Commercialization Pathways: Synegies Between Small And Medium Scale Farmers In Tanzania

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Abstract

The changing farm structures in sub-Saharan countries, with the emergence of medium and large scale farmers, has elicited opposing views in the literature. While much of this is largely positive, pointing to positive spillover effects in the larger agro-food industry, some studies point to some evidence of negative spill overs, especially due to land scarcity in the rural areas due to holding of land for speculation purposes, or higher food prices where large producers dedicate land to production for non-food crops. Nevertheless, evidence on the effects of these investments is scarce, with much of the evidence coming from case studies. This study investigates spillover effects of medium-scale farms and large scale farms on small scale farms productivity and commercialization in Tanzania. The study utilizes a sample of about 600 small scale farmers (less than 5 hectares of cultivated land) and about 600 large farmers, 300 medium scale (5 hectares to 10 hectares of cultivated land) and 300 large scale (greater than 10 hectares cultivated land) farmers drawn from eight district in rural Tanzania. A spatial econometric method is used to capture spillover effects from the large farms to small scale farms. Results show positive significant spatial dependence and spillover effects among medium scale and large scale farms on small scale maize productivity and commercialization, but not on rice, another major crop in the region.

Keywords: Spillover, Small, Medium and Large Scale Farms, Spatial Approach, Maize, Rice

1. Introduction

Fairly recent evidence point to a rise in medium-scale farmers (>5 ha) in sub-Saharan Africa (SSA) (Jayne et al., 2016; Sitko and Jayne, 2014). A recent study done in Ghana, Kenya and Zambia report that land controlled by medium scale farms now exceed that controlled by large scale farms; and in Zambia and Ghana fams between 5 and 100ha account more land than small scale farms with zero to 5 ha (Jayne et al., 2014). This transformation has important implications for farming in SSA, which largely remains smallholder. Key issues pointed out in the agricultural development literature in the developing world is poor use of intensification inputs and mechanization, partly due to small land-holdings and liquidity constraints. With the rise in farmers holding more than five hectares, significant economies of scale could mean a rise in use of mechanization, and subsequent use of intensification inputs as access to credit relax binding liquidity constraints. More importantly, the rise of these medium scale farms within the confines of smallholder farms could have significant implications in agricultural mechanization and in the uptake of intensification amongst small farms. This has important implications in raising the stagnant agricultural productivity among small holder farmers (3.9% the annual agricultural growth Vs 6-8% Tanzania's robust economic growth) (ASDP II, 2016).

The Large- and medium- scale farms can also be an important source of employment for people living at the proximity of these farms. Given the extent of scale of these farms and their involvement in processing along the value chain, they can also offer non-farm opportunities for local populations, thus helping in livelihoods diversification of low paying smallholder agriculture (Sitko, Burke, and Jayne, 2018). This could have important implication in terms of stemming further land sub-division, and welfare improvement.

In addition, medium and large scale farms increase access to markets for nearby smallholder farms. That is; as a result of high concentration of medium and large scale farms, the demand for agricultural inputs and agricultural related services is likely to spring up markets for such inputs and services in the area. The spillover effect or positive externalities can also increase access to output markets, when big market actors start operations in areas with higher concentrations of medium and large farms, thereby opening up markets for farmers holding smaller pieces of land. Having access to these big market actors in itself could also lead to a higher uptake of intensification inputs (see Mulwa et al., forthcoming; Sitko and Chisanga, 2016 for details). More on these hypothesized channels of spillover effects from large scale farm investments is discussed under the conceptual framework. On the other hand, medium and large scale farms may be adverse to smallholder farmers. Such farms can replace the farming system of the smallholder farmers with unaffordable capital intensive investments; create land scarcity in favorable rural areas; rise land prices, crowd out the poor with access to land for agriculture, interrupt their natural resources (water, forest, and savannah), grab their land and displace the vulnerable smallholders from their farms (Jayne et al. 2016)

Even though the effect of plantations and large farms on rural structures have been documented through case studies (see Smalley, 2013 for a detailed review). There is a dearth of literature on the rise of independent medium and large scale commercial farms and its impact on rural small holder farms. Some of the few empirical studies quantifying spillover effects of large farms on small farms are largely reporting heterogeneous results(Jayne et al., 2015; Jayne et al., 2016; Ali, Deininger and Harris, 2016; Deininger and Xia, 2016; Hall et al., 2017; Lay, Nolte and Sipangule, 2018). Part of the explanation for contrast in findings is due to the fact that in some countries most of the land owned by medium and large scale farms is underutilized, while in others is halfly or fully utilized (Chapoto et al., 2013; Jayne et al., 2008)

Therefore necessitating much more research to effectively guide policies towards agricultural transformation, this study contributes to the growing literature on the spillover effects of medium- and large- scale farms on smallholder farms in rural locations using total cultivated land in categorizing landholding size/status. Analyzing the spillover effects of these agricultural transformations could be confounded by the fact that such farms self-select into areas with particular characteristics such as good infrastructure and agro-ecology favoring high productivity. Therefore, with longitudinal data, panel data methods, like, fixed effects and difference in difference approaches can be used to discount this problem, which remains a challenge for cross-sectional studies such as ours. To overcome these challenges, panel data methods such as difference in difference and fixed effect are usually used in longitudinal data, this study uses a cross-sectional dataset using spatial econometric methods used elsewhere to quantify spillover effects while controlling for spatial dependence (Anselin & Bera, 1998; Kondo, 2017). The physical distance to Medium scale farms (MSFs) and Large Scale farms (LSFs) as well as concentration of LSFs in a ward are used to estimate the spillover effects on outcome variables such as crop yields (productivity); the extent of commercialization for particular crops (access to markets); the use of inputs/technology and conservation practices; and welfare (food security-calories produced).

2. Changing farm structure in rural Africa

While agricultural production in SSA remains predominantly small-scale, evidence points to significant transformation in the sector, for example, large-scale agricultural investments now cover about 10 million hectares of African farmland (Nolte, Chamberlain, & Giger, 2016; Zaehringer, Atumane, Berger, & Eckert, 2018). This rise in large-scale farms (LSFs) in developing countries has partly been attributed to the 2008 world food crises which brought attention of foreign and local urban investors to 'idle' and 'underutilized' agricultural land in Africa (Deininger and Byerlee, 2011; Schoneveld, 2014), ; rapid population growth, urbanization and rising incomes which has resulted in massive growth for the demand of food in African countries; development of land markets (rental, purchase and long-term lease markets); and weak land governance (Deininger & Byerlee, 2011; Osabuohien, 2014; Schoneveld, 2014).

In addition to LSFs, medium scale farms (MSFs) are also on the rise in the region and are now thought to control more than a third of total farmland in most countries (20% in Kenya, 32% in Ghana; 39% in Tanzania and over 50% in Zambia, and the share is rising) in east and southern Africa and accounts for most of the marketed agricultural produce, for example in Tanzania they account more than 40% of the country's marketed agricultural produce (Jayne et al., 2016). The literature advances two main reasons for this unprecedented transformation in agricultural production in the region; the first refers to an endogenous growth pattern where initially smallholder farmers expand their production to reach the 5 hectare threshold in total agricultural land under cultivation, and the second reason refers to exogenous agricultural investments by non-rural dwellers in the rural areas (Anseeuw et al., 2016; Sitko & Jayne, 2014). Anseeuw et al. (2016) show that half of the MSFs in Malawi followed the former pattern and the other half the latter, while Sitko & Jayne (2014) find little evidence to support the endogenous growth pattern in Zambia and posit that emerging structural transformation in the country is the equivalent of an elite land capture.

These emerging trends have important implications for the agro-food industry in these developing countries. For example, emergence of large scale traders has been documented in the rural grain markets of small holder farmers, which is associated with an increase in commercialization and intensification at the small holder farm level (Mulwa et al., forthcoming; Muyanga and Jayne, 2016). Other studies have documented negative effects of large scale investments in rural areas, key issues being around crowding out small scale farmers out of the scarce land resource (Smalley, 2013). There is thus a need for more rigorous analysis on the impact of these investments in the rural economy with different contexts.

3. Channels of spillover effects

Several mechanisms through which spillovers from large farms to small farms occur have been discussed in the literature. First, owners of large farms can enhance small farms' access to improved inputs and new technologies by leveraging on their social capital and scale economies to bring these resources to the areas in which they operate thus making them easily available to neighboring small farms (Gibbon, 2011; Jayne et al, 2014; Kojo and Amanor, 2011). These influential individuals tend to have access to government agencies, agribusiness entities and distribution networks which give them easy access to downstream markets and upstream suppliers of inputs, therefore improving access to smallholder farmers in the area. Furthermore, they are able to leverage on their social networks to attract public goods such as roads, electricity, subsidized inputs, water and irrigation facilities, which would otherwise not have been possible. Improvement in public infrastructure reduces transaction costs (Barrett, 2008) which facilitates access to inputs and output markets.

In some cases, large farms also rent out farm machinery or provide these services for free to neighboring small farms, hence freeing labor can be utilized in other parts of the value chain or non-agricultural related activities (Boamah, 2011; Jayne et al., 2015). Large farms might also induce knowledge or input quality spillovers that may affect overall input use. That is, smallholder farmers may be able to adopt and access more quality inputs if they gain knowledge about the inputs or have access to such input markets (Ali et al., 2016). As large farms tend to demand specific (often high) input quality standards (Prowse, 2012). Additionally, they have a greater incentive than small farms to check the quality of these inputs given that they purchase inputs in large quantities. Thus, if smallholder farmers are able to procure from or with these large farms, they can avoid low quality inputs which are very common in many retail markets (Bold et al, 2017). This spillover may be complemented by knowledge spillovers that occur as large farms hire labor from the local community— resulting in positive learning effects (Deininger & Xia, 2016).

Large farms provide work opportunities for straddles who depend on a combination of wages from on-commercial farm employment and own farm income. By working on these farms, they are potentially able to invest parts of their wages into expanding their farms through increased acreage or use of productive inputs. Workers may also transfer skills and knowledge obtained through training and working on large farms to their own farms thus inducing positive learning effects. However, this channel rests on the assumption that large and small farms cultivate the same crop (Deininger & Xia, 2016; Hammar, 2010; Oya, 2013).

Studies that look at the impact of large scale agricultural investments on the labor market, in many cases report employment generation or increased demand for labor , hence increased wage rate as an effect from such investments (World Bank, 2014; Deininger and Xia, 2016; Herrmann, 2017). However such investments do not always have an impact on all agents where the investment is, for example Hermann (2017) reported impact on the agro-industry workers and out growers, and that the effect depended on the type of investment (rice vs sugar) and size of scheme (bigger effect for land rich than land poor out growers); while Ahlerup and Tengstam (2015), using three waves of panel data from Zambia found large investments in agriculture to have a moderate positive effects on wage income; and that land-poor households had the greatest effect. Further (Giger et al, 2018; Zähringer et al, 2018, Ali et al., 2018) concluded that the effect of a large scale farm investment on the labor market is not geographical context specific, but is rather influenced by the type of production (mechanization, diversification) and business (large-scale plantation, commercial farms, out grower schemes). Conversely, large farms may induce negative spillovers on small farms. These include high food prices in areas with commercial farms (Schoneveld, German, & Nutako, 2011) as labor shift from food production on small farms to large single cash nonfood-crop farms (Pryor & Chipeta, 1990). In addition, proximity to large farms has been found to decrease perceived well-being among local people (Deininger & Xia, 2016) due to disruptions in rural socioeconomic structures (Smalley, 2013).

This negative externality may be reinforced by the acquisition of large areas of lands by real estate firms as they speculate on the land prices in the vicinity of new large farms (Smalley, 2013) thus making it harder for poor landless people to obtain lands. Contrary to the perceived "idle" land hypothesis that explains springing up of large farms, Messerli et al. (2014) and Lay et al (2018) find that large scale farms tend to concentrate in regions with good infrastructure, good soil quality, water sources, natural resources, or with a conducive environment for production, thus increasing frictions in land, water (von Braun and Meinzen-Dick, 2009; Rulli et al. 2013); and access to natural resources (Breu et al., 2016; Rulli et al., 2013; German et al. 2013) in these regions (von Braun and Meinzen-Dick, 2009; Rulli et al. 2013); while leaving low producing areas with idle land.

3.1 The effect of large scale investment on different farm outcomes

Different scholars studying the effect of large investments in agriculture find that such investments have spillover effects in some situations and not in others (Zaehringer et al., 2018;Lay et al., 2018; Ali et al., 2017; Herrmann, 2017; Deininger and Xia, 2016; Ahlerup and Tengstam, 2015; The World Bank, 2014 and Chu, 2013). Assuming spatial proximity is important for spillovers to be transmitted to smallholder farmers; Deininger and Xia (2016) used distance and time since a large farm was established to quantify spillover effects from large farms between 467 and 966 ha in Zambia; and found no spillover effects on output market participation and crop yields; but positive spillover effects on adoption of new practices (e.g. agronomic practices) and access to inputs (extension service, credit service, traction, improved seeds, fertilizer and pesticides); and negative on perceived wellbeing. Similarly, spatial proximity studies in Ethiopia found no spillover effects on job creation but positive spillovers on fertilizer use, improved seed use, risk coping mechanisms and yield; and the spillovers increased with increased proximity to the commercial farms (Ali et al., 2017).

Furthermore studies find adverse impacts of large agricultural investment on the ecosystem either directly through intensive monoculture plantation or indirectly though changes in small scale crop management or land use activities (Johansson and Isgren, 2017; von Maltitz et al., 2016); and; increased conflicts and material inequality within communities surrounded by large scale investments. On the other hand studies report that the geographical context has a bigger effect than a large scale investment. That difference in national policies and politics; business environment; land and water resource endowment has a bigger impact on land use change, the ecology, food security and livelihood than a large scale investment (Giger et al, 2018; Zähringer et al, 2018, Ali et al., 2018).

4 Hypotheses

Guided by literature, we assume investments in large farms may benefit neighboring small producers by providing employment; access to input and output markets; access to credit; or knowledge of improved techniques that can increase yield. Conversely, such investments can also have negative effects such as displacing small producers; monopolistic conducts by large farms; conflicts and competition for natural resources. This study therefore assumes spatial proximity to be the main channel for spillover transmission, e.g. via learning about new technology or functioning of local factor markets. This can happen from the effect of physical and social distance. Therefore in this section we develop three hypotheses based on the literature on large scale investment and its impact on smallholder farms.

These are: assuming there are more social interactions between medium and small scale farmers than there is with large scale farmers; that is, the social distance is shorter. We hypothesize that, physical distance, has a significant effect on different crop production outcomes. That the shorter the physical distance from a medium/large scale farmer, the better the outcome (yield per ha; CI; soil quality; Use of input/technology). Here we are interested in examining how distance from medium (5-10ha) /large scale (>10ha) farmers affect different outcomes in small scale farms (productivity, participation in output and input markets, soil quality), use of modern inputs (tractor, fertilizer, animal traction, hybrid seed)) or adoption of conservation practices.

The study also asks if geographic areas with high concentration of large scale farm investments (>10ha), have more spillover effects on smallholder farms in the geographic areas (yield, CI, soil quality; conservation practices and use of inputs). Under the assumption that interactions and spillovers are likely to be felt in areas highly concentrated with large scale farms. We hypothesize that, concentration of large scale farms in a village/wards, positively influences outcomes (productivity, commercialization, soil quality, use of inputs) in small scale farms.

5. Methods

4.1 Data

The study uses data collected in October 2016 as part of a bigger project on land dynamics in Tanzania. Eight districts were purposefully selected based on their land use and migration patterns, land availability, proximity to towns/cities, and potential for large scale investments. One ward was randomly selected from each district, followed by a complete listing of all farms with 10 ha and above landholding all as one piece, in all villages in each of the identified wards.

A total of 1200 farmers were sampled from the listed wards, where each ward's share of the sample was based on its proportion of the total number of farmers with more than 10ha landholding in all the listed wards. Similarly, each village's share of the ward's sub-sample was directly proportional to its share of farms with more than 10ha landholding in the ward. At the village level, farms with more than 10ha land holdings were randomly sampled for interviews. Each sampled farm with more than 10ha landholding was matched with a farm with less than 10ha in the same village.

Thus 600 farmers with a landholding of less than 10ha were selected from a government listing of all smallholder farms, while 600 farmers with a landholding of more than 10ha were randomly selected from the listed farmers. Due to logistical reasons, the number of households in the sampled village was limited to a minimum of 10 households. Out of the 1200 farmers sampled, only 1188 completed the interviews, with 610 being those with less than 10ha in landholding, and 578 those with more than 10ha of landholding.

In this study, farmers were re-categorized into three groups based on the size of their cultivated land (added up together) i.e. those cultivating less than 5 ha 656 farmers (small scale farmers, hereafter SSFs); those with 5-10 ha of total cultivated land 254 farmers (medium-scale farmers, hereafter MSFs); and lastly, those with total cultivated land of more than 10ha 295(Large scale farmers, hereafter LSFs). Data collected included crop production data across the three types of farmers for the 2015/16 cropping year, plot characteristics data like soil fertility and GIS coordinates, and household characteristics data. For this study we will focus on only maize, rice and sunflower farmers. Maize farmers include 570 SSF; 234 MSF and 267 LSF; rice farmers include 198 SSF; 67 MSF and 113 LSF; while sunflower farmers include 149 SSF; 82 MSF and 158 LSF. While maize farmers are spread through the six districts, rice farmers are mainly concentrated in Kilombero, Mvomero and Magu district; while sunflower farmers are mainly in Kiteto district.

4.2 Description of key variables

GIS information collected on farmers' homesteads was used to calculate distances between the small scale farms and the medium and large scale farms i.e. SSF to MSFs, and SSF to LSF. This is also the information used to create the spatial weight matrix discussed later under the methodology section, which is used to create the key variable for capturing spatial dependence and spillover effects in the empirical model.

The study tests for spillover effects on productivity in maize, rice and sunflower crops, two of the most commonly grown staples in the study region, and sunflower one of the most potential cash-crop in the study region. Productivity spill overs from large-scale to small-scale farms may be due to channels discussed earlier in this paper, i.e. passing knowledge on better farming practices, including better use of intensification inputs. Adoption of sustainable intensification inputs like fertilizer and improved seed is output enhancing, while the inclusion of other practices like soil and water conservation measures not only improve yields but also long term soil quality.

Commercialization index (CI) also to a large extent depends on households' productivity, since this determines amount of surplus output the household has for marketing, thus can also be thought of as a subset of the productivity function as a spillover effect. However, other channels of effect could also be easier access to a diversified portfolio of market actors due to proximity to large scale farmers (Burke, Jayne, & Sitko, 2019), as well as a reduction in transaction costs by having output markets move closer. This explains the choice of this variable as an outcome variable to test for spillover effects. The study follows von Braun and Kennedy (1994), with slight modification to define the CI at crop levels as;

$$\mathrm{CI}_{ji} = \frac{S_{ji}}{P_{ji}} * 100$$

where CI is crop j ($j = \frac{\text{maize}}{\text{rice}}/\text{sunflower}$) commercialization index for household i; and S_{ji} and P_{ji} are the sales and output values for crop j by household i, respectively. Using the value of crop output and sales, instead of the ratio of sales to output quantity reflects price offered for produce by various market actors, which is also a hypothesized spill over channel in the conceptual framework.

4.3 Spillover effects and spatial dependence

Quantifying spillover effects of large scale investments is challenging. Large scale agricultural investments mostly cluster around areas with certain characteristics, for example, geographical areas with good access to water or irrigation systems, good roads, electricity, good soil quality and access to markets (Messerli et al., 2014). Spatial heterogeneity arises whenever there is clustering of the indicators for spillover effects for some sets of units i.e. $Cov\ (y_i, y_j) \neq 0$ for $i \neq j$. Two cases for spatial heterogeneity can be differentiated; spatial clustering, where the outcome of one household is correlated with that of another, OR spatial dependence, where the outcome of one household is a function of the another (spillover effect) (Cook, Hays, & Franzese, 2015). The former can be corrected by fixed effects methods, without the use of spatial methods, while in the latter, failure to apply spatial correction methods leads to unbiased estimates.

Spatial econometric methods have in the past been used to investigate spillovers in situations where location and spatial interactions are important (Anselin & Bera, 1998; Dubin, 1988, 1992). Most of these studies use proximity to a large investment (or metropolitan for real estate studies) as the source of spillover effects, and analyze how this affects neighboring units. For instance, Dubin (1992) finds that the price of a house is not only a function of its proximity to the central business district and the house structure, but also on the quality of its neighborhood and accessibility. In the agricultural context, extant studies follow this framework to examine spatial dependence and spillover effects with reference to the spatial distribution of agricultural production (Ali et al., 2016; Deininger & Xia, 2017; Schmidtner et al., 2012).

In analyzing the spatial distribution of organic farms in Germany, Schmidtner et al. (2012) use aggregated information at the county level, due to lack of individual data on organic farms and their neighbors. The study uses a Lesage (2014)-type of model where a linear combination of the dependent variable is included as an additional explanatory variable to control for spatial dependence in the outcome variable among neighboring counties. Our study follows Schmidtner et al. (2012) in estimating a spatial model for spillover effects from LSFs and MSFs to SSFs. Our access to individual plot specific data and household data allows us to investigate spillover effects among neighbors at these levels.

To create spatially lagged variables, a spatial matrix is necessary. Normally, a spatial matrix involves the use of existing shape files of the study area, which can be decoded into programs like STATA; Coordinates data from these can then be used to create neighborhood spatial matrices, whether based on distance or boundary sharing. The spatial weight has diagonal elements with a value of 0 and sum of each row equal to 1 (row standardized), thus;

$$W = \begin{pmatrix} 0 & w_{1,2} & w_{1,3} \ldots & w_{1,n} \\ w_{2,1} & 0 & w_{2,3} \ \ldots & w_{2,n} \\ w_{3,1} & w_{3,2} & 0 \ \ \ldots & w_{2,n} \\ & & . & \\ & & . & \\ & & . & \\ w_{n,1} & w_{n,2} & w_{n,3} \ \ldots & 0 \end{pmatrix}$$

Most existing Stata packaging are based on these type of process, for example *spmat* (Drukker et al., 2013) and *splagvar* (Jeanty, 2010). This is a challenge for researchers with micro data where there are no existing shape files for the regions to study, for example, calculating spatial weights for sample households in a village or ward. Kondo (2017) developed the *spgen* computing procedure which utilizes the GIS information of the study units to calculate the spatial weight matrix, without the need for an existing shape file. The method calculates the spatially lagged variable directly, without first having to calculate the spatial weight matrix, and is suitable for this type of a study.

4.4 Empirical model and estimation strategy

Based on the conceptualized channels of spillover effect discussed in preceding earlier, we adopt an empirical model that tests for the effect of proximity to a large farm on smallholder farms' input costs reduction and knowledge spillovers, and access to output markets. The basic model representing this relationship is given as;

$$y_i = \alpha + \beta X_i + \mu_i \qquad (1)$$

Where is y_i is farmer i's outcome indicator variable of interest (maize, rice OR sunflower yields in Kgs, and rice,maize OR sunflower commercialization index); X is a vector of farm, farmer and location variables, including proximity variables like distance from SSFs to MSFs or LSFs, and concentration of these large farms in particular ward; and μ is the error term. To estimate spatial dependence and therefore spillover effects, the above model is estimated by including spatially lagged variables from the spatial weights created as discussed above.

Lesage (2014) argues that it is important to distinguish between global and spatial spillover effects when specifying spatial econometric models. A global spillover effect involves an endogenous interaction and feedbacks, with a change in one entity leading to changes others in the sample. Adoption decisions of commercial farms, for example, may influence the adoption decisions of smallholder farms, and this endogenous spatial effect amplify as farms of different sizes and orientation interact. This specification is also used when spillovers occur between neighbors, and neighbors of neighbors. The Spatial Durbin Model (SDM) to estimate global spillover effects specified by including the spatially lagged dependent variable in equation 1 to the set of exogenous explanatory variables, thus;

$$y_i = \rho \mathrm{W} y_i + \alpha D_i + \beta X_i + \mu_i \qquad (2)$$

where $\mathrm{W}y_i$ is the linear combination of the spatial weight matrix as shown above and the dependent variable as in equation (1).

In local spillover effects on the other hand, endogenous interaction and feedback effects are not present. For example, certain spillovers might only be observed among farms of similar characteristics, regardless of the interaction. Thus, while the presence of a large commercial farm may improve the access of medium to-large-size farms to input markets, this spillover may not be observed in smaller farms. Local spillover effects thus vary with the exogenous characteristics of the farm or the social group of the farmer. The Spatial Durbin Error Model (SDEM) to estimate local spillover effects is specified by including the spatially lagged independent variables in equation 1, thus;

$$y_i = \alpha D_i + \rho \mathrm{W} X_i + \beta X_i + \mu_i \qquad (3)$$

where $\mathrm{W}y_i$ is the linear combination of the spatial weight matrix as above and the vector of unit $i's$ independent variables.

Following established literature (Kondo, 2017), the study utilize the global spillover effects to estimate the model. The inclusion of spatially lagged dependent variables clearly brings an endogeneity issue, and OLS estimates would be inconsistent. To overcome this problem, these equations are estimated using the generalized method of moments (GMM). Following Anselin & Bera (1998) and Kondo (2017), spatial lags of the exogenous variables, WX are used in the GMM estimation of the model, as instruments for the spatially lagged dependent variable, Wy. The model is also estimated using OLS, with and without the inclusion of lagged variables, and these results are also presented for comparison with the GMM estimated results.

In the estimation strategy, we create subsamples of SSFs and MSFs, and SSFs and LSFs separately. The spatial lag of the dependent variable is then created from these subsamples, to capture spillover effects, for example within the SSFs and MSFs subsample, before creating a further subsample of only SSFs which is used for the estimations. The spatial weight matrix is created within a radius of 5km to capture the dependence of SSFs and MSFs or LSFs within that radius. Yields, or commercialization indices, of these smallholder farms are then regressed on the spatially lagged variable, plus other controls including the distance and concentration of MSFs or LSFs variables, to establish how the outcome variables of the SSFs depend on the outcome variables of the larger farms, and the proximity to them.

Finally, in estimating the spillovers on technological adoption, we further modify our specification so that we can estimate the spillover conditional on the medium scale farm's adoption of the same technology. This will allows us to answer questions such as: does proximity to a medium scale farm that uses fertilizer increase the likelihood of fertilizer use? Or does proximity alone increase likelihood of fertilizer usage by the small scale farm regardless of usage by the medium/large scale farm. Specified as

$$f_{id} = \alpha + \beta M_{id} + \sigma f_{id}^{N} + \vartheta M_{id} * f_{id}^{N} + \gamma X_{id} + \gamma X_{id} + \delta_d + \epsilon_{id} \quad (2)$$

Where f is a dummy variable for a practice adopted by a small scale farm, f_{id}^{N} is a dummy for whether the nearest medium/large scale farm adopted a similar practice and ϑ is the coefficient measuring how distance affect the likelihood of a small scale farm adopting practice f conditional on the nearest medium/large scale farm using practice f.

5. Results

5.1 Non-parametric results

Non-parametric results indicate higher significant mean differences in the commercialization for maize and rice sunflower by both MSFs and LSFs compared to SSFs, but interestingly, no significant differences in the means yields across these groups (Table 2). The low and nonsignificance in means for rice sunflower commercialization respectively, is an indication of producing for market for these crops, such that all types of farmers have high CR's for these cash crops. Figures 1-6 provide a closer inspection of these variables using kernel density distributions. For commercialization, there is a lot of clustering at zero for SSFs maize commercialization ratio, as compared to the rice and sunflower commercialization for these farmers. Distributions for the CR's for the three crops is more spread out for medium and large scale farmers.

5.2 Empirical model results

Tables 3-8 present the estimated empirical model results. First, yield-related spillover effects of MSF on SSF are presented in table 3, while table 4 presents spillover effects on commercialization. Tables 5 and 6 present the spillover effects of LSF on SSF, for yields and commercialization respectively. In all these tables, the first three columns relate to maize crop, the third to fifth relate to rice crop, and fifth to eighth to sunflower crop. In these pairs of columns for each crop, the first column (OLS1); presents a benchmark OLS estimation of the model without the inclusion of the spatially lagged dependent variable to capture spatial dependence; the second column (OLS2) present an OLS estimation of the model with the inclusion of a spatially lagged dependent variable that captures spillover effects; and the third column (GMM) present results of a GMM estimation of the model. Each of these results are discussed briefly below:-

Spillover effects of MSFs on SSFs

From the empirical model results (Table 3), positive spatial dependence is established in maize and sunflower yields, but not in rice yields. The spatial lags of maize and sunflower yields are positive and significant, implying spillover effects among MSFs and SSFs in determination of yields in these crops. Given the construction of the spatially dependent variable, where yields from MSFs were paired with yields from SSFs within a 5km radius, this implies a positive spillover effect of MSFs and SSFs yields. The number of MSFs within a ward's boundaries, another measure of spillover in the estimation, was found to be correlated with SSF rice and sunflower yields, but not with maize yields. SSF rice and sunflower yields are an increasing function of the ward's concentration of medium scale rice farmers. The key variable hypothesized to affect spillover effects, proximity of SSFs to MSFs, was however found not to be significant in explaining crop yields. The dispersion of the distance variable is a maximum of 10km, and the construction of the spatial lag within a radius of 5km could be a factor in crowding out this result.

In terms of crop specific commercialization, positive spatial dependence is again established between MSFs and SSFs in the case of maize and sunflower, but not for rice (Table 4). This implies positive spillover effects in the sales of maize and sunflower within these farm-types. Possible reasons for this include the hypothesized channels of spillover effects in commercialization, where MSFs may lower the transaction costs of SSFs by bringing markets closer hence increasing crop sales to output ratios. It could also be the case that nearby MSFs increase the value of output sold by attracting a diversified portfolio of market actors, for example, large grain traders (Burke et al., 2019), who offer higher prices for output.

Other factors that significantly determine SSF yields include off-farm income, access to credit, gender of the household head and asset ownership. Maize yields increase with an increase in household off-farm income, while female-headed households have lower yields than their male counterparts. Credit constrained households are also likely to have lower yields than those that are not constrained. These results are in line with established literature on technology adoption studies among smallholder farms, and the effect on crop yields. Similarly, households with more valuable assets are more likely to realize higher rice yields, which could be an implication of mechanization in rice farming, and how this affects yields realized from the enterprise.

On the other hand, SSFs who sell to MSFs were found to be highly commercialized in maize, while household size in terms of adult equivalent is negatively correlated with commercialization (Table 4). The former implies a direct spillover effect, where MSFs may act as markets for SSFs, who lack the output volumes to sell to big market actors directly. The MSFs may then aggregate their own production with purchases from nearby SSFs, then sell off to bigger markets, leveraging on their scale of operation. The latter is also intuitive; higher household sizes imply more consumption of own production, hence less remains as surplus for marketing.

Spillover effects of LSFs on SSFs

The results on spillover effects of LSFs to SSFs differ slightly to those of MSFs to SSFs (Table 5). A positive spillover result between LSFs and SSFs is obtained for maize yield, but unlike in the case of MSFs and SSFs, there is no significant positive spill overs between LSFs and SSFs for sunflower. The descriptive statistics show a low proportion of sunflower producers by farmer-type, perhaps a reason for the non-significant spillover effect, given the neighborhood spatial weights are calculated within 5km bands. Like before, the results show no spill over results in rice yields.

In terms of commercialization (Table 6), the spatially lagged dependent variables are positively correlated with maize and sunflower commercialization, but not with rice commercialization. In addition, the concentration of LSFs in the ward significantly explain maize commercialization but not sunflower and rice commercialization. There are thus positive spillover effects between LSFs and SSFs for both maize and sunflower commercialization, an effect that is further amplified by the number of LSFs in the ward, for maize marketing.

In other results, female-headed households are still shown to have lower maize yields, with off farm income positively correlated with both maize and sunflower yields. Credit constrained farmers are realize lower yields, among both maize and sunflower SSFs. Curiously, higher fertilizer application rates are shown to decrease maize yields, perhaps an indication of soil degradation among small holder farms, leading to negative returns to fertilizer use (Kihara et al., 2016). The use of improved seed on the other hand is shown to increase sunflower yields.

Use of inputs (fertilizer, improved seeds, conservation practice, tractor, animal traction

- Fertilizer-(maize, rice, sunflower)
- Improved seeds-(maize, rice, sunflower)
- Tractor-(maize, rice, sunflower)
- Animal traction-(maize, rice, sunflower)
- Conservation practice-(maize, rice, sunflower)

Conclusions

This study set out to establish the spillover effects of large and medium scale farms to small scale farms, with specific reference to crop yields and crop commercialization in Tanzania. Using a spatial econometric approach, the study identifies positive yield and commercialization related spillover effects for maize and sunflower farmers, but not for rice farmers. The positive spillover effect for maize yields is observed between both large and small scale farmers, as well as medium and small scale farmers. On the other hand, this effect is observed only between medium and small scale farmers for the case of sunflower yields, but not between large and small scale farmers rice.

In terms of commercialization, the study identifies positive and highly significant positive spillover effects for maize and sunflower commercialization, between both small scale and medium scale, and small scale and large scale farmers.

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Tables

Table 1: Sample size

	SSF (N=656)	MSF (N=254)	LSF (N=295)	Overall (N=1205)
Njombe (N=283)	65	16	20	24
Kilombero (N=73)	64	19	16	6
Mvomero (N=135)	58	18	24	11
Kiteto (N=315)	37	28	35	27
Magu (N=78)	64	18	18	7
Liwale (N=152)	55	30	16	13
Moshi Rural (N=28)	68	18	14	2
Mkuranga (N=124)	64	17	19	10
Overall	54	21	24	100

Table 2: Mean differences in yields and commercialization by farmer-type

	SSF	MSF	t	SSF	LSF	t
Mean maize yields	843.99	782.56	-1.0467	843	775	-1.0721
Mean rice yields	1445	1810	1.58	1445	1390	-0.2371
Mean maize CI	16.66	24.17	3.1235***	16.66	27.21	4.2026***
Mean rice CI	20.10	28.95	1.7533*	20.10	18.40	-0.2987

Table 3: Effect of proximity to MSFs on SSFs yields

	Maize yields			Rice yields		
VARIABLES	OLS1	OLS2	GMM	OLS1	OLS2	GMM
W_yield		0.823***	0.854***		-0.321	-0.607
		(0.218)	(0.168)		(0.278)	(0.465)
Distance to medium scale farm	-13.58	27.47	31.61	99.45	168.4	248.5
	(66.76)	(68.46)	(71.31)	(168.2)	(249.5)	(276.3)
Ward concentration of medium	0.800	0.203	0.459	10.91	16.31	18.35*
Scale farms	(1.440)	(1.431)	(1.110)	(9.232)	(13.31)	(9.875)
Adult equivalent	-22.73	-15.21	-22.31	-41.49	-17.30	80.08
	(41.63)	(43.42)	(43.11)	(111.9)	(104.8)	(142.0)
Education of hhld head	33.55	-1.708	-0.999	-38.68	-17.53	64.44
	(33.12)	(38.48)	(29.78)	(128.6)	(116.5)	(112.9)
Female headed hhld	-166.6	-242.7	-294.9**	147.6	281.3	716.4
	(124.8)	(156.5)	(145.0)	(845.4)	(728.2)	(481.8)
Ln off-farm income	118.4	130.4*	136.1**	-171.8	-181.2	-115.1
	(70.84)	(72.47)	(60.04)	(154.4)	(153.9)	(141.2)
Credit constrained	-712.3**	-673.9***	-642.1***	1,051	1,076	1,662
	(271.8)	(189.7)	(161.4)	(1,501)	(1,569)	(1,427)
Fertilizer (kg/ha)	-2.622	-3.143	-3.184	20.51	21.81	10.65
	(3.415)	(3.419)	(2.877)	(13.57)	(14.66)	(7.605)
Area improved seed	-119.5	-117.6	-92.12	-102.1	-123.8	-150.6
	(76.32)	(78.45)	(66.58)	(178.5)	(213.9)	(201.1)
Ln asset value	68.63	29.85	15.20	435.1*	416.6*	368.3**
	(89.21)	(76.61)	(59.77)	(218.9)	(199.2)	(152.3)
lmsq9	-0.267	-0.314	-0.332	0.398	0.431	0.227
	(0.471)	(0.463)	(0.415)	(0.692)	(0.699)	(0.714)
District controls	YES	YES	YES	YES	YES	YES
Constant	-884.1	-1,445		-3,636	-3,158	
	(1,811)	(1,886)		(3,024)	(2,581)	

W_yield captures the spatial lag of the dependent variable, crop yields

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Effect of proximity to MSFs on SSFs crop commercialization

	Maize commercialization			Rice commercialization		
VARIABLES	OLS1	OLS2	OLS1	OLS2	OLS1	OLS2
W_CI		0.406**	0.668***		0.404	0.469
		(0.196)	(0.161)		(0.633)	(0.384)
Distance to medium scale farm	-0.522	0.0692	-0.956	-0.313	1.173	0.332
	(1.416)	(1.446)	(1.515)	(5.436)	(4.687)	(4.520)
Ward concentration of medium	-0.0480	-0.0277	0.0326	0.189	0.0786	-0.00593
Scale farms	(0.0700)	(0.0673)	(0.0401)	(0.312)	(0.357)	(0.0962)
Adult equivalent	-2.282**	-2.103**	-2.066**	-0.152	-0.115	-1.074
	(0.975)	(1.019)	(0.971)	(2.489)	(2.682)	(2.154)
Education of hhld head	-0.678	-0.554	-0.115	0.714	1.490	1.526
	(0.995)	(1.027)	(1.091)	(3.296)	(3.608)	(2.778)
Female headed hhld	3.489	2.790	4.322	0.903	3.333	1.857
	(7.508)	(7.676)	(9.524)	(12.11)	(12.00)	(10.68)
Ln off-farm income	2.487	2.124	1.892	-6.666*	-6.680	-5.398*
	(1.878)	(1.988)	(1.712)	(3.678)	(3.884)	(2.946)
Ln asset value	0.852	0.932	0.220	-1.037	-1.013	-1.765
	(1.821)	(1.781)	(1.653)	(2.607)	(2.739)	(2.721)
lmsq3	0.00309	0.00380	0.00920*	-0.00619	-0.00664	-0.00466
	(0.00493)	(0.00505)	(0.00470)	(0.0176)	(0.0177)	(0.0162)
District controls	YES	YES	YES	YES	YES	YES
Constant	-13.26	-18.41		130.1**	120.7**	
	(30.60)	(30.46)		(52.78)	(45.72)	

W_CI captures the spatial lag of the dependent variable, commercialization index (CI)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of proximity to LSFs on SSFs yields

	Maize commercialization			Rice commercialization		
VARIABLES	OLS2	OLS1	OLS2	OLS1	OLS2	OLS1
W_yield		0.769***	0.796***		0.0154	0.249
		(0.194)	(0.167)		(0.312)	(0.277)
Distance to medium scale farm	13.98	-18.10	1.412	121.0	121.8	55.33
	(54.82)	(55.55)	(58.10)	(102.8)	(111.9)	(94.69)
Ward concentration of medium	-1.480	-2.131	-1.555	-3.367	-3.013	12.19
Scale farms	(3.226)	(1.978)	(1.462)	(12.65)	(15.02)	(9.142)
Adult equivalent	-25.36	-31.69	-36.66	-112.2	-112.0	-15.55
	(46.10)	(43.67)	(41.14)	(109.9)	(100.8)	(116.3)
Education of hhld head	11.61	-22.42	-18.70	-102.1	-101.1	-17.03
	(34.91)	(37.03)	(32.53)	(121.9)	(122.2)	(138.2)
Female headed hhld	-234.0	-297.1	-303.5**	-181.5	-200.9	322.3
	(162.5)	(180.4)	(151.9)	(824.2)	(797.1)	(588.9)
Ln off-farm income	84.68	71.30	73.27*	-42.68	-40.79	36.73
	(53.37)	(48.00)	(39.82)	(143.4)	(147.6)	(131.5)
Credit constrained	-364.2	-426.5*	-417.8*	912.9	907.3	1,292
	(340.3)	(246.5)	(218.4)	(1,228)	(1,248)	(1,466)
Fertilizer (kg/ha)	-0.666	-1.163**	-1.200**	21.58	21.53	6.329
	(0.440)	(0.515)	(0.477)	(14.09)	(15.64)	(7.718)
Area improved seed	-68.83	-62.71	-40.55	-169.2	-168.6	-155.9
	(68.93)	(68.34)	(52.07)	(195.3)	(207.4)	(199.8)
Ln asset value	76.08	29.32	19.22	324.5	323.0	248.5
	(85.62)	(73.22)	(55.77)	(221.4)	(210.2)	(161.6)
lmsq9	-0.152	-0.166	-0.203	0.515	0.484	0.460
	(0.395)	(0.377)	(0.345)	(0.563)	(0.587)	(0.505)
District controls	YES	YES	YES	YES	YES	YES
Constant	-478.3	-449.6		-2,600	-2,643	
	(1,363)	(1,156)		(3,047)	(2,536)	

W_yield captures the spatial lag of the dependent variable, crop yields

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect of proximity to LSFs on SSFs crop commercialization

	Maize commercialization			Rice commercialization		
VARIABLES	OLS1	OLS2	OLS1	OLS2	OLS1	OLS2
W_CI		0.322**	0.534***		0.163	0.104
		(0.152)	(0.155)		(0.381)	(0.225)
Distance to medium scale farm	-0.735	-0.320	-0.656	0.224	-0.0665	0.183
	(1.436)	(1.421)	(1.316)	(2.243)	(2.480)	(1.572)
Ward concentration of medium	0.0993	0.104	0.137*	0.222	0.224	0.0977
Scale farms	(0.0776)	(0.0652)	(0.0701)	(0.296)	(0.296)	(0.159)
Adult equivalent	-2.040**	-2.065**	-1.996**	-0.711	-0.708	-1.500
	(0.843)	(0.843)	(0.858)	(2.306)	(2.397)	(1.574)
Education of hhld head	-0.266	-0.228	-0.146	1.235	1.470	0.932
	(0.803)	(0.820)	(0.837)	(3.296)	(3.123)	(2.366)
Female headed hhld	5.288	5.440	7.594	5.574	5.889	3.186
	(7.028)	(7.200)	(9.294)	(8.740)	(8.739)	(9.932)
Ln off-farm income	0.900	0.809	1.186	-6.179*	-6.054	-5.449**
	(1.576)	(1.618)	(1.397)	(3.514)	(3.557)	(2.634)
Ln asset value	0.446	0.732	0.709	-0.570	-0.651	-1.016
	(1.769)	(1.723)	(1.639)	(2.457)	(2.572)	(2.312)
lmsq3	0.00297	0.00238	0.00621	0.00177	0.00128	0.000843
	(0.00420)	(0.00398)	(0.00414)	(0.0167)	(0.0170)	(0.0143)
District controls	YES	YES	YES	YES	YES	YES
Constant	-2.171	-10.00		112.7**	107.7**	
	(23.81)	(21.70)		(49.06)	(43.92)	

W_CI captures the spatial lag of the dependent variable, commercialization index (CI)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figures

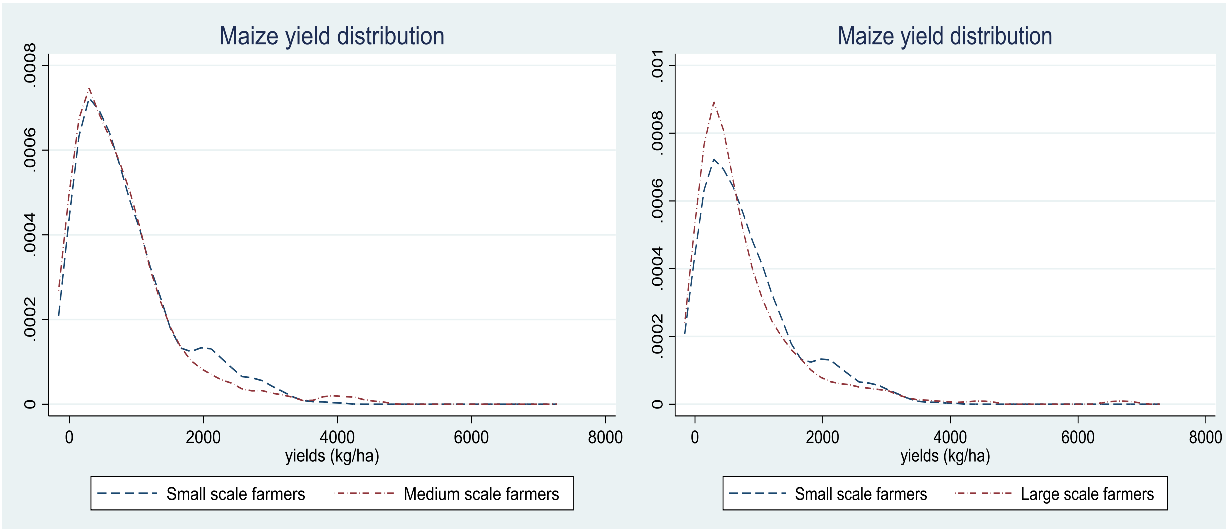

Figure 1: Maize yield distributions

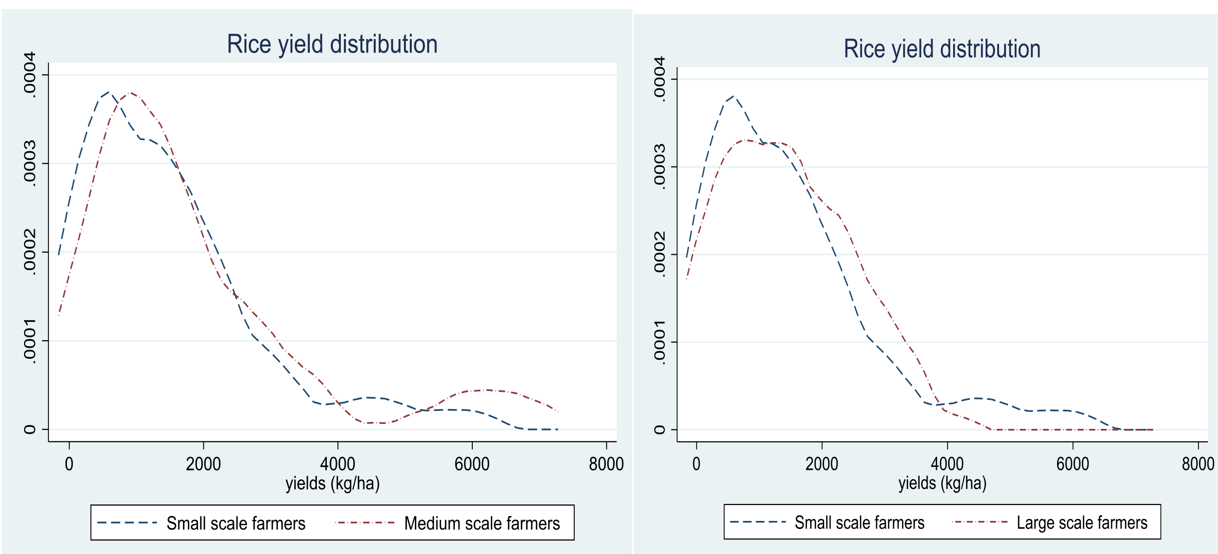

Figure 2: Rice yield distributions

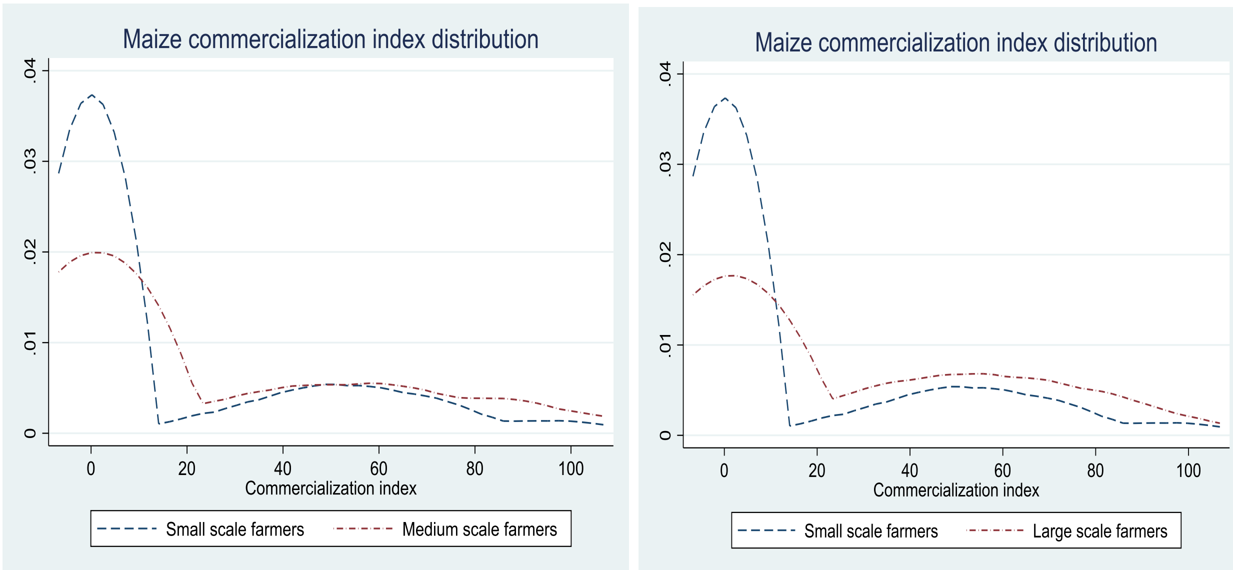

Figure 3: Maize commercialization distributions

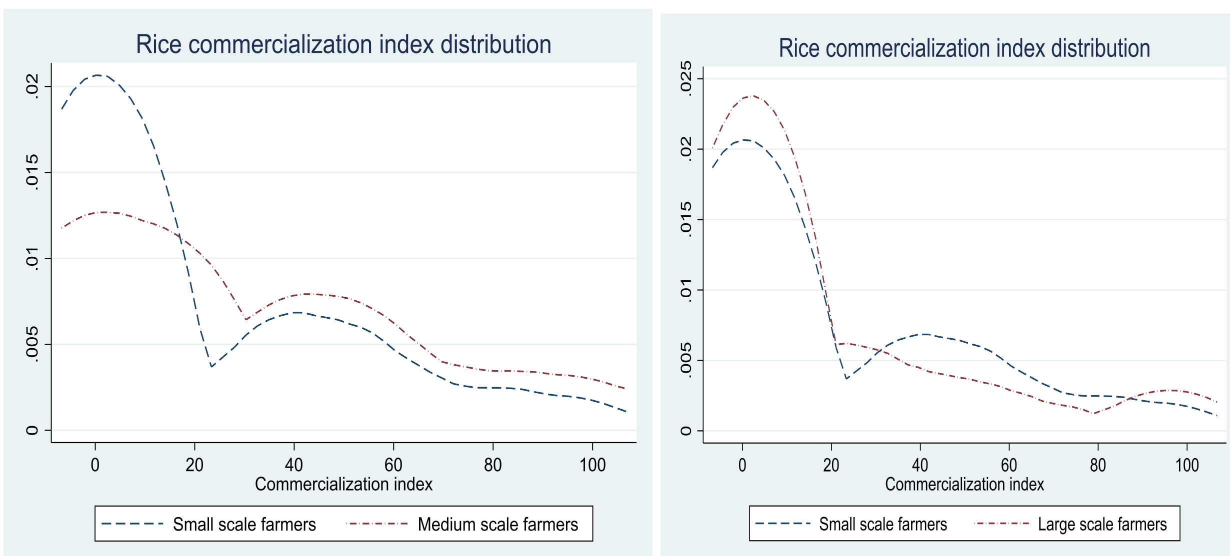

Figure 4: Rice commercialization distributions