Non-convex transaction costs and land rental market participation in Malawi

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Abstract

We assess how non-convex transaction costs constrain access to and participation in the land rental market by smallholder farmers within Sub-Saharan Africa. The theory suggests a dynamic externality due to such transaction costs and that orchestrated participation can reduce such costs and enhance future participation. We use dynamic random effects probit and Tobit models with balanced panel data from Malawi to assess participation on the tenant side of the market. We observe that initial and earlier land rental market participation significantly increases participation in the subsequent years, consistent with dynamic non-convex transaction costs and possible entry barriers in the market.

Keywords: Land rental markets, non-convex transaction costs, dynamic random effects models, Malawi

JEL Codes: Q15, Q12

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1. Introduction

Land markets develop as an efficiency-enhancing mechanism in allocating productive resources in agriculture (de Janvry, Gordillo, Platteau, and Sadoulet 2002). Imperfections in the non-land factor markets create a rationale for land markets to balance factors of production across farms and in agricultural systems with low elasticities of substitution (Holden, Otsuka, and Place 2010). Binswanger and Rosenzweig (1986) showed how the biophysical characteristics of land and non-land factors of production influence the factor market characteristics, distribution and redistribution of such factors among farm households in rural societies. These biophysical characteristics plus the institutional factors (cultural norms and political history), climatic conditions, population pressure, information and moral hazard (human behaviour) potentially lead to non-missing but imperfect factor markets in rural societies (Binswanger and Rosenzweig 1986; Holden et al. 2010). With imperfect factor markets that are spatially dispersed and not well integrated, market participants face dynamically variable non-linear transaction costs (Holden et al. 2010).

Theory and empirical evidence indicate that such non-linear transaction costs characterise both the land and non-land factor markets in Sub-Saharan Africa (SSA) and that such costs are high from policies, institutions and social factors that influence the degree of information asymmetry, access and use of production resources (Fafchamps 2004; Gebru, Holden, and Tilahun 2019; Holden, Deininger, and Ghebru 2007; Holden et al. 2010; Ricker-Gilbert and Chamberlin 2018). In the land markets, such transaction costs include access to market information related to searching for a willing buyer and willing seller, transport costs to where land is located and contract negotiation costs. Additionally, participants in the land rental markets can incur monitoring and enforcement of rental contract costs in short to medium-term. Since land is immobile, access to market information and transport costs can vary across space and over time as a result of land valuation that is based on both production practices and land use across space, and development of market and related transport infrastructure over time, especially in urban hinterland (Bigelow, Ifft, and Kuethe 2020; Tione and Holden 2020). Thus, the extent to which participants transact and the associated transaction costs are key in explaining the degree to which the land rental market is a level playing field and enhances allocative efficiency of factor markets (Baland, Gaspart, Platteau, and Place 2007; Bell and Sussangkarn 1988; Deininger 2003; Skoufias 1995).

In contrast, the theory on factor markets in SSA also suggests that market participants overcome such market imperfections by establishing networks of information in short to medium-term period, to deal with the challenge of information asymmetry, as opposed to transport costs that can require long-term plans to develop the infrastructure (Fafchamps 2004). Specifically, participants establish localised information networks that are inter-personal, as a way of reducing transaction costs over time (Fafchamps 2004; Fafchamps and Minten 2001). That is, upon entering the markets, participants invest in establishing inter-personal networks of information, trust and reputation that are important for searching and negotiating, monitoring and enforcing market contracts in subsequent years. In line with Fafchamps (2004) and Holden et al. (2010), such initial investment costs can be high and non-linear upon entry but reduce over time from repeated engagements, thereby resulting in intertemporal non-linear and non-convex transaction costs.

Non-convex transaction costs imply marginally decreasing costs mainly from participants overcoming the first hurdle related to market entry and with repeated market engagements over time (Fafchamps 2004). With repeated engagements, searching and contracting costs reduce over time hence giving an advantage to experienced market participants compared to new entrants, thereby leading to participation in the factor market that is state-dependent. Participation that is state-dependent implies that market participants capitalise on their experience and the established networks to identify trading partners, as opposed to new entrants without established trust or reputation networks in the market. Thus, it is the state of a market participant in the network that can determine participation and the level of transaction costs incurred by individuals in subsequent years (Fafchamps 2004).

Overall, both policies and institutional factors that govern the use and trade of production resources can influence transaction costs in ways that either promote or constrain participation in the markets. Despite extant literature indicating that factor markets in SSA are characterised by high and non-linear transaction costs (Holden et al. 2010; Ricker-Gilbert and Chamberlin 2018), empirical evidence on the extent to which non-convex transaction costs characterise or restrict participation, and whether participation in the land markets developing in SSA is dependent on experience in the market, remains an empirical question. Thus, we add to this limited literature by hypothesizing that land rental markets ration the participation of potential tenants[1], and such participation is state-dependent and creates time-recursive dynamic decisions.

We are only aware of studies in Ethiopia that have assessed the non-convexity of transaction costs on land rental markets with dominant sharecropping and dominance of kinship related land rental contracts (Gebru et al. 2019; Holden et al. 2007). We are no aware of studies that have focused on land rental markets dominated by fixed and short-term contracts, which might be considered less dependent on market networks (Alston, Datta, and Nugent 1984). However, with market imperfections in SSA, assessing the non-convexity of transaction costs in the land rental markets should be key for understanding contract formulation with respect to search and negotiation costs. Such empirical evidence should be emphasized when developing policies that can lift entry barriers and further enhance the allocative efficiency of productive resources through markets.

We use three panel rounds of the Malawi Living Standards Measurement Survey (LSMS) data collected in 2010, 2013 and 2016, from which we constructed a balanced household panel data. Malawi is a country in SSA with emerging spatially dispersed land rental markets, dominated by short-term and fixed-rent contracts under customary land tenure systems (Lunduka, Holden, and Øygard 2010). The country has an instituted legal framework that allows households to trade their private or customary land according to land-use guidelines compared to other countries that strictly limit land market activities in SSA (Government of Malawi 2016, 2002). For instance, the legal framework in Ethiopia prohibits land sales and only allows renting up to 50 percent of owned land per household (Holden and Ghebru 2016). Thus, the focus on transaction costs in this paper should be important for the development policy and lessons for the region as land rental markets develop in SSA. To our knowledge, this is the first empirical study on dynamic and non-convex transaction costs in the land rental markets literature within SSA that uses nationally representative household data, with a focus on land rental markets dominated by short-term and fixed land rental contracts.

To achieve our objective, we use the farm household model and the theory of dynamic non-linear transaction costs in the land rental markets (Holden et al. 2007; Holden et al. 2010). By applying the probit and Tobit dynamic random effect models (Wooldridge 2010), we use the initial and lagged participation in the land rental markets to assess the specified hypotheses, while controlling for the unobservable heterogeneity that may influence entry and extent of participation in the market, including an initial investment in networks of information, trust and reputation (Wooldridge 2005). By observing the size, sign and significance of the lagged and initial participation and extent of participation variables, we are able to assess the extent to which the market is characterized by non-convex (non-linear) transaction costs.

We have organised the rest of the paper as follows. The next section presents the theoretical framework and hypotheses followed by a section on the estimation methods and data. After describing the data, we present the descriptive statistics, results and discussion sections before concluding the paper.

2. Theoretical Model and Hypotheses

Fundamentally, under a fixed-rent contract, a potential landlord and a potential tenant will have to search for a potential partner for the preferred period. Imperfect information contributes to the initial search costs for the matching of potential landlords and tenants. Social networks may help to reduce these search costs and facilitate matchmaking in the market. At an early stage of market development, when the market is thin, such costs may still be high. After finding a potential partner, a contract must be negotiated and agreed upon by both parties. The minimum conditions for a fixed rent contract are the duration of the contract, land area to be rented, payment and timing of payment. Costs involved in searching for a partner and finding suitable land given the spatial immobility of land, seasonality and risks in agriculture, the time requirement, skills and additional non-land factors of production needed in biological production, elasticity of substitution between land and non-land factors, social relations and norms important for trust, reputation and contract reliability, and other forms of uncertainty and risk, influence perceived and actual transaction costs in the markets. This complexity implies that experience and connections or networks are important for determining the level of transaction costs and success in the land rental market. Thus, the theoretical model applied in this paper integrates the farm household model with a dynamic non-linear transaction costs model (Holden et al. 2007; Holden et al. 2010, pp. 27-36).

We consider a farm household endowed with land $(\bar{A})$ and labour $(\bar{L})$ and with the potential to trade these resources in a market. Focusing on a potential tenant household, such a household will aim at maximizing income utility $(Max\, U = U[Y])$ from renting-in land and achieving the desired resource use level on own-farm (Holden et al. 2010). Assuming net use of labour on the farm and non-linear transaction costs from imperfect factor markets as discussed above, equation [1] specify the potential tenant farm household objective function.

$$\underset{A^i,L}{\operatorname{Max}} U[Y] = U[P_q q(A, L) - \{\rho A^i + \eta(A^i) + \omega L + P_m M\}] \qquad \text{and } A^i \geq 0,\ L > 0 \qquad [1]$$

From the equation, Y is the income function for a potential tenant household and the choice variables are renting-in land (A^i) and labour (L) use on own-farm. The income is the net market equivalent output value from production revenue less expenditure. That is, P_q is the output price while $q(A, L)$ is the production function where (A) is the operational holding of farmland that is equal to the total owned land ($\bar{A}$) plus rented-in land (A^i), i.e. [$A = \bar{A} + A^i$]. The equation [$\rho A^i + \eta(A^i)$] is the expenditure function for renting-in land. That is, ρ is the constant land rental price that does not include other non-linear transaction costs related to the search and negotiation costs in contract formulation and η is the non-linear transaction cost with respect to rented land among market participants. On net labour use (L), the parameter ω is for the market wage rate or shadow wage rate at the household level, and the (ωL) is a labour cost function aggregated at the household level. This net labour use-value implicitly captures both labour time used for work and leisure for all labour available at the household level (Singh, Squire, and Strauss 1986). Furthermore, the function ($P_m M$) is for expenditure on other market inputs (M), with P_m as the market input price.

Based on the income utility maximisation function and using the duality theory, we focus on the twice differentiable quasi-convex income function to assess the non-linearity in the transaction costs. When we normalise to one the output price P_q and the other market input price P_m, the first-order condition (FOC) from equation [1] with respect to rented-in land (A^i) is specified in equation [2].

$$\frac{\partial Y}{\partial A^i} = \frac{\partial q}{\partial A^i} - \rho - \frac{\partial \eta}{\partial A^i} \leq 0 \qquad \perp \qquad A^i \geq 0 \qquad [2]$$

i.e. $\frac{\partial q}{\partial A^i} = \rho + \frac{\partial \eta}{\partial A^i}$ if $A^i > 0$ or $\frac{\partial q}{\partial A^i} < \rho + \frac{\partial \eta}{\partial A^i}$ if $A^i = 0$

From equation [2], the potential tenant will only trade if the marginal revenue from rented-in land $\left(\frac{\partial q}{\partial A^i}\right)$ is greater or equal to the marginal cost of renting-in land $\left(\rho + \frac{\partial \eta}{\partial A^i}\right)$, and will not trade if otherwise. To assess the non-linearity of the transaction costs in the land rental markets, the second-order condition (SOC) from equation [2] is given as $\left[\frac{\partial^2 q}{\partial {A^i}^2} \leq \frac{\partial^2 \eta}{\partial {A^i}^2}\right]$. That is, the extent of land trade adjustment depends on the level of varying non-linear transactions costs $\left(\frac{\partial^2 \eta}{\partial {A^i}^2}\right)$ hence resulting in a local maximum and not a global maximum solution (Carter and Yao 2002).

Bliss and Stern (1982) indicated that in a well-functioning land rental market, the coefficient on own land is equal to minus one (-1) indicating linear costs. To assess such linearity in land rental market costs, we conduct a comparative analysis of the change in rented-in land (A^i) with respect to owned land $(\bar{A})$ or the rate of market adjustment at the household level $\left[\frac{\partial A^i}{\partial \bar{A}}\right]$. Assuming an interior solution $(A^i > 0)$, the derivative function for the comparative analysis is given as $\left[\frac{\partial A^i}{\partial \bar{A}} = \frac{\partial^2 q}{\partial {A^i}^2} - \frac{\partial^2 \eta}{\partial {A^i}^2}\right]$ or simply given as $\left[q_{A^i\bar{A}} = q_{A^iA^i} - \eta_{A^iA^i}\right]$ based on the demand functions estimated from the FOC in equation [2]. This implies that the rate of market adjustment at household level will only be linear $\left[\frac{\partial A^i}{\partial A} = -1\right]$ if the variable transaction costs are linear $(\eta_{A^iA^i} = 0)$. However, from the SOCs, the variable transaction costs are non-linear $\left[\frac{\partial A^i}{\partial A} > -1 \;\; or \left(\frac{\partial A^i}{\partial \bar{A}} < -1\right)\right]$. Thus, the area adjustment at the household level will deviate from the linear smooth adjustment when transaction costs are non-linear. We have presented the detailed farm household model and the detailed comparative statics in Appendix A, in line with Holden et al. (2010).

Considering that the discussed farm household model is static and mainly focuses on the rental decision for one period across space, e.g. a year in rain-fed agriculture, we extend the theoretical framework by applying the dynamic transaction cost model for tenant households (Holden et al. 2007). Equation [3] specifies the intertemporal decision to rent-in land among tenant households.

$$A_{jt}^{i} = \sum_{\mathcal{R}} A_{jt}^{\mathcal{R}} \left[c_0 + c_{jt}^{\mathcal{R}} \left(\bar{A}_{jt}, \bar{L}_{jt}, \int_{-\gamma}^{t} A_{jt-n}^{L}\, dt, \int_{-\Gamma}^{t} \varphi_t^{p}\, dt; z_{jt}^{h}, z_{jt}^{\varsigma} \right) \right] \quad [3]$$

The model indicates that amount of land rented-in (A_{jt}^{i}) by household *j* at time *t* is an aggregate of accessed land from one or several landlord households ($\mathcal{R}$), given as $\sum_{\mathcal{R}} A_{jt}^{\mathcal{R}}\, [.]$. Access to rented land is furthermore a function of transaction costs (c) which include an initial fixed transaction cost (c_0) and a non-linear variable transaction cost ($c_{jt}^{\mathcal{R}}$). The variable transaction cost is a function of both observable and unobservable factors. These factors include the tenant household endowments of land ($\bar{A}_{jt}$) and labour ($\bar{L}_{jt}$), and previous participation in the land rental markets ($\int_{-\gamma}^{t} A_{jt-n}^{L}\, dt$) that affect decision-makers' knowledge (information), trust and reputation in the market, which changes recursively over time and contribute to the non-convexity of transaction costs. These non-convex transaction costs are not directly observable but may be identified by studying the impact of past participation on later participation in the market using household panel data. Thus, the household-level lagged participation variables include both the participation and degree of participation (measured in area) in line with dependent variables in the analysis. Lastly, the model captures the dynamic effect of the policy mix (changes) ($\int_{-\Gamma}^{t} \varphi_t^{p}\, dt$) that may influence transaction costs in the rental market over time. This model specification is conditional on household and community characteristics ($z_{jt}^{h}, z_{jt}^{\varsigma}$). Therefore, in this paper we hypothesize that;

H1. The entry of potential tenants into land rental markets is rationed.

We assume that the initial search and negotiation costs create a barrier to entry in the land rental markets from information asymmetry and high entry costs if land rental markets are thin, like in Malawi.

H2. The extent of participation by tenants in the land rental markets is higher for those who participated in the market in the past (state-dependency).

Experience in land rental market should help in later participation decisions due to non-convex transaction costs related to accessing relevant market information, social networks and building of trust and reputation.

H3. The likelihood of entry into the land rental market declines with owned land size.

Farm households with more owned land are less likely to be potential tenants, especially in hand-hoe based farming systems like in Malawi where we assume no economies of scale and that the market is thin and underdeveloped from having few potential tenants accessing rented land. We consider potential tenants as land-poor households with sufficient non-land resources and limited access to non-farm employment.

H4. High non-linear transaction costs characterise the extent of participation by tenant households and results in the coefficient on owned land to be close to 0.

In well-functioning land rental markets with linear transaction costs, the coefficient on owned land should be equal to minus one (-1) (Bliss and Stern 1982). Lunduka et al. (2010), Ricker-Gilbert and Chamberlin (2018) and Holden et al. (2010) studies in Africa have found that the coefficient on owned land to be closer to 0 than to -1 when analysing participation in land rental markets developing in most countries in this region. However, most of these studies have used cross-section data.

3. Estimation Methods and Data

To assess our hypotheses, we estimate the reduced form of the dynamic participation decision in the land rental market for potential tenant households (A_{jt}) as specified in equation [4].

$$A_{jt}^{i} = \alpha + A_{jt-n,}^{i}\rho + \gamma\bar{A}_{jt} + \pi\bar{L}_{jt} + z_{jt}\beta + \tau + \mu_j + \varepsilon_{jt} \quad [4]$$

The variable A_{jt}^{i} is for participation in the land rental market for household j and at time t. From the variable, i represents either entry into or extent of participation to avoid repeating the equation. While participation is captured by a dummy variable, the extent of market participation is measured by the amount of land rented-in, given in hectares (ha) at the household level. Our parameters of interest in equation [4] are ρ for the lagged participation variables and γ for the land endowment. The lagged dependent variables also control for unobserved heterogeneity, which is an alternative way that can be compared to using household fixed effects in panel data methods. The household random effects specification is used, and unobserved heterogeneity is modelled on the initial participation variable in the first-round panel (Wooldridge 2005), see further details below. Furthermore, the parameter π is for labour endowment while β is a parameter vector for household and community characteristics. τ is a vector of year dummy variables that partially controls for policy and other shocks over time. The μ_j captures time-constant unobserved heterogeneity and ε_{jt} is the idiosyncratic error that is independent and identically distributed.

From equation [4], the variable $\bar{A}_{jt}$ is for owned farmland area in hectares (ha) for household j at time t. Owned farmland includes inherited land through customary systems or government distribution and purchases, which represents land endowment in our model. The variable excludes land borrowed for free, farmland for those on wage contract in estate farms providing tenant labour, encroached government land and if a household only used rented-in land. These categories mainly imply operational farmland without secure tenure right

(Holden, Otsuka, and Deininger 2013). We consider households accessing land from only the excluded sources to be landless in the ownership sense, as they only hold tenure as a land user (Holden et al. 2013). We did not consider households who rented-in land in addition to owned land as landless in the analysis. Thus, our model includes a dummy for landless households to control for operational farmland but not the extent of owned land that we have already specified.

The model also controls for owned-farmland-to-labour-endowment ratio, where labour endowment is estimated as the total adult equivalent labour units from all household members present in the household for at least a month within the panel year. The labour is measured in adult male equivalents, while adult female members are assigned 0.8 units, and children between 5 and 15 years are assigned 0.5 units despite their sex. The focus was to estimate total household labour endowment as opposed to labour used on the farm that is more endogenous and difficult to measure in a reliable way. Considering the dominant use of hand hoes for cultivation in Malawi that requires more human strength (Takane 2008), we assume that the labour endowment measured in this way is associated with a higher demand for agricultural land. To further test whether this specification generates a gender-bias or under-estimates the strength advantage of male labour, we also control for the share of male labour at the household level by dividing total adult male labour units to the total household adult equivalent labour endowment at household level.

Additionally, our model controls for other household and community characteristics. These include sex, age and education of the household head; consumer to worker ratio; and both the current and one-year lag Total Livestock Units (TLU) per labour unit ratio. On the consumer to worker ratio, our analysis uses headcount of individuals or household size compared to the adult equivalent labour endowment at household level. Although this is a crude measure of a consumption needs, it should provide insights on whether household size per labour equivalents influences demand for rented land. Furthermore, we consider livestock to be an indicator of wealth that households can easily liquidate to support production and labour use decisions. At the community level, we include the distance to urban centres with a population of more than 20,000 people for proximity to urban areas.

To estimate equation [4], we use dynamic panel data models with binary and censored response variables (Wooldridge 2010). Assuming data observation is from *t=0* so that A_{jt}^{i} is the first observation of outcome (A^{i}), for *t*=1, …., T, the dynamic random effects probit model can be specified as;

$$P\left(A_{jt}^{i} = 1 \middle| A_{j,t-n}^{i}, \ldots, A_{jo}^{i}, z_j, \mu_j\right) = \Phi(z_{jt}\delta + A_{j,t-n}^{i}\rho + \mu_j) \qquad [5]$$

Where A_{jt}^{i} is the dependent variable and the subscript $(t-n)$ is for the previous survey round denoted as (n). The z_j is a vector of explanatory variables and Φ is for a standard normal distribution function with the probability of success at time *t* and also the outcome from the previous $(t-n)$ period. The μ_j is for the unobserved heterogeneity. With this specification, one can test $H_0\colon \rho = 0$ to assess initial conditions and state dependency in the model, once we control for μ_j. The model assumes μ_j to be additive and given as $\mu_j = \psi + \alpha_0 A_{jo}^{i} + z_j\alpha_1 + \epsilon_j$. Where $\epsilon_j \sim Normal(0, \sigma_\epsilon{}^2)$ and independent of $(A_{jo}^{i} + z_j)$. The ψ is a constant. This structure allows the use of a likelihood function similar to random effect probit model if we add the initial period rental market participation variable given as A_{jo}^{i} and z_j as defined above, to the list of explanatory variables, resulting in $x_{jt} = \{1, z_{jt}, A_{j,t-n}^{i}, A_{jo}^{i}, z_j\}$. By doing so, we control for the unobserved effects of μ_j and the initial household conditions (Wooldridge 2010, p. 625).

On the extent of participation, Wooldridge (2010 p. 713) specifies the dynamic random effects Tobit model as indicated in equation [6].

$A_{jt}^{i} = max\left[0, z_j\delta + \rho A_{j,t-n}^{i} + \mu_j + \varepsilon_{jt}\right]$. For all t =1, ..., T and j=1,2,..,N households. [6]

The idiosyncratic error term is $\varepsilon_{jt}|\left(z_j, A_{j,t-n}^{i} \ldots A_{jo}^{i}, \mu_j\right) \sim Normal(0, \sigma_\varepsilon{}^2)$. Unlike the probit, the lagged outcome variable in Tobit depends on whether $(A_{j,t-n}^{i})$ is equal to or greater than zero. Hence $(\rho A_{j,t-n}^{i})$ can be replaced with $\xi r_{jt-n} + \rho(1 - r_{jt-n})A_{j,t-n}^{i}$. Where (r_{jt-n}) is binary and equal to one if $A_{jt-n}^{i} = 0$ and zero otherwise. Like the probit, this reduces the list of explanatory variables to $x_{jt} = \left\{z_{jt}, A_{j,t-n}^{i}, A_{jo}^{i}, z_j\right\}$. With these model specifications, one can compute the conditional or unconditional partial average effects similar to the probit and Tobit models using balanced panel data (Wooldridge 2010, p. 714).

For our analysis, we constructed a three round balanced household-level panel data of 1,480 households from the 1,619 households in the 2010 baseline survey round. We used the Malawi Living Standards Measurement Surveys (LSMS) conducted in 2010, 2013 and 2016. By construction, we observed an 8.6 percent attrition rate that we used to test for attrition bias. We estimated the inverse mills ratio with a probit model presented in Appendix B, Table B1, which we included in our estimations. We did not observe a significant attrition bias effect in our analysis and hence we present the results that exclude the inverse mills ratio. Results with inverse mills ratio are available in Appendix B, Table B3 for comparison. Overall, our balanced data accounted for changes in household head over time, parcel-level information like sources of land, and aggregated parcel area to household level in hectares (ha) measured using handheld GPSs.

As per the dynamic random effects model, we used the entry and extent of participation in the 2010 survey round as the initial year participation variable in all three survey rounds. At the same time, we used the 2010 participation as lagged participation variable in 2013, and the participation decision in 2013 as lagged participation variable in 2016. Using 2010 as the initial year, this first observation is a function of past unobserved participation and is considered to be a proxy for accumulated information, trust and reputation that affects the initial transaction costs and thereby participation (Wooldridge 2005). Households that are participating in the initial year are, based on our theory, in a favourable position that reduces the transaction costs associated with later participation, which we assume to be an effect that lasts for many years. This is what we test for in our analysis across the survey rounds, although to an extent our analysis is limited in testing for things happening between the survey rounds. If the lagged and initial participation variables are still significantly enhancing market participation across the three year survey gap, this would be a clear indication of the importance of these dynamic state-dependent effects, which is in line with our theory on non-convex transaction costs in the land rental market. Overall, this implies that after these markets have been kick-started, they may evolve and become more efficient and enhance efficiency of resource allocation over time.

4. Descriptive Statistics

From Table 1, the percent of households that participated in the land rental markets were 7.3, 10.1 and 8.9 for 2010, 2013 and 2016 survey rounds, respectively. The table shows that owned and operational farmland per household in our sample was on average 0.55 ha across the years. Among tenant households, the average rented-in land was 0.5 ha with the land endowment of 0.33 ha that is significantly lower than 0.52 ha owned land among non-tenant households. The percent of landless households among the tenant households was 48 percent, which is significantly higher than the 30 percent landless households among the non-tenant households. These statistics show that the rental market possibly transfers land towards landless and land-poor households although we do not know how land-rich those renting out this land are. A possible extension of the paper would be to assess both potential landlords and tenants using longitudinal data if available.

Table 1 further shows that the tenant households are operating an average of 0.82 ha, which is significantly larger than the average operational and owned farmland (0.52 and 0.53 ha) for non-tenant households. The data could imply that tenants are non-land resource-rich households (labour and capital), that could manage to increase their operational land size. Ricker-Gilbert et al. (2019) observed a similar distribution in Malawi using one-year matched landlord-tenant data in selected districts. On labour endowment, our data show no significant differences in the share of male labour between tenant and non-tenant households considered important for hand-hoe based farming systems like in Malawi. On the contrary, land relative to the labour endowment is higher for non-tenant households. Since the percent of landless households was not constant over the years, we could not directly drop the landless household and test the differences in labour units. Such data required creating a new balanced panel that excludes landless households, which is outside the scope of this study.

[Table 1 here]

Table 1 also shows that tenant households are less likely to be headed by a female and that land rental markets are common in rural areas. A tenant household is more likely to be headed by a slightly younger person and a household head who is slightly more educated than non-tenant households. Among the tenants and non-tenant households, there are no significant differences in consumer to worker ratio, which is a possible indicator of self-sufficiency objectives among all households. To confirm the short-term and fixed-rent contracts in our data, we observed that almost all contracts were for one growing season or one calendar year. Only 4 percent of the households combined upfront cash payment with sharecropping contracts across the years and we maintained these households in our sample. Furthermore, Table 1 shows that the rate of market re-entry from the initial baseline year (2010) was 51 percent in 2013 and 36 percent in 2016. Those who participated in 2013, 43 percent also participated in 2016 survey round. This shows a land rental market with participation from both experienced participants and new entrants across the survey years that is important for the dynamic assessment of the land rental market.

5. Results and Discussion

Table 2 presents the average partial effects $[E(y|\boldsymbol{X})]$ from the dynamic random effects probit and Tobit models. Parsimonious models are followed by three models with additional controls for each of the probit and Tobit specifications. The first three models (P1 to P3 and T1 to T3) include initial participation, lagged participation and resource endowment variables only, while the fourth model (P4 and T4) includes all the other household and community control variables. We chose to focus on the unconditional mean partial effects $[E(y|\boldsymbol{X})]$ for us to assess participation decisions that include potential tenant households in the land rental markets in line with our hypotheses. In addition, Table 3 present the conditional average partial effects $[E(y|\boldsymbol{X}, y > 0)]$ for the dynamic random effects Tobit model for observed market participants. Appendix B, Tables B2 further presents the corresponding coefficients for the presented average partial effects, for both the dynamic random effects probit and Tobit models. In what follows, we present and discuss the results in line with the specified hypotheses.

To assess hypothesis one (H1), we evaluate the dynamic random effects probit model results presented in Table 2. The hypothesis stated that the entry of potential tenants into land rental markets is rationed. From the table, we note a significant positive effect of initial year participation dummy and the lag participation variables, significant at 1 and 10 percent, respectively. The average marginal effects show that the initial participation year (2010) variable increase the probability of participation in later years by 11 percentage points (model P4). The lagged rent-in dummy increase participation by 6.8 percentage points but significant at the 10 percent level. The results imply that potential tenant households with experience, after getting over the first hurdle of entering into the market, are more likely to re-enter the market. This supports the theory of non-convex transaction costs in the land rental markets developing in Malawi. Fafchamps (2004) indicated that entry into a market and establishing information networks is a sunk cost that potential traders must overcome and later use this information for future transactions. Thus, we cannot reject hypothesis one (H1) and conclude that entry of potential tenants into land rental markets is rationed by giving an advantage to participants with experience in the market compared to new entrants.

To assess hypothesis two (H2), we use the unconditional margins for initial and lagged participation variables from the Tobit model results. Hypothesis two stated that the extent of participation by tenants in the land rental markets is higher for those who participated in the market in the past (state-dependency). From T4 model results, we note that it is only the initial year participation variables (entry and extent of participation) that are significant but not the lagged participation variables. Considering the initial year variables, the marginal increase in the average amount of land area rented-in is 0.02-0.03 ha in model T4. By not observing a significant effect of lagged participation variables, our results show that it is mainly the initial entry and extent of participation in the market that increases the extent of participation in the subsequent years but not necessarily the market participant status in the years after entering the market in Malawi. These results confirm the challenge of getting over the first hurdle of entry into the market and that participation in subsequent years is a factor of initial market investment costs that are non-convex over time. Thus, the results give less support for state-dependent land rental markets after participants have entered the market that could imply high and non-linear transaction costs in the markets, which is our next discussion point.

For the third hypothesis (H3), we stated that the likelihood of entry into the land rental market declines with owned land size. To assess this hypothesis, we refer to the results from the probit model P1 presented in Table 2. The results indicate that a one ha increase in own farmland area reduces the probability of participation by 3 percentage points. However, given that the average farm size is below one hectare in our data, we consider this to be a very small effect. Thus, considering the percent of landless households in our sample, when we add the dummy for landless households in models P2-P4, we note a significant effect on being landless. By construction, the summary statistics showed that almost 32 percent of our sample are landless in the land ownership sense. Since landless implies zero owned land, we tried to run the analysis without the landless dummy in models P2 to P4 to assess the independent effect of owned land. With this specification, the owned land variable was still not significant in all P2 to P4 models, hence supporting the need to separately assess the landless households. From the results, landless households have a 2-4 percentage point higher likelihood of accessing land in the rental market than households who own land. Our results imply that the rental market transfers land to landless households to some extent or that the landless households (in the ownership sense) are more willing to participate than those with some owned land.

[Table 2 here]

[Table 3 here]

Our observations concur with the study of Baland et al. (2007) in Uganda, who observed that landless households were able to purchase more land than those with initial land inheritance. Furthermore, the community members in Uganda were more willing to trade land to those with a low probability of inheriting land, a sign of social-network based exchange that reduces transaction costs. Thus, our results only provide weak support for hypothesis three (H3) since owning land is not significant but being landless in the ownership sense. We proceed to inspect hypothesis four (H4) on the extent of market allocation (amount of land rented-in per household) using the dynamic Tobit models.

In H4 we stated that high non-linear transaction costs characterise the extent of participation by tenant households if the coefficient on owned land is close to 0. To assess this hypothesis, we compared the Tobit model results from Table 2 (unconditional margins) and Table 3 (conditional margins). From Table 2, the unconditional average partial effects of both owned farmland and the landless dummy are close to zero (0.01) while significantly different from zero. Contrasting these results with the conditional marginal effects, we note a significant change to only 0.02 ha (model T1-margins) for those who own land and to 0.04 ha (model T4-margins) for landless households. The small changes in land area rented-in from both the conditional and unconditional marginal effects indicate high non-linear transaction costs, even for households already participating in the market. Therefore, we cannot reject hypothesis four (H4) which implies the inefficient allocation of land rental markets in Malawi despite dynamic non-convex transaction costs.

6. Conclusion

Land markets, and more so land rental markets with short-term and fixed-rent contracts are developing in many countries across Sub-Saharan Africa (SSA). Theory of agricultural factor markets in SSA indicates that, upon entry, market participants in the land and non-land factor markets invest in information, trust and reputation networks that lead to non-linear and dynamic non-convex (marginally reducing) transaction cost over time and across space. Participants invest in such networks if market information and contract formation costs are high and state-dependent but perceived to be reducible through investments that can overcome initial market entry barriers.

Despite the theory of transaction costs in agricultural factor markets, the extent to which non-convex costs characterise or restrict participation in the land rental markets that are developing in SSA remains an empirical question. In this paper, we contributed to this literature by assessing the extent to which non-linear and non-convex transaction costs ration potential tenants' entry into the land rental markets and whether the extent of participation is state-dependent on previous engagements in the market. We used a nationally representative balanced household panel data, constructed from the Malawi Living Standards Measurement Surveys (LSMS) conducted in 2010, 2013 and 2016.

Our study revealed high non-linear transaction costs in the land rental markets developing in Malawi, an indicator of a thin land market that has a long way to go before it can ensure allocative efficiency. That is, non-linear transaction costs continue to constrain land-use efficiency and hinder efficient resource recombination across farms. However, the problem is likely to reduce over time as overcoming the first hurdle of entering the market reduces transaction costs and improves access to rented land despite the dominance of short-term and fixed-rent contracts.

Potential tenants (and the corresponding potential landlords) who have entered the markets are more likely to benefit from their experience and networks of information, trust and reputation in a market that is a non-level playing field. Thus, targeted policies may contribute to reducing externalities related to entry barriers and the associated information asymmetry. Policy interventions can include orchestrated community meetings between potential landlords and tenants. This can reduce transaction costs and improve the allocative efficiency of land rental markets in Malawi with lessons for countries in SSA, particularly for land constrained households.

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References

Alston, L. J., Datta, S. K., and Nugent, J. B. 1984. "Tenancy choice in a competitive framework with transactions costs". *Journal of Political Economy*, 92(6): 1121-1133.

Baland, J.-M., Gaspart, F., Platteau, J.-P., and Place, F. 2007. "The distributive impact of land markets in Uganda". *Economic Development and Cultural Change*, 55(2): 283-311.

Bell, C., and Sussangkarn, C. 1988. "Rationing and Adjustment in the Market for Tenancies: The Behavior of Landowning Households in Thanjavur District". *American Journal of Agricultural Economics*, 70(4): 779-789. doi:10.2307/1241919

Bigelow, D. P., Ifft, J., and Kuethe, T. 2020. "Following the Market? Hedonic Farmland Valuation Using Sales Prices versus Self-reported Values". *Land Economics*, 96(3): 418-440.

Binswanger, H. P., and Rosenzweig, M. R. 1986. "Behavioural and material determinants of production relations in agriculture". *The Journal of Development Studies*, 22(3): 503-539.

Bliss, C. J., and Stern, N. H. 1982. "Palanpur: The economy of an Indian village". *OUP Catalogue*.

Carter, M. R., and Yao, Y. 2002. "Local versus global separability in agricultural household models: The factor price equalization effect of land transfer rights". *American Journal of Agricultural Economics,* 84(3): 702-715.

de Janvry, A., Gordillo, G., Platteau, J.-P., and Sadoulet, E. 2002. *Access to land, rural poverty, and public action*. Oxford University Press Inc., New York: Oxford University Press.

Deininger, K., Savastano, S., and Xia, F. 2017. "Smallholders' land access in Sub-Saharan Africa: A new landscape?". *Food Policy*, 67: 78-92.

Deininger, K. W. 2003. *Land policies for growth and poverty reduction*. World Bank Publications.

Fafchamps, M. 2004. *Market institutions in sub-Saharan Africa: Theory and Evidence*. MIT Press.

Fafchamps, M., and Minten, B. 2001. "Social capital and agricultural trade". *American Journal of Agricultural Economics,* 83(3): 680-685.

Gebru, M., Holden, S. T., and Tilahun, M. 2019. "Tenants' land access in the rental market: evidence from northern Ethiopia". *Agricultural Economics*. doi:10.1111/agec.12484

Government of Malawi. 2002. *Malawi National Land Policy*. Lilongwe, Malawi: Ministry of Lands Physical Planning & Survey.

Government of Malawi. 2016. *Land Act, 2016*. Malawi: Malawi Legal Information Institute. Retrieved from https://www.malawilii.org/mw/legislation/act/2016/16

Holden, S. T., Deininger, K., and Ghebru, H. 2007. *Impact of Land Certification on Land Rental Market Participation in Tigray Region, Northern Ethiopia.* MPRA Paper, (5211). The Munich University Library.

Holden, S. T., and Ghebru, H. 2016. "Land tenure reforms, tenure security and food security in poor agrarian economies: Causal linkages and research gaps". *Global Food Security,* 10: 21-28.

Holden, S. T., Otsuka, K., and Deininger, K. 2013. *Land Tenure Reform in Asia and Africa: Assessing Impacts on Poverty and Natural Resource Management*. Palgrave Macmillan, London: Springer.

Holden, S. T., Otsuka, K., and Place, F. M. 2010. *The Emergence of Land Markets in Africa: "Impacts on Poverty, Equity, and Efficiency"*. Washington, DC, USA: Resources for the Future.

Lunduka, R., Holden, S. T., and Øygard, R. 2010. "Land rental market participation and tenure security in Malawi". In *The Emergence of Land Markets in Africa: Impacts on Poverty, Equity and Efficiency*, ed. S. T. Holden, K. Otsuka, & F. M. Place, (pp. 112-130). Washington, DC, USA: Resources for the Future.

Ricker-Gilbert, J., and Chamberlin, J. 2018. "Transaction Costs, Land Rental Markets, and Their Impact on Youth Access to Agriculture in Tanzania". *Land Economics,* 94(4): 541-555.

Ricker-Gilbert, J., Chamberlin, J., Kanyamuka, J., Jumbe, C. B., Lunduka, R., and Kaiyatsa, S. 2019. "How do informal farmland rental markets affect smallholders' well-being? Evidence from a matched tenant–landlord survey in Malawi". *Agricultural Economics,* 50(5): 595-613. doi:10.1111/agec.12512

Singh, I., Squire, L., and Strauss, J. 1986. *Agricultural household models: Extensions, applications, and policy*. Johns Hopkins University Press, Baltimore.

Skoufias, E. 1995. "Household resources, transaction costs, and adjustment through land tenancy". *Land Economics*: 42-56.

Takane, T. 2008. *Labor use in smallholder agriculture in Malawi: six village case studies*. doi:https://doi.org/10.14989/68928

Tione, S. E., and Holden, S. T. 2020. "Urban proximity, demand for land and land shadow prices in Malawi". *Land use policy*, 94,104509: 1-14. doi:https://doi.org/10.1016/j.landusepol.2020.104509

Wooldridge, J. M. 2005. "Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity". *Journal of applied econometrics*, 20(1): 39-54.

Wooldridge, J. M. 2010. *Econometric analysis of cross section and panel data*. MIT Press.

Table 1: Summary statistics

Variable	Average values all survey rounds			
	Total sample	**Tenant households (1)**	**Non-tenant households (2)**	**t-test (1 vs. 2)**
Participation in the land rental market				
Initial year (2010) – (*percent*)	7.3			
Subsequent year (2013)– (*percent*)	10.1			
Subsequent year (2016) – (*percent*)	8.9			
Initial year (2010) rented-in land				
mean (*median*) in *ha*	0.03 (0.00)	0.45 (0.36)		
Subsequent years rented-in land				
mean (*median*) in *ha*	0.05 (0.00)	0.50 (0.36)		
Land area				
Owned farmland				
mean (*median*) in *ha*	0.50 (0.35)	0.33 (0.11)	0.52 (0.36)	****
Operational farmland				
mean (*median*) in *ha*	0.55 (0.40)	0.82 (0.61)	0.53 (0.37)	****
Landless/zero own farmland (p*ercent*)	31.53	48.07	29.94	****
Labour				
Own farmland to labour ratio (*mean*) (*ha/adult equiv. labour unit*)	0.18	0.10	0.18	****
Share of male labour (*mean*)	40.67	41.04	40.63	
Control Variables				
Sex of HH head (*%Females*)	23.65	14.65	24.51	****
Age of HH head (*mean –years*)	45	42	45	***
Education of HH head (*mean –years*)	6.15	7.11	6.06	****
Household size to labour ratio (*mean No. of persons/adult equiv. labour unit*)	1.66	1.69	1.66	
Total Livestock Units (TLU) to labour ratio (*mean TLU No./ labour unit*)	0.11	0.13	0.11	

One-year lag TLU	0.07		0.09		0.07	
Distance to urban center (*mean km*)	28.38		30.89		28.14	***
N (Panel households)	**4440** (1480)		**389**		**4051**	
Land rental market participation in the initial year and subsequent years						
	2013 (%)		**2016 (%)**			
Initial year = 2010	*No*	*Yes*	*No*	*Yes*	Total (N)	
No	93.15	6.85	93.22	6.78	1,372	
Yes	49.07	50.93	63.89	36.11	110	
Total (N)	1,331	149	1,348	132	1,480	
%	89.93	10.07	91.08	8.92	100	
Survey year = 2013	**2016 (%)**					
No	*No*	*Yes*	Total (N)			
Yes	94.9	5.1	1,331			
	57.1	43.0	149			
Total (N)	1,348	132	1,480			
%	91.1	8.9	100			

Note: The t-tests compare the overall differences in 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.

Table 2: Dynamic random effects probit and Tobit models for renting-in land (average partial effects – [$E(y|X)$] for probit and Tobit).

(Coefficient results are in Appendix B, Table B2)

VARIABLES	**P1**	**P2**	**P3**	**P4**	**T1**	**T2**	**T3**	**T4**
Initial year (2010) rent-in dummy	0.129****	0.129****	0.135****	0.111****	0.035**	0.035**	0.036**	0.023**
	(0.04)	(0.04)	(0.04)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Lag rent-in dummy	0.083*	0.080*	0.073*	0.068*	0.022*	0.021	0.019	0.015
(previous survey round)	(0.04)	(0.04)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
Initial year (2010) rent-in land (ha)					0.049*	0.051**	0.053**	0.032*
					(0.02)	(0.02)	(0.02)	(0.02)
Lag total rent-in land (ha)					0.028	0.025	0.022	0.021
(previous survey round)					(0.02)	(0.02)	(0.02)	(0.01)
Own farmland (ha)	-0.031***	-0.019*	0.006	-0.006	-0.011***	-0.005	0.006	0.001
	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)
Landless/zero own farmland (1= yes)		0.027**	0.021	0.040***		0.013**	0.011*	0.015***
		(0.01)	(0.01)	(0.02)		(0.01)	(0.01)	(0.01)
Own farmland to labour ratio			-0.091	-0.110*			-0.040*	-0.039**
(ha/adult equiv. labour unit)			(0.06)	(0.07)			(0.02)	(0.02)
Share of male labour			0.020	0.000			0.009	-0.001
			(0.02)	(0.03)			(0.01)	(0.01)

Share of purchased own farmland	-0.022	-0.011	-0.010	-0.004
	(0.03)	(0.03)	(0.01)	(0.01)
Sex of HH head (1=Female)		-0.041***		-0.016***
		(0.02)		(0.01)
Age of HH head (years)		-0.001*		-0.000
		(0.00)		(0.00)
Education of HH head (years)		-0.000		0.000
		(0.00)		(0.00)
Household size to labour ratio		0.019*		0.007*
(No. of persons/adult equiv. labour unit)		(0.01)		(0.00)
Total Livestock Units (TLU) to labour		0.005		0.002
ratio *(TLU No./ adult equiv. labour unit)*		(0.00)		(0.00)
One-year lag TLU to labour ratio		0.004		0.002
(lag TLU No./ adult equiv. labour unit)		(0.00)		(0.00)
Distance to urban centers (km)		0.002****		0.001****
		(0.00)		(0.00)
Regional dummy (1= Central)				
2. Northern region		-0.105****		-0.037****
		(0.01)		(0.01)

3. Southern region				-0.051****				-0.020****
				(0.01)				(0.01)
2016.year	-0.016*	-0.016*	-0.016*	-0.011	-0.007*	-0.007*	-0.007*	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-1.735****	-1.879****	-1.951****	-1.986****	-1.226****	-1.316****	-1.339****	-1.356****
	(0.21)	(0.25)	(0.29)	(0.43)	(0.08)	(0.10)	(0.12)	(0.25)
lnsig2u	-0.547	-0.496	-0.372	-0.531				
	(0.72)	(0.71)	(0.70)	(0.70)				
sigma_u					0.522****	0.538****	0.557****	0.480****
					(0.12)	(0.11)	(0.11)	(0.11)
sigma_e					0.708****	0.694****	0.681****	0.674****
					(0.07)	(0.07)	(0.07)	(0.06)
Observations	2,960	2,960	2,960	2,960	2,960	2,960	2,960	2,960
Left Censored (_n)					2,679	2,679	2,679	2,679
Uncensored (_n)					281	281	281	281
Number of Panel households	1,480	1,480	1,480	1,480	1,480	1,480	1,480	1,480

Note: The table presents Average Partial Effects. Specifically, the Tobit model presents the unconditional average partial effects. The asterisks denote **** = p<0.001, *** = p<0.01, ** = p<0.05, * = p<0.1. Standard errors in parentheses. For the probit model, the standard errors are cluster robust, clustered at the household level while the Tobit model presents normal standard errors.

Table 3: Dynamic random-effects Tobit models for renting-in land – conditional average partial effects [$E(y|X, y > 0)$]. (Coefficient results are in Appendix B, Table B2)

VARIABLES	T1-Margins	T2-Margins	T3-Margins	T4-Margins
Initial year (2010) rent-in dummy	0.071**	0.071**	0.073**	0.054**
	(0.03)	(0.03)	(0.03)	(0.03)
Lag rent-in dummy	0.044	0.042	0.039	0.036
(previous survey round)	(0.03)	(0.03)	(0.03)	(0.02)
Initial year (2010) rent-in land (ha)	0.099**	0.103**	0.108**	0.077*
	(0.05)	(0.05)	(0.05)	(0.04)
Lag total rent-in land (ha)	0.057	0.051	0.045	0.050
(previous survey round)	(0.04)	(0.04)	(0.04)	(0.03)
Own farmland (ha)	-0.023***	-0.010	0.012	0.002
	(0.01)	(0.01)	(0.02)	(0.02)
Landless/zero own farmland (1= yes)		0.027**	0.023*	0.036***
		(0.01)	(0.01)	(0.01)
Own farmland to labour ratio			-0.081*	-0.094**
(ha/adult equiv. labour unit)			(0.05)	(0.05)
Share of male labour			0.019	-0.002
			(0.02)	(0.03)
Share of purchased own farmland			-0.020	-0.009
			(0.03)	(0.02)
Sex of HH head (1=female)				-0.039***
				(0.01)
Age of HH head (years)				-0.001
				(0.00)
Education of HH head (years)				0.000
				(0.00)
Household size to labour ratio				0.018*

(No. of persons/adult equiv. labour unit)				(0.01)
Total Livestock Units (TLU) to labour				0.005
ratio *(TLU No./ adult equiv. labour unit)*				(0.01)
One-year lag TLU to labour ratio				0.005
(lag TLU No./ adult equiv. labour unit)				(0.01)
Distance to urban centers (km)				0.002****
				(0.00)
Regional dummy (Compared to Central)				
Northern region				-0.109****
				(0.02)
Southern region				-0.041****
				(0.01)
Year 2016	-0.015*	-0.015*	-0.015*	-0.010
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	2,960	2,960	2,960	2,960
Number of Panel households	1,480	1,480	1,480	1,480

Note: Normal standard errors in parentheses. The asterisks denote levels of significance at **** = p<0.001, *** = p<0.01, ** = p<0.05, and * = p<0.1. The table omitted the constant, sigma_u, sigma_e and number of censored variables because the information is similar to that presented in Table 2.

Notes

[1] We focus on the tenant side of the land rental market mainly because of the LSMS data constraints on capturing landlord households. In our data, out of a balanced panel data of 1480 households, the classification in 2010 was 7.3% tenants and 0.1% landlords; in 2013 it was 10.1% tenants and 0.5% landlords; and in 2016 it was 8.9% tenants and 1.7% landlords. The reason for this strong imbalance is still unclear, but it limits the suitability of the data for analysis on the supply side. See Deininger, Savastano, and Xia (2017) for a full discussion on the limitations of the LSMS data on capturing landlord households.