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Effects of social networks on technical efficiency in smallholder agriculture: The case of cereal producers Tanzania

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The use of improved crop varieties is key to increasing food production, but in Sub-Saharan Africa traditional varieties still dominate smallholder farming. Lack of information is a major constraint to the adoption of improved varieties and the role of social networks in their diffusion is increasingly being studied. Social networks can, however, also affect the efficiency with which farmers use these technologies. In this paper we investigate the influence of social networks on technical efficiency of smallholder cereal producers. Using the case of Tanzania, we apply stochastic frontier analysis on data from sorghum and maize producers. Results show that the effects of social networks on efficiency differ by crop. Inter-village networks positively influence technical efficiency of improved sorghum varieties, but have no effect in case of maize. We further find that links to public extension officers increase efficiency of improved maize varieties. Some wider research and policy implications are discussed.

Keywords: Improved varieties, social networks, information, technical efficiency, stochastic frontier.

JEL codes: D24, D83, O33, Q16

1 Introduction

Global demand for food and agricultural products is on the rise and there is need to increase production to meet this growing demand. Smallholders, who form the majority of farmers around the world, will play a significant role in this regard (FAO, 2014). The use of improved crop varieties (ICVs) has been identified as an important strategy by which smallholders can increase productivity and food production (World Bank, 2007). However, in most of Sub-Saharan Africa, traditional varieties still dominate smallholder production systems (Walker et al., 2014), limiting the envisaged output and productivity gains. Lack of agricultural information has been identified as a key constraint to ICV diffusion, and its role is increasingly being studied (Diagne and Demont, 2007; Simtowe et al., 2011; Kabunga, Dubois and Qaim, 2012). Based on this information constraint paradigm, a number of ICV diffusion studies (Matuschke and Qaim, 2009; Maertens and Barrett, 2013) have assessed the role of social ties and interactions, also known as social structures or social networks (Borgatti et al., 2009). This is anchored on the understanding that social networks are powerful informal institutions for information diffusion in farming communities, and that flows of information, beliefs and attitudes within social networks can influence farmers' technology adoption decisions (Baerenklau, 2005).

Social networks, however, can affect not only the adoption by farmers, but also the efficiency with which farmers use these technologies. Based on information obtained from network members, individual farmers adjust the type and timing of crop husbandry methods used (such as seedbed preparation, sowing, and management of soil fertility, pests and diseases), which then influences their technical efficiency. While there have been a number of studies assessing the impact of ICVs on efficiency and productivity (Huang and Bagi, 1984; Adesina and Djato, 1996; Sherlund, Barrett and Adesina, 2002; Aye and Mungatana, 2010), we are not aware of any study that has investigated explicitly the effect of farmer-to-farmer social networks. We hence add to the literature by investigating the role of these social networks for technical efficiency. We use data from 231 plots of sorghum and 287 of maize, collected from 345 cereal producers in Central Tanzania. Another interesting aspect of our study refers to the characteristics of social networks themselves. Past studies report that social networks cross geographical boundaries (De Weerdt, 2004; Fafchamps and Gubert, 2007), but previous studies of network effects primarily focus on intra-village links, ignoring inter-village networks that may play an important role in information dissemination. Hence, an attempt is made to assess the effects of social networks both within and across villages.

The rest of the paper is structured as follows. Section 2 discusses the methodology of our study. After describing the data and empirical models in Section 3, we present our results in Section 4. In Section 5, we conclude and discuss implications of the study for policy and future research.

2 Methodology

2.1 Technical efficiency and its measurement

Efficiency in resource allocation is the central concept in neoclassical theory of production, in which firms are assumed to be profit maximizing. According to Kumbhakar and Lovell (2000), we define technical efficiency (TE) of a farm as the ratio of its observed output to the maximum feasible output. Following Kumbhakar and Lovell (2000) and Greene (2008), we use stochastic frontier analysis to estimate the production frontier and to obtain measures of technical efficiency. The stochastic frontier model is specified as

$$lnY_i = f(\boldsymbol{X}_i, \boldsymbol{\beta}) + v_i - u_i \tag{1}$$

where Y_i is the quantity of output produced by farm i (i=1,2,….N), $\boldsymbol{X_i}$ is a vector of inputs into the production process, and $\boldsymbol{\beta}$ is a vector of parameters to be estimated, $(v_i - u_i)$ is the *composed error* term, ε_i, with v_i being the stochastic component that accounts for measurement errors, omitted variables, model (mis)specification and random variation across farms. This stochastic error is assumed to be normally distributed and can take negative, zero, or positive values. It is further assumed that $E(v_i) = 0$; $E(v_i^2) = \sigma_v^2$ and $E\left(v_i v_j\right) = 0$ for all $i \neq j$ (Coelli *et al.*, 2005). The term $u_i \geq 0$ represents the technical inefficiency, and captures the extent to which observed yield deviates from potential output, given inputs and production technology. This term is assumed to follow a half-normal, truncated-normal, exponential or gamma distribution. It is also assumed that $E(u_i^2) = \sigma_u^2$ and $E\left(u_i u_j\right) = 0$ for all $i \neq j$ (Coelli *et al.*, 2005). From this term, a farm's level of technical efficiency (TE) is calculated using equation (2). Jondrow *et al*. (1982) and Greene (2008) discuss the derivation of these terms is in detail.

$$TE_i = \exp(-u_i) \tag{2}$$

Letting technical inefficiency to be influenced by farm and management characteristics, then the inefficiency model can be specified as

$$u_i = \alpha_0 + \boldsymbol{s}_i\boldsymbol{\alpha} + \boldsymbol{z}_i\boldsymbol{\delta} + w_i \qquad (3)$$

where $\boldsymbol{\alpha}$ and $\boldsymbol{\delta}$ are vectors of parameters to be estimated, $\boldsymbol{s}$ represents a vector of *social network* characteristics of farmer i, $\boldsymbol{z}_i$ is a vector of farm and farmer characteristics, and w_i represents unobserved normally distributed random factors that influence inefficiency. Equations (1) and (3) are then estimated simultaneously by maximum likelihood methods (Kumbhakar and Lovell, 2000). We assume half-normal distribution and test for the presence of inefficiency (i.e., null hypothesis that $\lambda = 0$, against the alternative that $\lambda > 0$) using a special likelihood ratio test for on-boundary values described by Gutierrez, Carter and Drukker (2001).

2.1.1 Information, social networks and technical efficiency

The key sources of new agricultural information in our study area are seed and agro-chemical companies/dealers; government agricultural extension officers; non-governmental organizations; and public agricultural research and development organizations (Figure 1). Farmers obtain this information through two main channels. One, they may directly access the information by participating in the activities offered by these institutions such as farmer field days, on-farm trials and demo plots. The second pathway is informal, i.e., farmers obtain the information from other farmers, through their social networks. We define a *social network* as a set of actors or nodes (individuals or households) that have relationships or ties with one another (Marin and Wellman, 2011).

Social networks affect an individual farmer's behavior through *social learning* or *social influence* (Young, 2009; Hogset and Barrett, 2010). In the case of social learning, the farmer actively searches for information within his/her networks. The information obtained may in turn influence the farmers' decision to adopt a more efficient farming method. By contrast, social influence results from *imitation* or *mimicry*, which means that a farmer adjusts their farming practice mainly to *conform* to observed behavior of other farmers, and not necessarily based on any factual information about the motivation for their peers' adoption of the given farming method (Hedström, Sandell and Stern, 2000; Easley and Kleinberg, 2010). According to these pathways, we hypothesize that the information obtained from formal sources and from farmer-to-farmer networks influences individual farmers to adjust the type and timing of crop husbandry methods used (such as seedbed preparation, sowing, and management of soil fertility, pests and diseases), resulting to changes in technical efficiency.

<FIGURE 1 ABOUT HERE>

2.1.2 Potential endogeneity in adoption of improved varieties

The type of seed technology (improved or traditional varieties) used is an important factor influencing productivity. The adoption of improved varieties is, however, potentially endogenous. Mutter *et al*. (2013) argue that efficiency estimation procedures that do not account for endogeneity introduce bias in the results due to correlation between the endogenous variable and the composed error of the stochastic frontier. In our study, it is likely that endogeneity is present due to farmers self-selecting or being selected non-randomly into adoption. Information on and seeds of improved varieties are often passed to farmers in a selective manner. For instance, agricultural research and extension staff often target particular geographic locations, individual farmers or groups of farmers (Diagne and Demont, 2007) for ICV research, extension and development activities. In the case of Tanzania, Monyo *et al.* (2004) and Lyimo, Mduruma and de Groote (2014) document heavy involvement of the public agricultural extension service and development organizations in disseminating improved varieties of sorghum and maize. Moreover, in our data, the seeds used in 26.3% of the improved sorghum plots were sourced from agricultural extension officers. It is therefore very likely that the adoption of improved varieties is non-random and that an endogeneity problem is present due to sample selection.

2.2 Addressing endogeneity in variety adoption

Recently, studies employing SFA have begun to address the problem of endogeneity in technology adoption (Solís, Bravo-Ureta and Quiroga, 2007; Rao, Brümmer and Qaim, 2012; Wollni and Brümmer, 2012). In this study, we use a matching method known as propensity score matching (PSM) (Rosenbaum and Rubin, 1983) to correct for potential endogeneity. This non-parametric method enables us to construct a group of plots sown with traditional varieties (control or counterfactual group) which is comparable to those plots sown with improved varieties (treatment or treated group). An advantage of this grouping is that it gives us the flexibility to analyze technical efficiency of the two groups separately. Technological differences between the improved and traditional varieties imply that production constraints and information needs are different, hence separate analyses are interesting. We implement PSM by first computing a propensity score, which is the probability to adopt an ICV, using a Logit model. Next we use kernel matching (for sorghum) and nearest neighbor matching (for maize) algorithms to construct the treatment and control groups within the region of common support (Caliendo and Kopeinig, 2008). One shortcoming of PSM is its reliance on observables to address confoundedness, but self-selection can also be influenced by unobserved variables, resulting in hidden bias (DiPrete and Gangl, 2004). The Rosenbaum bounding procedure (RBP) has been commonly used to assess the sensitivity of the results to unobservables (Rosenbaum, 2005). In this study, we follow DiPrete and Gangl (2004) to perform the RBP. For brevity, since we do not use the results of the matching directly, we do not show the matching models, but refer the reader to the cited references.

3 Data and empirical model

3.1 Data sources

The data we use were collected in Singida Rural and Kondoa Districts in Central Tanzania between September and November 2012. Central Tanzania is mainly semi-arid, and farmers in the region cultivate mainly cereals (sorghum and maize are the staples), but also grow some pulses, oil, root and tuber crops, and keep livestock (United Republic of Tanzania, 2012). The data were collected through a household survey involving 345 farmers from 21 villages. In each district, 3 village clusters (2-5 villages each) were purposively selected. Each cluster consists of villages that are geographically close to each other and that share the same local agricultural extension officer. This approach was chosen because it enables us to investigate the effect of inter-village networks. In each village, households were then selected by simple random sampling, and their heads interviewed by enumerators using a pre-tested structured questionnaire. We collected information on respondent, household and farm characteristics, and plot-level data on crops cultivated in the 2011/12 season. Plot-level data was preferred to data for total area allocated to these crops because it is easier to remember for the respondent, given that the farmers do not keep formal records. To improve accuracy and reliability of labor data, respondents were asked to select only one plot of sorghum and maize, respectively, and recall the labor use by production activity for this plot.

To elicit data on social networks, we sampled pairs of the selected farmers using the random matching within sample approach (Conley and Udry, 2010; Maertens and Barrett, 2013). Each farmer *(i)* was randomly paired with six other respondents *(j)* from our sample: three from his/her village and three from neighboring villages[1]. The respondents were asked questions about their six random matches in this sequence: "Do you know *j* (the match)?" If the answer was "no", no further network questions about the particular match were asked. If the answer was "yes", the respondent was asked: "Do you discuss sorghum (maize) farming issues with *j*?" Based on these answers, we interpret a "yes" response as presence of a network link for sorghum (maize), between the respondent and his/her match, and a "no" response as absence of such a link. Similar information about the respondent was not sought from his/her matches, implying that we use undirected network links. In addition to the farmer-to-farmer networks, respondents were asked about their frequency of interactions with village administrators (chair or other executives at village or sub-village level) and public extension officers.

3.2 Model specification

The models used in this study are shown in equations (4) and (5). Different functional forms have been used for *f (.)* in equation (1), but the most common are Cobb-Douglas (CD) and Translog (TL). Although TL is usually preferred in empirical work due to its flexibility, we use the CD function in this paper, because it best fits our data. The dataset showed high multicollinearity between input variables and their cross-products, which rendered estimation of the frontier impossible, or to produce coefficients that were unstable or with counterintuitive signs. Such challenges have been reported in studies by Dawson, Lingard, and Woodford (1991) and Wilson, Hadley and Asby (2001).

Thus, our empirical production frontier takes the following form:

$$lnProduction_{ic} = \beta_{0c} + \sum_{x=1}^{X} \boldsymbol{\beta}_{xc}\boldsymbol{Input}_{xic} + \beta_{vc}Variety_{vic} + \sum_{e=1}^{E} \boldsymbol{\beta}_{ec}\boldsymbol{Environment}_{eic} + v_{ic} - u_{ic} \qquad i=1,2,\ldots,N; \quad c=1,2 \qquad (4)$$

[1] When using the random matching approach, there is no explicit rule regarding the number of matches per respondent, which rarely exceeds seven in most studies.

where the subscripts *i* and *c* represent individual farmers and crops, respectively, and $\boldsymbol{\beta}$ are the parameters to be estimated. ***Input*** is a vector of discretionary inputs: *land, labor* and *seeds*. None of the farmers reported using fertilizers or irrigation in production of either crop, while the use of pesticides was negligible. This is consistent with minimal use of these inputs reported in recent national surveys (World Food Programme, 2010; United Republic of Tanzania 2012). *Variety* is a dummy variable representing the type of seed technology used (traditional or improved[2]), and we hypothesize that improved varieties would have a positive effect on grain output. ***Environment*** is a vector of dummy variables controlling for the effect of physical production environment on crop output. Sherlund *et al*. (2002) show that omitting such environmental factors can bias efficiency estimates. Hence, we use *soil types* to control for differences in soil fertility (Sommer *at al.*, 2013), *distance* from the homestead to the plots, to control for differences in other soil and environmental characteristics (Rowe *et al.*, 2006) and crop management challenges associated with plots located away from the homestead (Tan, Kruseman and Heerink, 2007). A district dummy is also included to control for unobserved heterogeneity due to agro-climatic factors.

We estimate the determinants of inefficiency simultaneously with the production frontier, using the following model

$$u_{ic} = \alpha_{0c} + \sum_{k=1}^{K} \boldsymbol{\alpha}_{kc} \boldsymbol{Network}_{kic} + \sum_{m=1}^{M} \boldsymbol{\delta}_{mc} \boldsymbol{z}_{mic}$$

$$i=1,2,\ldots,N; \qquad c=1,2 \qquad (5)$$

where subscripts *i* and *c* are as previously defined, and $\boldsymbol{\alpha}$ and $\boldsymbol{\delta}$ are coefficients to be estimated. ***Network*** is a vector of variables capturing the effect of different types of network links on efficiency. We use the total *network degree* (number of network links out of the six random matches) as a proxy for total farmer-to-farmer network size and further split it into intra-village and inter-village network degrees. The vector also includes variables measuring the link of farmers with village administrators and public agricultural extension officers. Our hypothesis is

[2] In this study, we categorize recycled seeds of improved varieties as improved, because from the perspective of the farmer, the varieties are still distinct from the traditional ones and failure to acquire fresh seeds may due to farmer or market constraints rather than their unwillingness to do so. Since recycled hybrid seeds tend to lose vigor over time, we acknowledge that this categorization could potentially underestimate their productivity.

that farmers with a higher network degree or stronger ties with formal institutional actors are better placed to obtain more or higher quality production information, which may enhance technical efficiency. Finally, $\boldsymbol{z}$ is a vector of control variables hypothesized to affect efficiency, such as farming experience, wealth-related variables, ownership of information asset such as radio, and membership to community associations that engage in agricultural activities.

3.3 Descriptive statistics of model variables

In this section we present descriptive statistics for the variables used in the frontier and inefficiency models. Additional variables that we use only for the estimation of the propensity scores are presented in Table A1 in the Appendix. Table 1 shows summary statistics of the plot-level variables disaggregated by crop and seed technology (traditional vs. improved). About 27% of sorghum plots are sown with improved varieties, while for maize, improved varieties occupy 63% of the plots. On average, plots of traditional sorghum varieties are significantly larger (0.78 ha) than those of improved varieties (0.57 ha), but for maize, it is the plots of improved varieties that are larger (0.85 ha) than those of traditional varieties (0.69 ha). Input use shows some significant differences only for sorghum, with farmers using more seeds and labor in plots sown with traditional varieties than in plots sown with improved varieties. Plots on sandy soil are the most common, followed by those on clay and loam soils, respectively. Most of the plots are located within the homestead or can be reached within 30 walking minutes. However, for a sizeable proportion of plots, farmers have to walk for a longer time to reach them and in this study we refer to them as “far plots”. For maize, the proportion of far plots is significantly higher for improved than traditional varieties.

<TABLE 1 ABOUT HERE>

Table 2 presents a summary of the social network, respondent, and household characteristics of our sample, disaggregated by crop and type of seed technology used. Social network data shows that the measures of crop network degree for sorghum are significantly different between growers of improved and traditional varieties. The total sorghum network degree is 1.9 for adopters of improved varieties and 1.1 for non-adopters. Similarly, both intra-village and inter-village network degrees are higher for adopters than for non-adopters. For maize, only the inter-village network degree differs significantly between adopters and non-adopters. The proportion of farmers with ties to extension officers is higher for growers of improved varieties than for growers of traditional varieties for both crops. For maize, adopters of improved varieties have more frequent communication with members of the village administration compared to non-adopters. Finally, the proportion of farmers with membership in a community group or association that engages in some agricultural activities is significantly higher for adopters of improved varieties of both crops.

<TABLE 2 ABOUT HERE>

Turning to respondent and household characteristics, we find that farming experience of respondents is about 25 years and crop-specific farming experience does not differ much from overall experience. Furthermore, adopters of improved sorghum tend be wealthier – they own more land (6.0 ha) than growers of traditional varieties (4.2 ha). Adopters of improved maize have significantly more maize plots than non-adopters, but the difference in number of sorghum plots does not differ significantly between adopters and non-adopters of improved sorghum. Ownership of radios is higher among adopters for the case of maize, but does not differ between adopters and non-adopters of improved sorghum.

4 Results

4.1 Results for propensity score matching

Results for the logit models are shown in Table A2 in the appendix. We summarize the matching quality in Table 3. The test for the balancing of covariates shows that the bias drops well below 10% after matching. The mean bias reduced by 83.5% for sorghum and 61% for maize. In addition, the Pseudo R-squared values of the Logit models were reduced to less than 5%, while the LR Chi-squared values dropped to statistically insignificant levels, implying that matched improved and traditional variety plots do not differ systematically with respect to observable physical and management characteristics. The critical values of gamma at 10% level of significance are about 2.3 for sorghum and 2.0 for maize. This means, if there is an unobserved variable that is significantly influencing adoption of ICVs, then its value must at least double, to invalidate our results. We hence conclude that PSM substantially reduced covariate biases and is quite robust to hidden bias. The distribution of the propensity scores is shown in Figure 2 indicating sufficient common support. Detailed results on covariate balancing are reported in the Appendix (Table A3).

<TABLE 3 ABOUT HERE>

<FIGURE 2 ABOUT HERE>

4.2 Results for technical efficiency analysis

For each crop, we estimated a pooled model and separate models for traditional and improved varieties using the matched samples. To test the effect of social networks, we included different proxies into the model. We begin our discussion with results of the frontier models presented in Table 4. The first three models of each crop (models 1-3 and 6-8) use the total crop (sorghum/maize) network degree, while in the last two models (4-5 and 9-10) we split the network into intra- and inter-village network degrees. Variance estimators provided at the bottom of the table show that λ is greater than one, implying that variation of output is more due to inefficiency than random errors. Based on the likelihood ratio (LR) test statistics (chibar2) we reject the null hypotheses that $\sigma\_u=0$ in all models, implying that the component of inefficiency in the composed error is significant. The estimated coefficients for all discretionary inputs (land, labor and seeds) have the expected positive signs in all models. The pooled models reveal that improved sorghum varieties have no significant effect on the yield, contrary to our hypothesis. Maredia, Byerlee and Pee (2000) demonstrate that in Sub-Saharan Africa, yield gains from use of improved sorghum varieties are likely to be marginal in drier regions, if, like in our study, other inputs especially inorganic fertilizers are not used. However, for maize, improved varieties produced about 43% more grain than traditional varieties, which is comparable to a nationally representative figure of 38% (Lyimo, *et al*., 2014). Turning to the seed technology-specific models, results show that grain yields of improved varieties of both crops are more sensitive to environmental factors than traditional ones, suggesting that yields of traditional varieties are stable over a wider range of growing conditions than those of improved varieties.

<TABLE 4 ABOUT HERE>

Table 5 shows the results of the technical inefficiency models including the determinants and levels of technical efficiency. The model numbers correspond to those in Table 4. Since it is our aim to compare the effects of model covariates between improved and traditional varieties, we discuss the results for the seed technology-specific models only. The results show that for sorghum, the total social network degree does not have any significant effect on technical efficiency. However, by splitting the social network degree (models 4-5) we find that the inter-village network degree has a significant positive effect on technical efficiency for improved varieties, while the intra-village network degree has no significant effect. This implies that a bigger sorghum network with other farmers outside the village may be a more important source of information on productivity-enhancing farming practices than intra-village links. These results agree with Schaefer (2010) who argues that strong ties within an established network (for instance, those in intra-village networks) can make such networks conservative and less exposed to new ideas. In a similar vein, Rauch (2010) posits that bridging network clusters (for example, establishing network links to other villages) produces synergies that lead to higher outcomes. Moreover, Van den Broeck and Dercon (2011) report using data from a Tanzanian village that farming techniques that farmers learnt from others outside the village were more likely to be applied than those learnt from other farmers inside the village. As mentioned earlier, previous studies that investigated the effects of social networks on technology diffusion primarily focused on intra-village networks, thus the potentially important role of inter-village networks may have been missed.

The strength of links with village administrators had a small and insignificant effect. Having links to agricultural extension officers and attending technology and information dissemination events had a positive effect on technical efficiency of improved varieties and a negative effect on efficiency of traditional varieties, but these effects were statistically insignificant. Lack of evidence of positive effects of extension services on technical efficiency is often reported in developing countries (Coelli, Rahman and Thirtle, 2002; Theriault and Serra, 2014). Possible explanations for this is that due to some infrastructural, institutional or cultural challenges, extension messages are not disseminated effectively, or a number of farmers may find it difficult to apply recommendations from extension workers (Davis, 2008). We hypothesized that farmers linked to agricultural officers or attending their events would receive more information and hence achieve higher technical efficiency. However, since improved varieties of sorghum are OPVs, and many farmers obtain seeds from their networks, it seems that information from these networks is more important for technical efficiency than that from formal sources such as extension officers and events.

Results for maize show that, when controlling for other information sources and producer characteristics, the maize network degree has a negative and significant effect on technical efficiency of traditional varieties, but no effect on technical efficiency of improved varieties (models 7-8). By disaggregating the network degree into intra- and inter-village degree (models 9-10), we show that the effect for traditional varieties is driven by information received from farmers inside the village. This is rather surprising, but we hypothesize that since adoption of improved maize in our sample is quite high, discussions about maize farming mostly entail new farming methods associated with improved varieties. Some of the methods may be unsuitable for traditional varieties leading to lower technical efficiency. The strength of farmer links with members of the village administration did not have any significant effect on technical efficiency. We find, however, that links to public extension officers and attending information and technology dissemination events had significant positive effects on technical efficiency for improved but not traditional varieties. This finding is consistent with our hypothesis in section 2.2. It highlights that the information disseminated through formal sources is specific to improved varieties and underscores the complementarity between ties with extension officers and other formal information dissemination approaches such as extension meetings or farmer field days.

<TABLE 5 ABOUT HERE>

Predicted technical efficiency (TE) scores are shown at the bottom of Table 5. Assuming common production technology for each crop, the pooled models show almost equal mean TE scores of about 45% for sorghum and 46% for maize. When making comparisons between the seed technology-specific models, we find that the mean TE for sorghum is significantly higher for traditional varieties (63% and 65%) than for improved ones (42% and 43%). For maize, the TE scores are higher for traditional varieties, but this difference is not significant. These overall low TE scores imply that opportunities exist for farmers to increase their technical efficiency and hence productivity.

5 Conclusions and policy implications

This paper has investigated the role of social networks for technical efficiency of smallholder farmers, using the case of cereal producers in Tanzania. Unlike previous social network studies, which mostly focused on cash crops, we have looked at sorghum and maize, which are grown mainly for home consumption. While previous studies concentrated primarily on intra-village social networks, we have extended the approach and have also considered inter-village networks. We applied stochastic frontier analysis to simultaneously estimate the production frontiers and the determinants of technical efficiency after correcting for potential self-selection in adoption of improved varieties using propensity score matching.

Our results show that for sorghum, while the total and intra-village network degrees (proxies for farmer-to-farmer network size) do not significantly influence technical efficiency, the inter-village sorghum network degree has a positive effect on technical efficiency of improved but not of traditional varieties. For the case of maize, we find no significant effect of maize network degree on technical efficiency of improved varieties. However, for traditional varieties, the intra-village network degree has a significant negative effect on technical efficiency. This demonstrates that social network effects on technical efficiency vary by crop and seed technology. The strength of ties with village administrators does not have any significant effect on technical efficiency of either crop. Consistent with our hypothesis, we find that having links to public extension officers and attending information and technology dissemination events organized through the officers has a positive effect on technical efficiency for improved varieties, which is significant only for maize. This result shows that efficiency-enhancing production information for the largely commercialized seed technologies may be much more technical, hence requiring more specialized dissemination, than for the less commercialized technologies. Further results show that the average technical efficiency scores are below 50% for both crops, meaning there is potential for farmers to more than double their productivity. The mean technical efficiency score of traditional varieties exceeds that of improved varieties, although this is significant for sorghum only. This implies that information or other production constraints that limit efficient utilization of production inputs are more severe for growers of improved than of traditional varieties.

These findings raise a number of implications for policy and further research. First, the finding that social networks are a key determinant of technical efficiency of improved sorghum varieties calls for further research into how these networks can be best used to raise technical efficiency and consequently crop productivity. Special emphasis should be given to inter-village networks, whose role for agricultural outcomes is rarely assessed. In addition, since this study assessed the effect of only one farmer network characteristic (degree) due to data limitations, future studies could consider the effects of other network characteristics as well. Secondly, from the findings on the positive effect of extension links and attendance of technology and information transfer events on technical efficiency, it is imperative that interactions between farmers and extension officers are increased, perhaps by facilitating their mobility into the villages and having more officers and extension activities at the lower administrative levels. However, more research may be necessary to identify the most cost-effective ways of doing this. Thirdly, since technical efficiency scores of both crops and seed technologies are generally low, there is need to train farmers on farming practices that can raise their technical efficiency and hence productivity. One strategy would be to investigate the extent to which recommended crop management practices are currently being applied by farmers and focus farmer advisory services on practices that need more attention.

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Tables and Figures

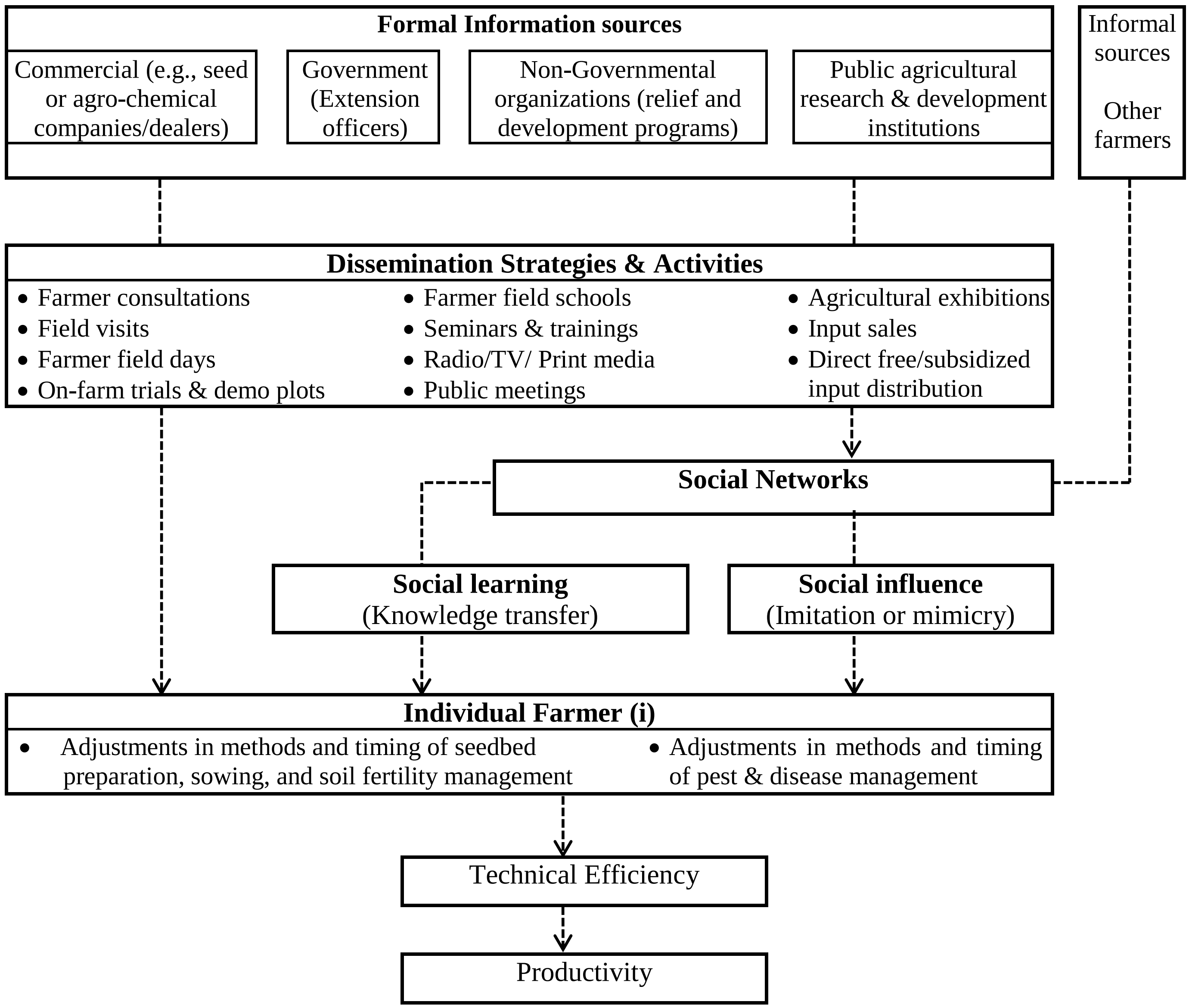

Figure1: Information sources and pathways, and the role of social networks for technical efficiency.
Source: Authors' impressions.

Table1: Descriptive statistics for variables used in the production frontier models

Variable	**Description**	**Sorghum**		**Maize**	
		Traditional (N=169)	Improved (N=62)	Traditional (N=106)	Improved (N=181)
Variables used in the frontier model					
Output					
Output	Grain output per plot (tons)	0.47 (0.57)	0.31** (0.41)	0.40 (0.70)	0.58** (0.68)
Inputs					
Land	Plot size (ha)	0.78 (0.80)	0.57** (0.63)	0.69 (0.48)	0.85 ** (0.76)
Labor	Total labor used (Days)	113.9 (95.4)	87.8** (72.3)	82.0 (57.0)	79.9 (76.8)
Seed	Total seed used (kg)	8.95 (10.3)	4.60*** (5.67)	10.0 (10.4)	10.6 (12.4)
Production environment					
Sand soil	Soil type is mostly sandy (1=Yes, 0=otherwise)	0.56 (0.50)	0.55 (0.50)	0.44 (0.50)	0.41 (0.49)
Clay soil	Soil type is mostly clay (1=Yes, 0=otherwise)	0.23 (0.42)	0.24 (0.06)	0.34 (0.48)	0.37 (0.48)
Loam soil	Soil type is mostly loam (1=Yes, 0=otherwise)	0.21 (0.41)	0.19 (0.40)	0.22 (0.41)	0.22 (0.41)
Far plot	Plot is located far from the homestead (1=Yes, 0=otherwise)	0.12 (0.32)	0.13 (0.34)	0.12 (0.33)	0.22** (0.42)
Kondoa	Plot is in Kondoa district (1=Yes, 0=Otherwise)	0.43 (0.50)	0.45 (0.50)	0.52 (0.50)	0.58 (0.50)

Note: Figures are mean values, with their standard deviations in parenthesis. *,**,*** differences in means between traditional and improved varieties are significant at 10, 5 and 1% respectively.

Table 2: Descriptive statistics for variables used in the technical inefficiency models

Variable	Description	Sorghum		Maize	
		Traditional (N=169)	Improved (N=62)	Traditional (N=106)	Improved (N=181)
Informal Networks					
Sorghum network degree	Total sorghum network degree (no. of links out of all six random matches)	1.09 (1.36)	1.86*** (1.62)		
Sorghum network degree1	Intra-village sorghum network degree (no. of links out of three random matches within the village)	0.92 (1.07)	1.47*** (1.10)		
Sorghum network degree2	Inter-village sorghum network degree (no. of links out of three random matches outside the village)	0.17 (0.52)	0.39*** (0.84)		
Maize network degree	Total maize network degree (no. of links out of all six random matches)			0.95 (1.30)	1.14 (1.49)
Maize network degree1	Intra-village maize network degree (no. of links out of three random matches within the village)			0.81 (1.09)	0.91 (1.09)
Maize network degree2	Inter-village maize network degree (no. of links out of three random matches outside the village)			0.14 (0.45)	0.24* (0.63)
Association membership	Household head is a member of a community association that engages in agricultural activities	0.10 (029)	0.21*** (0.41)	0.08 (0.27)	0.13* (0.34)
Formal Networks					
Extension link	Talks with public extension officer at least once per month (1=Yes; 0=otherwise)	0.65 (0.48)	0.74* (0.44)	0.56 (0.50)	0.68** (0.47)
Admin link	Strength of links with village administration (no. of contact days per month with a village administrator)	13.7 (9.97)	14.3 (8.96)	12.4 (8.91)	14.7** (10.1)
Other farmer/farm characteristics					
Farming experience	Experience in own farming activities (years)	25.6 (11.5)	24.6 (9.86)	25.3 (12.5)	26.1) (10.8)
Maize farming experience	Maize farming experience (years)			21.9 (12.1)	22.7 (11.5)
Land owned	Total land owned (Ha)	4.16 (4.82)	6.04** (9.31)	3.81 (5.65)	5.13 (6.17)
Plots	Number of sorghum (maize) plots cultivated	1.54 (0.76)	1.66 (0.70)	1.14 (0.51)	1.50*** (0.69)
Radio	Household owns a radio (1=yes; 0=otherwise)	0.75 (0.43)	0.69 (0.47)	0.68 (0.47)	0.79** (0.41)
Nonfarm income	Household head earns a non-farm income	0.43 (0.50)	0.39 (0.49)	0.37 (0.49)	0.40 (0.49)
Livestock wealth	Total value of livestock owned (Millions of Shillings. 1,560 Shillings=1USD during survey)	2.15 (3.45)	2.32 (3.43)	2.45 (4.31)	2.16 (3.10)
Tech2011	Attended a technology/information dissemination event in 2011	0.45 (0.50)	0.68*** (0.47)	0.39 (0.49)	0.50** (0.50)

Note: Figures are mean values, with their standard deviations in parenthesis. *,**,*** differences in means between traditional and improved varieties are significant at 10, 5 and 1% respectively.

Table 3: Matching quality

Variable	Sorghum			Maize		
	Before matching	After matching	Bias reduction	Before matching	After matching	Bias reduction
Biases						
Median bias (%)	21.3	5.9	72.3%	17.7	8.0	53.2%
Mean bias (%)	26.0	4.3	83.5%	20.5	8.0	61.0%
Pseudo R^2	0.20	0.02		0.23	0.04	
LR Chi squared	54.5	3.20		85.9	18.5	
p> Chi squared	0.00	0.99		0.00	0.49	
Bounding						
Critical Gamma (Γ) at 5%		1.9 – 2.0			1.7 – 1.8	
Critical Gamma (Γ) at 10%		2.2 – 2.3			1.9 – 2.0	

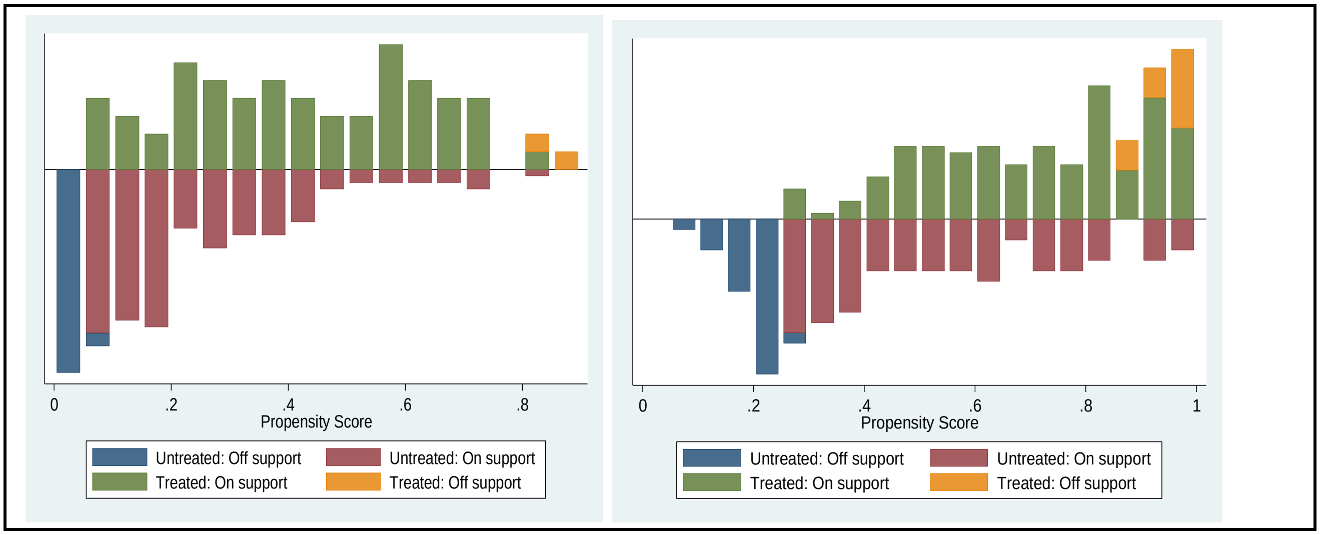

Figure 2: Distribution of propensity scores for sorghum (left) and maize (right), showing common support.

Table 5: Results of the production frontier models

Variable	Sorghum					Maize				
	Total sorghum network degree			*Intra- vs. inter- village sorghum network degree*		*Total maize network degree*			*Intra- vs. inter- village maize network degree*	
	Pooled (1)	Traditional (2)	Improved (3)	Traditional (4)	Improved (5)	Pooled (6)	Traditional (7)	Improved (8)	Traditional (9)	Improved (10)
Land	0.46***	0.28**	0.60**	0.27**	0.63**	0.47***	0.52***	0.47***	0.52***	0.44***
	(0.12)	(0.12)	(0.26)	(0.12)	(0.26)	(0.09)	(0.11)	(0.12)	(0.11)	(0.13)
Labor	0.20***	0.35***	0.01	0.34***	0.06	0.09	0.01	0.07	0.01	0.10
	(0.07)	(0.07)	(0.10)	(0.07)	(0.11)	(0.08)	(0.13)	(0.12)	(0.13)	(0.12)
Seed	0.24***	0.23**	0.10	0.24**	0.08	0.32***	0.36***	0.30***	0.36***	0.31***
	(0.09)	(0.10)	(0.22)	(0.10)	(0.23)	(0.07)	(0.12)	(0.10)	(0.12)	(0.10)
Improved	-0.14					0.43***				
	(0.14)					(0.11)				
Clay soil	0.24	0.15	0.58**	0.13	0.64**	-0.02	0.02	0.14	0.02	0.11
	(0.15)	(0.17)	(0.25)	(0.17)	(0.25)	(0.12)	(0.21)	(0.16)	(0.21)	(0.16)
Loam soil	-0.09	0.14	-0.03	0.12	-0.06	0.12	0.23	0.28*	0.21	0.27*
	(0.17)	(0.17)	(0.46)	(0.17)	(0.47)	(0.14)	(0.25)	(0.16)	(0.25)	(0.16)
Far plot	-0.30	0.14	-1.21***	0.14	-1.12***	0.17	0.48	0.15	0.48	0.16
	(0.19)	(0.21)	(0.45)	(0.21)	(0.42)	(0.15)	(0.30)	(0.17)	(0.30)	(0.18)
Kondoa	0.19	-0.03	0.44	-0.04	0.44	-0.04	0.07	-0.27	0.07	-0.26
	(0.16)	(0.21)	(0.34)	(0.21)	(0.34)	(0.18)	(0.28)	(0.23)	(0.28)	(0.23)
Constant	-1.39***	-2.52***	-0.51	-2.49***	-0.72	-1.24***	-1.14**	-0.76	-1.14**	-0.90
	(0.42)	(0.39)	(0.68)	(0.39)	(0.73)	(0.43)	(0.51)	(0.63)	(0.51)	(0.66)
N	196	136	60	136	60	237	79	158	79	158
σ_u	1.49	0.98	2.03	0.98	2.03	1.38	1.60	1.33	1.60	1.33
σ_v	0.42	0.49	0.00	0.49	0.00	0.48	0.24	0.50	0.24	0.50
Λ	3.58	2.01	1.88e+07	2.01	1.88e+07	2.90	6.64	2.65	6.64	2.65
Chibar2	21.27***	3.40**	19.89***	3.40**	19.89***	22.74***	16.80***	9.18***	16.80***	9.18***

Note: In brackets are robust standard errors. *p<0.1, **, p<0.05, *** p<0.01.

Table 4: Determinants of technical inefficiency and estimated technical efficiency scores

Variable	**Sorghum**					**Maize**				
	Total sorghum network degree			*Intra- vs. inter- village sorghum network degree*		*Total maize network degree*			*Intra- vs. inter- village maize network degree*	
	Pooled (1)	Traditional (2)	Improved (3)	Traditional (4)	Improved (5)	Pooled (6)	Traditional (7)	Improved (8)	Traditional (9)	Improved (10)
Sorghum network	-0.01	-0.02	-0.11							
degree	(0.08)	(0.13)	(0.11)							
Sorghum network				-0.17	0.26					
degree1				(0.26)	(0.30)					
Sorghum network				0.39	-0.58**					
degree2				(0.45)	(0.29)					
Maize network						0.02	0.43**	-0.09		
degree						(0.08)	(0.22)	(0.10)		
Maize network									0.47*	0.01
degree1									(0.25)	(0.17)
Maize network									0.24	-0.33
degree2									(0.48)	(0.29)
Association	0.08	-0.88	0.93*	-1.00	0.63	-0.07	-1.28	-0.27	-1.22	-0.23
membership	(0.37)	(0.58)	(0.49)	(0.62)	(0.53)	(0.38)	(0.91)	(0.46)	(0.88)	(0.46)
Admin link	0.01	-0.01	0.02	-0.01	0.03	0.01	0.00	0.01	-0.00	0.02
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Extension link	0.17	0.29	-0.58	0.36	-0.46	-0.63**	-0.35	-0.58**	-0.34	-0.63**
	(0.26)	(0.45)	(0.45)	(0.49)	(0.46)	(0.26)	(0.38)	(0.28)	(0.39)	(0.29)
Tech2011	0.10	0.34	-0.04	0.38	-0.13	-0.49**	0.68	-0.88***	0.70	-0.97***
	(0.22)	(0.37)	(0.38)	(0.41)	(0.43)	(0.25)	(0.52)	(0.31)	(0.51)	(0.33)
Radio	-0.21	-0.26	-0.27	-0.28	-0.41	-0.08	0.01	-0.15	0.03	-0.14
	(0.25)	(0.41)	(0.45)	(0.42)	(0.42)	(0.22)	(0.42)	(0.33)	(0.45)	(0.32)
Farming experience	0.02*	0.00	0.07**	0.00	0.08***					
	(0.01)	(0.01)	(0.03)	(0.01)	(0.03)					
Maize farming						0.01*	-0.02	0.02*	-0.02	0.02*
experience						(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Non-farm income	0.08	0.94**	-0.70*	1.01**	-0.69**	0.12	0.33	0.10	0.35	0.11
	(0.24)	(0.42)	(0.39)	(0.48)	(0.34)	(0.22)	(0.41)	(0.32)	(0.42)	(0.31)
Land owned	-0.09***	-0.28***	-0.09**	-0.33***	-0.07*					
	(0.03)	(0.10)	(0.04)	(0.13)	(0.04)					
No of plots	0.39**	0.14	0.73***	0.14	0.82***	-0.33*	-1.74**	-0.24	-1.72**	-0.24
	(0.17)	(0.21)	(0.24)	(0.23)	(0.21)	(0.18)	(0.74)	(0.20)	(0.74)	(0.20)
Livestock wealth	0.01	-0.16**	0.05	-0.15**	-0.01	-0.01	-0.37**	0.00	-0.36**	-0.00
	(0.05)	(0.07)	(0.06)	(0.07)	(0.08)	(0.04)	(0.15)	(0.05)	(0.16)	(0.05)
Kondoa	1.31***	2.15***	1.65***	2.23***	1.46***	0.39	1.30**	-0.16	1.26**	-0.17
	(0.32)	(0.57)	(0.47)	(0.60)	(0.47)	(0.30)	(0.63)	(0.39)	(0.62)	(0.39)
Constant	-0.94*	-1.08	-1.87*	-1.18	-2.88**	0.92**	1.92*	1.10**	1.88*	1.09**
	(0.54)	(1.20)	(1.00)	(1.21)	(1.41)	(0.41)	(1.06)	(0.52)	(1.06)	(0.51)
Mean Technical	0.45	0.63	0.42***	0.65	0.43***	0.46	0.50	0.48	0.50	0.48
Efficiency	(0.24)	(0.22)	(0.28)	(0.22)	(0.28)	(0.22)	(0.26)	(0.22)	(0.25)	(0.22)
N	196	136	60	136	60	237	79	158	79	158

Note: In brackets are robust standard errors (standard deviations for technical efficiency). *p<0.1, **, p<0.05, *** p<0.01. For mean technical efficiency, comparisons are made between Traditional and Improved varieties.

Appendices

Table A1: Additional variables used in the logit models

Variable	Description	Sorghum		Maize	
		Traditional (N=169)	Improved (N=62)	Traditional (N=106)	Improved (N=181)
Striga plot	Plot gets infested with *striga* weeds (1=Yes, 0=Otherwise)	0.28	0.11***	0.20	0.16
		(0.45)	(0.32)	(0.40)	(0.36)
Female	Respondent is a female (1=yes; 0=otherwise)	0.27	0.19	0.32	0.23**
		(0.44)	(0.40)	(0.47)	(0.42)
Education	Respondent has more than four years of formal education (1=yes; 0=otherwise)	0.84	0.90	0.79	0.83
		(0.37)	(0.30)	(0.41)	(0.38)
Sorghum farming experience	Sorghum farming experience (years)	23.6	21.1 *		
		(12.4)	(12.1)		
Exposure	Level of exposure to improved varieties (number of sorghum/maize varieties known)	1.44	2.34***	0.94	2.51***
		(1.30)	(1.23)	(1.29)	(1.53)
Ever adopted	Ever adopted an improved sorghum (maize) variety (1=Yes, 0=otherwise)	0.54	0.82	0.26	0.91***
		(0.50)	(0.39)	(0.44)	(0.29)
Extension strength	Strength of links with public extension officer (no. of contact days per month)	3.36	4.11	3.05	4.12*
		(5.98)	(5.79)	(5.84)	(6.25)
Muslim	Respondent is Muslim (1=yes; 0=otherwise – mostly Christian)	0.49	0.50	0.53	0.62*
		(0.50)	(0.50)	(0.50)	(0.49)
Mobile phone	Household owns a mobile phone (1=yes; 0=otherwise)	0.68	0.71	0.61	0.74**
		(0.47)	(0.46)	(0.49)	(0.44)

Note: Figures are mean values, with their standard deviations in parenthesis. *,**,*** differences in means between traditional and improved varieties are significant at 10, 5 and 1% respectively.

Table A2: Logit results for the estimation of propensity scores

Variable	Coefficient sorghum	Coefficient Maize
Constant	-2.15***	-0.67
	(0.83)	(0.71)
Sorghum network degree1	0.39**	
	(0.18)	
Sorghum network degree2	0.11	
	(0.33)	
Maize network degree1		0.02
		(0.14)
Maize network degree2		0.26
		(0.33)
Admin link		-0.08
		(0.06)
Admin link squared		0.00
		(0.00)
Extension strength		-0.00
		(0.03)
Tech2011	0.84**	
	(0.36)	
Farming experience		-0.01
		(0.01)

Variable	Coefficient sorghum	Coefficient Maize
Ever adopted	1.19***	
	(0.45)	
Exposure		0.81***
		(0.16)
Radio	-0.48	0.07
	(0.41)	(0.37)
Mobile phone		0.09
		(0.32)
Education	0.88*	
	(0.54)	
Female	-0.36	
	(0.41)	
Muslim	-0.22	-0.20
	(0.40)	(0.34)
Land owned	0.01	0.23***
	(0.03)	(0.08)
Land owned squared		-0.01**
		(0.00)
Livestock wealth		-0.09*
		(0.05)

Variable	Coefficient sorghum	Coefficient Maize
Striga plot	-1.40***	-0.41
	(0.51)	(0.36)
Village cluster2	-0.30	-0.37
	(0.63)	(0.52)
Village cluster3	-1.73**	-0.35
	(0.72)	(0.49)
Village cluster4	-0.56	-0.02
	(0.65)	(0.49)
Village cluster5	-0.43	0.02
	(0.72)	(0.63)
Village cluster6	-1.39*	-0.47
	(0.78)	(0.50)
Mean propensity score	0.27	0.63
	(0.21)	(0.25)
Pseudo R-squared	0.20	0.24
N	231	287

Robust standard errors in brackets.
* p<0.1, ** *p<0.05*, *** *p<0.01*

Table A3: Covariate balancing before and after matching

Variable	Sample	Sorghum				Maize			
		Mean		% reduction	t-test	Mean		% reduction	t-test
		Treated	*Control*	in |bias|	p>|t|	*Treated*	*Control*	in |bias|	p>|t|
Village cluster1	Unmatched	0.18	0.10		0.11	0.33	0.19		0.01
	Matched	0.17	0.12	33.6	0.43	0.30	0.23	55.9	0.20
Village cluster2	Unmatched	0.19	0.13		0.23	0.14	0.17		0.55
	Matched	0.18	0.18	99.4	1.00	0.15	0.23	-215	0.06
Village cluster3	Unmatched	0.08	0.20		0.04	0.10	0.16		0.13
	Matched	0.08	0.09	99.0	0.98	0.10	0.08	58.4	0.43
Village cluster4	Unmatched	0.29	0.26		0.65	0.20	0.25		0.36
	Matched	0.30	0.33	11.6	0.76	0.22	0.27	-9.20	0.29
Village cluster5	Unmatched	0.16	0.15		0.80	0.12	0.10		0.75
	Matched	0.17	0.19	-45.8	0.78	0.12	0.07	-313	0.13
Village cluster6	Unmatched	0.10	0.17		0.19	0.11	0.13		0.59
	Matched	0.10	0.10	95.0	0.95	0.12	0.13	70.7	0.87
Striga plot	Unmatched	0.11	0.28		0.01	0.16	0.20		0.35
	Matched	0.12	0.12	99.1	0.98	0.17	0.22	-16.6	0.25
Sorghum network	Unmatched	1.47	0.92		0.00				
degree1	Matched	1.42	1.43	97.0	0.94				
Sorghum network	Unmatched	0.39	0.17		0.02				
degree2	Matched	0.32	0.46	35.5	0.34				
	Unmatched	1.47	0.92		0.00	0.91	0.81		0.48
Maize network degree1	Matched	1.42	1.43	97.0	0.94	0.91	1.00	-0.20	0.45
	Unmatched	0.39	0.17		0.02	0.24	0.14		0.17
Maize network degree2	Matched	0.32	0.46	35.5	0.34	0.18	0.22	67.1	0.64
Radio	Unmatched	0.69	0.75		0.38	0.79	0.68		0.05
	Matched	0.70	0.67	49.0	0.73	0.79	0.77	82.0	0.69
Muslim	Unmatched	0.50	0.49		0.84	0.62	0.53		0.13
	Matched	0.48	0.48	62.7	0.95	0.59	0.65	30.1	0.25
Tech2011	Unmatched	0.68	0.45		0.00				
	Matched	0.68	0.69	99.0	0.98				
Ever adopted	Unmatched	0.82	0.54		0.00				
	Matched	0.82	0.76	79.9	0.46				
Education	Unmatched	0.90	0.84		0.23				
	Matched	0.90	0.91	82.8	0.84				
Female	Unmatched	0.20	0.27		0.26				
	Matched	0.20	0.17	56.9	0.66				
Land owned	Unmatched	6.04	4.16		0.05	5.13	3.81		0.07
	Matched	4.89	5.83	49.8	0.50	4.77	4.79	98.6	0.98
Land owned squared	Unmatched					64.1	46.2		0.50
	Matched					56.2	57.3	94.2	0.97
Livestock wealth	Unmatched					2.16	2.45		0.51
	Matched					2.27	1.86	-39.9	0.32
Admin link	Unmatched					14.7	12.4		0.06
	Matched					14.2	14.2	97.2	0.96
Admin link squared	Unmatched					316	233		0.03
	Matched					303	317	84.2	0.74
Extension strength	Unmatched					4.12	3.05		0.15
	Matched					3.98	3.48	52.9	0.47
Exposure	Unmatched					2.51	0.93		0.00
	Matched					2.24	2.22	98.9	0.91
Mobile phone	Unmatched					0.74	0.61		0.03
	Matched					0.72	0.78	48.0	0.20
Farming experience	Unmatched					26.1	25.34		0.60
	Matched					26.2	26.23	94.9	0.98