management strategies are costly, as they reduce the average agricultural production. Ultimately, formal insurance, like the rainfall index insurance described by Karlan et al. (2014) seem to be the best option of addressing risk without reducing agricultural output. Bellemare (2012a) and Bellemare (2018) show that contract farming provides another form of insurance, even for farmers in developing countries, because it provides certainty on prices. Where these more sophisticated forms of risk coping are not yet available, sharecropping could provide a pragmatic solution.

We discuss theoretical aspects of sharecropping and provide a stylized model of input choice and tenure choice in Section 2. The data are described in Section 3. The empirical approach and results are presented in Section 4. Section 5 concludes.

2. The theoretical framework

The data set used for this paper (see Section 3.1 for details) reveals that land tenure in Africa is quite complex. Farmers cultivate their own land, rented land or communal land (that is land belonging to the community and used jointly) or enter a sharecropping contract with a land owner. In addition, many farmers make use of several of these land tenure systems simultaneously and can also function as both a landlord and a tenant. In our theoretical analysis we abstract from this complexity and just consider the difference between purely renting, owning and sharecropping farmers.

2.1. Effort choice, tenure security and project choice

Renting and owning farmers have a fixed (opportunity) cost and receive a variable income from their harvest. Sharecropping farmers have no fixed cost for the land so that their net income depends less on their own choices and is less variable.

Marshall (1920) described one major implication of this difference in payment: Since the farmer cannot appropriate the full reward for his effort, he will invest less effort than he would under a renting contract. According to Otsuka et al. (1992), the land owner receives 50% of the harvest in most sharecropping contracts, making it quite plausible that the effort of the farmer is affected by the contract type. Shaban (1987) and Laffont and Matoussi (1995) provide empirical evidence on this effect.

Weinschenk (2019) identified a further effect, the project choice of the farmer. The theoretical literature has considered risk as an element to explain sharecropping for a long time, see Otsuka et al. (1992) for a review. Weinschenk (2019) adds a crucial element to this literature: The possibility for the tenant farmer to choose between projects. The farmer thus is not only subjected to an exogenous source of risk, but can gauge the risk-return profile. One example is the use of fertilizer. Fertilizer use increases the average harvest, but also the variance of profits since the expenses for the fertilizer are not matched with higher income in years of very poor harvest.

Considering both the effect on effort and on risk behavior, sharecropping is not an ideal form of risk coping. The insurance effect is socially beneficial, since the only source of revenue for the farmer is the harvest so that he has no incentive to take more risk than what would maximize his expected income. The effect on effort is socially harmful

[1] When we write in the following 'variability of precipitation' we always refer to interannual variability.

and the lower land tenure security, which causes a reduction in investment (Abdulai and Goetz, 2014; Abdulai et al., 2011), is a further disadvantage. The provision of agricultural credit as analyzed in Wossen et al. (2014) or formal insurance as applied in Karlan et al. (2014) would thus be preferable to sharecropping. A country with weak institutions, however, might benefit from the simple insurance mechanism of sharecropping.

2.2. Model

In this paper we analyze risk management choices of renting and sharecropping farmers by considering both an effort and project choice component. The project choice in our model concerns the amount of fertilizer used by the farmer but it can be interpreted as any kind of investment that increases yields. The relevance and potential of this kind of technology choice for Africa has recently been shown by Larson et al. (2016). Fertilizer is a productive, but risk increasing investment. Any reduction in fertilizer use thus has similar effects to an insurance. Below we also discuss how the model can be adjusted to livestock ownership.

Bellemare (2009) reviews the history of modeling sharecropping and concludes that "for economists, a rich landlord-poor tenant match usually means that the former is risk-neutral and the latter risk-averse". We follow this modeling tradition and assume that land owners are risk neutral. We thus assume that the land owner is indifferent between a sharecropping and a renting contract and lets the farmer choose between the two contract types. For land owners who are not risk neutral, the model would have to be adjusted.

In addition to the risk neutrality of land owners, the model employs several simplifying assumptions. These simplifications include further behavioral options as well as constraints on market functioning like infrastructural limitations, access to market and credit constraints. The idea is to test whether the main mechanism can be empirically identified even though the mechanism may not work in individual cases. An inflexible land market, for example, may keep some farmers from using sharecropping even though they might want to. Other constraints, in particular missing financial services, are a precondition for the model to work. If insurance would be available, farmers would likely chose a product like rainfall index insurance instead of sharecropping.

The farmer's profit Π per unit of land is composed of three parts. The first is his revenue, which consists of the harvest size times the farmgate price (productivity), H. Fertilizer application F increases production and we assume for the production function (in monetary terms) $g(F)H$ with $g(0) = 1, g'(F) > 0, g''(F) < 0$. Hence, production equals the 'natural' harvest H if no fertilizer is applied; fertilizer increases production but shows decreasing returns to scale in fertilizer application.

The second component of farmer's profit is the purchase of fertilizer at price k. Dercon and Christiaensen (2011) identified the amount of fertilizer applied as a major investment decision governing the degree of risk. The third component is the payment made to the land owner. For the renting farmer this is given by the land rent r. The sharecropper pays $(1 - s)g(F)H$ of his harvest and retains fraction s of his harvest. The net profits for a renting farmer Π_{rent} and a sharecropping farmer Π_{SC} are thus given by

$$\Pi_{rent} = g(F)H - r - kF \tag{1}$$

$$\Pi_{SC} = g(F)sH - kF \quad . \tag{2}$$

According to the Modigliani and Miller (1958) theorem, the formulation for the renter would also apply to farmers who own the land on which they farm. Even though financial markets in rural Africa are far from perfect, we consider the two cases to be sufficiently similar for investment behavior since the main difference to the sharecropper is the share of the harvest retained by the farmer. Because of this we consider the cases of owned land and rented land jointly under the label of "renting farmer".

We define $E[H] = \mu$ the mean natural productivity, i.e. productivity before fertilizer use, and $Var[H] = \sigma^2$ the variance of natural productivity. While soil conditions, exposure to pests as well as farmgate prices net of transportation costs are important determinants of μ and σ, we will consider average precipitation and precipitation variability in the later empirical analysis as major control variables for μ and σ.

Farmers are risk averse and therefore reduce investments in risky production techniques unless they have the means for self insurance or risk diffusion. We therefore assume utility to be concave and choose an exponential utility function for analytical tractability,

$$U(\Pi) = -\exp(-\eta\Pi), \tag{3}$$

where $\eta > 0$ is the coefficient of absolute risk aversion. The farmer's certainty equivalent is

$$CE(\Pi) = E[\Pi] - \frac{\eta}{2} Var[\Pi] \quad . \tag{4}$$

$E[\Pi]$ and $Var[\Pi]$ are the expected value and variance of profits. The certainty equivalent is a monotonic transformation of expected utility, so that we can assume that farmers maximize the certainty equivalent (Ben-Tal and Teboulle, 2007).

Farmers choose input F to maximize Eq.(4). Thus, we obtain the first-order conditions for optimal input choice F_R^* and F_{SC}^* for a land renting Eq. (5) and as a sharecropping Eq. (6) farmer, respectively:

$$(\mu - \eta\sigma^2 g(F_R^*))g'(F_R^*) = k \tag{5}$$

$$s(\mu - s\eta\sigma^2 g(F_{SC}^*))g'(F_{SC}^*) = k \tag{6}$$

We assume in the following that an interior solution exists, thus, $\mu > \eta\sigma^2 g(F)$ (for renter) and $\mu > s\eta\sigma^2 g(F)$ for a sharecropper. Hence, both farmers would always apply fertilizer.[2] As we cannot solve for optimal fertilizer use in this general case, we use comparative static analysis to derive some basic propositions that explain fertilizer and sharecropping choice.

Proposition 1. *For a renting as well as a sharecropping farmer, fertilizer use increases in expected natural productivity μ and decreases in the variability of natural production σ^2.*

Proof. (i) Fertilizer use for sharecropper: Taking the total derivative of (6) with respect to μ and solving for $\frac{dF_{SC}^*}{d\mu}$ gives $\frac{dF_{SC}^*}{d\mu} = \frac{g'}{g''(s\eta\sigma^2 g - \mu) + s\eta\sigma^2(g')^2}$. As $g'' < 0$ and, for an interior solution, $\mu > s\eta\sigma^2 g(F)$, it follows that $\frac{dF_{SC}^*}{d\mu} > 0$. Likewise, the total derivative of Eq. (6) with respect to σ^2 gives $\frac{dF_{SC}^*}{d\sigma^2} = -\frac{sg\eta g'}{g''(sg\eta\sigma^2 - \mu) + s\eta\sigma^2(g')^2}$ which is always negative. (ii) The same signs result for a renter farmer as the first-order condition of the renter Eq. (5) is a special the condition of the sharecropper Eq. (6) for $s = 1$.

The first order conditions of the two types of farmers reveal that both the effort and the project choice effect identified in Section 2.1 are present. In particular, Eq. (6) can be re-stated as

$$\underbrace{s\mu}_{\text{effort effect}} - \underbrace{\eta s^2\sigma^2 g(F_{SC^*})}_{\text{insurance effect}} = \frac{k}{g'(F_{SC}^*)} \tag{7}$$

Suppose there is no production risk and $\sigma^2 = 0$. Since the sharecropping farmer retains only a fraction s of the harvest, the farmer's incentive to invest into fertilizer is reduced, expressed by the term $s\mu$. The farmer thus exerts less effort because a lower $s\mu$ term implies a lower F_{SC}^* as $g' > 0$. If there is production risk and $\sigma^2 > 0$, the sharecropping farmer is not exposed to the same amount of risk as the renting farmer, expressed by the term $\eta s^2\sigma^2 g(\cdot)$. A lower s, i.e. a lower fraction of crops he can retain after harvest, reduces his risk exposure. Because of the

[2] Considering the case of corner solution where no fertilizer is applied is straight forward but creates additional clutter in the propositions and proofs due to considering two additional cases of corner solutions. The corner solution basically occurs if production risk is so high that it is not optimal to apply any fertilizer at all as it would increase revenue risk too much.

negative sign of the risk term, a high $s\sigma^2$ reduces fertilizer input. A sharecropping farmer (with $s < 1$) is thus willing to purchase more of the risky, but profitable fertilizer than the renter ($s = 1$) when the risk term is large enough compared to the effort term. The relative size of these two effects determines the relative investment of the two tenure types:

Proposition 2. *There exists a level of risk for which sharecropping farmers apply more fertilizer than renting farmers.*

Proof. Taking the total derivative of Eq. (6) with respect to s and solving for $\frac{dF(\cdot)}{ds}$ gives

$$\frac{dF_{SC}^{*}}{ds} = \frac{g'(\cdot)(\mu - 2g(\cdot)\eta s\sigma^2)}{s(g''(\cdot)(s\eta\sigma^2 g(\cdot) - \mu) + s\eta\sigma^2(g'(\cdot))^2)}$$

As $\mu > g(\cdot)\eta s\sigma^2$ for an interior solution and $g' > 0, g'' < 0$, the denominator is always positive and $\frac{dF(\cdot)}{ds} < 0$ if and only if $\sigma^2 > \hat{\sigma}^2 := \frac{\mu}{2g(\cdot)\eta s}$. Hence, if σ^2 is sufficiently large (higher than $\hat{\sigma}^2$) a farmer who retains a higher share of his harvests (high s) uses less fertilizer. This is particularly true for a renting farmer where $s = 1$.

With the endogenous fertilizer choice of the two tenure systems (5) and (6) we can determine which tenure system the farmer would prefer. Holden et al. (2008) show that the land market in Africa started emerging only recently: Some countries like Ghana, Kenya, Uganda and Rwanda have active land sales markets, while other like Zambia, Burkina Faso, Senegal, and Niger do not even have very active land rental markets. Reforms encouraged land sales or land rentals in Ethiopia in the early 2000s and in Uganda in 1998 for example. If farmers do not have a choice of the contract they would like to choose it might be of little consequence what farmers prefer. Gebregziabher and Holden (2011) and Bellemare (2012b), however, provide direct evidence that contract choice is to some degree endogenous in Africa with the former finding that "sharecropping is more likely where production risk is high".

Proposition 3. *The advantage of sharecropping over renting (i) decreases in mean natural productivity μ and (ii) increases in variability of natural productivity σ^2.*

Proof. The basic idea of the proof is first to assess how a marginal change in μ and σ^2 affects the expected utility of the sharecropper at the optimum, i.e. $\Omega_\mu := \frac{dCE(\Pi_{SC}(F_{SC}^{*}))}{d\mu}$ and $\Omega_{\sigma^2} := \frac{dCE(\Pi_{SC}(F_{SC}^{*}))}{d\sigma^2}$. After that, we take the total derivative of Ω_μ and Ω_{σ^2} with respect to s, i.e. the fraction of the harvest the sharecropper can retain. As it turns out, $\frac{d\Omega_\mu}{ds} > 0$ and $\frac{d\Omega_{\sigma^2}}{ds} < 0$. A positive sign implies that a higher s is more beneficial if μ and σ^2 increase. Thus, the sharecropper would gain more strongly from a higher μ if s is high – a renter (with $s = 1$) would gain most. Contrary, the sharecropper would loose more from an increase in risk σ^2 if s is high. See the Appendix for the full formal proof.Proposition 3 predicts that sharecropping is a more favorable tenure type in regions with low productivity and high production risk. The first part can be related to the effort effect: In highly productive regions, sharecropping is more costly because it distorts the production incentives substantially. The second part is related to the insurance aspect: In highly risky regions, sharecropping provides an insurance and reduces production risks. The insurance allows the farmer to choose projects with a higher expected return. When variance is high this benefit might become more important than the harmful effort choice effect.

The model developed here can also be applied to the use of livestock ownership as risk management option. In many rural areas in Africa, farming households do not have access to the formal banking sector. One of the most important forms of saving is thus to accumulate livestock (Dercon, 1996; Hoddinott, 2006). This works far from perfectly (Fafchamps et al., 1998), but it does provide farmers with the possibility to self-insure by allowing them to sell livestock and thus to generate some income in years of poor harvests.

To consider livestock ownership, the production function reads $g(1 - L)H$ and additional revenues from livestock are kL. Hence, the model is formally equivalent to the model of fertilizer use with $L = 1 - F$. The negative impact of livestock ownership on harvest is related to the lower availability of cropland for the production of food and cash crops due to grazing or due to the production of fodder. The concavity of $g(\cdot)$ reflects that livestock will graze first on those lands which have lowest productivity for crops. Note that *less* livestock is the equivalent of *more* fertilizer, since the informal insurance consists of buying livestock or reducing fertilizer use.[3]

Fig. 1 summarizes the key options of farmers to cope with risks through sharecropping or to reduce income variability through increased livestock or reduced fertilizer use as risk management strategies. All of these measures are substitutes for reducing disutility of risk but they influence each other as well when maximizing expected utility: Through the effort effect, sharecropping reduces incentives to apply fertilizer and increase productivity; through the risk reduction effect, sharecropping increases fertilizer use. The latter effects dominates when risks are high (Proposition 2). A key hypothesis analyzed in this paper is that risk coping and risk management are more beneficial when risks are high and productivity levels (i.e. precipitation) are low (Propositions 1 and 3).

3. Data

3.1. Data

In order to link the local climate to household decisions, we combine two types of data. One is a household survey, the other is climate data. Using the information on the administrative unit a survey household belongs to, we assign the climate data of these units to the respective household entry.

3.1.1. Household survey

The household survey was conducted as part of a World Bank/Global Environmental Facility project, coordinated by the Centre for Environmental Economics and Policy for Africa (CEEPA) at the University of Pretoria, South Africa in association with Yale University (Dinar et al., 2008) and is described in more detail in Waha et al. (2016). The project was coordinated by the Centre for Environmental Economics and Policy for Africa (CEEPA) at the University of Pretoria, South Africa in association with Yale University (USA).

The survey was conducted in eleven African countries: Burkina Faso, Cameroon, Ghana, Niger and Senegal in western Africa; Egypt in northern Africa; Ethiopia and Kenya in eastern Africa; South Africa, Zambia and Zimbabwe in southern Africa. The total number of households in the data set is 9597. Multi-stage stratified random sampling was used to select households. After selecting the eleven countries to represent four sub-regions of Africa (first stage), districts in each country were selected to represent diverse agro-climatic conditions (second stage). Within each district villages and farms were selected in collaboration with respective district level agricultural authorities (for details see Waha et al. (2016)). Most of the surveys are for the 2002–2003 agricultural year, collected in 2003–2004. Data from Cameroon, Ethiopia, Kenya and Zimbabwe are for the 2003–2004 agricultural year, collected in 2004–2005. Between 416 (South Africa) and 1087 (Burkina Faso) households per country were sampled. Fig. 2 shows the spatial coverage of the surveyed districts.

In over 70% of the households the head of the household was the respondent. Households were asked to classify their farm as small, medium or large-scale farm. In the entire sample, half of the households are small-scale farmers, the other half are medium- or large-scale farmers. Each farm type was surveyed in each country but in Ghana,

[3] Note further that Propositions 1–3 can also be derived when the coefficient of variation $CV = \sigma/\mu$ is used instead of σ^2 as indicator of production risk.

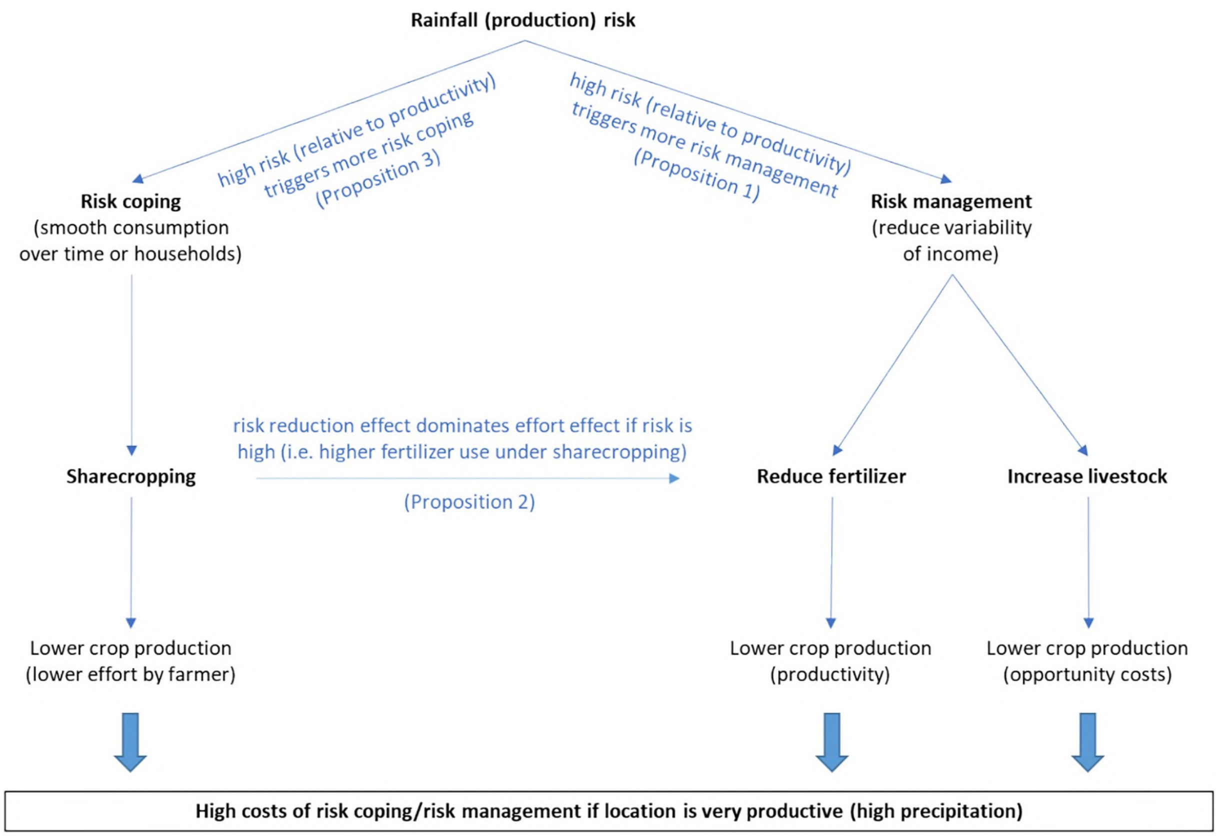

Fig. 1. Choices to reduce or cope with production risk.

Zambia and Zimbabwe more than 80% of the households were smallholders while in all countries except Kenya, Senegal and South Africa more than 80% of the farms were small or medium-scale farms. In contrast, 73% of all households in Senegal belong to a large-scale farm. The size of a small farm differs between countries and can vary between 0.7 ha in Egypt and 51 ha in South Africa.

The majority of households grew at least one crop on one plot in a season and continuous cropping with or without a fallow period is the most common farming system in most of the countries except for South Africa and Kenya where livestock farming dominates. About 350 households did not grow any crops.

The household survey reports cropping activities for 56 crops and tree crops which are grown on up to three plots in up to three seasons within 12 months. Some households grow up to six crops simultaneously on a plot. More than 5000 farmers were livestock farmers. The livestock data identify the five major types of livestock in the surveyed districts as beef cattle, dairy cattle, goats, sheep, and chickens.

3.1.2. Climate data

From CRU TS 3.10 gridded monthly climatology (Harris et al., 2014) we calculate annual average temperature and annual total precipitation in the surveyed agricultural year as well as the variance and the coefficient of variation of precipitation and long-term averages for the 10 years before the surveyed year.

As the geographic coordinates of the surveyed households are unknown we aggregate gridded climate variables to the same administrative units as used in the household survey. For the majority of countries these are administrative units of level 2 i.e. districts or departments except for Egypt (level 1, "governorate" and Senegal (level 3, "arrondissment"). If grid cells overlap with more than one administrative unit their climate variables are used to calculate an average value for all these units depending on their area share.

Although several households are assigned to the same climate data within their district, we have climate data for 331 different districts with, on average, 22.2 households per district (see Appendix). While annual mean temperature varies hardly between districts, mean precipitation and the temporal variability of precipitation (risk) exhibits substantial spatial variability within each country (see Appendix). Thus precipitation exhibits sufficient variability in our sample for including country-fixed effects in our regression.

3.2. Data cleaning and preparation

There are several issues regarding data quality that need some consideration. First, for only 14 of 816 Kenyan households land tenure types have been recorded – for the remaining households, land tenure type information was missing. We therefore dropped Kenya completely from our data set.

Other data on household characteristics are missing or incomplete for some countries. Education and gender data is, for example completely missing for Zimbabwe (and therefore not used as co-variate later) and data on distance to markets is always zero in Zimbabwe. Market distance to input and selling markets is also incomplete or contains zeros (10% missing values for distance to input market and 13% missing values for distance to selling market). We use distance to selling market and distance to input market as major geographical variables. We create a dummy, if market distance is zero in the original dataset. If data and distance is missing, we treat it as zero and add an additional dummy for missing distance data to account for potential biases. For farm value, we proceed similarly: we consider the farm selling value and use the farm buying value (together with an interaction term) if the selling value is missing but the buying value is available. We create a dummy if the farm value is zero in the original data set. As after this procedure, more than 13% of the farm values are still

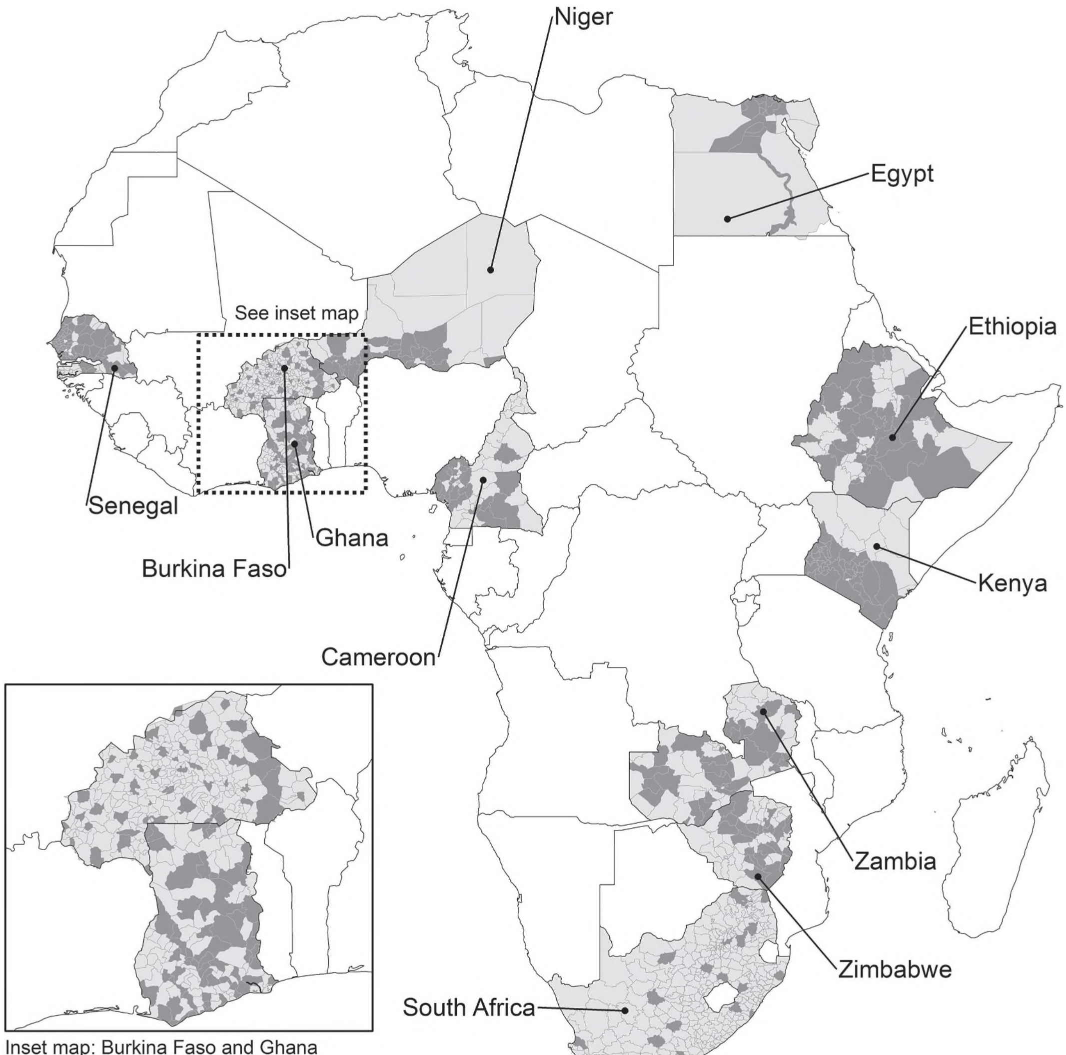

Fig. 2. Map of countries (in grey) surveyed. The districts, in which the survey was taken, are highlighted in dark grey.

missing and dropping them from the analysis would reduce sample size remarkably, we set the missing values to zero and add an additional dummy to control for missing value. For few households, missing household size data was replaced by calculating the number of persons of the same household for which age data was available.

Table 1 shows the descriptive statistics of the data used for the subsequent analysis. We use the inverse hyperbolic sine function transformation for market distance, farm value, land size, tropical livestock units owned and kg of fertilizer applied as these variables contain also zeros.[4] We measure sharecropping as the fraction of the plots households possess or cultivate and that are under a sharecropping tenure regime. This gives us a continuous number ranging from zero to one. Alternatively, we use a dummy variable for sharecropping if a certain fraction of the agricultural area is under sharecropping regimes. We use this definition with varying thresholds for robustness checks. In our data, 3% of the households (262 households) have at least one plot under sharecropping tenure and the average fraction of sharecropping area per household is 2% of the total area the household cultivates. In three countries, Ghana, Cameroon and South Africa, sharecropping is more common (more than 8% of the households have one sharecropping plot). As sharecropping has been described as an important form of land tenure in Africa (Abdulai et al., 2011; Fenske, 2011), our data suggests that the prevalence strongly varies regionally.

4. Empirical analysis

The underlying idea of the subsequent analysis is that farmers who are more exposed to risk will have a different demand for risk coping and risking management. We therefore want to assess (i) whether sharecropping is endogenous to climate risk and (ii) to what extent fertilizer application and livestock ownership as well-known and widely used risk management strategies interact with sharecropping.

Dercon (2002) shows that harvest failure is the most important source of risk for farmers. Variability in rain and temperature in turn are important drivers of harvest variability, see Cooper et al. (2008), Wossen et al. (2014) and Karlan et al. (2014) for Africa, Rosenzweig and Binswanger (1993) for India and McCarl et al. (2008) for the United States. As annual temperature is rather uniform across Africa with low spatial variability, we thus use variability in precipitation variables as main risk variable for farmers in Africa. This is not to say that changes in temperature and temperature variability within a year and between years will not be important drivers of agricultural productivity in the future.

[4] The inverse hyperbolic sine function $f(x) = \ln(x + (x^2 + 1)^{1/2})$ is a monotonic transformation similarly to the logarithmic transformation with $f(0) = 0$.

Table 1
Descriptive statistics of variables used in the regression models.

Variable	Variable description	Type/Unit	Obs	Mean	SD	Min	Max
Explanatory variables							
Mean Prec	The annual precipitation averaged over the ten years before planting	100 mm	7749	9.06	4.72	1.89	26.68
CV Prec	Coeffiecient of variation of precipitation over the ten years before planting		7749	0.171	0.076	0.51	0.80
Mean Temp	The mean annual temperature averaged over the ten years before planting	Kelvin	7749	298	3.76	287.27	302.97
CV Temp	Coefficient of variation of temperature over the ten years before planting		7749	0.001	0.0003	0.001	0.002
Dist O-Mrkt	Distance to selling market; transformed using inverse hyperbolic sine (similar to log)	km	7881	14.67	197.54	0	10,000
Dist I-Mrkt	Distance to input market; transformed using inverse hyperbolic sine (similar to log)	km	7881	11.39	25.18	0	550
Land size	The sum of the plots farmed by the household in the last 12 months before the interview	ha	7881	72.12	1169.59	0	76,708
Household size	The number of household members of the owner of the farm	Integer	7881	7.41	4.39	1	48
Farm value	The sale value of the farm (incl. land, buildings, equipment and livestock)	Local currency $\times 10^6$	7881	12.1	86.8	0	6000
Dependent variables							
Sharecropping	Fraction of area under sharecropping regime		7793	0.02	0.14	0	1
Livestock owner	Dummy = 1 if farm owns livestock	Binary	7813	0.80	0.39	0	1
TLU owned	Tropical livestock units owned		7776	10.76	118.34	0	8650
Fertilizer use	Dummy = 1 if fertilizer has been applied in the growing season 12 months prior to the interview	Binary	7881	0.45	0.50	0	1
Fertilizer use (kg)	Amount of fertilizer applied	kg	5689	3096.13	42259.52	0	1,744,400

Price volatility for agricultural products has also been identified as a source of risk in African agriculture (Barrett, 1996; Haile et al., 2017, 2019; Jayne et al., 2010). We do not include this additional risk into our analysis for two reasons. First, prices are endogenous to several of the variables included in our data and farmers are affected by higher prices both negatively (as buyers) and positively (as sellers). These complex interactions would thus require a separate, detailed analysis. Second, we are not aware of suitable data for our entire study area.

We use one form of risk coping, sharecropping, and two forms of risk management, fertilizer use and livestock ownership, as dependent variables. In Subsections 4.2 to 4.3 we test whether these variables are indeed, as predicted by theory, measures used by farmers to adapt to risk.

4.1. Empirical approach

Based on the theoretical model in Section 2.2, in particular Proposition 3, we estimate the household's decision to choose a specific fraction of its area under sharecropping, SC_{idc}, with the latent variable model:

$$SC_{idc} = \beta_1 C_d + \beta_2 X_i + \mu_c + \varepsilon_{id} \tag{8}$$

where subindex i refers to the household, d to the district and c to the country. SC_{idc} ranges from zero to one and follows from the difference between the certainty-equivalent utility between choosing sharecropping or not (see the proof of Proposition 3). β_1 measures the impact of a set of climate-related covariates C_d that are available at the district level. We include mean precipitation and temperature as well as the variability of precipitation and temperature, measured by the coefficient of variation (CV) in our standard specification. We use CV rather than variance or standard deviation of precipitation as the CV is scale invariant. We provide robustness checks on alternative risk measures like standard variation, variance and skewness as well as an alternative for appropriateness of rainfall, the Standardized Precipitation Evapotranspiration Index (SPEI), in the Appendix. These alternative measures are largely insignificant whereas mean precipitation remains significant in most cases.[5] Climate variables refer to the 10-year period prior to the cultivation decision of the household.[6]

X_i includes distance to selling market as well as distance to input markets as major exogenous geographical variables as they affect the value of production negatively due to higher transportation costs. Sichoongwe et al. (2014) have shown that the distance to a market has an important role for farming households, since it allows them, among others, to buy farming inputs and to sell their harvest more easily. Additionally, market distance controls for the possibility that remote areas systematically vary both in customs on land tenure and climate. X_i may also include important household characteristics like household size, size of land cultivated and value of the farm. As these variables are, however, also endogenous to tenure type and input choice, they need to be interpreted carefully. They are therefore excluded in the main regression and only included in additional specifications.

We employ rather few covariates for the regressions mainly because of limited data availability but also because of potential endogeneity issues. Additionally, there is good reason to believe that many variables will be affected by climate (e.g. income, production decisions, wealth, education etc.) so that adding them would additionally create an overcontrolling issue which biases the coefficients of the (purely exogenous)

[5] One should be aware that estimating higher moments (like skewness or kurtosis) suffers from much larger standard errors than estimating mean or standard deviations (Wright and Herrington, 2011), even if bootstrapping techniques are used. Standard errors for estimating kurtosis are typically twice as high as for skewness. Hence, estimates of skewness – and in particular of kurtosis – are highly imprecise when applied to climate data for an interval of 10 or 30 years. One should therefore interpret the results of the analysis on higher moments with caution.

[6] This choice is the result of a trade-off between choosing the more conventional 30-year base for calculating climate conditions and the fact that households might respond to changing climate conditions within the past years. Using a 30-year climate definition gives, however, very similar results.

climate variables (Dell et al., 2014).[7] We estimate Eq. (8) using a univariate probit model.[8] Because the climate data is only available on the district level, we cluster standard errors at the district level in all regressions.

For testing Proposition 1, we model fertilizer use and livestock ownership with the same set of covariates as for Eq. (8). As the amount of fertilizer applied and the livestock owned is a truncated variable (there are no negative values possible), we use a tobit model. We alternatively use a dummy variable if fertilizer is applied or livestock is owned and run a probit model. The probit model might be less prone to measurement errors with respect to the exact quantity of fertilizer applied or livestock owned. Most importantly, using a dummy variable for fertilizer and livestock ownership allows to study the simultaneous adoption of risk management strategies with multivariate probit models (as the sharecropping variables only ranges from zero to one).

Note that we do not include sharecropping as co-variate in the fertilizer and livestock ownership regression as model (Eq. (8) as well as Proposition 3 suggest that sharecropping is endogenous). To account for the possibility that sharecropping and other risk management strategies are employed simultaneously, we estimate the bivariate probit model for sharecropping SC_{idc} and fertilizer use F_{idc}

$$SC_{idc} = \beta_1 C_d + \beta_2 X_i + \mu_c + \varepsilon_{1id} \tag{9}$$

$$F_{idc} = \beta_1 C_d + \beta_2 X_i + \mu_c + \varepsilon_{2id} \tag{10}$$

$$\rho = Cov(\varepsilon_{1id}, \varepsilon_{2id}) \tag{11}$$

The same model is estimated for sharecropping and livestock ownership. This model addresses Proposition 2 as the covariance ρ of the error term is estimated. A positive ρ indicates that households who are sharecroppers are also more likely of using fertilizer, conditional on all other covariates that influence both choices. Thus, sharecropping and fertilizer use can be interpreted as complements, or, sharecropping can be interpreted as substitute to the risk management strategy *no fertilizer use*. A similar reasoning (with opposite signs) holds for livestock ownership.

4.2. Sharecropping

Results concerning sharecropping are presented in Table 2. The first two columns use the full sample of all countries available in the data set, columns (3) and (4) reflect the results only for the countries where more than 5% of households make use of sharecropping: Ghana, Cameroon and South Africa. Columns (1) and (3) use only exogenous control variables from climate and geography. Columns (2) and (4) include household characteristics, which might be endogenous. Country dummies, regression constant and several dummies on non-missing entries in covariates (as discussed in Section 3.2) are included in the regression but not always displayed in the regression tables to save space.

Consistent with Proposition 3, we find that lower precipitation leads in all specifications to a higher likelihood of using sharecropping. The results provide evidence of the 'effort effect' as production becomes more valuable. As sharecropping taxes production, the costs of sharecropping are higher for households living in favorable climatic conditions.

We find, however, no significant impact of rainfall risk on sharecropping. Average precipitation levels are negatively correlated to precipitation risk (correlation coefficient is − 0.44). Hence, regions with low precipitation are also regions with high rainfall variability. Nevertheless, excluding mean precipitation and mean temperature from the regression does not lead to significant coefficients for variability neither (see Table 8 in the Appendix). Likewise, using other indicators of production risk does not change the insignificance of the risk insurance channel (Table 9). These results are also robust when using sharecropping dummy variables at various cut-off points as endogenous variable (see Table 10 in the Appendix).

Given these results, we conclude that there is no clear evidence that sharecropping is more prevalent in regions with higher climate variability. Apparently, the effort effect and other reasons for adopting sharecropping dominate the tenure type decision.[9] Nevertheless, we also cannot completely deny the role of production risk because low precipitation levels might constitute a more relevant indicator of farmers' revenue risk than the second moment of the weather probability distribution.

Besides climate variables, we find evidence that sharecroppers live

Table 2
Area fraction under sharecropping.

	(1) Full sample	(2) Full sample	(3) SC sample	(4) SC sample
Mean Prec	−0.0690***	−0.0681***	−0.0871***	−0.0847***
	(−3.46)	(−3.44)	(−3.41)	(−3.39)
CV Prec	−1.438	−1.552	0.921	0.825
	(−1.45)	(−1.54)	(0.57)	(0.50)
Mean Temp	0.0129	0.0127*	−0.121**	−0.125**
	(0.35)	(0.36)	(−2.11)	(−2.14)
CV Temp	296.1	307.1	−357.4	−354.0
	(1.17)	(1.22)	(−1.21)	(−1.20)
Dist I-Mrkt	0.0809	0.0817	0.120**	0.121**
	(1.34)	(1.34)	(2.24)	(2.30)
Dist I-Mrkt Missing	0.346	0.336	0.781***	0.781***
	(1.50)	(1.46)	(3.16)	(3.21)
Dist O-Mrkt	−0.225***	−0.221***	−0.195***	−0.187***
	(−3.64)	(−3.64)	(−3.94)	(−4.04)
Dist O-Mrkt Missing	−0.640***	−0.638***	−0.995***	−0.987***
	(−3.22)	(−3.23)	(−3.93)	(−3.86)
HH size		0.0105		0.0917
		(0.16)		(1.16)
Land size		0.0113		0.00305
		(0.28)		(0.06)
Farm value		−0.0174		−0.00412
		(−0.59)		(−0.11)
Observations	7661	7622	2078	2067
chi2	200.9	214.1	81.98	100.4
p	6.69e−33	1.94e−32	1.73e−12	7.51e−14
N districts	332	332	106	106
Country dummies	Yes	Yes	Yes	Yes

t statistics in parentheses. Endogenous variable: Fraction of area under sharecropping.
Standard errors clustered at district level. SC Sample includes only countries GHA, CMR, ZAF.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

[7] Ideally, we would also control for risk preferences but the dataset does not contain such information. As climate co-variates are not influenced by risk preferences, leaving them out does not bias our regression results.

[8] Logit as well as complementary log-log models have been used as a robustness check. The results hardly changed by these alternative models. We use the probit model for the univariate case to be consistent with the bivariate probit model used later.

[9] Another possible explanation for the low role of rainfall variability versus rainfall levels could be due to information costs for farmers: Assessing rainfalls levels and their implication for production is easier than assessing rainfall risk. Given limited resources, information and capacity by small-holder farmers, capturing the complete extent of rainfall risk might be challenging. Therefore, farmers' sharecropping decision might be guided stronger by easy-to-assess first-order climate characteristics than by higher moments of the rainfall distribution.

Table 3
Fertilizer use.

	(1) Full sample	(2) Full sample	(3) Full sample	(4) Full sample	(5) SC sample	(6) SC sample
Mean Prec	0.0191	0.0205	0.0965	0.104	−0.00454	−0.0547
	(0.97)	(1.07)	(0.94)	(1.03)	(−0.24)	(−0.46)
CV Prec	1.185*	1.182*	5.789*	5.956*	1.249	5.358
	(1.76)	(1.73)	(1.82)	(1.82)	(0.58)	(0.46)
Mean Temp	−0.137***	−0.136***	−0.738***	−0.701***	0.0280	0.0537
	(−3.98)	(−4.07)	(−4.34)	(−4.26)	(0.53)	(0.18)
CV Temp	303.5*	337.4**	1441.4*	1554.8**	21.91	438.1
	(1.72)	(1.97)	(1.81)	(1.98)	(0.06)	(0.24)
Dist I-Mrkt	0.0874*	0.0795*	0.442*	0.367	−0.0586	−0.305
	(1.87)	(1.75)	(1.84)	(1.62)	(−1.13)	(−1.00)
Dist I-Mrkt Missing	−0.0833	−0.122	−0.402	−0.740	−0.379**	−2.232*
	(−0.47)	(−0.68)	(−0.42)	(−0.76)	(−2.01)	(−1.95)
Dist O-Mrkt	0.0592	0.0638	0.417*	0.394	0.0545	0.523
	(1.26)	(1.35)	(1.70)	(1.63)	(0.90)	(1.50)
Dist O-Mrkt Missing	0.239	0.289*	1.176	1.496*	−0.334	−2.041
	(1.36)	(1.66)	(1.25)	(1.66)	(−1.41)	(−1.33)
HH size		0.264***		1.337***		
		(5.26)		(5.29)		
Land size		0.00605		0.389**		
		(0.18)		(2.20)		
Farm value		0.0150		0.0927		
		(0.68)		(0.86)		
Observations	7749	7696	7749	7696	2086	2086
chi2	111.8	165.0			113.1	
p	1.45e−15	5.10e−23	1.15e−24	1.09e−37	1.46e−18	3.58e−27
N districts	332	332	332	332	106	106
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Model	Probit	Probit	Tobit	Tobit	Probit	Tobit
Endog variable	F Dummy	F Dummy	IHS F Use	IHS F Use	F Dummy	IHS F Use

t statistics in parentheses. Endogenous variable: Fertilizer use.
Standard errors clustered at district level. SC Sample includes only countries GHA, CMR, ZAF.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

more closely to output markets. As these are typically in urban centers, this may indicate that the urban landowners might be the ones who engage in sharecropping contracts with farmers. This is plausible given their higher wealth and, thus, tolerance to volatile harvests. Nevertheless, we cannot test for this hypothesis due to lack of data.

4.3. *Fertilizer*

The results of the regression on fertilizer use are shown in Table 3. Columns (1) and (2) show the results for the probit model (fertilizer use as dummy) and columns (3) and (4) show tobit model results with kg fertilizer applied. Finally, columns (5) and (6) show the probit and the tobit model for the subset of countries with larger prevalence of sharecropping. We again include only strictly exogenous variables as controls while columns except for (2) and (4) where we include (potentially endogenous) the household variables.

The regression model for fertilizer is not consistent with the predictions from the theoretical model. Precipitation levels do not show any impact on fertilizer application, precipitation risk tends to increase fertilizer application (although only at the 10% significance levels and not for the subset of sharecropping countries). Hence, against expectations, precipitations seems to play a minor role for the choice to use fertilizer.

Contrary, temperature levels show a positive and significant impact on fertilizer application: the lower the temperature, the more fertilizer is used. Temperature variability tends also to increase fertilizer use, but results are less clear among the various specifications. Besides climate, household size has a strong and significant positive impact on fertilizer use. The role of distance to markets is again counter-intuitive (despite low significance levels).

The finding on rainfall and temperature risk is also at odds to related literature: Morris et al. (2007), Chapter 4, notes that “Weather-related uncertainty has a negative impact on farmers' incentives to use yield-enhancing inputs (or to use them at recommended levels) because this can be unprofitable in years of poor rainfall”. Dercon and Christiaensen (2011) find that the possibility of low consumption outcomes when harvests fail discourages the use of fertilizer in Ethiopia. Our contrasting results could indicate that the (generally low) fertilizer use in Africa is driven by other considerations than precipitation, be it access to input markets, credit constraints, education, participation in subsidy or voucher schemes, or soil conditions. As we have no data for these factors in our data set, we cannot control for these additional covariates.

4.4. *Livestock ownership*

Table 4 shows the results of the regression on livestock ownership. We include livestock ownership in our empirical model as it is similarly to fertilizer use a choice affecting the risk-return profile of the farm (see discussion at the end of Section 2.2). Owning more livestock reduces agricultural production but also production risk. It has therefore exactly opposite effects than the decision to apply fertilizer.

Columns (1) and (2) show the results for the probit model (livestock ownership as dummy) and columns (3) and (4) show tobit model results with the tropical livestock units the farm owns. Finally, columns (5) and (6) show the probit and the tobit model for the subset of countries with larger prevalence of sharecropping. We again include only strictly exogenous variables as controls while columns except for (2) and (4)

Table 4
Livestock ownership.

	(1) Full sample	(2) Full sample	(3) Full sample	(4) Full sample	(5) SC sample	(6) SC sample
Mean Prec	−0.0273**	−0.0231*	−0.0571***	−0.0461***	−0.0309**	−0.0888***
	(−2.15)	(−1.84)	(−3.24)	(−3.02)	(−2.40)	(−3.42)
CV Prec	1.221*	1.207*	0.0212	0.0782	3.632**	6.439
	(1.69)	(1.74)	(0.03)	(0.14)	(1.98)	(1.61)
Mean Temp	0.00692	0.00386	0.0183	0.0257	0.0367	−0.0739
	(0.23)	(0.12)	(0.60)	(0.88)	(0.96)	(−0.77)
CV Temp	−63.32	−102.4	108.5	64.68	306.8	476.1
	(−0.39)	(−0.67)	(0.53)	(0.42)	(0.97)	(0.72)
Dist I-Mrkt	0.00990	−0.00255	0.0511	0.0191	−0.0173	0.0437
	(0.32)	(−0.08)	(1.40)	(0.55)	(−0.43)	(0.53)
Dist I-Mrkt Missing	0.241*	0.204	0.357**	0.186	0.105	0.177
	(1.91)	(1.54)	(2.43)	(1.43)	(0.54)	(0.53)
Dist O-Mrkt	0.0594*	0.0478	0.153***	0.111***	0.0462	0.239***
	(1.82)	(1.35)	(3.98)	(2.97)	(1.12)	(2.73)
Dist O-Mrkt Missing	0.0547	0.0866	0.269*	0.344**	−0.0211	0.408
	(0.38)	(0.59)	(1.66)	(2.55)	(−0.11)	(1.04)
HH size		0.380***		0.425***		
		(8.60)		(8.41)		
Land size		0.130***		0.399***		
		(4.40)		(10.19)		
Farm value		0.0271		0.0740***		
		(1.50)		(4.32)		
Observations	7682	7646	7645	7609	2037	2020
chi2	476.3	630.3			60.77	
p	1.01e−89	1.08e−117	3.39e−70	6.50e−211	1.63e−08	1.17e−37
N districts	332	332	332	332	106	106
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Model	Probit	Probit	Tobit	Tobit	Probit	Tobit
Endog variable	L Dummy	L Dummy	IHS TLU	IHS TLU	L Dummy	IHS TLU

t statistics in parentheses. Endogenous variable: Livestock ownership.
Standard errors clustered at district level. SC Sample includes only countries GHA, CMR, ZAF.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

where we include (potentially endogenous) the household variables.

Consistent with our theoretical model, we find that livestock ownership is more likely in dry regions. There is also evidence that rainfall risk increases the likelihood of livestock ownership (but not the amount of livestock owned). Hence, livestock ownership is clearly related to climate and more prevalent in dry and drought-risk regions.

Besides climatic factors, distance to selling markets, household size, land size and farm value tend to increase the ownership likelihood as well as the quantity of livestock owned.

4.5. *Substitution between risk strategies*

Farming households apply risk management and risk coping techniques in order to smooth consumption and in particular to avoid very low consumption levels in years of failed harvests. If one way of smoothing consumption is available, other ways will be less likely to be used. The purpose of this section is thus to analyze to what extent these risk adaptation strategies are substitutes, using bivariate probit regressions. Since the effect of sharecropping is of principal interest we test for correlation of sharecropping first with fertilizer use and then with livestock ownership.

Table 5 presents the bivariate probit regression results of the area fraction under sharecropping and fertilizer use (dummy) (1) and sharecropping and livestock ownership (dummy) (2). Magnitude and significance levels are highly consistent to the univariate models in Tables 2, 3 and 4. The new result here appears as the estimated covariance of the error terms, ρ, in the bottom part of the table. It shows a highly significant positive correlation of the error terms for sharecropping and fertilizer use. Thus, sharecropping and fertilizer use are complements[10]: Those who are sharecroppers are more likely use fertilizer as well, conditional on the other covariates.

We find an analogous outcome for livestock ownership and sharecropping: Sharecroppers are less likely to own livestock, conditional on all covariates. The highly significant effect for the livestock ownership model holds also for the subset of sharecropper countries (see Table 11 in the Appendix) and the regression with additional household characteristics (see Table 12 in the Appendix). The significance level for the fertilizer model is less strong. We also perform a multivariate probit model where the choice of being a sharecropper, owning livestock and applying fertilizer is simultaneous (see Table 13 in the Appendix). The results are again in line with the bivariate models as well as the univariate models of the previous section. Moreover, they confirm that fertilizer use and livestock ownership are substitutes with respect to risk management strategies.

Since *reductions* in fertilizer use is a risk management strategy a positive value for ρ implies that sharecropping and fertilizer use are substitutes as risk adaptation strategies. Both results provide additional evidence that sharecropping is a substitute to risk management strategies (livestock ownership, no fertilizer use). Because sharecroppers rely less on risk management, these findings can further be interpreted as evidence that the risk reduction effect dominates the effort reduction effect of those households who use sharecropping (Proposition 2; Fig. 1).

[10] Notice that the reduction of fertilizer use is a risk management strategy, which is a substitute to sharecropping. More sharecropping thus allows for less of the fertilizer reduction strategy. As a consequence sharecropping and fertilizer use are positively correlated.

Table 5
Bivariate probit model on risk management strategies.

	(1) Sharecropping–Fertilizer		(2) Sharecropping–Livestock	
	Sharecropping	Fertilizer	Sharecropping	Livestock
Mean Prec	−0.0681***	0.0168	−0.0664***	−0.0275**
	(−3.45)	(0.86)	(−3.33)	(−2.19)
CV Prec	−1.445	1.148*	−1.588	1.201*
	(−1.45)	(1.71)	(−1.53)	(1.69)
Mean Temp	0.0113	−0.132***	0.0164	0.00426
	(0.31)	(−3.86)	(0.45)	(0.14)
CV Temp	287.8	309.1*	305.3	−71.39
	(1.16)	(1.77)	(1.22)	(−0.45)
Dist I-Mrkt	0.0807	0.0879*	0.0801	0.00746
	(1.36)	(1.86)	(1.32)	(0.24)
Dist I-Mrkt Missing	0.340	−0.0667	0.320	0.269**
	(1.49)	(−0.37)	(1.35)	(2.11)
Dist O-Mrkt	−0.223***	0.0597	−0.225***	0.0600*
	(−3.68)	(1.25)	(−3.68)	(1.82)
Dist O-Mrkt Missing	−0.616***	0.261	−0.683***	0.0477
	(−3.18)	(1.47)	(−3.37)	(0.32)
Observations	7661		7609	
chi2	313.3		664.5	
p	6.05e−46		1.10e−116	
rho	0.0927		−0.137	
p rho	0.0629*		0.0102**	
N districts	332		332	
Country dummies	Yes		Yes	
HH controls	No		No	

t statistics in parentheses.
Standard errors clustered at district level.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

The substitution between sharecropping and fertilizer might have more dramatic consequences for aggregate productivity than the substitution with livestock ownership. While the decision to buy livestock does not affect the quality of crop production directly, the decision to not buy fertilizer reduces the yields. Livestock owners, however, might grow less food crops as some of the area is needed for grazing or growing feed crops. Thus, aggregate food production might also be affected negatively by livestock ownership. Both risk management strategies (livestock ownership, no fertilizer use) can be a rational response of the individual farmer to insure against very low income events. From the point of view of society in which idiosyncratic risks are poorly correlated and 'average out', however, both risk management strategies might incur efficiency losses or lower food production.

5. Conclusion

In this paper, we present comprehensive empirical evidence for eleven African countries that sharecropping tenure is endogenous to climate and related to risk management decisions, particularly fertilizer use and livestock ownership. We confirm the role of the 'effort effect' for sharecropping because sharecropping is less prevalent in regions with high productivity: As sharecropping can be understood as a tax on production, this traditional tenure type would be too expensive in highly productive areas. Additionally, theory predicts that sharecropping should be more common in areas of high production risk as it provides an insurance against crop losses. However, we fail to find empirical evidence that interannual variability of rainfall increases the prevalence of sharecropping. Low levels of precipitation might provide a more relevant indicator of production risk than variance of precipitation or related measures of variability.

Although the evidence of weather variability is poor, we find that sharecropping clearly interacts with other risk management decisions, particularly, the choice to apply fertilizer or to hold livestock. Sharecroppers tend to apply more fertilizer and own less livestock. This provides support for the theoretical hypothesis that sharecropping, livestock ownership and (reduced) fertilizer use serve partially as substitutes with respect to risk adaption options. Our empirical results also suggest that the risk reduction effect from sharecropping dominates the effort effect for sharecropping households. The partial insurance provided by sharecropping might thus provide farmers with the means to reduce the use of other risk coping and, importantly, risk management techniques. Based on this evidence we conclude that sharecropping, as a risk coping mechanisms available even in countries with weak institutions, has the potential of increasing efficiency in African agriculture.

As climate change is likely to increase climate variability and change precipitation levels, agriculture is likely to become more risky as well. When farmers adapt to this risk in the form of risk management, agricultural productivity might decrease beyond the direct effect of the changed climate. This will have obvious negative consequences for food security. Governments will thus need a precise understanding of risk management strategies of farmers. This paper points out the role of land tenure in risk management and the role of substitution between different risk adaption strategies in general. Some forms of land tenure, like sharecropping, involve less risk for farmers, while others, like renting land, involve more risk. Governments which are unable to offer sophisticated risk coping strategies (like formal insurance) for farmers could thus consider encouraging land tenure systems like sharecropping as a way of increasing the resilience of agricultural production.

The paper supplies some first empirical support to the novel theoretical prediction that project choice is an important component in understanding the investment efficiency of sharecropping in contrast to other forms of land tenure. This idea could thus become a promising avenue for refining the understanding of risk behavior in agriculture. As land reform in Africa is the subject of an active and ongoing debate (Bezu and Holden, 2014; Lipton, 2009; Lovo, 2016) and first results show that it is not as effective as hoped (Deininger et al., 2008; Sitko et al., 2014) a better understanding of the benefits of sharecropping could have substantial political relevance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Proof of Proposition 3. We first calculate Ω_μ. With the envelope theorem,

$$\Omega_\mu = \frac{dCE(\Pi_{SC}(F_{SC}^*))}{d\mu} = \frac{\partial CE(\Pi_{SC}))}{\partial\mu}_{|F_{SC}=F_{SC}^*} = sg(F_{SC}^*) \tag{12}$$

As $\Omega_\mu > 0$ a sharecropping farmer as well as a renter farmer (where $s = 1$) always benefits from higher mean productivity μ.
Next, we calculate

$$\frac{d\Omega_\mu}{ds} = sg'(\cdot)\frac{dF(\cdot)}{ds} + g(\cdot) \tag{13}$$

Substituting $\frac{dF(\cdot)}{ds}$ from the proof of Proposition 2 gives after simplification

$$\frac{d\Omega_\mu}{ds} = -\frac{(g(\cdot)g''(\cdot) - (g'(\cdot))^2)(\mu - g(\cdot)\eta s\sigma^2)}{g''(\cdot)(s\eta\sigma^2 g(\cdot) - \mu) + s\eta\sigma^2(g'(\cdot))^2} \tag{14}$$

As $\mu > g(\cdot)\eta s\sigma^2$ for an interior solution and $g' > 0, g'' < 0$, it follows that $\frac{d\Omega_\mu}{ds} > 0$.
For the impact of production risk, we proceed similarly,

$$\Omega_{\sigma^2} = \frac{dCE(\Pi_{SC}(F_{SC}^*))}{d\sigma^2} = \frac{\partial CE(\Pi_{SC})}{\partial\sigma^2}_{|F_{SC}=F_{SC}^*} = -\frac{1}{2}\eta s^2 g(F_{SC}^*)^2 \tag{15}$$

As $\Omega_{\sigma^2} < 0$ a sharecropping farmer as well as a renter farmer (where $s = 1$) always looses from higher production risk σ^2.
Calculating $\frac{d\Omega_{\sigma^2}}{ds} = -\eta sg(\cdot)\left(sg'(\cdot)\frac{dF(\cdot)}{ds} + g(\cdot)\right)$ turns out to be $\frac{d\Omega_{\sigma^2}}{ds} = -\eta sg(\cdot)\frac{d\Omega_\mu}{ds}$ and has therefore the opposite sign to Eq. (4). Hence, $\frac{d\Omega_{\sigma^2}}{ds} < 0$.

Appendix B. Tables

Table 6
Number observations (household and district level).

Country	Number of districts	Obs. per district			Total N
		Mean	Min	Max	
Burkina Faso	48	21.7	3	30	1043
Cameroon	30	25.6	17	50	769
Ethiopia	32	27.0	9	60	864
Ghana	59	13.8	1	24	814
Niger	30	28.5	23	30	855
Senegal	62	14.5	3	20	896
South Africa	17	8.5	1	35	144
Zambia	30	29.9	18	48	897
Zimbabwe	23	29.9	14	68	687
Sum	331				6969
Mean	36,8	22.2	9.9	40.6	774.3

Table 7
Spatial variability of climate variables within countries.

Country	Variation (CV) between districts within country		
	Temperature (annual mean)	Precipitation (annual mean)	Precipitation (CV over years)
Burkina Faso	0,002	0,221	0,192
Cameroon	0,006	0,230	0,225
Ethiopia	0,011	0,348	0,253
Ghana	0,002	0,097	0,240
Niger	0,002	0,264	0,255
Senegal	0,004	0,418	0,468
South Africa	0,007	0,409	0,328
Zambia	0,003	0,215	0,233
Zimbabwe	0,005	0,204	0,094

Appendix C. Robustness checks

Table 8
Sharecropping – various specifications of climate risk variables (1).

	(1) Full sample	(2) Full sample	(3) Full sample	(4) Full sample	(5) SC sample	(6) SC sample	(7) SC sample	(8) SC sample	(9) sharecrop_A_7	(10) sharecrop_A_8
Mean Prec	−0.0690***	−0.0694***		−0.0617***	−0.0642***	−0.0871***	−0.0866***		−0.106***	−0.108***
	(−3.46)	(−3.64)		(−3.01)	(−3.27)	(−3.41)	(−3.43)		(−3.64)	(−3.68)
CV Prec	−1.438		−0.815			0.921		0.812		
	(−1.45)		(−0.92)			(0.57)		(0.46)		
SD Prec				−0.0527					0.222	
				(−0.48)					(1.31)	
Var Prec					−0.00888					0.0803
					(−0.48)					(1.60)
Mean Temp	0.0129	0.00594		0.0102	0.0107*	−0.121**	−0.107**		−0.123**	−0.128**
	(0.35)	(0.17)		(0.28)	(0.30)	(−2.11)	(−1.99)		(−2.21)	(−2.26)
CV Temp	296.1		348.7			−357.4		−128.0		
	(1.17)		(1.25)			(−1.21)		(−0.39)		
SD Temp				0.901					−1.270	
				(0.99)					(−1.15)	
Var Temp					1.023					−1.383
					(0.99)					(−1.09)
Observations	7661	7661	7661	7661	7661	2078	2078	2078	2078	2078
chi2	200.9	174.1	205.6	193.0	196.7	81.98	74.41	69.01	82.02	83.38
p	6.69e−33	1.29e−28	5.97e−35	2.48e−31	4.56e−32	1.73e−12	6.20e−12	6.88e−11	1.70e−12	9.33e−13
N districts	332	332	332	332	332	106	106	106	106	106
Cntry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	No	No	No	No	No	No	No	No	No	No

t statistics in parentheses.
Endogenous variable: Fraction of area under sharecropping.
Standard errors clustered at district level. SC Sample includes only countries GHA, CMR, ZAF.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 9
Sharecropping – various specifications of climate risk variables (2).

	(1) Full sample	(2) Full sample	(3) Full sample	(4) Full sample	(5) SC sample	(6) SC sample	(7) SC sample	(8) SC sample
Mean Prec			−0.0672***	−0.0709***			−0.0841***	−0.0840***
			(−2.87)	(−3.11)			(−3.13)	(−3.15)
SPEI	0.0532	0.0499			0.0911	0.102		
	(0.83)	(0.74)			(0.81)	(0.94)		
CV Prec	−0.854		−1.584		1.937		0.104	
	(−0.97)		(−1.25)		(0.96)		(0.05)	
Skewness Prec			0.0374	−0.0811			0.163	0.171
			(0.20)	(−0.60)			(0.60)	(0.85)
Mean Temp	0.0499		0.0116	0.0144*	−0.0556		−0.133**	−0.133**
	(1.39)		(0.32)	(0.40)	(−0.80)		(−2.22)	(−2.22)
CV Temp	392.7		299.1	265.0	−274.6		−311.7	−305.3
	(1.45)		(1.18)	(0.97)	(−0.77)		(−1.06)	(−0.95)
Dist I-Mrkt	0.0925	0.100	0.0801	0.0838	0.122**	0.114**	0.114**	0.114**
	(1.44)	(1.53)	(1.33)	(1.37)	(2.19)	(2.11)	(2.06)	(2.11)
Dist O-Mrkt	−0.211***	−0.222***	−0.224***	−0.227***	−0.155***	−0.151***	−0.194***	−0.193***
	(−3.32)	(−3.42)	(−3.64)	(−3.62)	(−3.19)	(−3.18)	(−3.88)	(−3.88)
Observations	7661	7661	7661	7661	2078	2078	2078	2078
chi2	203.5	172.9	201.2	194.4	71.66	62.99	84.02	80.01
p	2.03e−33	6.29e−29	1.93e−32	1.33e−31	1.56e−10	3.54e−10	1.92e−12	4.11e−12
N districts	332	332	332	332	106	106	106	106
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses. Endogenous variable: Fraction of area under sharecropping.
Standard errors clustered at district level. SC Sample includes only countries GHA, CMR, ZAF.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 10
Sharecropping – various specifications of the endogenous variable.

	(1) Full sample	(2) Full sample	(3) Full sample	(4) Full sample	(5) Full sample	(6) SC sample	(7) SC sample	(8) SC sample	(9) SC sample	(10) SC sample
Mean Prec	−0.0690***	−0.0680***	−0.0718***	−0.0958***	−0.105***	−0.0871***	−0.0864***	−0.0927***	−0.134***	−0.151***
	(−3.46)	(−3.45)	(−3.56)	(−4.43)	(−4.87)	(−3.41)	(−3.40)	(−3.55)	(−3.97)	(−3.87)
CV Prec	−1.438	−1.382	−2.158**	−2.074*	−2.162*	0.921	0.960	−0.644	−1.036	−1.170
	(−1.45)	(−1.42)	(−2.08)	(−1.82)	(−1.80)	(0.57)	(0.60)	(−0.40)	(−0.62)	(−0.66)
Mean Temp	0.0129	0.00982	0.0106	0.0174	0.0137	−0.121**	−0.120**	−0.104*	−0.114	−0.146*
	(0.35)	(0.28)	(0.27)	(0.39)	(0.29)	(−2.11)	(−2.09)	(−1.67)	(−1.53)	(−1.74)
CV Temp	296.1	296.0	258.8	304.3	222.0	−357.4	−324.6	−242.3	−219.2	−194.9
	(1.17)	(1.22)	(0.95)	(1.08)	(0.84)	(−1.21)	(−1.15)	(−0.91)	(−0.86)	(−0.75)
Observations	7661	7749	7749	7749	7749	2078	2086	2086	2086	2086
chi2	200.9	202.8	188.4	162.8	160.2	81.98	82.13	53.65	50.17	43.72
p	6.69e−33	2.77e−33	2.05e−30	2.38e−25	7.48e−25	1.73e−12	1.62e−12	0.000000315	0.00000130	0.0000170
N districts	332	332	332	332	332	106	106	106	106	106
Cntry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	No	No	No	No	No	No	No	No	No	No
Engog variable	Continous	SC > 0.00	SC > 0.33	SC > 0.50	SC > 0.66	Continous	SC > 0.00	SC > 0.33	SC > 0.50	SC > 0.66

t statistics in parentheses.
Standard errors clustered at district level. SC Sample includes only countries GHA, CMR, ZAF.
Endogenous variable is =1 (dummy) if sharecropping fraction is above threshold indicated in last row of table, except (1) and (6) (continous).
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 11
Bivariate probit model on risk management strategies (SC sample).

	(1) Sharecropping–Fertilizer		(2) Sharecropping–Livestock	
	Sharecropping	Fertilizer	Sharecropping	Livestock
Mean Prec	−0.0874***	−0.00663	−0.0845***	−0.0308**
	(−3.41)	(−0.35)	(−3.32)	(−2.44)
CV Prec	0.891	1.141	0.255	3.498*
	(0.55)	(0.53)	(0.14)	(1.94)
Mean Temp	−0.120**	0.0258	−0.111*	0.0392
	(−2.11)	(0.49)	(−1.91)	(1.02)
CV Temp	−365.8	−33.64	−358.6	321.8
	(−1.25)	(−0.09)	(−1.16)	(1.04)
Dist I-Mrkt	0.117**	−0.0604	0.119**	−0.0186
	(2.21)	(−1.15)	(2.21)	(−0.46)
Dist O-Mrkt	−0.194***	0.0486	−0.201***	0.0456
	(−3.95)	(0.80)	(−4.11)	(1.09)
Observations	2078		2029	
chi2	203.1		136.8	
p	2.60e−30		8.91e−18	
rho	0.0614		−0.134	
p rho	0.2767		0.0494**	
N districts	106		106	
Country dummies	Yes		Yes	
HH controls	No		No	

t statistics in parentheses.
Standard errors clustered at district level.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 12
Bivariate probit model on risk management strategies (with HH controls).

	(1) Sharecropping–Fertilizer		(2) Sharecropping–Livestock	
	Sharecropping	Fertilizer	Sharecropping	Livestock
Mean Prec	−0.0673***	0.0185	−0.0655***	−0.0223*
	(−3.44)	(0.97)	(−3.31)	(−1.79)
CV Prec	−1.551	1.163*	−1.750*	1.196*
	(−1.53)	(1.70)	(−1.66)	(1.76)
Mean Temp	0.0109	−0.133***	0.0161	0.000735
	(0.31)	(−4.00)	(0.46)	(0.02)
CV Temp	299.6	327.4*	317.0**	−103.0
	(1.22)	(1.91)	(1.27)	(−0.69)
Dist I-Mrkt	0.0810	0.0805*	0.0816	−0.00456
	(1.36)	(1.75)	(1.34)	(−0.14)
Dist O-Mrkt	−0.220***	0.0641	−0.221***	0.0476
	(−3.68)	(1.34)	(−3.69)	(1.35)
HH size	0.00899	0.264***	0.0110	0.378***
	(0.13)	(5.26)	(0.16)	(8.50)
Land size	0.0141	−0.00231	0.00641	0.137***
	(0.35)	(−0.06)	(0.16)	(4.57)
Farm value	−0.0156	0.0198	−0.0204	0.0224
	(−0.53)	(0.87)	(−0.69)	(1.22)
Observations	7622		7573	
chi2	425.7		892.8	
p	5.50e−62		4.94e−156	
rho	0.0929		−0.140	
p rho	0.0581*		0.0082***	
N districts	332		332	
Country dummies	Yes		Yes	
HH controls	Yes		Yes	

t statistics in parentheses.
Standard errors clustered at district level.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 13
Multivariate probit model on risk management strategies.

	Sharecropper (1)	Fertilizer (2)	Livestock (3)
Mean Prec	−0.0919***	0.0181	−0.0263**
	(−4.29)	(0.92)	(−2.06)
CV Prec	−2.052*	1.192*	1.207*
	(−1.75)	(1.77)	(1.68)
Mean Temp	0.0164	−0.137***	0.00570
	(0.36)	(−3.96)	(0.19)
CV Temp	299.3	310.9*	−63.13
	(1.08)	(1.76)	(−0.39)
Dist I-Mrkt Missing	0.229	−0.0601	0.238*
	(0.91)	(−0.34)	(1.89)
Dist O-Mrkt Missing	−0.548***	0.260	0.0622
	(−2.58)	(1.46)	(0.43)
Dist I-Mrkt	0.0692	0.0895*	0.0111
	(1.15)	(1.92)	(0.35)
Dist O-Mrkt	−0.250***	0.0567	0.0580*
	(−4.21)	(1.20)	(1.78)
Observations	7682		
chi2	775.7		
p	1.93e−128		
$\rho_{2,1}$	0.1171**		
$\rho_{3,1}$	−0.1623***		
$\rho_{3,2}$	0.1139***		
N districts	332		
Country dummies	Yes		
HH controls	No		

t statistics in parentheses.
Standard errors clustered at district level.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

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