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Centre for Land Tenure Studies Working Paper 05/20
ISBN: 978-82-7490-288-6

Can rainfall shocks enhance access to rented land? Evidence from Malawi

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Abstract

This study investigates whether and to what extent rainfall shocks recurring in Sub-Saharan Africa, that have been associated with distress land rentals, enhance short-term and medium-term access to rented land by tenant households. Tenant households' rental decisions are modeled in the state-contingent framework with renting-in of land as a risky input choice. Our data is from three rounds of LSMS data from Malawi used to construct a balanced household panel, combined with corresponding district rainfall data that are used to generate seasonal district-wise rainfall shock variables. Panel probit and Tobit models controlling for unobserved heterogeneity were used. Regional heterogeneities were revealed. The results from the Central Region of Malawi, where land rental markets are most active, indicates that the one-year and two-year lagged downside rainfall shocks help tenant households accessing land not only the first year after a rainfall shock but also in the following years. For the more land constrained Southern Region of Malawi, with less prevalence of land rental markets, we observed that the two-year lagged downside rainfall shock is associated with less access to rented land. These results reveal surprising intertemporal and regional variations that are important for policy discussions and lessons on land rental markets amidst recurring rainfall shocks in SSA.

Keywords: Rainfall shocks; Land rental markets; State-contingent framework; Malawi.

JEL Codes: Q51; Q15

1. Introduction

The rainfall variations associated with climate change continue to expose farm households to production and consumption shocks in Sub-Saharan Africa (Asfaw et al., 2019; IPCC, 2014). The upside and downside variations that happen within and across production seasons are constantly affecting the decisions of farm households in this region. These are farm households that mainly depend on rainfed production while having poor access to weather-related information (Cooper et al., 2008). Such households also pursue food self-sufficiency objectives considering market imperfections, limited access to credit and insurance, limited off-farm opportunities and the growing land scarcity challenges in the region (Dercon, 2002; Holden et al., 2010; Jayne et al., 2014). When confronted with rainfall-related shocks, literature shows that the farm households manage or cope with such shocks using different strategies based on their resource endowments (land, labour and assets), and these strategies are evolving (Alobo Loison, 2015; Asfaw et al., 2019; Cooper et al., 2008; Dercon, 2002).

One way that farm households in Sub-Saharan Africa (SSA) are responding to the challenge of access and use of productive resources is through participation in the land rental markets that are developing in this region. The land markets theoretically develop as an efficiency-enhancing mechanism in the allocation of productive resources, amidst imperfections in the non-land factor markets (de Janvry et al., 2002; Holden et al., 2010). Although the literature shows that these land markets are thin, spatially dispersed (due to the immobility of land) and characterised by high transaction costs, their impact is positive on household income and welfare (Holden et al., 2010; Ricker-Gilbert & Chamberlin, 2018; Ricker-Gilbert et al., 2019). Empirical evidence also shows that farm households use these markets as a coping strategy in the form of distress land rentals after downside rainfall shocks (Gebregziabher & Holden, 2011; Kusunose & Lybbert, 2014).

Despite literature indicating that farm households are utilising the land rental markets as a coping strategy *ex-post* the rainfall shocks, the corresponding effect on the uptake of the supplied land has not been subject to much research in the land rental market literature in Africa. This is in addition to the general limited empirical evidence on how rainfall variations or shocks recurring in SSA are influencing households' decisions to rent-in farmland. We are only aware of the study by Kusunose and Lybbert (2014) in Morocco that assessed how limited access to credit affect who can rent-in or rent-out farmland after a drought year. However, the study mainly focused on credit constraints and not the rainfall variations or shock effects on tenant households' renting behaviour. Thus, to our knowledge, there is limited empirical evidence on how rainfall variations or shocks that are recurring in SSA are influencing the uptake of rented land. If the downside rainfall shocks are shifting the supply of land in the rental markets, we consider understanding the extent to which tenant households are utilizing these opportunities as a missing link in the land rental market literature in SSA. Therefore, we assess whether lagged rainfall shocks are kick-starting the land rental markets by shifting supply and hence affecting demand for rented land, observed from the tenant households' side.

In line with Quiggin and Chambers (2006) the decision to rent-in the land is state-contingent but also a risky input choice because tenant households make such a decision and cover costs before the state of nature is revealed. Thus, previous rainfall shocks that shift supply should be important for tenant household decisions in the subsequent years. With a production shock, farm households can experience the associated effect in the immediate future or beyond a single production season. Thus, the rainfall shocks that shift the supply of rented land could also result in both immediate and lasting effects beyond one production season among tenant households.

Considering that land rental markets that are developing in SSA are thin and spatially dispersed, access to market information after the shocks should be key for participating in the subsequent years. Fafchamps (2004) indicated that overcoming the first hurdle of entering a factor market in SSA increases the likelihood of re-entering the market. This is mainly from reduced access to market information and contract formulation costs that are based on trust and reputation. Following this literature, we use previous participation[1] in the land rental markets to control for transaction costs related to accessing market information or contract formulation. That is, tenant households with experience in the market should face relatively lower transaction costs compared to new entrants (Gebru et al., 2019; Kusunose & Lybbert, 2014). This is also a possible entry barrier that we should control for when assessing the long-term rainfall shock effects in the land rental markets. To our knowledge, our study is the first to present such empirical evidence in SSA, which is key for initiating policy discussions on land rental markets in this region.

[1] Our analysis uses participation in the reference production season for each survey rounds that have a three-year production season gaps between the three survey rounds. We did not use the one-year lag participation variables as this was not observed in the data. However, the observed participation in the previous survey round should account for the lag entry and extent of participation across the survey years.

Our analysis uses rainfall data combined with household balanced panel data from Malawi, a country in SSA. The household data is from the Malawi Living Standards Measurement Surveys (LSMS) conducted in 2010, 2013 and 2016 from which we constructed a three-year balanced panel. The data from Malawi is suitable for this context because the country is an agricultural-based economy that heavily depends on a unimodal rainfall pattern for income and food security (Government of Malawi, 2016b). Over the last two decades, the country has been experiencing not only frequent droughts but also floods (Government of Malawi, 2016a; Katengeza et al., 2018). Land rental markets are also evolving as land scarcity challenges increase in Malawi (Chamberlin & Ricker-Gilbert, 2016; Ricker-Gilbert et al., 2014).

We measure rainfall shock as the district-level deviation of the total amount of rainfall observed in the early to mid-season periods (x_i) from their 10-year period[2] mean $(\bar{x})$ values, i.e. $(x_i - \bar{x})$. See the maps of Malawi in Appendix A, Figures A1 and A2 for the regional and district boundaries plus weather stations across the country. The district-level deviation variable is an indicator of rainfall shocks that are covariate and affect many households at the same time within the district. The variable captures the within-region and not the within-district rainfall shock effects, hence it may not capture all the relevant rainfall variations or shocks at the household level. However, such district level and the within-region variations should capture the farm household heterogeneity that is relevant for assessing the effect of rainfall shocks on participation in the land rental markets.

Our assessment of rainfall shock effects mainly focuses on the early to mid-season deviations in each production season. We chose early to mid-season periods based on the fact that early-season deviations can affect input use and crop germination while mid-season deviations can affect crop development and production compared to the late-season deviations that coincide with crop harvesting period (Government of Malawi, 2012). Thus, early to mid-season deviations should account for previous production shocks that can push other households to rent out the land hence offering the opportunity for tenant households to rent-in the land in subsequent years. In the Malawi context, we constructed the early-season period to correspond to the first three months (October to December) while the mid-season corresponds to the next two months (January and February) of the production season. We based this categorization on a unimodal rainfall pattern that goes from November to April. We included October in the

[2] We generated the 10-year mean by calculating the average for the seasonal variations for the past 10 years in the context of Malawi production seasons (2005/2006 to 2016/2017 production seasons).

early-season as a preparation month and also the time some areas in the country receive early rains but not effective planting rains (Government of Malawi, 2012).

In addition to assessing the early to mid-season deviations, our analysis split the rainfall deviations into downside (absolute negative) and upside (positive) values. The absolute downside deviation values should capture the implicit shift in supply reported in the literature as a driver of distress rentals among poor landlords (Gebregziabher & Holden, 2011). By including the upside deviations, we go beyond only focusing on the downside effect that is mostly reported in SSA. Thus, we propose that an increase in either lag downside or upside absolute rainfall deviation values, that happens early to mid-season increases entry and extent of tenant households' participation in the land rental markets. Our analysis uses the household random effects and dynamic random effects estimation methods that control for unobserved heterogeneity in household decisions plus unobservable initial market entry conditions.

The rest of the paper proceeds as follows. The next section presents a conceptual framework underlying the recursive state-contingent decision in the land rental market before stating the specific hypotheses. We discuss the data and estimation methods in section three and present the descriptive statistics in section four. In section five, we present and discuss the results before concluding the paper in section six.

2. Conceptual framework and hypotheses

A farm household whose objective is to maximize utility based on their beliefs about the likelihoods and production outcomes under alternative states of nature make state-contingent input decisions accordingly (Quiggin & Chambers, 2006). Farm households make *ex-ante* input decisions before weather conditions are revealed based on their beliefs, expectations, preferences and consumption needs that are implicit in such decisions (Dercon & Christiaensen, 2011; Quiggin & Chambers, 2006). In an intertemporal setting with sequential decisions, households are repeatedly engaged in these decision processes and adjust their beliefs based on past experiences about states of nature and their past decisions outcome. Households acquire experience that shapes their subjective production risk assessment, input choices and consumption decisions, *ex-ante* and *ex-post* the production period. Land rental markets open an additional adjustment opportunity across farms in terms of balancing land and non-land resource use. Overall, the state-contingent framework indicates that household input use is decided before the state of nature is revealed to the farmer (Quiggin & Chambers, 2006).

According to Holden and Quiggin (2017) "any increase in exogenous risk, defined as the increase in the probability of a less favourable state of nature like drought or flood, leads to an increased share of risk substituting inputs in the vector of non-stochastic input mix for a given expected output". That is, in a state-contingent decision, farm households are more likely to allocate non-stochastic inputs like owned land in a way that reduces the production risks depending on their endowment and needs. However, renting-in the land is a state-contingent but risky decision because households have to invest their wealth in the decision before the state of nature is revealed compared to using only owned land. Dercon and Christiaensen (2011) further indicated that farm households make these state-contingent and risky input decisions based on expected consumption needs as an *ex-ante* risk management strategy to hedge against *ex-post* consumption shocks. Overall, the state-contingent decisions go beyond risk aversion to include risk-reducing mechanisms when the probability of accessing the input credit, insurance and consumer credit is low, as experienced in most countries in SSA (Dercon & Christiaensen, 2011; Holden & Quiggin, 2017). Figure 1 below summarizes the recursive state-contingent decisions mainly for tenant household renting-in the land over time.

In Figure 1, we consider a rural farm household that heavily depends on a varying unimodal rainfall pattern, like in Malawi. Such a household is endowed with farmland ($\bar{A}$), labour ($\bar{L}$) and capital (K) factors of production. Markets for land and labour are non-missing but with imperfections (Binswanger & Rosenzweig, 1986; Holden et al., 2010). We assume that land is scarce and that there are limited off-farm opportunities except for seasonal casual labour on other farms within the communities. Land constrained households may rent-in more land to ensure food self-sufficiency, increase income or production utility. We also assume that downside rainfall shocks that lead to distress rentals result in favourable rental prices for tenant households. However, this effect does not affect transaction costs related to market information or contract formulation because of localised and not well-integrated land rental markets.

From Figure 1, the shaded arrows define the main pathways in which lag rainfall deviations can affect tenant household participation in the land rental markets. The figure shows that the initial year or the two-year lagged upside or downside deviations that can affect the household consumption needs, can push farm households to cope with such shocks by either renting out the land in distress or trading the non-land factors (assets and labour). Thus, in the subsequent year (one-year lag), the farm households who are capable of smoothing consumption, and with the ability to increase the operational farmland can rent-in the land or increase the amount of rented land. Such a decision is state-contingent where crop outcome is known after the state of nature is revealed.

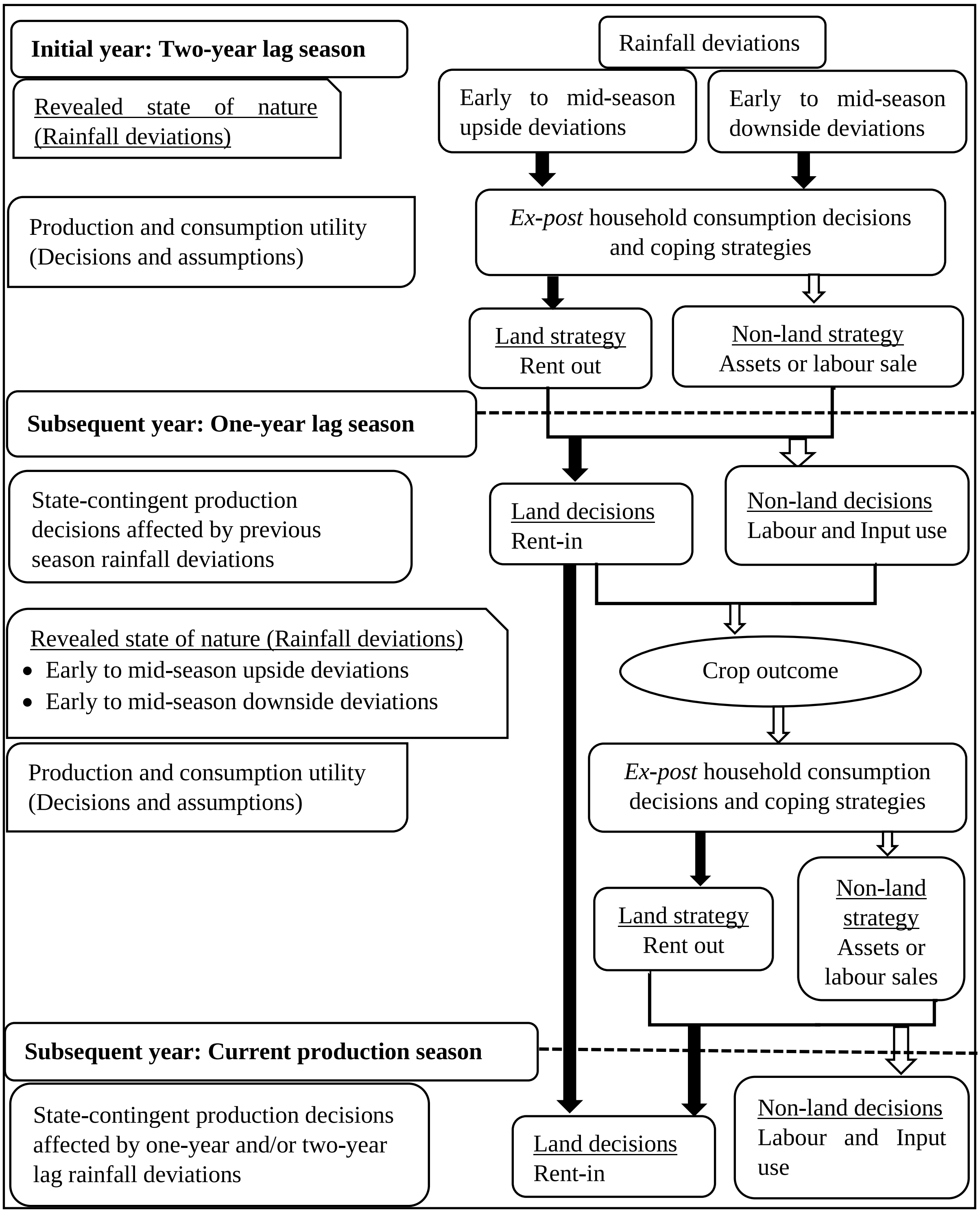

Figure 1: Recursive household state-contingent decisions for renting-in the land over time

Depending on the crop outcome after the state of nature is revealed in the subsequent year, households that are not able to cope with consumption shocks will again engage in either renting out the land or trading non-land factors. Again, this allows potential tenants to rent-in the land in the subsequent year (current production season), implying the recursive state-contingent decisions that households continue to engage in overtime. Apart from the year to year effect, long-term shock effects beyond one production season can also push potential tenant households to re-enter the market from earlier participation in the markets. This implies that rainfall shocks can have both immediate and long-term effects in the land rental markets for tenant households, conditional on the supply. Therefore, we hypothesize that;

H1: One-year lag downside rainfall deviations (early to mid-season) increase entry and extent of tenant household participation in land rental markets in the subsequent year.

H2. One-year lag upside rainfall deviations (early to mid-season) increase entry and extent of subsequent year tenant household participation in land rental markets.

H3. Rainfall shocks trigger more land rental market participation beyond the immediate effect in the following year.

If one-year lag rainfall deviations push tenant households' over the first hurdle of entering the market, such households are more likely to re-enter beyond the immediate effect from gaining the experience in the market.

3. Data and estimation methods

Our data is from three rounds of the Malawi Living Standards Measurement Surveys (LSMS). The survey periods were from (i) March 2010 to March 2011; (ii) April to December 2013; and (iii) April 2016 to April 2017. The survey data collection period coincides with the end of production period for a unimodal rainfall season in Malawi (November to April season). Thus, the reference production seasons for each survey round in our data were (i) November 2009 to April 2010; (ii) November 2012 to April 2013; and (iii) November 2015 to April 2016[3]. In 2010, the total number of surveyed households was 1,619 that we used to construct a balanced panel of 1,480 households. This represented an 8.6 percent attrition rate which we used to test for attrition bias in our results[4].

[3] For the survey periods that crossed to the next production season like in 2010 and 2016 rounds, we verified that the reference production period remained the same for all households. For instance, if a household was interviewed in April 2017, the reference period remained 2015-16 production season and not 2016-17 production season.

[4] We did not observe any significant attrition bias effects in our results based on including the inverse mills ratio in our estimations. The results with inverse mills ratio are available from the authors upon request.

For the rainfall variables, we used monthly rainfall data (accessed in millimetre) from October 2006 to April 2017 observed at the district level weather stations across Malawi (Appendix A, Figure A2). We sourced the data upon official request to the Department of Climate Change and Metrological Services in Malawi (www.metmalawi.gov.mw). In Malawi, the administrative boundaries are categorised as national, regional, district and community. In total, the country has 28 districts which are grouped into 3 regions (see Figures A1 and A2 in Appendix A) that vary in rainfall pattern, population density and land distribution (Chinsinga, 2011; Government of Malawi, 2018). Thus, our focus in this paper is on district-level rainfall deviations that capture the within-region rainfall shock effects. For the early to mid-season lag rainfall deviations, we use the period from October to February in the previous seasons for each reference production period in the survey rounds as mentioned above. We further used the decimetre (dm) as a unit of measure[5] in our analysis to have suitable coefficient sizes in our estimated models.

As a risky state-contingent input decision subject to random states of nature (rainfall shocks), observable and unobservable heterogeneity affect tenant household participation decisions. Thus, we specify the decision to participate in the land rental markets (R_{jt}) as reduced functional form models of stochastic rainfall variables in equations (1) and (2) below. The equations are for both entry and extent of participation hence the parameter (R_{jt}) is for either the probit or censored Tobit models. Our study applies both the Correlated Random Effects (CRE) and the Dynamic Random Effects (DRE) probit and Tobit models to control for time-invariant unobservable household and farm heterogeneity because we have limited dependent variables (Wooldridge, 2010). The CRE approach in equation (1), first suggested by Mundlak (1978) and Chamberlain (1982), is equivalent to using the household fixed effect in models with continuous dependent variables. The DRE model specification in equation (2) is important for assessing the intertemporal rainfall shock effects because the model can also control for initial unobserved conditions in the decision or dependent variable. This specification requires balance panel data (Wooldridge, 2010) and hence the use of balanced panel data in our analyses.

The parameters of interest in the equations are λ and ϱ for lag downside *(N)* and lag upside *(H)* absolute values of rainfall deviations from means that happens from early to mid-season, respectively. After a pooled analysis we noticed significant regional differences in the data, hence instead of just controlling for these differences with regional dummies, we found that

[5] We multiplied the millimetres by 0.01 to obtain the decimetre units (1dm = 100 millimetres)

region-wise models gave better results and revealed important regional differences. However, based on the constructed household balanced panel data from the LSMS, the number of households renting in the land in the Northern Region was too low to do meaningful analysis[6]. Thus, our analysis only focused on the Central and Southern Regions of Malawi. Apart from dropping the Northern Region due to data limitations, the Central and Southern Regions also differ in population density, agro-ecological zones and land distribution which we consider important for assessing region-wise models compared to a pooled analysis (Chinsinga, 2011; Government of Malawi, 2018; Kanyama-Phiri et al., 2000). Thus, our analysis runs separate models for the Central and Southern Regions of Malawi to obtain region-specific coefficients. The superscript (*k*) in the equations is either 1 for Central Region or 2 for Southern Region for both probit and Tobit models.

CRE-models by region:

$$R_{jt}{}^{k} = \alpha + \lambda N_{t-1} + \varrho H_{t-1} + \gamma \bar{X}_j + \pi \hat{X}_j + \bar{Z}_j \beta + \hat{Z}_j \delta + \tau + \mu_j + \varepsilon_{jt} \quad (1)$$

Dynamic RE-models by region:

$$R_{jt}{}^{k} = \alpha + \lambda N_{t-1} + \varrho H_{t-1} + \varphi X_{jt} + \phi Z_{jt} + \tau + R_{jt-n} \rho + \mu_j + \varepsilon_{jt} \quad (2)$$

Based on CRE specifications, equation (1) controls for the means ($\bar{X}_j, \bar{Z}_j$) and deviations from the mean ($\hat{X}_j, \hat{Z}_j$) of farm and households characteristics while the DRE model specification controls for the observed farm (X_{jt}) and household (z_{jt}) characteristics. From both equations (1) and (2), the τ is for time (year) dummies and the $\mu_j + \varepsilon_{jt}$ is the error term. We assume the error term to be additive in line with the specified random effects models (Wooldridge, 2010). The variable μ_j is the time constant unobserved heterogeneity at the household level and the variable ε_{jt} is the idiosyncratic error that is independent and identically distributed. This specification applies to both the CRE and the DRE probit and Tobit models. However, the DRE model has a further specification for the variable μ_j in the error term.

According to Wooldridge (2010), the μ_j in the dynamic random effects (DRE) models with limited dependent variable is also additive and given as $\mu_j = \psi + \alpha_0 R_{j0} + z_j \alpha_1 + \epsilon_j$. Where ψ is a constant and the variable ϵ_j is the error term independent of $R_{j0} + z_j$ and specified as

[6] Only 11 households out of 525 sample (2 percent) in the Northern Region participated in the rental market against 250 households out of 1830 (14 percent) in the Central Region, and 133 households out of 2085 (6 percent) in the Southern Region.

$\epsilon_j \sim Normal(0, \sigma_\epsilon{}^2)$. The R_{j0} is the initial year observation for the dependent variable and z_j is for exogenous explanatory variables. This structure allows the use of a likelihood function similar to assessing the marginal effects in the random effect probit or Tobit models. However, the DRE model must include the lagged dependent variables to the list of explanatory variables. Specifically, for the probit model, we add the initial year and lag dependent binary variables to the list of explanatory variables, which changes to $x_{jt} = \{1, z_{jt}, R_{j,t-n}, R_{j0}, z_j\}$ as indicated in equation (2) above.

The Tobit models require that we replace $\alpha_0 R_{j0}$ with $\rho R_{j,t-n} = \omega r_{j,t-n} + \rho(1 - r_{j,t-n})R_{j,t-n}$. Where $R_{j,t-n}$ is the lagged participation in the previous survey round (n) and the $r_{j,t-n}$ is a binary variable that is equal to one if $R_{j,t-n} = 0$ and zero otherwise. Like the probit, this reduces the Tobit explanatory variable list to $x_{jt} = \{z_{jt}, R_{j,t-n}, R_{j0}, z_j\}$. That is, we include both the initial year and lag observations for the entry and extent of participation in the dynamic Tobit models (Wooldridge, 2010). By doing so, we control for the unobserved effect (μ_j) and the initial household conditions that are likely to facilitate entry and extent of participation in the subsequent years. This include transaction costs related to accessing market information that households can easily acquire upon entering and gaining experiencing in the market.

Specifically, the data for equation (1) included the observed participation in all three survey rounds and the respective rainfall deviation variables. In equation (2) we included the lag of the dependent variable observed in the previous survey round $[R_{jt-n}]$ and not the one-year lagged participation which was not observed in the data. Following Wooldridge (2010), we used the observed participation in 2010 as the initial year in our data and also the lag participation variable for the 2013 survey round. Subsequently, we also included the observed participation in 2013 survey round as the lag participation variable in the 2016 survey round. Thus, the total number of observations for equation (1) in the Central and Southern Regions were 1830 and 2085, while for equation (2) the sample observations were 1220 and 1390, respectively. This is based on the three rounds of balanced household panel from 610 Central Region households and 695 Sothern Region households.

The farm and household-level characteristics in the equations include owned farmland area (GPS measured); owned farmland to labour ratio; share of male labour; sex, age and education of household head; household size to labour ratio; Total Livestock Units (TLU); one-year lagged TLU, capital asset index to labour ratio and distance to urban centres. We considered owned farmland to be the land acquired through customary inheritance systems; government distribution and/or purchases. We considered acquiring land through borrowing, encroachment and farming under estate management to be an endogenous right in our model (Holden et al., 2013), hence we categorize such households as landless in the land ownership sense. We estimated the capital asset index from Factor Component Analysis (FCA) based on household ownership of durable assets and farm implements. The index ranges from negative to positive values. Considering the long asset list used in FCA, we present these durable goods and farm implements in Appendix A.

4. Descriptive Statistics

The statistics on rainfall deviations in Figure 2 shows the early to mid-season average rainfall amount for the two regions in Malawi over ten seasons (intertemporal rainfall distribution). The early to mid-season periods capture the average monthly rainfall amounts as defined above. The shaded bar graphs indicate the rainfall deviations in the previous two production seasons for each survey round while the empty bars reflect the reference production season in the survey periods. The horizontal lines represent the regional 10-year mean rainfall values for the period 2006 to 2016. With the horizontal line, the bars in the graph further show the average regional deviations from the means. We dropped the 2006-07 and 2016-17 production seasons in the figure to emphasize the period of interest in this analysis.

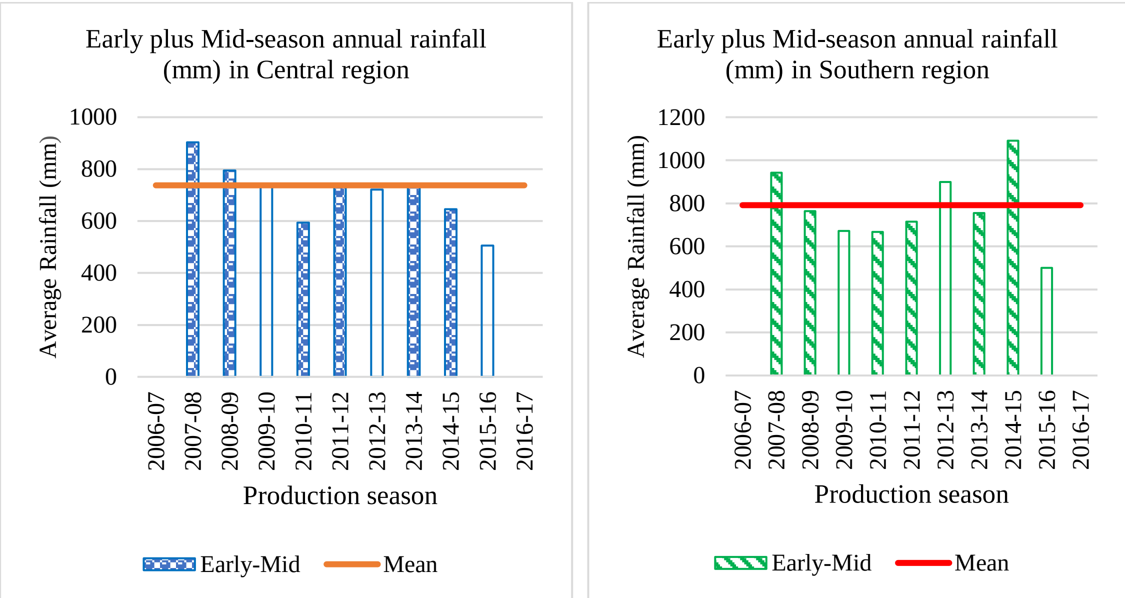

Figure 2: Regional early to mid-season annual rainfall (mm) for each survey round

From Figure 2, the 2007-08 season shows upside deviations in both regions while 2008-09 slightly vary across the regions. The rainfall seasons between 2010 and 2012 both exhibit a downside effect in both regions with a slightly higher downside effect in the Southern Region for the 2011-12 season. The rainfall seasons between 2013 and 2016 were characterized by both flood and drought in Malawi (Government of Malawi, 2015; Government of Malawi, 2016a). The upside deviations in 2014-15 production season reflect such flood effect that severely affected the Southern Region in January 2015. However, during the same time, the Central Region experienced relatively downside rainfall deviations. Overall, these are the rainfall deviations that support the need to understand their effect on farm household participation in the land rental markets.

Table 1 present statistics for the household and farm variables that we controlled for in our model summarized across all survey rounds and for each region. In the table, we first present the statistics for the overall sample and then present for the tenant and non-tenant households[7]. We use the t-test to show the overall mean differences between tenant and non-tenant households in our data. Since we control for previous participation in our analysis, we also present a detailed table on the extent of re-entry into the market in Appendix A, Table A1.

For the household variables, Table 1 shows that participation in the land rental markets is more prevalent in the Central Region (14 percent) compared to the Southern Region (6 percent). Tenant households in both regions rent-in an average of 0.5 ha which is almost equivalent to the average landholding size for non-tenant households in our data (0.6 ha and 0.5 ha in the Central and Southern Regions, respectively). In both regions, non-tenant households are relatively land rich and have a higher land to labour ratio compared to tenant households. However, we did not observe significant differences in the share of male labour that might be considered more important in a farming system that requires more human labour based on using a hand-hoe like in Malawi (Takane, 2008).

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[7] Due to LSMS data constrains, we were not able to specify a landlord category hence we combined those renting out and not participating into non-tenant households. In our data, we constantly observed a very small percentage of households renting out land. That is, in 2010, we observed 7.3% tenants and 0.1% landlords; in 2013 9.9% tenants and 0.5% landlords; and in 2016 8.9% tenants and 1.7% landlords in our data. We refer to Deininger et al. (2017) for a detailed discussion on LSMS data, land markets and capturing landlord households.

Table 1: Descriptive statistics

VARIABLES		Central Average values across all years: Total sample	Tenant household (1)	Non-tenant household (2)	ttest 1 vs. 2	Southern Average values across all years: Total sample	Tenant household (3)	Non-tenant household (4)	ttest 3 vs. 4
Rental participation variables									
Rent-in dummy	Percent	13.5				6.3			
Rent-in land (ha)	Mean		0.47				0.52		
	(Std. Error)		(0.03)				(0.04)		
Farm and Household variables									
Own farmland (ha)	Mean	0.56	0.36	0.59	****	0.48	0.27	0.49	****
	(Std. Error)	(0.02)	(0.03)	(0.02)		(0.01)	(0.04)	(0.01)	
Own farmland to labour ratio	Mean	0.19	0.11	0.20	****	0.18	0.09	0.18	****
(ha/adult equiv. labour unit)	(Std. Error)	(0.01)	(0.01)	(0.01)		(0.01)	(0.02)	(0.01)	
Share of male labour	Mean	0.42	0.42	0.42		0.39	0.40	0.39	
	(Std. Error)	(0.01)	(0.01)	(0.01)		(0.00)	(0.02)	(0.01)	
Sex of HH head (1=Female)	Mean	0.20	0.15	0.20	*	0.29	0.14	0.29	****
	(Std. Error)	(0.01)	(0.02)	(0.01)		(0.01)	(0.03)	(0.01)	
Age of HH head (years)	Mean	45	43	46	***	44	42	44	
	(Std. Error)	(0.36)	(0.81)	(0.39)		(0.34)	(1.03)	(0.35)	
Education of HH head (years)	Mean	6.33	7.20	6.19	***	5.62	6.77	5.54	***
	(Std. Error)	(0.11)	(0.31)	(0.12)		(0.10)	(0.47)	(0.10)	
Household size to labour ratio	Mean	1.64	1.66	1.63		1.70	1.74	1.69	
(No. of persons/adult equiv. labour unit)	(Std. Error)	(0.01)	(0.02)	(0.01)		(0.01)	(0.04)	(0.01)	
Total Livestock Units (TLU) to labour ratio	Mean	0.11	0.15	0.11	*	0.11	0.10	0.11	
	(Std. Error)	(0.01)	(0.02)	(0.01)		(0.02)	(0.02)	(0.02)	

One-year lag TLU to labour ratio	Mean	0.07	0.08	0.07		0.08	0.02	0.08	
(lag TLU No./ adult equiv. labour unit)	(Std. Error)	(0.01)	(0.01)	(0.01)		(0.02)	(0.02)	(0.02)	
Capital asset index to labour ratio	Mean	-0.02	0.01	-0.02	**	-0.06	0.02	-0.06	**
	(Std. Error)	(0.01)	(0.02)	(0.01)		(0.01)	(0.03)	(0.01)	
Distance to the urban center (km)	Mean	27.4	29.9	27.0	**	28.5	31.5	28.3	*
	(Std. Error)	(0.39)	(0.92)	(0.42)		(0.42)	(1.59)	(0.44)	
Observations **(N)**		1830	247	1563		2085	132	1953	

Note: The t-tests compare the overall mean over the years between the tenant and non-tenant households. The asterisks denote levels of significance at **** = p<0.001, *** = p<0.01, ** = p<0.05, and * = p<0.1

On the contrary, tenant households are rich in capital asset index to labour ratio and slightly more educated than the non-tenant households in both regions. In the Central Region, a tenant household is on average headed by a younger head. We also observed a significant gender difference in the Southern Region where tenant households are less likely to be headed by a female despite the data indicating that female-headed households in both regions owned less land compared to male-headed households on average. The average community level distance to urban centres among tenant households is significantly higher than non-tenant households (significant at 5 percent in the Central Region and 10 percent in the Southern Region).

In general, these are the regional variations that are important for assessing the within-region rainfall shock effects in our analysis. A research question beyond this study would be to assess the spatial effect of population pressure on the development of land rental markets considering that in Malawi we have observed that land rental markets are more active in the Central Region than in the Southern Region where population pressure is higher.

5. Results and discussion

We present the key probit and Tobit model results in Table 2. The average marginal effects are for the Correlated Random Effects (CRE) and Dynamic Random Effect (DRE) probit and Tobit models for the Central and Southern Regions. The CRE and DRE Tobit models present the conditional average partial effects [$E(y|\boldsymbol{X}, y > 0)$]. The more detailed result tables for both the average marginal effects and the coefficients are found in Appendix A, Tables A2 to A9 for both regions. The detailed Appendix A tables first present the parsimonious random effects model which were our starting point in the analysis before estimating the CRE and DRE models. The combination of models helped to assess the robustness of the key results to the alternative model specifications. We discuss our hypotheses using the joint results from the CRE and DRE probit and Tobit models across the regions.

Our hypothesis H1 stated that one-year lag downside rainfall deviations (early to mid-season) increase entry and extent of tenant household participation in land rental markets in the subsequent year. For this hypothesis, we use both the CRE and DRE probit and Tobit results from both regions. The results from the Central Region CRE and DRE probit models show that one-year lag downside rainfall deviations significantly increase entry into the rental markets in the subsequent year. On average, if the one-year lag downside rainfall deviations (absolute values) increases by one dm (100 mm), entry into the land rental markets increase by 3.6-3.8 percentage points in the subsequent year (significant at 5 and 10 percent levels). However, the effect is only significant at the 10 percent level in the CRE Tobit model and is insignificant in the DRE Tobit. The one-year lagged variables were insignificant for the Southern Region. Thus, our results provide support for hypothesis H1 only in the Central Region.

On hypothesis H2, our results provide no support for the flood effect. The hypothesis was stated as one-year lag upside rainfall deviations (early to mid-season) increase entry and extent of subsequent year tenant household participation in land rental markets. This may be because the floods effect in the Central Region was not sufficiently severe, where land rental markets are more prevalent or that the flood effect observed in the Southern Region was not significantly important to affect land rental market participation where such markets are less prevalent. As observed in Figure 2 and as discussed in Katengeza et al. (2018), Malawi mostly experience downside shocks like drought or in-season dry spells but fewer floods. This takes out discussion to hypothesis three.

Hypothesis H3 stated that rainfall shocks trigger more land rental market participation beyond the immediate effect in the following year. We assess this hypothesis using the two-year lagged rainfall deviation variable results from the CRE and DRE models. Table 2 shows that a one dm absolute negative deviation in the two-year lagged rainfall variable resulted in a 3.3 percentage point increase in land rental market participation. In both the CRE and DRE probit models, this effect was significant at 5 percent level in the Central Region. Furthermore, the effect was also significant in the CRE and DRE Tobit models with an increase of 0.019 ha area rented in per dm rainfall deficit in both models (significant at 5 and 10 percent levels). This demonstrates robust support for hypothesis H3 in the Central Region.

In the Southern Region, the two-year lagged rainfall variable was on the contrary negatively and significantly associated with renting-in the land. Both the CRE and DRE probit and Tobit models provide strong evidence to reject hypothesis H3 in this region. It appears that such past rainfall shocks cause households to cling more to their limited land as a self-sufficiency food security strategy. However, households with experience in the markets are more likely to re-enter the land rental markets in this region, a possible indicator of demand by land constrained households over time. These are surprising findings considering that land rental markets in the Southern Region of Malawi do not necessarily start to work better with increasing population. This imply a non-linear relationship between population pressure and land rental market activity that requires further research.

Table 2: Regional probit and Tobit random effects models for renting-in land (Average partial effect for Tobit model – [$E(y|X, y > 0)$]): Full regional model results (coefficients and margins) are in Appendix A, Tables A2 to A9.

	Correlated Random Effects (CRE) and Dynamic Random Effects (DRE) models with control variables							
	Central Region Models				Southern Region Models			
	Probit Models		Tobit Models		Probit Models		Tobit Models	
VARIABLES	**CRE**	**DRE**	**CRE**	**DRE**	**CRE**	**DRE**	**CRE**	**DRE**
One-year lag rainfall variables								
Positive deviation (dm) one-year lag	0.000	0.003	0.001	-0.001	-0.002	-0.006	-0.005	-0.007
(Early plus mid-season)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Absolute Negative deviation (dm) one-year lag	0.036**	0.038*	0.018*	0.009	-0.001	-0.003	0.002	-0.001
(Early plus mid-season)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Two-year lag rainfall variables								
Positive deviation (dm) two-year lag	-0.008	-0.018	-0.009	-0.008	-0.008	-0.013	-0.013	-0.012
(Early plus mid-season)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Absolute Negative deviation (dm) two-year lag	0.033**	0.033**	0.019**	0.019*	-0.026***	-0.022**	-0.026**	-0.021*
(Early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lag rental participation dummies								
Initial year (2010) rent-in dummy		0.084		0.021		0.092		0.051
		(0.08)		(0.04)		(0.06)		(0.03)
Lag rent-in dummy		0.136		0.041		0.100		0.105****
(previous survey round)		(0.09)		(0.04)		(0.07)		(0.03)
Initial year (2010) rent-in land (ha)				0.120*				-0.041
				(0.06)				(0.06)
Lag total rent-in land (ha)				0.045				0.116***
(previous survey round)				(0.05)				(0.04)
Farm and Household Characteristics								
Observed control variables	No	Yes	No	Yes	No	Yes	No	Yes
Mean of observed control variables	Yes	No	Yes	No	Yes	No	Yes	No
Deviations from the mean	Yes	No	Yes	No	Yes	No	Yes	No
Year dummies								
2013.year	-0.010		-0.006		0.054***		0.052**	
	(0.03)		(0.02)		(0.02)		(0.03)	

2016.year	-0.039*	-0.040	-0.014	-0.015	0.045**	0.005	0.057**	0.002
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Constant	-1.726**	-1.662****	-1.248**	-1.333****	-0.906	-1.869**	-0.653	-1.278**
	(0.82)	(0.47)	(0.49)	(0.33)	(1.43)	(0.89)	(0.82)	(0.52)
lnsig2u	0.117	-1.847			0.956****	-0.750		
	(0.23)	(2.75)			(0.26)	(1.70)		
sigma_u			0.601****	0.390**			0.938****	0.000****
			(0.05)	(0.18)			(0.10)	(0.00)
sigma_e			0.571****	0.662****			0.617****	0.824****
			(0.03)	(0.09)			(0.05)	(0.07)
Observations	1,830	1,220	1,830	1,220	2085	1390	2,085	1,390
Left Censored (_n)			1,583	1,048			1,953	1,288
Uncensored (_n)			247	172			132	102
Number of Panel households	610	610	610	610	695	695	695	695

Note: The asterisks represent **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1. The parenthesis shows cluster robust standard errors for Probit models and Normal standard errors in for Tobit models.

The farm and household control variables include (1) own farmland (ha), (2) own farmland to labour ratio *(ha/adult equiv. labour unit),* (3) share of male labour, (4) sex of HH head (1=Female), (5) age of HH head (years), (6) education of HH head (years), (7) household size to labour ratio *(No. of persons/adult equiv. labour unit)*, (8) Total Livestock Units (TLU) to labour ratio, (9) one-year lag TLU to labour ratio *(lag TLU No./ adult equiv. labour unit),* (10) capital asset to labour ratio, and (11) distance to the urban centre (km).

6. Conclusion

Rainfall variations within and across production seasons, that result in either drought or floods, are recurring states of nature. In Sub-Saharan Africa (SSA), farm households renting out their land in distress as an *ex-post* coping strategy can be an outcome of such shocks. If rainfall shocks are shifting supply of rented land, the extent to which tenant households are utilizing these opportunities is a missing link in the land rental market literature in SSA. In this paper, we assessed whether rainfall shocks are kick-starting the land rental markets by shifting the supply of rented land and creating opportunities for tenant household to access land, observed from tenant households' side. We used three rounds of household balanced panel data constructed from the Malawi Living Standards Measurement Surveys (LSMS) conducted in 2010, 2013 and 2016 to investigate this.

To assess the rainfall shock effects, we used the district level rainfall data that captured the within-region effect in Malawi. Our analysis used the one-year and two-year lagged downside and upside deviations from average district-level rainfall data in the early to mid-season periods based on a unimodal rainfall pattern in Malawi. Using the state-contingent framework for risky input choice, we proposed that increase in either downside or upside absolute rainfall deviation values increases entry and extent of tenant households' participation in land rental markets in the subsequent years. Our data revealed regional variations when we categorised the sample into the three administrative regions of North, Central and South in Malawi. We observed that land rental markets are most active in the Central Region followed by the Southern Region and least active in the Northern Region. We also found that our analysis of the relation between rainfall shocks and land rental market activity only made sense in the Central and Southern Regions and therefore we dropped the Northern Region sample. We estimated our results using both the correlated random effects and the dynamic random effects probit and Tobit models that control for unobserved heterogeneity and initial market entry conditions.

The results show that, where the land rental markets are most active, that is in the Central Region of Malawi, the one-year and two-year lagged downside rainfall shocks significantly increased tenant households' access to rented land. This implied both an immediate and a medium-term rainfall shock effect on land rental market participation in this region. However, we did not observe any similar effects from the lagged upside rainfall shocks in the two regions. In the Southern Region where the farm sizes are very small and with high population pressure, the two-year lagged absolute negative rainfall shock was associated with less access to rented land, an indicator of households holding owned land for self-sufficiency objectives than trading in the market.

Overall, our results indicate that where land rental markets are most active, the rainfall shocks in the form of droughts are helping to kick-start tenant household participation. Thus, orchestrating access to land rental market information together with climate shock response strategies can help improve land allocation through markets so that where markets are active, tenant households can access land offered by landlords in distress for productive use. However, the heterogeneity in the results calls for more research on rainfall shock effects on tenant households' participation beyond regional effects and the need to further understand the spatial development of land rental markets with respect to population pressure.

Acknowledgements

We acknowledge the support rendered to this work through the Capacity Building for Climate Smart Natural Resource Management and Policy (CLISNARP) project under NORAD-funded NORHED program. We sincerely thank the Norwegian University of Life Sciences (School of Economics and Business), Mekelle University in Ethiopia and the Lilongwe University of Agriculture and Natural Resources (LUANAR) in Malawi for facilitating this work through CLISNARP. We also recognise the World Bank for the LSMS data used in this paper.

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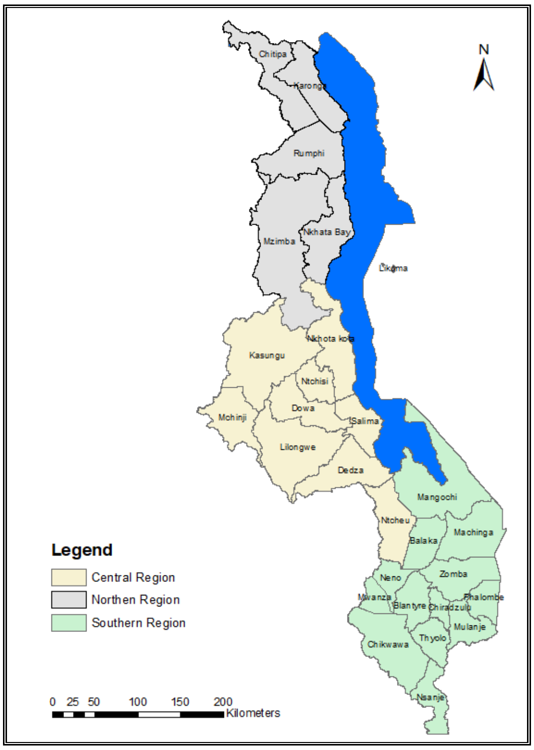
Appendix A

Map of Malawi



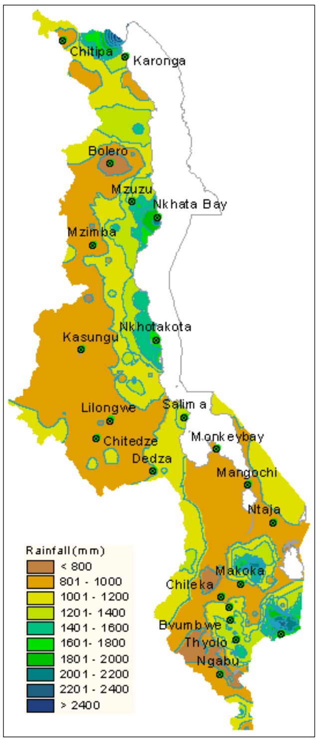


Figure A1: Map of Malawi showing districts   Figure A2: Rainfall map with weather stations across Malawi
Source: Department of Climate Change and Meteorological Services: www.metmalawi.gov.mw

Factor Component Analysis variables for Capital Asset index:

(i) Durable assets

Mortar/pestle (Mtondo), Bed, Table, Chair, Fan, Air conditioner, Radio ('wireless'), Tape or CD/DVD player or HiFi, Television, VCR, Sewing machine, Kerosene/paraffin stove, Electric or gas stove; hot plate, Refrigerator, Washing machine, Bicycle, Motorcycle/scooter, Car, Mini-bus, Lorry, Beer-brewing drum, Upholstered chair, sofa set, Coffee table (for the sitting room), Cupboard, drawers, bureau, Lantern (paraffin), Desk, Clock, Iron (for pressing clothes), Computer equipment & accessories, Satellite dish, Solar panel, Generator, Radio with flash drive/micro CD.

(ii) Farm implements

Hand Hoe, Slasher, Axe, Sprayer, Panga Knife, Sickle, Treadle Pump, Watering Can, Ox Cart, Ox Plough, Tractor, Tractor Plough, Ridger, Cultivator, Motorised Pump, Grain Mill, Chicken House, Livestock Kraal, Poultry Kraal, Storage House, Granary, Pig Sty

Table A1: Initial year and subsequent land rental market participation

Participation	2013 (%)		2016 (%)		Total (N)	Participation	2016 (%)		Total (N)
Initial year = 2010	*No*	*Yes*	*No*	*Yes*		**Survey year = 2013**	*No*	*Yes*	
No	93.3	6.8	93.2	6.8	1,372	*No*	94.9	5.1	1,331
Yes	49.1	50.9	63.9	35.1	108	*Yes*	57.1	43.0	149
Total (N)	1,331	149	1,348	132	1,480	Total (N)	1,348	132	1,480
%	89.9	10.1	91.1	8.9	100	%	91.1	8.9	100

Central Region Results

Table A2: Central Region Random Effect Probit Models for Renting-in Land (Average Partial Effects – [E(y|X)])

	Parsimonious Random Effects (RE) models		Random Effects (RE) models with controls variables		
VARIABLES	**RE**	**Dynamic RE (DRE)**	**RE**	**Correlated Random Effects (CRE)**	**Dynamic RE (DRE)**
One-year lag rainfall variables					
Positive deviation (dm) one-year lag	0.000	-0.007	0.002	0.000	0.003
(early plus mid-season)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Absolute Negative deviation (dm) one-year lag	0.040**	0.048**	0.038**	0.036**	0.038*
(early plus mid-season)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Two-year lag rainfall variables					
Positive deviation (dm) two-year lag	-0.006	-0.025	-0.009	-0.008	-0.018
(Early plus mid-season)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)

Absolute Negative deviation (dm) two-year lag	0.028**	0.035***	0.032**	0.033**	0.033**
(Early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lag rental participation dummies					
Initial year (2010) rent-in dummy		0.082			0.084
		(0.07)			(0.08)
Lag rent-in dummy		0.167*			0.136
(previous survey round)		(0.09)			(0.09)
Farm and Household Characteristics					
Observed control variables					
Own farmland (ha)			-0.014		-0.009
			(0.03)		(0.03)
Own farmland to labour ratio			-0.356***		-0.259**
(ha/adult equiv. labour unit)			(0.12)		(0.13)
Share of male labour			-0.015		0.011
			(0.05)		(0.05)
Sex of HH head (1=Female)			-0.025		-0.015
			(0.03)		(0.03)
Age of HH head (years)			-0.001*		-0.001**
			(0.00)		(0.00)
Education of HH head (years)			0.004		-0.000
			(0.00)		(0.00)
Household size to labour ratio			0.008		0.016
(No. of persons/adult equiv. labour unit)			(0.02)		(0.02)
Total Livestock Units (TLU) to labour ratio			0.047**		0.056***
			(0.02)		(0.02)
One-year lag TLU to labour ratio			0.008		0.006

(lag TLU No./ adult equiv. labour unit)	(0.03)		(0.03)
Capital asset index to labour ratio	0.007		0.015
	(0.03)		(0.03)
Distance to the urban center (km)	0.003****		0.003****
	(0.00)		(0.00)
Mean of observed control variables			
Own farmland (ha)		-0.014	
		(0.04)	
Own farmland to labour ratio		-0.340***	
(ha/adult equiv. labour unit)		(0.12)	
Share of male labour		-0.060	
		(0.08)	
Sex of HH head (1=Female)		-0.044	
		(0.04)	
Age of HH head (years)		-0.001	
		(0.00)	
Education of HH head (years)		0.005*	
		(0.00)	
Household size to labour ratio		0.001	
(No. of persons/adult equiv. labour unit)		(0.03)	
Total Livestock Units (TLU) to labour ratio		0.130****	
		(0.04)	
One-year lag TLU to labour ratio		0.025	
(lag TLU No./ adult equiv. labour unit)		(0.08)	
Capital asset index to labour ratio		-0.011	
		(0.04)	

Distance to the urban center (km)	0.003****
	(0.00)
Deviations from the mean	
Own farmland (ha)	-0.032
	(0.05)
Own farmland to labour ratio	-0.374**
(ha/adult equiv. labour unit)	(0.15)
Share of male labour	0.010
	(0.07)
Sex of HH head (1=Female)	-0.011
	(0.04)
Age of HH head (years)	-0.001
	(0.00)
Education of HH head (years)	0.001
	(0.00)
Household size to labour ratio	0.013
(No. of persons/adult equiv. labour unit)	(0.03)
Total Livestock Units (TLU) to labour ratio	0.017
	(0.02)
One-year lag TLU to labour ratio	-0.011
(lag TLU No./ adult equiv. labour unit)	(0.04)
Capital asset index to labour ratio	-0.005
	(0.04)
Distance to the urban center (km)	0.003**
	(0.00)
Year dummies	

2013.year	-0.009		-0.013	-0.010	
	(0.03)		(0.03)	(0.03)	
2016.year	-0.058***	-0.060**	-0.044**	-0.039*	-0.040
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
N	1,830	1,220	1,830	1,830	1,220

Note: The asterisks represent **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1. Cluster robust standard errors in parenthesis.

Table A3: Central Region Random Effect Tobit Models for Renting-in Land (Average Partial Effects – [$\mathbf{E(y|X, y > 0)}$])

	Parsimonious Random Effects (RE) models		**Random Effects (RE) models with controls variables**		
VARIABLES	**RE**	**Dynamic RE (DRE)**	**RE**	**Correlated Random Effects (CRE)**	**Dynamic RE (DRE)**
One-year lag rainfall variables					
Positive deviation (dm) one-year lag	0.000	-0.012	0.002	0.001	-0.001
(early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Absolute Negative deviation (dm) one-year lag	0.024**	0.018	0.019*	0.018*	0.009
(early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Two-year lag rainfall variables					
Positive deviation (dm) two-year lag	-0.006	-0.016	-0.009	-0.009	-0.008
(Early plus mid-season)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Absolute Negative deviation (dm) two-year lag	0.019*	0.022**	0.019**	0.019**	0.019*
(Early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lag rental participation dummies					
Initial year (2010) rent-in dummy		0.027			0.021
		(0.04)			(0.04)

Lag rent-in dummy	0.054		0.041
(previous survey round)	(0.04)		(0.04)
Initial year (2010) rent-in land (ha)	0.123*		0.120*
	(0.07)		(0.06)
Lag total rent-in land (ha)	0.070		0.045
(previous survey round)	(0.06)		(0.05)
Farm and Household Characteristics			
Observed control variables			
Own farmland (ha)		-0.003	0.004
		(0.02)	(0.02)
Own farmland to labour ratio		-0.269****	-0.203***
(ha/adult equiv. labour unit)		(0.07)	(0.07)
Share of male labour		0.004	0.026
		(0.03)	(0.04)
Sex of HH head (1=Female)		-0.018	-0.010
		(0.02)	(0.02)
Age of HH head (years)		-0.001	-0.001
		(0.00)	(0.00)
Education of HH head (years)		0.003*	0.001
		(0.00)	(0.00)
Household size to labour ratio		0.011	0.017
(No. of persons/adult equiv. labour unit)		(0.02)	(0.01)
Total Livestock Units (TLU) to labour ratio		0.038***	0.042***
		(0.01)	(0.02)
One-year lag TLU to labour ratio		0.006	0.009
(lag TLU No./ adult equiv. labour unit)		(0.03)	(0.03)

Capital asset index to labour ratio	0.013		0.010
	(0.02)		(0.02)
Distance to the urban center (km)	0.002****		0.002****
	(0.00)		(0.00)
Mean of observed control variables			
Own farmland (ha)		0.001	
		(0.03)	
Own farmland to labour ratio		-0.260****	
(ha/adult equiv. labour unit)		(0.08)	
Share of male labour		-0.024	
		(0.06)	
Sex of HH head (1=Female)		-0.029	
		(0.03)	
Age of HH head (years)		-0.001	
		(0.00)	
Education of HH head (years)		0.005**	
		(0.00)	
Household size to labour ratio		0.009	
(No. of persons/adult equiv. labour unit)		(0.03)	
Total Livestock Units (TLU) to labour ratio		0.092***	
		(0.03)	
One-year lag TLU to labour ratio		0.027	
(lag TLU No./ adult equiv. labour unit)		(0.05)	
Capital asset index to labour ratio		-0.004	
		(0.03)	
Distance to the urban center (km)		0.002****	

			(0.00)
Deviations from the mean			
Own farmland (ha)			-0.016
			(0.03)
Own farmland to labour ratio			-0.272***
(ha/adult equiv. labour unit)			(0.09)
Share of male labour			0.021
			(0.04)
Sex of HH head (1=Female)			-0.015
			(0.03)
Age of HH head (years)			-0.001
			(0.00)
Education of HH head (years)			-0.000
			(0.00)
Household size to labour ratio			0.014
(No. of persons/adult equiv. labour unit)			(0.02)
Total Livestock Units (TLU) to labour ratio			0.018
			(0.02)
One-year lag TLU to labour ratio			-0.007
(lag TLU No./ adult equiv. labour unit)			(0.03)
Capital asset index to labour ratio			0.008
			(0.03)
Distance to the urban center (km)			0.002**
			(0.00)
Year dummies			
2013.year	-0.004	-0.008	-0.006

	(0.02)		(0.02)	(0.02)	
2016.year	-0.033**	-0.034*	-0.019	-0.014	-0.015
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	1,830	1,220	1,830	1,830	1,220

Note: The table presents conditional margins for those participating in the market (y>0). The asterisks represent **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1. Normal standard errors in parenthesis.

Table A4: Central Region Random Effect Probit Models for Renting-in Land (Coefficients)

	Parsimonious Random Effects (RE) models		Random Effects (RE) models with controls variables		
VARIABLES	**RE**	**Dynamic RE (DRE)**	**RE**	**Correlated Random Effects (CRE)**	**Dynamic RE (DRE)**
One-year lag rainfall variables					
Positive deviation (dm) one-year lag	0.003	-0.039	0.011	0.002	0.018
(early plus mid-season)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)
Absolute Negative deviation (dm) one-year lag	0.280**	0.262**	0.275**	0.263**	0.221*
(early plus mid-season)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)
Two-year lag rainfall variables					
Positive deviation (dm) two-year lag	-0.040	-0.138	-0.066	-0.059	-0.103
(Early plus mid-season)	(0.08)	(0.13)	(0.09)	(0.09)	(0.15)
Absolute Negative deviation (dm) two-year lag	0.195**	0.189***	0.234**	0.242**	0.196**
(Early plus mid-season)	(0.09)	(0.07)	(0.10)	(0.10)	(0.08)
Lag rental participation dummies					
Initial year (2010) rent-in dummy		0.447			0.491
		(0.43)			(0.52)

Lag rent-in dummy	0.905**		0.794*
(previous survey round)	(0.36)		(0.42)
Farm and Household Characteristics			
Observed control variables			
Own farmland (ha)		-0.104	-0.054
		(0.24)	(0.19)
Own farmland to labour ratio		-2.581***	-1.512*
(ha/adult equiv. labour unit)		(0.91)	(0.82)
Share of male labour		-0.112	0.067
		(0.37)	(0.31)
Sex of HH head (1=Female)		-0.180	-0.087
		(0.18)	(0.16)
Age of HH head (years)		-0.009*	-0.009*
		(0.01)	(0.00)
Education of HH head (years)		0.026	-0.000
		(0.02)	(0.01)
Household size to labour ratio		0.059	0.094
(No. of persons/adult equiv. labour unit)		(0.17)	(0.11)
Total Livestock Units (TLU) to labour ratio		0.338**	0.327**
		(0.15)	(0.13)
One-year lag TLU to labour ratio		0.056	0.034
(lag TLU No./ adult equiv. labour unit)		(0.24)	(0.20)
Capital asset index to labour ratio		0.050	0.087
		(0.19)	(0.18)
Distance to the urban center (km)		0.022****	0.015***
		(0.00)	(0.01)

Mean of observed control variables	
Own farmland (ha)	-0.105
	(0.26)
Own farmland to labour ratio	-2.499***
(ha/adult equiv. labour unit)	(0.93)
Share of male labour	-0.441
	(0.58)
Sex of HH head (1=Female)	-0.321
	(0.27)
Age of HH head (years)	-0.009
	(0.01)
Education of HH head (years)	0.040*
	(0.02)
Household size to labour ratio	0.008
(No. of persons/adult equiv. labour unit)	(0.25)
Total Livestock Units (TLU) to labour ratio	0.959****
	(0.28)
One-year lag TLU to labour ratio	0.187
(lag TLU No./ adult equiv. labour unit)	(0.57)
Capital asset index to labour ratio	-0.078
	(0.27)
Distance to the urban center (km)	0.019****
	(0.01)
Deviations from the mean	
Own farmland (ha)	-0.233
	(0.36)

Own farmland to labour ratio				-2.753**	
(ha/adult equiv. labour unit)				(1.12)	
Share of male labour				0.072	
				(0.49)	
Sex of HH head (1=Female)				-0.077	
				(0.27)	
Age of HH head (years)				-0.010	
				(0.01)	
Education of HH head (years)				0.005	
				(0.03)	
Household size to labour ratio				0.099	
(No. of persons/adult equiv. labour unit)				(0.19)	
Total Livestock Units (TLU) to labour ratio				0.122	
				(0.12)	
One-year lag TLU to labour ratio				-0.078	
(lag TLU No./ adult equiv. labour unit)				(0.27)	
Capital asset index to labour ratio				-0.035	
				(0.30)	
Distance to the urban center (km)				0.023**	
				(0.01)	
Year dummies					
2013.year	-0.054		-0.086	-0.072	
	(0.18)		(0.19)	(0.19)	
2016.year	-0.418***	-0.326**	-0.326**	-0.294*	-0.235
	(0.15)	(0.15)	(0.16)	(0.17)	(0.15)
Constant	-1.826****	-1.610****	-1.815****	-1.726**	-1.662****

	(0.18)	(0.24)	(0.55)	(0.82)	(0.47)
lnsig2u	0.209	-2.582	0.128	0.117	-1.847
	(0.21)	(4.26)	(0.23)	(0.23)	(2.75)
Observations	1,830	1,220	1,830	1,830	1,220
Number of y3_hhid	610	610	610	610	610

Note: The asterisks represent **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1. Cluster robust standard errors in parenthesis.

Table A5: Central Region Random Effect Tobit Models for Renting-in Land (Coefficients)

	Parsimonious Random Effects (RE) models		**Random Effects (RE) models with controls variables**		
VARIABLES	**RE**	**Dynamic RE (DRE)**	**RE**	**Correlated Random Effects (CRE)**	**Dynamic RE (DRE)**
One-year lag rainfall variables					
Positive deviation (dm) one-year lag	0.001	-0.069	0.011	0.007	-0.008
(early plus mid-season)	(0.05)	(0.07)	(0.05)	(0.05)	(0.07)
Absolute Negative deviation (dm) one-year lag	0.129**	0.102	0.109*	0.102*	0.053
(early plus mid-season)	(0.06)	(0.08)	(0.06)	(0.06)	(0.08)
Two-year lag rainfall variables					
Positive deviation (dm) two-year lag	-0.031	-0.090	-0.053	-0.051	-0.047
(Early plus mid-season)	(0.05)	(0.09)	(0.05)	(0.05)	(0.09)
Absolute Negative deviation (dm) two-year lag	0.101*	0.124**	0.108**	0.109**	0.111*
(Early plus mid-season)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
Lag rental participation dummies					
Initial year (2010) rent-in dummy		0.152			0.123
		(0.22)			(0.21)

Lag rent-in dummy	0.299		0.236
(previous survey round)	(0.23)		(0.21)
Initial year (2010) rent-in land (ha)	0.684*		0.696*
	(0.39)		(0.37)
Lag total rent-in land (ha)	0.388		0.261
(previous survey round)	(0.32)		(0.29)
Farm and Household Characteristics			
Observed control variables			
Own farmland (ha)		-0.015	0.022
		(0.12)	(0.12)
Own farmland to labour ratio		-1.522****	-1.174***
(ha/adult equiv. labour unit)		(0.41)	(0.42)
Share of male labour		0.025	0.150
		(0.20)	(0.23)
Sex of HH head (1=Female)		-0.102	-0.058
		(0.11)	(0.11)
Age of HH head (years)		-0.004	-0.005
		(0.00)	(0.00)
Education of HH head (years)		0.017*	0.007
		(0.01)	(0.01)
Household size to labour ratio		0.064	0.099
(No. of persons/adult equiv. labour unit)		(0.09)	(0.08)
Total Livestock Units (TLU) to labour ratio		0.216***	0.244***
		(0.08)	(0.09)
One-year lag TLU to labour ratio		0.035	0.053
(lag TLU No./ adult equiv. labour unit)		(0.15)	(0.16)

Capital asset index to labour ratio	0.072		0.056
	(0.11)		(0.14)
Distance to the urban center (km)	0.014****		0.012****
	(0.00)		(0.00)
Mean of observed control variables			
Own farmland (ha)		0.007	
		(0.14)	
Own farmland to labour ratio		-1.481****	
(ha/adult equiv. labour unit)		(0.45)	
Share of male labour		-0.134	
		(0.32)	
Sex of HH head (1=Female)		-0.166	
		(0.14)	
Age of HH head (years)		-0.003	
		(0.00)	
Education of HH head (years)		0.029**	
		(0.01)	
Household size to labour ratio		0.050	
(No. of persons/adult equiv. labour unit)		(0.16)	
Total Livestock Units (TLU) to labour ratio		0.524***	
		(0.16)	
One-year lag TLU to labour ratio		0.155	
(lag TLU No./ adult equiv. labour unit)		(0.30)	
Capital asset index to labour ratio		-0.023	
		(0.17)	
Distance to the urban center (km)		0.012****	

			(0.00)
Deviations of the mean			
Own farmland (ha)			-0.093
			(0.17)
Own farmland to labour ratio			-1.551***
(ha/adult equiv. labour unit)			(0.52)
Share of male labour			0.118
			(0.25)
Sex of HH head (1=Female)			-0.085
			(0.18)
Age of HH head (years)			-0.006
			(0.01)
Education of HH head (years)			-0.000
			(0.01)
Household size to labour ratio			0.080
(No. of persons/adult equiv. labour unit)			(0.10)
Total Livestock Units (TLU) to labour ratio			0.103
			(0.09)
One-year lag TLU to labour ratio			-0.038
(lag TLU No./ adult equiv. labour unit)			(0.16)
Capital asset index to labour ratio			0.047
			(0.16)
Distance to the urban center (km)			0.013**
			(0.01)
Year dummies			
2013.year	-0.022	-0.042	-0.032

	(0.10)		(0.10)	(0.10)	
2016.year	-0.178**	-0.187*	-0.107	-0.083	-0.087
	(0.09)	(0.10)	(0.09)	(0.10)	(0.10)
Constant	-1.087****	-1.133****	-1.207****	-1.248**	-1.333****
	(0.11)	(0.14)	(0.30)	(0.49)	(0.33)
sigma_u	0.679****	0.358*	0.611****	0.601****	0.390**
	(0.06)	(0.21)	(0.05)	(0.05)	(0.18)
sigma_e	0.603****	0.724****	0.576****	0.571****	0.662****
	(0.04)	(0.10)	(0.04)	(0.03)	(0.09)
Observations	1,830	1,220	1,830	1,830	1,220
Left Censored (_n)	1,583	1,048	1,583	1,583	1,048
Uncensored (_n)	247	172	247	247	172
Number of y3_hhid	610	610	610	610	610

Note: The asterisks represent **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1. Normal standard errors in parenthesis.

Southern Region Results

Table A6: Southern Region Random Effect Probit Models for Renting-in Land (Average Partial Effects – [$E(y|X)$])

	Parsimonious Random Effects (RE) models		**Random Effects (RE) models with controls variables**		
VARIABLES	**RE**	**Dynamic RE (DRE)**	**RE**	**Correlated Random Effects (CRE)**	**Dynamic RE (DRE)**
One-year lag rainfall variables					
Positive deviation (dm) one-year lag	-0.002	-0.005	-0.002	-0.002	-0.006
(early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Absolute Negative deviation (dm) one-year lag	-0.000	-0.004	-0.001	-0.001	-0.003

(early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Two-year lag rainfall variables					
Positive deviation (dm) two-year lag	-0.004	-0.010	-0.008	-0.008	-0.013
(Early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Absolute Negative deviation (dm) two-year lag	-0.019**	-0.017*	-0.026***	-0.026***	-0.022**
(Early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lag rental participation dummies					
Initial year (2010) rent-in dummy		0.150***			0.092
		(0.05)			(0.06)
Lag rent-in dummy		0.055			0.100
(previous survey round)		(0.06)			(0.07)
Farm and Household Characteristics					
Observed control variables					
Own farmland (ha)			-0.075**		-0.056*
			(0.03)		(0.03)
Own farmland to labour ratio			0.009		-0.010
(ha/adult equiv. labour unit)			(0.09)		(0.10)
Share of male labour			-0.037		0.023
			(0.03)		(0.04)
Sex of HH head (1=Female)			-0.050***		-0.066***
			(0.02)		(0.02)
Age of HH head (years)			-0.000		-0.000
			(0.00)		(0.00)
Education of HH head (years)			-0.000		-0.001
			(0.00)		(0.00)
Household size to labour ratio			0.017		0.034**

(No. of persons/adult equiv. labour unit)	(0.01)	(0.02)
Total Livestock Units (TLU) to labour ratio	-0.003	-0.006
	(0.00)	(0.01)
One-year lag TLU to labour ratio	0.001	0.001
(lag TLU No./ adult equiv. labour unit)	(0.00)	(0.00)
Capital asset index to labour ratio	0.033*	0.032
	(0.02)	(0.02)
Distance to the urban center (km)	0.001***	0.001***
	(0.00)	(0.00)
Mean of observed control variables		
Own farmland (ha)	-0.066*	
	(0.04)	
Own farmland to labour ratio	-0.013	
(ha/adult equiv. labour unit)	(0.11)	
Share of male labour	-0.148**	
	(0.06)	
Sex of HH head (1=Female)	-0.101****	
	(0.03)	
Age of HH head (years)	-0.000	
	(0.00)	
Education of HH head (years)	0.001	
	(0.00)	
Household size to labour ratio	-0.014	
(No. of persons/adult equiv. labour unit)	(0.03)	
Total Livestock Units (TLU) to labour ratio	-0.005	
	(0.00)	

One-year lag TLU to labour ratio	-0.003
(lag TLU No./ adult equiv. labour unit)	(0.01)
Capital asset index to labour ratio	0.018
	(0.02)
Distance to the urban center (km)	0.001***
	(0.00)
Deviations from the mean	
Own farmland (ha)	-0.087**
	(0.04)
Own farmland to labour ratio	0.038
(ha/adult equiv. labour unit)	(0.10)
Share of male labour	0.011
	(0.04)
Sex of HH head (1=Female)	-0.012
	(0.02)
Age of HH head (years)	0.001
	(0.00)
Education of HH head (years)	-0.001
	(0.00)
Household size to labour ratio	0.021
(No. of persons/adult equiv. labour unit)	(0.02)
Total Livestock Units (TLU) to labour ratio	-0.001
	(0.01)
One-year lag TLU to labour ratio	0.001
(lag TLU No./ adult equiv. labour unit)	(0.00)
Capital asset index to labour ratio	0.040

				(0.03)	
Distance to the urban center (km)				0.001	
				(0.00)	
Year dummies					
2013.year	0.046***		0.052***	0.054***	
	(0.02)		(0.02)	(0.02)	
2016.year	0.041**	0.003	0.049***	0.045**	0.005
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
N	2085	1390	2085	2085	1390

Note: The asterisks represent **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1. Cluster robust standard errors in parenthesis.

Table A7: Southern Region Random Effect Tobit Models for Renting-in Land (Average Partial Effects – $[E(y|X, y > 0)]$)

	Parsimonious Random Effects (RE) models		Random Effects (RE) models with controls variables		
VARIABLES	**RE**	**Dynamic RE (DRE)**	**RE**	**Correlated Random Effects (CRE)**	**Dynamic RE (DRE)**
One-year lag rainfall variables					
Positive deviation (dm) one-year lag	-0.005	-0.007	-0.006	-0.005	-0.007
(early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Absolute Negative deviation (dm) one-year lag	0.002	-0.004	0.002	0.002	-0.001
(early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Two-year lag rainfall variables					
Positive deviation (dm) two-year lag	-0.008	-0.011	-0.014	-0.013	-0.012
(Early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Absolute Negative deviation (dm) two-year lag	-0.021*	-0.017	-0.027**	-0.026**	-0.021*

(Early plus mid-season)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lag rental participation dummies					
Initial year (2010) rent-in dummy		0.103**			0.051
		(0.05)			(0.03)
Lag rent-in dummy		0.068			0.105****
(previous survey round)		(0.05)			(0.03)
Initial year (2010) rent-in land (ha)		0.021			-0.041
		(0.08)			(0.06)
Lag total rent-in land (ha)		0.082			0.116***
(previous survey round)		(0.06)			(0.04)
Farm and Household Characteristics					
Observed control variables					
Own farmland (ha)			-0.079**		-0.051*
			(0.03)		(0.03)
Own farmland to labour ratio			-0.005		0.007
(ha/adult equiv. labour unit)			(0.09)		(0.07)
Share of male labour			-0.070		0.007
			(0.04)		(0.04)
Sex of HH head (1=Female)			-0.076****		-0.076****
			(0.02)		(0.02)
Age of HH head (years)			-0.000		-0.000
			(0.00)		(0.00)
Education of HH head (years)			-0.001		-0.001
			(0.00)		(0.00)
Household size to labour ratio			0.015		0.037**
(No. of persons/adult equiv. labour unit)			(0.02)		(0.02)

Total Livestock Units (TLU) to labour ratio	-0.003	-0.006
	(0.01)	(0.02)
One-year lag TLU to labour ratio	0.002	0.001
(lag TLU No./ adult equiv. labour unit)	(0.01)	(0.01)
Capital asset index to labour ratio	0.041*	0.034
	(0.02)	(0.02)
Distance to the urban center (km)	0.001***	0.001***
	(0.00)	(0.00)
Mean of observed control variables		
Own farmland (ha)	-0.077*	
	(0.04)	
Own farmland to labour ratio	-0.013	
(ha/adult equiv. labour unit)	(0.11)	
Share of male labour	-0.194**	
	(0.08)	
Sex of HH head (1=Female)	-0.140****	
	(0.04)	
Age of HH head (years)	-0.000	
	(0.00)	
Education of HH head (years)	0.001	
	(0.00)	
Household size to labour ratio	-0.015	
(No. of persons/adult equiv. labour unit)	(0.03)	
Total Livestock Units (TLU) to labour ratio	-0.008	
	(0.02)	
One-year lag TLU to labour ratio	-0.001	

(lag TLU No./ adult equiv. labour unit)	(0.02)
Capital asset index to labour ratio	0.019
	(0.04)
Distance to the urban center (km)	0.001***
	(0.00)
Deviations from the mean	
Own farmland (ha)	-0.089**
	(0.04)
Own farmland to labour ratio	0.022
(ha/adult equiv. labour unit)	(0.11)
Share of male labour	-0.016
	(0.05)
Sex of HH head (1=Female)	-0.025
	(0.03)
Age of HH head (years)	0.001
	(0.00)
Education of HH head (years)	-0.002
	(0.00)
Household size to labour ratio	0.017
(No. of persons/adult equiv. labour unit)	(0.02)
Total Livestock Units (TLU) to labour ratio	0.001
	(0.02)
One-year lag TLU to labour ratio	0.002
(lag TLU No./ adult equiv. labour unit)	(0.01)
Capital asset index to labour ratio	0.055
	(0.04)

Distance to the urban center (km)				-0.000	
				(0.00)	
Year dummies					
2013.year	0.055**		0.053**	0.052**	
	(0.03)		(0.03)	(0.03)	
2016.year	0.063**	0.003	0.065***	0.057**	0.002
	(0.02)	(0.04)	(0.02)	(0.03)	(0.03)
N	2085	1390	2085	2085	1390

Note: The table presents conditional margins for those participating in the market (y>0). The asterisks represent **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1. Normal standard errors in parenthesis.

Table A8: Southern Region Random Effect Probit Models for Renting-in Land (Coefficients)

	Parsimonious Random Effects (RE) models		Random Effects (RE) models with controls variables		
VARIABLES	**RE**	**Dynamic RE (DRE)**	**RE**	**Correlated Random Effects (CRE)**	**Dynamic RE (DRE)**
One-year lag rainfall variables					
Positive deviation (dm) one-year lag	-0.024	-0.064	-0.041	-0.032	-0.071
(early plus mid-season)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)
Absolute Negative deviation (dm) one-year lag	-0.001	-0.056	-0.009	-0.013	-0.033
(early plus mid-season)	(0.11)	(0.12)	(0.11)	(0.11)	(0.10)
Two-year lag rainfall variables					
Positive deviation (dm) two-year lag	-0.060	-0.125	-0.137	-0.139	-0.149
(Early plus mid-season)	(0.11)	(0.13)	(0.12)	(0.12)	(0.14)
Absolute Negative deviation (dm) two-year lag	-0.300**	-0.206*	-0.431***	-0.446***	-0.263**

(Early plus mid-season)	(0.12)	(0.12)	(0.14)	(0.14)	(0.13)
Lag rental participation dummies					
Initial year (2010) rent-in dummy		1.872*			1.092
		(1.03)			(1.00)
Lag rent-in dummy		0.689			1.186*
(previous survey round)		(0.61)			(0.61)
Farm and Household Characteristics					
Observed control variables					
Own farmland (ha)			-1.244**		-0.660
			(0.54)		(0.44)
Own farmland to labour ratio			0.148		-0.123
(ha/adult equiv. labour unit)			(1.58)		(1.19)
Share of male labour			-0.608		0.271
			(0.57)		(0.48)
Sex of HH head (1=Female)			-0.832***		-0.780***
			(0.26)		(0.29)
Age of HH head (years)			-0.003		-0.004
			(0.01)		(0.01)
Education of HH head (years)			-0.005		-0.012
			(0.03)		(0.02)
Household size to labour ratio			0.275		0.407*
(No. of persons/adult equiv. labour unit)			(0.23)		(0.21)
Total Livestock Units (TLU) to labour ratio			-0.044		-0.070
			(0.05)		(0.08)
One-year lag TLU to labour ratio			0.014		0.010
(lag TLU No./ adult equiv. labour unit)			(0.04)		(0.03)

Capital asset index to labour ratio	0.547*		0.381
	(0.30)		(0.26)
Distance to the urban center (km)	0.016***		0.011**
	(0.01)		(0.01)
Mean of observed control variables			
Own farmland (ha)		-1.106*	
		(0.66)	
Own farmland to labour ratio		-0.227	
(ha/adult equiv. labour unit)		(1.83)	
Share of male labour		-2.501**	
		(0.99)	
Sex of HH head (1=Female)		-1.709****	
		(0.49)	
Age of HH head (years)		-0.007	
		(0.01)	
Education of HH head (years)		0.014	
		(0.04)	
Household size to labour ratio		-0.243	
(No. of persons/adult equiv. labour unit)		(0.44)	
Total Livestock Units (TLU) to labour ratio		-0.088	
		(0.07)	
One-year lag TLU to labour ratio		-0.058	
(lag TLU No./ adult equiv. labour unit)		(0.17)	
Capital asset index to labour ratio		0.301	
		(0.42)	
Distance to the urban center (km)		0.016***	

			(0.01)
Deviations from the mean			
Own farmland (ha)			-1.466**
			(0.62)
Own farmland to labour ratio			0.639
(ha/adult equiv. labour unit)			(1.67)
Share of male labour			0.185
			(0.73)
Sex of HH head (1=Female)			-0.210
			(0.37)
Age of HH head (years)			0.008
			(0.02)
Education of HH head (years)			-0.025
			(0.03)
Household size to labour ratio			0.361
(No. of persons/adult equiv. labour unit)			(0.26)
Total Livestock Units (TLU) to labour ratio			-0.011
			(0.09)
One-year lag TLU to labour ratio			0.025
(lag TLU No./ adult equiv. labour unit)			(0.04)
Capital asset index to labour ratio			0.671
			(0.47)
Distance to the urban center (km)			0.009
			(0.01)
Year dummies			
2013.year	0.797***	0.955***	0.980****

	(0.27)		(0.30)	(0.29)	
2016.year	0.733**	0.035	0.916***	0.870***	0.059
	(0.29)	(0.40)	(0.31)	(0.33)	(0.40)
Constant	-3.072****	-1.803***	-2.749***	-0.906	-1.869**
	(0.38)	(0.58)	(0.85)	(1.43)	(0.89)
lnsig2u	1.006****	-0.026	0.934****	0.956****	-0.750
	(0.25)	(1.01)	(0.26)	(0.26)	(1.70)
Observations	2,085	1,390	2,085	2,085	1,390
Number of y3_hhid	695	695	695	695	695

Note: The asterisks represent **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1. Cluster robust standard errors in parenthesis.

Table A9: Southern Region Random Effect Tobit Models for Renting-in Land (Coefficients)

	Parsimonious Random Effects (RE) models		**Random Effects (RE) models with controls variables**		
VARIABLES	**RE**	**Dynamic RE (DRE)**	**RE**	**Correlated Random Effects (CRE)**	**Dynamic RE (DRE)**
One-year lag rainfall variables					
Positive deviation (dm) one-year lag	-0.036	-0.053	-0.046	-0.039	-0.051
(early plus mid-season)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)
Absolute Negative deviation (dm) one-year lag	0.011	-0.028	0.012	0.013	-0.004
(early plus mid-season)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)
Two-year lag rainfall variables					
Positive deviation (dm) two-year lag	-0.055	-0.080	-0.103	-0.100	-0.094
(Early plus mid-season)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)
Absolute Negative deviation (dm) two-year lag	-0.146*	-0.119	-0.194**	-0.193**	-0.159*

(Early plus mid-season)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Lag rental participation dummies					
Initial year (2010) rent-in dummy		0.730**			0.395
		(0.35)			(0.25)
Lag rent-in dummy		0.481			0.807****
(previous survey round)		(0.34)			(0.23)
Initial year (2010) rent-in land (ha)		0.149			-0.318
		(0.56)			(0.43)
Lag total rent-in land (ha)		0.583			0.892***
(previous survey round)		(0.45)			(0.34)
Farm and Household Characteristics					
Observed control variables					
Own farmland (ha)			-0.578**		-0.395*
			(0.25)		(0.22)
Own farmland to labour ratio			-0.034		0.057
(ha/adult equiv. labour unit)			(0.63)		(0.57)
Share of male labour			-0.510		0.054
			(0.32)		(0.31)
Sex of HH head (1=Female)			-0.553****		-0.588****
			(0.16)		(0.17)
Age of HH head (years)			-0.002		-0.003
			(0.01)		(0.00)
Education of HH head (years)			-0.004		-0.012
			(0.01)		(0.01)
Household size to labour ratio			0.110		0.287**
(No. of persons/adult equiv. labour unit)			(0.13)		(0.14)

Total Livestock Units (TLU) to labour ratio	-0.024		-0.045
	(0.08)		(0.12)
One-year lag TLU to labour ratio	0.013		0.006
(lag TLU No./ adult equiv. labour unit)	(0.06)		(0.06)
Capital asset index to labour ratio	0.299*		0.259
	(0.17)		(0.16)
Distance to the urban center (km)	0.009***		0.007***
	(0.00)		(0.00)
Mean of observed control variables			
Own farmland (ha)		-0.568*	
		(0.33)	
Own farmland to labour ratio		-0.097	
(ha/adult equiv. labour unit)		(0.85)	
Share of male labour		-1.436**	
		(0.58)	
Sex of HH head (1=Female)		-1.037****	
		(0.28)	
Age of HH head (years)		-0.003	
		(0.01)	
Education of HH head (years)		0.007	
		(0.02)	
Household size to labour ratio		-0.115	
(No. of persons/adult equiv. labour unit)		(0.25)	
Total Livestock Units (TLU) to labour ratio		-0.057	
		(0.13)	
One-year lag TLU to labour ratio		-0.006	

(lag TLU No./ adult equiv. labour unit)	(0.18)
Capital asset index to labour ratio	0.141
	(0.28)
Distance to the urban center (km)	0.011***
	(0.00)
Deviations of the mean	
Own farmland (ha)	-0.661**
	(0.32)
Own farmland to labour ratio	0.163
(ha/adult equiv. labour unit)	(0.81)
Share of male labour	-0.121
	(0.38)
Sex of HH head (1=Female)	-0.188
	(0.22)
Age of HH head (years)	0.008
	(0.01)
Education of HH head (years)	-0.013
	(0.02)
Household size to labour ratio	0.125
(No. of persons/adult equiv. labour unit)	(0.16)
Total Livestock Units (TLU) to labour ratio	0.011
	(0.15)
One-year lag TLU to labour ratio	0.013
(lag TLU No./ adult equiv. labour unit)	(0.08)
Capital asset index to labour ratio	0.410
	(0.28)

Distance to the urban center (km)				-0.003	
				(0.01)	
Year dummies					
2013.year	0.395**		0.408**	0.402**	
	(0.19)		(0.19)	(0.19)	
2016.year	0.444***	0.021	0.489***	0.437**	0.018
	(0.17)	(0.26)	(0.17)	(0.19)	(0.25)
Constant	-1.884****	-1.162****	-1.469***	-0.653	-1.278**
	(0.25)	(0.23)	(0.51)	(0.82)	(0.52)
sigma_u	1.023****	0.477**	0.932****	0.938****	0.000****
	(0.10)	(0.23)	(0.10)	(0.10)	(0.00)
sigma_e	0.637****	0.759****	0.627****	0.617****	0.824****
	(0.05)	(0.12)	(0.05)	(0.05)	(0.07)
Observations	2,085	1,390	2,085	2,085	1,390
Left Censored (_n)	1,953	1,288	1,953	1,953	1,288
Uncensored (_n)	132	102	132	132	102
Number of y3_hhid	695	695	695	695	695

Note: The asterisks represent **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1. Normal standard errors in parenthesis.