WHAT IS DRIVING FARMLAND RENTAL PRICES IN SUB-SAHARAN AFRICA? EVIDENCE FROM MALAWI

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Abstract

Informal land markets, particularly land rental markets, are emerging rapidly in many parts of sub-Saharan Africa (SSA). Land rental markets have the potential to contribute to structural transformation if, for example, such markets facilitate the transfer of land from less productive to more productive farming households. Although there is a growing literature on the determinants of smallholder farm households' decisions to participate in land rental markets, relatively little is known about the factors driving land rental prices in SSA. This study aims to fill that gap using panel data from Malawi to estimate the effects of various plot-level characteristics and economic variables on plot-level land rental prices. Of particular interest is the effect of Malawi's Farm Input Subsidy Program (FISP) on land rental prices, as evidence from the US suggests that part of the value of agricultural subsidies is often capitalized in land rental prices. Our results suggest that FISP has no substantive effect on land rental prices, perhaps because FISP's effects on maize productivity have been modest. Expected crop prices, soil quality, and market access are more important determinants of land rental prices in Malawi; increases in these variables are associated with higher average rental prices, *ceteris paribus*.

Key Words: land rental markets, rental prices, structural transformation, input subsidy programs, Malawi, sub-Saharan Africa

What is driving farmland rental prices in sub-Saharan Africa? Evidence from Malawi

Land is often the key factor of production that determines whether or not a smallholder farm household is food secure. In many parts of rural sub-Saharan Africa (SSA), land is managed in a customary tenure system where local leaders grant households usufruct rights. Households may hold these rights for many years and transfer them down to younger generations but there is seldom a formal title that goes with the land (Holden et al. 2009). Economic theory suggests that lack of formal titles and tenure security should inhibit the development of land markets. However, a growing literature documents that informal land markets, particularly land rental markets, are emerging rapidly in many parts of SSA (see Holden et al. 2009 for a review of studies). If households are not coerced into participation in land rental markets, their development is potentially an encouraging sign for agricultural and economic development in SSA. Transferring productive resources such as land among households can help drive the structural transformation process if, for example, relatively more efficient farming households rent in land and expand their cultivated area, while relatively less efficient farming households rent out land and free up labor to engage in potentially more productive non-farm activities (Skoufias 1995; Holden et al. 2009; Jin and Jayne 2013).

Previous literature on land rental markets in SSA estimates the household-level factors associated with land rental market participation and associated impacts on household welfare (Holden et al. 2009; Jin and Jayne 2013, Chamberlin and Ricker-Gilbert 2016). These studies generally find that land rental markets transfer land from less efficient to more efficient producers and from households with more land to those with less land. However, to date there has been virtually no research on the factors driving land rental prices in SSA. The present study aims to fill that gap using garden-level panel data from Malawi to estimate the effects of various plot-level characteristics and economic variables on plot-level land rental prices.[1] Doing so is a crucial question for agricultural and economic development in SSA, because given land's fundamental importance to agricultural production, increases in land rental rates may raise barriers to entry in the agricultural sector that could inhibit the structural transformation process.

We focus on Malawi, in southern-eastern Africa, because land rental market participation there has increased substantially over the past 10 years (Chamberlin and Ricker-Gilbert 2016). Land rental prices in Malawi have also been increasing. For example, Chamberlin and Ricker-Gilbert find that, at the median, tenant households spend 23% of their gross crop revenue per hectare (ha) on renting in land, and nearly one quarter of tenants spend 50% or more of their gross crop revenue/ha on land rental. In addition, they find that in Malawi land rental costs account for an average of 37% of total input costs for tenant households. This is substantially higher than in the US, where land rental costs average only 10% of tenants' production costs (Kirwan and Roberts, 2013). The high and rising cost of renting land relative to agricultural productivity makes it essential for researchers and policy makers to understand the underlying forces that drive this process. Such empirical evidence will support the development of effective policies to ensure that land markets develop in an efficient and equitable manner.

Our study on the drivers of land rental prices in Malawi complements a large literature on the determinants of land rental prices in the United States and Europe. This literature points to major drivers as the land's potential to generate returns to agricultural production, amenity values, and potential for non-agricultural development (see Brochers et al. (2014) for a recent summary of the literature on this topic). In addition, there is an extensive literature that estimates the incidence of farm subsidies on land rental prices in the United States and Europe. Some important recent studies in this literature include Patton et al. (2008); Bhaskar and Beghin (2009); Kirwan (2009); Goodwin, Mishra, and Ortalo-Magne (2011); Hendricks, Janzen, and Dhuyvetter (2012); Weber and Key (2012); Kirwan and Roberts (2015); O'Neil, and Hanrahan (2016). To our knowledge there is very little empirical evidence from SSA on

[1] In the data used in this study, a 'garden' is a field that may contain one or more plots. Gardens were followed over time in the survey but individual plots within the garden were not. This is because plot boundaries often change from year-to-year but garden boundaries are more fixed.

drivers of farm land rental prices. The closest related study is by Holden and Bezu (2015). Based in Ethiopia, the authors survey rural households' perceptions on land rental prices and their views on whether or not it should be legal to buy and sell land.

Our study adds to the literature by providing empirical evidence on factors affecting farm land rental values in a developing country context. We estimate the extent to which farm land rental rates are driven by factors that affect agricultural profits in the current year such as output prices or other factors such as market access and population density in a given area. From a policy perspective, we are also interested in analyzing the role of Malawi's agricultural input subsidy program, the Farm Input Subsidy Program (FISP), in driving land rental prices. The FISP program mainly distributes roughly US $100 worth of inorganic fertilizer and improved maize seed to approximately half of the smallholder households in Malawi at the beginning of each agricultural year. Considering the fact that Malawi's Gross National Income per capita is estimated at US $790 in purchasing power parity terms in 2014 (World Bank 2015), the FISP represents a significant transfer to recipient households. If, as has been found in the US, part of the value of agricultural subsidies is capitalized in land rental prices, then the recent expansion of FISP could be putting upward pressure on land rental prices in Malawi. More broadly, we hypothesize that better soil conditions and increases in expected crop prices, market access, population density, and FISP receipt positively affect land rental prices in Malawi.[2] Indeed, there is some *prima facie* evidence of a positive relationship between FISP and land rental prices in Malawi. As shown in Figure 1, both the scale of FISP and real median land rental prices have increased over time in Malawi.

To test these hypotheses, we use data from the Third Integrated Household Survey (IHS3) and the IHS Panel Survey collected in Malawi by the World Bank in 2009/10 and 2012/13, respectively. The surveys are nationally representative and interviewed 3,246 households in 26 districts in both rounds of data collection. In addition, we include spatially disaggregated data on population density and growing

[2] Crop prices are in "expected" terms because these values would not be realized at the time that land rental decisions are made, which is before planting time. Lagged crop prices are used as proxies for expected prices.

season weather. A total of 13,840 plots are included in the IHS3/IHS Panel dataset. For each plot, respondents were asked how much they would charge if they were to rent out the plot. This information, coupled with GPS-measured plot area, is used to compute the (hypothetical) per hectare rental rate for each plot. In addition, realized rental rate information was collected for all plots actually rented in by households. We use both sets of rental price information (hypothetical and realized) to identify the factors driving land rental prices in Malawi.

By estimating the impact of key demand- and supply-side drivers of land rental prices, the present study makes a direct contribution to the literature on land markets in SSA. As land markets are unquestionably continuing to grow in the region, our results should be useful for both policy makers and researchers who are interested in understanding the broader linkages and impacts related to input subsidies, population growth, and land access. The study is also a useful complement to Kirwan and Roberts (2015), which analyzes the relationship between agricultural subsidies and farmland rental prices in the US. While the US subsidies studied by Kirwan and Roberts are allocated to plots of land based on expected productivity, FISP in Malawi is allocated to households and is not typically linked to expected productivity of the household or its land. A second difference is that Kirwan and Roberts (2015) use cross-sectional data, whereas we use garden-level panel data. These panel data allow us to control for time invariant garden-level unobserved heterogeneity that could be correlated with both land rental prices and the observed covariates whose effects on land rental prices we seek to measure; failure to control for this unobserved heterogeneity could result in biased estimates of the factors driving rental prices.

The rest of the article is organized as follows. The next section describes the data. We then outline the empirical model and the estimation and identification strategies. Subsequent sections present the results, conclusions, and policy implications.

Data

Data used in this analysis come from the Third Integrated Household Survey (IHS3) and the IHS Panel Survey collected by the World Bank in 2009/10 and 2012/13, respectively. The surveys are nationally representative and interviewed 3,246 households in 26 districts of Malawi in both rounds of data collection. The survey has some important improvements over earlier smallholder household surveys in Malawi that allow us to measure factors driving land rental markets in the country. Respondents are asked how all plots that they cultivate have been acquired, giving us an accurate picture for renting in land. If the plot is rented in, respondents are asked the price paid for renting it, the type of contract (fixed rent vs. sharecropped or other), and length of arrangement. In addition, for plots that are not rented, households are asked how much they could receive if they were to rent out the plot. IHS enumerators also measure size of the plot using GPS to ensure more accurate measures of plot size. Respondents are also asked how much subsidized fertilizer and seed the household acquires in the current year.

Other aspects of the HIS dataset that are useful to our analysis are that many of the same gardens are surveyed in both waves of data, allowing us to track pieces of land over time. Respondents are asked to rate the quality of the soil on each of their plots in both waves. In addition, the dataset includes geo-referenced data linked to each plot that measures soil quality information as well.

We include spatially disaggregated data on population density and growing season weather from the University of East Anglia's Climate Research Unit (CRU) TS 3.1 Climate Database (CRU, 2011). We match the household-level information in our dataset with monthly rainfall and temperature totals specified at locations across Malawi. Households are then assigned rainfall data according to their spatial proximity to the specified locations where rainfall data are collected. These data are publically available, and a detailed discussion can be found in Mitchell and Jones (2005). The authors explain the sources of the raw rainfall data, the methods for dealing with missing data points, and the way in which data were homogenized across weather stations.

Empirical Model

The empirical model to estimate the factors affecting the rental price of plot *i* of garden *g* by household *j* in district *k* in agricultural year *t* is specified as:

1) $P_{R,igjkt} = \boldsymbol{S}_{jkt}\boldsymbol{\alpha_1} + \boldsymbol{Z}_{kt}\boldsymbol{\alpha_2} + \boldsymbol{W}_{kt-1}\boldsymbol{\alpha_3} + \alpha_4 P_{m,kt-1} + \boldsymbol{A}_{ijkt}\boldsymbol{\alpha_5} + Y_t + d_k + b_{igk} + \varepsilon_{ijkt}$

The land rental price, P_R, is measured as Malawi Kwacha per hectare. We test whether or not changes in supply-side production affect rental price, by conditioning R on the value of subsidized inputs acquired by the household, $\boldsymbol{S}$, in year t. The statistical significance of the coefficient estimate of $\hat{\alpha}_1$, tests the hypothesis of whether or not acquiring subsidized inputs puts upward pressure on the rental price that households pay in time t. We test whether or not demand-side factors such as changes in local population density affect rental price by measuring the rate of migration in the household's district between survey waves. This measure denoted by Z, and the statistical significance of the corresponding parameter's coefficient estimate $\hat{\alpha}_2$ tests whether or not increases in demand in a particular district put pressure on land prices there.

We control for previous season rainfall to proxy for expected climatic and productivity conditions in the area are denoted by $\boldsymbol{W}$. Previous season maize prices, denoted by, P_m, represent a naïve expectation of the maize price. The agronomic conditions on the plot are represented by $\boldsymbol{A}$, and include erosion on the plot, slope of the plot, and soil quality, as reported by the responding farmer. Parameters to be estimated are represented by $\alpha_3 - \alpha_5$. A year fixed effect is represented by Y_t, and d_k represents a district fixed effect. The garden-level time-constant error term is represented by b_{igk}, while ε_{ijkt} represents the time-varying plot-level error term.

Equation 1 is estimated using two different values for P_R. The first value of P_R is the rental price (in MWK/ha/year) that the respondent believes s/he could charge if s/he were to rent out the plot; we refer to this as the stated preference rental price. This value is observed for all plots. The second value of P_R is the rental price paid by households for plots actually rented in; we refer to this as the revealed preference rental price. It is observed for the 12% of plots that are rented in in the sample during year t. Both of these measures for rental price provide useful information for our analysis, but they require slightly different estimation strategies that are discussed in the following section.

Estimation and Identification Strategies

There are several estimation challenges that we must deal with in order to make the case for identifying causal drivers of land rental prices in Malawi. The first three challenges are discussed in the existing literature on land rental prices and subsidies, and they include i) unobserved heterogeneity, ii) measurement error in the dependent variable, land rental prices; and iii) expectation error in receipt of subsidized fertilizer (Kirwan 2009; Kirwan and Roberts 2015). In addition, given the less developed state of land rental markets in Malawi we deal with the addition challenge of incidental truncation in our revealed preference price model as only about 12% of the plots in our sample are actually rented. The following sub-sections discuss how we address and correct for these issues. We start with incidental truncation and subsequently move to the other identification issues.

Incidental truncation

Given that only about 12% of the plots in our sample are actually rented-in, we would be biasing our estimates if we replaced the revealed preference measure of rental price, P_R in equation 1, with zero for plots that are not rented in or if we truncated the data to only include plots that are rented in.[3] Our problem is analogous to the classic incidental truncation or self-selection issue as described initially in Heckman (1976). Since households select plots to be rented, we need to model the decision to rent-in a particular plot at time t as follows:

$$2) \quad R_{ijkt} = \boldsymbol{X}_{ikt}\boldsymbol{\gamma_1} + \boldsymbol{S}_{jkt}\boldsymbol{\gamma_2} + \boldsymbol{Z}_{kt}\boldsymbol{\gamma_3} + \boldsymbol{W}_{kt-1}\boldsymbol{\gamma_4} + \gamma_5 P_{m,kt-1} + \boldsymbol{A}_{ijkt}\boldsymbol{\gamma_6} + Y_t + d_k + \mu_{ijkt}$$

Where R in equation 2 represents a binary variable equal to one if the plot is rented in and zero otherwise. In order to identify the coefficient estimates in equation 2 we need one or more variables that affect the decision to rent in plot i but do not directly affect the plot's rental price. Household-level factors (***X***) that

[3] Most studies on land rental markets in the United States and Europe take the latter approach to deal with the issue. Though the issue is less pronounced in the developed country context because a higher percentage of fields are rented (around 50% in the United States) the incidental truncation issue remains there as well.

affect access and ability to farm rented land, such as if the household head is female, age of the household head, number of adult equivalents, household educational equivalents, and value of assets are likely appropriate variables to use as exclusion restrictions for equation 2. The other variables in equation 2 are the same as equation 1 with $\gamma_1 - \gamma_6$ as parameters to estimate. Equation 2 is estimated via pooled probit with district and year fixed effects. This estimator control for correlation between the observed covariates and time-constant unobservable factors that may bias our coefficient estimates, in non-linear models.

When equation 1 is estimated using the revealed preference rental price (which is available only for rented in plots), we use the Heckman two-step procedure to correct for incidental truncation. First, equation 2 is estimated. Second, the inverse Mills ratio (IMR) is obtained from equation 2. Third, the inverse Mills ratio (IMR) from equation 2 is included as an additional regressor. In this situation, equation 1 is estimated via pooled ordinary least squares (POLS) with household and year fixed effects. The incidental truncation issue is non-existent when the dependent variable is the household's stated preference for rental price, because it is available for all plots in all years.

We note that the stated preference measure may have the alternative problem of hypothetical bias as is common when respondents are asked stated willingness to accept questions (Carson et al. 1996). However, having both stated and revealed preferences for rental prices for the household provides useful comparisons for our analysis.

Unobserved heterogeneity

Correlation between time-constant, unobserved factors that affect land rental prices and observable covariates could bias the coefficient estimates in the empirical models presented in this article. Of key concern is how unobserved heterogeneity may affect the coefficient estimate of S, for subsidized fertilizer in equation 1. Households clearly do not randomly decide which plots to rent in and out, and there is considerable empirical evidence to suggest that rented land is often of poorer quality than owner-operated land (Benin et al. 2006; Yamano et al. 2009). In addition, subsidized inputs are not randomly distributed in Malawi and there is considerable evidence that better-off households with higher education and better social connections are more likely to acquire subsidized inputs (Chibwana, Fisher, and Shively 2011; Ricker-Gilbert, Jayne and Chirwa 2011; Killic, Whitney, and Winters 2015). Potentially unobservable soil quality measures could create plot-level endogeneity, while non-random subsidy distribution to better off households could lead to household-level endogeneity.

Fortunately, the unique and detailed data in our analysis allow us to address these two concerns. As mentioned, the IHS surveys ask farmers to give their assessment of the plot's quality including slope of the plot, and whether the soil is of good, fair or poor quality. In addition, the data are geo-referenced so secondary data on soil quality including nutrient retention, conditions for roots to take hold, and workability of the soil are included. All of these secondary variables would be expected to be positively correlated with soil quality, land productivity, and land rental prices. We include the farmer assessed measures of soil quality and the geo-referenced soil quality variables as covariates in equation 1, to take them out of the error term to proxy for soil quality, and land productivity. These measures are arguable more exogenous proxies for soil quality, and land productivity than the farmer assessed fertilizer-decision yield goal used to control for unobservable land quality in Kirwan and Roberts (2015), because yield goal is likely due at least in part to management decisions of the farmer in the current year.

Subsidized inputs are distributed to the household in Malawi, so we control for the fact that better-off, better connected households may acquire more subsidized inputs, and be more likely to rent in land, in the following ways. First, we add numerous household demographic factors as controls in equation 2 that estimates factors affecting land rental market participation. These include gender and age of the household head, adult equivalents in the household, number of rooms in the home, value of livestock and durable assets, and years that the head of household has lived in the community. Previous literature on land rental markets in Malawi suggests that tenant households who rent in land have a higher value of assets, higher levels of education, and more adult equivalents than non-renters on average (Chamberlin and Ricker-Gilbert 2015). Since, many of these factors are also likely related to input subsidy acquisition, including them as observable covariates in our model brings them out of the error term reducing omitted variable bias. In addition, the panel nature of the IHS3 data allows us to use household fixed effects to demand the data and remove any left-over unobservable time-constant heterogeneity that may remain in the model.

Measurement error in land rental prices

Another potential source of bias that is often discussed in the land rental and subsidy literature relates to potential measurement error in the dependent variable. In our study, this would come from measurement error in the calculation of land rental prices. We argue that measurement error in the dependent variable is less of an issue in or context than in previous studies for the following reason. First, the vast majority of rental contracts in Malawi (greater than 95%) are upfront fixed-rent contracts, rather than share-cropping arrangements that occur in other contexts.[4] It is much easier to discern the price of a fixed-rental arrangement than a share arrangement, ensuring that the numerator in our measure of rental price is more accurately measured. Second, while we can reasonably expect that Malawian farmers remember the cash spent (received) for rented in (out) plots, a growing literature suggest that smallholder farmers in SSA often mis-estimate the size of their plots, and it may lead to biased coefficients when estimating production functions (Carletto et al. 2012). Fortunately, the IHS data measure the size of all plots operated by respondents using GPS, which should reduce or eliminate the concern of measurement error in the denominator of the rental price variable.

Estimating expected subsidy receipt and correcting for its potential endogeneity

A well-documented potential problem associated with measuring the impact of subsidies on land rental prices is that households typically make rental market decisions before the subsidy is allocated. This is the case in the U.S. context as documented in Kirwan (2009), and it is also the case in Malawi as subsidized input vouchers are distributed at the beginning of the rainy season in October and November,

[4] There is evidence to suggest that in areas where both share cropping and fixed-rental arrangements occur, as subsidy rates increase farms move from the former type of contract to the latter (Qui, Goodwin, and Gervais 2011).

potentially after land rental decisions have been made by households. Therefore, the plot manager has to have an expectation about how much subsidized inputs s/he will acquire in the coming months when negotiating the price for renting land.

As a result, we need to model expected subsidized fertilizer receipt. To do so, we model the expected quantity of subsidized inputs at a farmer expects to receive following Mason et al.'s (2015) adaptation of Nerlove and Fornari's (1998) quasi-rational expectations approach in the following equation:

3) $\hat{\boldsymbol{S}}_{\boldsymbol{n,jkt}} = \boldsymbol{X}_{jkt}\boldsymbol{\beta_1} + \boldsymbol{G}_{kt}\boldsymbol{\beta_2} + Y_t + d_k + c_{jk} + v_{jkt}$,

Where predicted values ($\hat{\boldsymbol{S}}$) represents expected subsidy acquisition and is the predicted value of subsidized input acquisition following tobit estimation. The dependent variable is regressed on factors that are observable to the household at the time rental market prices are determined and that are likely to affect the quantities of subsidized inputs s/he will receive.[5] These variables include household and community characteristics that previous studies have found to be important determinants of receipt of subsidized fertilizer in Malawi (e.g., landholding size, gender of the household head, productive assets, etc.). They are denoted by **X** in equation 3 with corresponding parameter, $\boldsymbol{\beta_1}$. We also include the amount of subsidized fertilizer distributed per capita to the household's district in the previous year, denoted by **G** in equation 3. The household should have some idea of the per-capita availability of subsidized inputs in their area, so the variable should help identify equation 3. The time-constant error term is represented by *c*, while *v* represents the time-varying error. Equation 3 is estimated via Mundlak-Chamberlain (MC) device that includes time averages of all time varying variables to control for unobserved time-constant heterogeneity in the model.

[5] We use a Tobit model because we need to ensure that predicted subsidized fertilizer receipt is not negative and, as discussed above, there is considerable variation in the quantities of subsidized fertilizer acquired by FISP beneficiaries in Malawi.

Estimation procedure

The estimation procedure in the article is carried out in the following steps. First, the auxiliary model for subsidized inputs, presented in equation 3 will be estimated to obtain predicted values $\hat{\boldsymbol{S}}$. Second, in the revealed preference rental price model $\hat{\boldsymbol{S}}$ will be included in the estimation of factors affecting rental market participation R, as in equation 2, to proxy for expected subsidized fertilizer acquisition at the time rental price determination occurs. Third the IMR is obtained from the estimation of equation 2, and both the IMR and $\hat{\boldsymbol{S}}$ are included in the estimation of land rental prices in equation 1. The IMR corrects for incidental truncation, and $\hat{\boldsymbol{S}}$ corrects for potential endogeneity in expectation about subsidized fertilizer acquisition. In the model where we use stated preference for land rental price, we skip step 2 because incidental truncation is not a problem so we do not need to generate the IMR. In this case only $\hat{\boldsymbol{S}}$ needs to be included when estimating equation 1. Bootstrapping is used to compute valid standard errors in this multi-step estimation procedure.

Results

Table 1 presents the descriptive statistics for the variables used in the analysis. Not surprisingly, on average the revealed preference rental prices are lower than the stated preference rental prices, which are hypothetical to some degree. The table reveals important differences between owner operated and rented in plots. For example, rented in plots are much less likely to belong to female headed households than owner operated plots. This difference is likely correlated with female headed households having limited labor and other assets making them more likely to rent out land and less likely to rent in land. In addition, the table suggests that rented in plots are managed by households with more adult equivalents, suggesting that they have more available labor to bring into cultivation. Also, households who rent in plots have a higher value of durable assets in both 2009/10 and 2012/13. This finding is consistent with other work in Malawi (Chamberlin and Ricker-Gilbert 2015). It suggests that potential tenant households have the resources to enter into upfront cash arrangements at the beginning of a season to expand their cultivated area through renting in land.

Table 2 provides some important information regarding differences in characteristics between owner operated and rented in plots. Some of these differences may help explain rental prices. For example rented in plots are slightly smaller on average than owner operated plots. Maize is the main crop grown on a significantly larger share of owner operated plots than rented in plots. The data suggest that a higher share of rented in plots are dedicated to tobacco, groundnuts and soybeans than are owner operated plots. This may indicate that some people rent in land with the intention of growing cash crops, while owner operated plots are more likely to grow maize for subsistence. However, it is important to note that maize is by far the main crop grown on the vast majority of plots in Malawi, regardless of rental status. The table also shows that operators of rented in plots are less likely to apply organic manure than are operators of owner operated plots. This is intuitive because organic manure improves soil structure and helps build up soil organic carbon. However, evidence suggests that it takes several years for the benefits of applying organic manure to impact yields. Therefore, tenants in short-term rental agreements have little incentive to invest in applying organic manure to rented-in plots. In contrast, we see that a higher percentage of operators self-report that the soil on rented in plots are of good quality than do operators of owner operated plots. Likewise, a lower percentage of operators report that rented in plots are of poor quality than do operators of owner operated plots. This finding would suggest that rented in plots are of better quality than owner operated plots. However, it is important to keep in mind that the assessments of soil quality are self-reported, so it makes sense that tenants would want to rent in land that they perceived to be of good quality. It could also be that tenants are renting in better quality land than that which is left to owner operated plots, but once they get the land they do not take steps such as applying organic manure to maintain or improve soil fertility.

Table 3 presents the results from equation 2, the factors affecting whether or not a plot is rented in. The model includes all of the variables in equation 1 plus household characteristics. The model is estimated as a pooled probit with region and year fixed effects. The p-value on the Inverse mills ratio is

(0.079), suggesting that there is marginal evidence of sample selection. Results suggest that plots belonging to households receiving more subsidized fertilizer have a lower probability of being rented in. Rented in plots are less likely to be operated by female headed households, and rented in plots are more likely to be operated by households with higher education per capita. In addition, operators of rented in plots are likely to have lived in the community for fewer years. This is consistent with the notion that tenants move to communities in order to acquire land to rent. Plots that are further away from towns with more than 20,000 people are less likely to be rented in, suggesting that rental markets are more developed closer to sources of demand. In addition, plots with higher nutrient retention capacity in the soil and soil that is more easily workable are less likely to be rented in, suggesting that rented in plots are of lower quality in those dimensions.

Table 4 presents the factors affecting land rental prices in Malawi. The stated preference results use the prices given by survey respondents for what they believe they could receive in rent if their plot were rented out at the time of the survey. The revealed preference results are obtained using the Heckman correction for sample selection method that corrects for the censoring problem created by the fact that only 12% of the plots in the data were rented in. Coefficient estimates on the fertilizer and seed subsidy variables are similar in magnitude for both models, and they suggest that, on average and *ceteris paribus*, FISP has no statistically significant effect on land rental prices or that an increase in FISP fertilizer receipt reduces the land rental price. However, the latter effect is very small in magnitude and not economically meaningful.

Although FISP has no substantive effect on land rental prices, plot characteristics may affect rental prices. Per table 4, plot size is negatively related to rental price per hectare in both the stated and revealed preference results. Market access (closer proximity to border crossings and/or population centers of 20,000+) is positively associated with higher land rental prices in both sets of results. Higher expected crop prices are correlated with higher stated preference rental prices but not revealed preference ones. The results for the various soil quality-related variables are also differ between the stated and revealed preference results but generally suggest that more desirable plots could or do command higher rental prices.[6] In general, the signs of the statistically significant determinants of land rental prices are consistent with *a priori* expectations.

Conclusions and Policy Implications

The objective of the present study is to estimate the drives of land rental market prices in sub-Saharan Africa using nationally representative panel data from Malawi. Results suggest that the main drivers of land rental prices are size of the plot, market access and soil quality. We also find that on average and *ceteris paribus*, FISP has no statistically significant effect on land rental prices or that an increase in FISP fertilizer receipt reduces the land rental price. However, the latter effect is very small in magnitude and not economically meaningful. Thus, in contrast to the US where 10-25 cents of each subsidy dollar are capitalized in land rental values (Kirwan and Roberts 2015), the expansion of FISP does not seem to be driving land rental prices in Malawi. This could be due to the fact that agricultural subsidies in Malawi are allocated to households, whereas in the US the agricultural subsidies studied by Kirwan and Roberts (2015) are allocated to fields based on expected productivity. Another difference is that, unlike Kirwan and Roberts (2015), we are able to control for garden fixed effects; their data are cross sectional. Another explanation is that the productivity gains form Malawi's FISP have been modest and thus have not been built into land prices in any meaningful way.

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[6] The main exception and counter-intuitive result is that improvements in nutrient retention capacity are associated with lower revealed preference rental prices on average, *ceteris paribus*.

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Figure 1: Land Rental Prices and Subsidized Fertilizer Distribution in Malawi

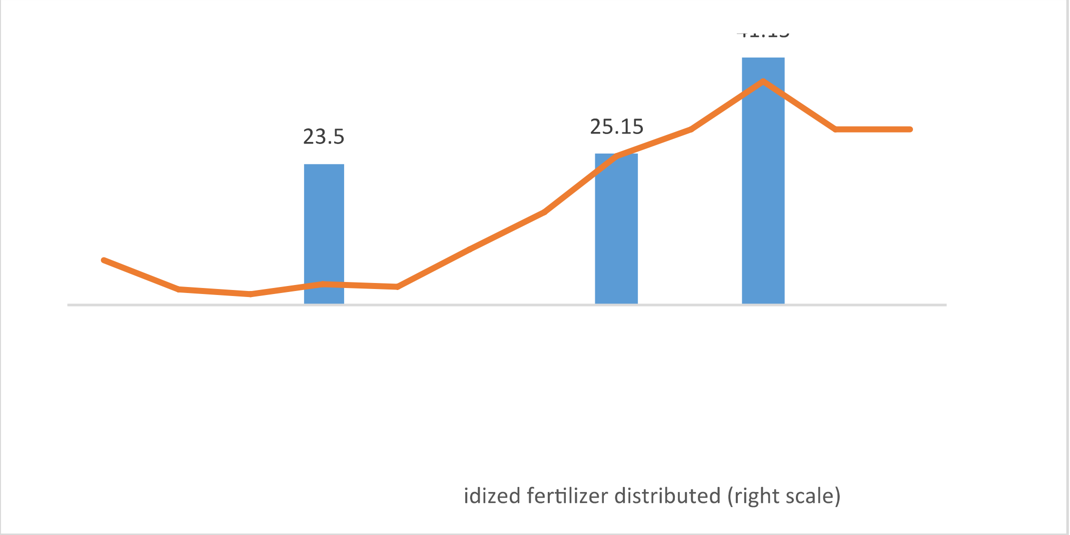

Table 1: Descriptive statistics for variables used in the analysis.

	2009/10		2012/13	
	owner operated plots	rented in plots	owner operated plots	rented in plots
Revealed preference rental prices Malawi Kwacha/kg	.	11,418	.	21,267
stated rental price Malawi Kwacha/kg	15,501	.	29,876	.
Kilograms of subsidized fertilizer acquired	63.29	66.07	69.90	34.33
Kilograms of subsidized maize seed acquired	1.39	1.50	1.24	1.21
=1 if female headed household	0.24	0.09	0.24	0.11
GPS measured plot size in ha	0.36	0.32	0.36	0.33
Adult Equivalents	3.83	4.15	4.07	4.28
Age of household head	43.80	39.79	44.78	40.52
years of education per capita	4.74	6.13	5.13	6.15
number of rooms	2.75	2.92	2.37	2.43
value of durable assets (Malawi Kwacha)	38,640	103,506	131,068	218,510
value of livestock assets (Malawi Kwacha)	39,144	21,218	75,871	74,944
Number of years HH head has been living in community	33.33	23.05	-	-
Distance in (KMs) to Nearest Population Center with +20,000	35.54	28.73	32.32	22.03
Distance in (KMs) to Nearest Border Crossing	26.64	22.79	35.57	30.85
=1 if plot has good soil	0.48	0.58	0.44	0.49
=1 if plot has fair soil	0.40	0.33	0.42	0.39
=1 if plot has poor soil	0.12	0.09	0.14	0.12
=1 if plot is flat	0.56	0.64	0.57	0.60

Table 2: Mean differences between owner operated and rented in plots

	owner operated plots	rented in plots	difference	difference significance level
plot size in hectare	0.35	0.33	0.02**	(0.021)
=1 if maize is main crop grown on plot	0.65	0.62	0.03***	(0.048)
=1 if apply organic manure	0.12	0.08	0.04***	(0.000)
=1 if soil reported as good quality	0.46	0.54	-0.07***	(0.000)
=1 if soil reported as poor quality	0.12	0.10	0.03***	(0.000)

Note: *, **, *** indicates that corresponding coefficients are statistically significant at the 10%, 5%, and 1% level respectively

Table 3: Factors affecting whether or not a plot was rented in

Dependent variable =1 if plot was rented in	Coef.		P-value
Kilograms of subsidized fertilizer acquired	-0.0000138	**	(0.042)
Kilograms of subsidized maize seed acquired	0.0006484		(0.482)
=1 if female headed household	-0.023257	**	(0.002)
Adult Equivalents	0.002916		(0.202)
Age of household head	0.000164		(0.607)
years of education per capita	0.0057695	***	(0.001)
number of rooms	0.0033066		(0.336)
value of durable assets	7.16E-09		(0.527)
value of livestock assets (Malawi Kwacha)	-5.10E-09		(0.576)
Number of years HH head has been living in community	-0.0014052	***	(0.000)
Distance in (KMs) to Nearest Population Center with +20,000	-0.0003425	*	(0.083)
Distance in (KMs) to Nearest Border Crossing	0.0001367		(0.305)
GPS measured plot size in hectares	0.0001467		(0.801)
=1 if plot is flat	-0.0143537		(0.147)
agro-ecological zone	0.0151042	**	(0.028)
nutrient retention capacity of soil	-0.0040732	***	(0.001)
rooting conditions of soil	0.0077218		(0.215)
workability of soil	-0.0157612	*	(0.077)
=1 if plot has good soil quality	0.0135891		(0.125)
=1 if plot has fair soil quality	0.0208347	**	(0.024)
R^2 = 0.07			
N=15,006			

Note: *, **, *** indicates that corresponding coefficients are statistically significant at the 10%, 5%, and 1% level respectively. Model estimated as a pooled linear probability model that includes region and year fixed effects that are not shown.

Table 4: Factors affecting plot-level rental prices (in Malawi Kwacha/kg)

	Stated Preference			Revealed Preference		
Dependent variable is rental price in Malawi Kwacha/kg	Coef.		P-value	Coef.		P-value
Kilograms of subsidized fertilizer acquired	-2	***	(0.002)	1		(0.808)
Kilograms of subsidized maize seed acquired	-55		(0.431)	-57		(0.397)
GPS measured plot size in hectares	-38,163	***	(0.000)	-19,204	***	(0.000)
output price index (Laspeyres)	259	***	(0.001)	27		(0.810)
Distance in (KMs) to Nearest Population Center with +20,000	-52	*	(0.079)	-36		(0.308)
Distance in (KMs) to Nearest Border Crossing	-4	*	(0.827)	-53	**	(0.026)
=1 if plot is flat	445		(0.606)	1,932	*	(0.082)
agro-ecological zone	253	*	(0.069)	-216		(0.204)
nutrient retention capacity of soil	-780		(0.202)	-1,541	**	(0.026)
rooting conditions of soil	-1,572		(0.169)	-203		(0.891)
workability of soil	2,596	**	(0.019)	917		(0.514)
=1 if plot has good soil	2,719	*	(0.069)	-1,095		(0.538)
=1 if plot has fair soil	-797		(0.579)	-1,497		(0.401)
	R^2=0.17					
	N=13,840			N= 1,008		

Note: *, **, *** indicates that corresponding coefficients are statistically significant at the 10%, 5%, and 1% level respectively. Stated preference model estimated linearly and includes year and region fixed effects, not shown, standard errors in stated preference model are clustered at household-level. Revealed preference model estimated as heckman two-step procedure