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FOOD SCIENCE & TECHNOLOGY | RESEARCH ARTICLE

The unequal efficiency gap: Key factors influencing women farmer's efficiency in Uganda

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Abstract: There is an assumed gap in efficiency between male and female farmers. Identifying the constraints of women farmers causing the gap is essential for improving local food security and well-being. Using stochastic frontier analysis, we compare the efficiency of men, women and jointly managed maize plots in Uganda and look at factors associated with inefficiency of women. Our results show that the average technical efficiency of women is lower than that of men or jointly managed plots. However, in relation to a group-specific frontier, the women are highly efficient. Women's inefficiency is associated with several household features. The overall number of household members has a negative effect on efficiency, suggesting that women are time constrained by the efforts they put into household productive work. There also seems to be an association between efficiency and cash-crop farming, disadvantaging women who more commonly grow crops for household consumption.

Subjects: Agricultural Development; Agricultural Economics; Gender and Development

Keywords: Africa; Uganda; small-scale farmers; women farmers; efficiency; stochastic frontier analysis; gender gap

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Mila Sell is a senior specialist and research scientist at the Natural Resources Institute Finland (Luke). She has a multidisciplinary academic background with an MSc in social sciences and a PhD in Agricultural Economics. Sell has a long experience in program development and coordination, teaching and fieldwork in several African countries, with particular focus on food security, the role of women farmers and empowerment of small-scale farmers in sustainable agricultural practices. Luke is Finland's national research and expert organization working to advance bio-economy and the sustainable use of natural resources globally. Sell's research for development team has expertize in sustainability issues relating to climate change, natural resource management, value chains, as well as socio-economic and political aspects. The research reported in this paper integrates several of these questions, in order to get a better understanding of some of the key challenges to sustainability and equality.

PUBLIC INTEREST STATEMENT

Feeding the world in the future is going to be a major challenge, due to growing populations and the negative impacts of climate change on agriculture. Future food systems will need to be extremely well functioning, starting from effective production systems. In Africa, agriculture is far from reaching its productive potential. There are many reasons for this, but one is that resources are not used as effectively as they could. This seems to be particularly true for women farmers. This is important because women produce much of the locally consumed food and the effect on household well-being if they were to improve their efficiency is potentially great. In our study, we have tried to identify the gender-specific constraints that influence women's efficiency, including family structure, farming system and access to inputs. We need to understand these underlying reasons in order to work together with local communities to find new solutions that support women.

1. Introduction

In a world faced with climate change, growing populations, biodiversity loss, and various other challenges, it is essential to use existing resources as efficiently as possible. This is especially important in order for people to achieve food security, livelihoods, and well-being. Improving current levels of agricultural efficiency is conceivable, as current production systems often do not reach their full potential. In sub-Saharan Africa, many countries face a substantial yield gap as they may achieve only 20% of the potential yields, especially within low-input agriculture (Deininger et al., 2011; Fischer & Shah, 2010). From a developmental perspective, this raises concerns, as agriculture accounts for around 30% of the gross domestic product in East Africa and employs over 70% of the population (Food and Agriculture Organization [FAO] of the United Nations, 2014). Improving efficiency and productivity of small-scale farmers can have a major impact on food security and livelihoods, while at the same time mitigating climate change. Women are reported to produce only 70–80% of the yields their male counterparts produce (Aguilar, Carranza, Goldstein, Kilic, & Oseni, 2015; Ali, Bowen, Deininger, & Duponchel, 2016; FAO, 2011). This difference is often referred to as the gender gap (Kilic, Palacios-Lopez, & Goldstein, 2013).

For most small-scale farmers, increasing yields by expanding the cultivated area is not an option, and therefore, increasing productivity is a very relevant alternative.

In order to support small-scale farmers to become more productive, the most important determinants of technical efficiency (TE) need to be identified, especially that of female farmers. It is currently agreed that the difference in productivity between men and women is due to gender-specific constrains, including limited access to resources, as well as cultural or socio-political factors (Aguilar et al., 2015; Peterman, Quisumbing, Behrman, & Nkonya, 2011).

Stochastic frontier analysis (SFA) can be used to compare the efficiency of different groups, as well as to identify particular factors; individual, household or agronomic, associated with higher or lower levels of efficiency.

The aim of this paper is to provide an insight into how gender influences efficiency in Uganda. Our assumption, based on literature on land- and asset ownership, and productivity, is that women farmers are more constrained than male farmers, which negatively affects their efficiency.

The specific objective of this study is to test whether female-managed plots differ from male-managed or jointly managed plots in terms of efficiency. We study the factors associated with efficiency of the female group. Through this, we identify some of the most important drivers of the gender gap. The results contribute to the literature by adding to the understanding of issues that impact women farmers' efficiency in Uganda and by comparing the results regarding efficiency of female-managed plots when estimated separately and jointly with male-and jointly managed plot.

2. Background

Traditionally, information on farming has been collected at the household rather than the individual level, which means that many important underlying factors that affect the productivity of women remain unrecognized (Doss, 2014). Even when gender-disaggregated data have been collected, sex of the household head has often been used to define gender differences in productivity, although such an approach leaves out all the women farmers working within male-headed households. In addition, the focus has often been simply on input and output, not taking into consideration the effect of the fewer resources or other constraints that the women in a household tend to have (Quisumbing, 1996). Such studies are not particularly helpful, when trying to determine recommendations that could improve women's productivity. Instead, the direct causes of the productivity gap between men and women, as well as the underlying reasons, need to be identified, analysed and reflected upon.

Some key factors inhibiting women's productivity have been identified. An important factor is women's lack of official land ownership or tenure documents, which hinders access to credit, and through that, investments in improved inputs and technologies (Combaz, 2013; Doss, Meinzen-Dick, & Bomuhangi, 2014). Other factors include lack of access to labour, time constraint, as well as unequal decision-making on household issues (Sell & Minot, 2018; Wa Gĩthĩnji, Konstantinidis, & Barenberg, 2014). Women also have much less ownership and control over other assets that could potentially enable pathways out of poverty and more stable livelihoods, such as livestock, equipment and resources (Quisumbing et al., 2013).

Another critical challenge, identified by several studies, is women's difficulty in accessing markets. The reasons for this may be partly cultural, making women less mobile, but is also due to women generally having smaller quantities to market and less contact to trader networks (Combaz, 2013; Hill & Vigneri, 2009). This has led women to be excluded from contract farming in high-value sectors such as export vegetable markets (Wa Gĩthĩnji et al., 2014). In practice, this means women have to rely on different strategies than men. It can be said that men produce for the market while women produce for household consumption.

Although these general factors provide a good overview of the challenges faced by women in agriculture, more detailed and context-specific analysis is needed in order to make useful policy recommendations. It is, therefore, encouraging to see that many contributions towards this end have been made recently. Some studies, starting from Kilic et al. (2013), have used decomposition, especially the Oaxaca–Blinder method to better understand the mechanisms and various underlying aspects influencing the productivity gap (Aguilar et al., 2015; Ali et al., 2016; Slavchevska, 2015). These studies not only split the productivity gap into endowment effects and structural effects but also for example decompose the productivity distribution into quintiles, to identify the effects at different points of the productivity scale (Aguilar et al., 2015). Although Aguilar et al. find that more than half of the productivity gap is related to structural issues, age and years of schooling are significant effects only at the higher levels of productivity. Factors such as child dependency ratio or women's time burden, related to greater child care responsibility, are factors that negatively affect women's productivity (Ali et al., 2016; Slavchevska, 2015). Surprisingly, Ali et al. conclude that the effect of material inputs, such as fertilizers and pesticides, is insignificant. This is likely due to the extremely low usage among Ugandan farmers in general.

Studies looking specifically at differences in TE, rather than productivity in general, are less common in the literature. The relationship between gender roles and efficiency is still a neglected research area (Addison, Ohene-Yankyera, & Fredua-Antoh, 2016). Some targeted, case studies have been conducted (e.g. Addison et al., 2016; Dadzie & Dasmani, 2010; Dossah & Mohammed, 2016) mostly aimed at identifying the determinants of efficiency of male and female farmers as two separate groups. The methods and variables associated with efficiency vary in the different studies, but most include factors such as family size, age and education of the farmer. In some cases also, other factors, such as marital status, have been included in the analysis (Simonyan, Umoren, & Okoye, 2011) and commonly also contact with extension agents.

These studies show mixed results regarding women farmer's efficiency. Most find women farmers to be less efficient than men, but some arrive at the opposite outcome (e.g. Oladeebo & Fajuyigbe, 2007; Simonyan et al., 2011). Also, the determinants of efficiency vary between these studies. One common determinant associated with higher efficiency, identified by several studies, is level of education. However, contact with extension services produced varied results. This suggests that context is an important part of inefficiency, and in order to make conclusions and suggestions, familiarity with the particular situation of the farmer group and community is essential.

2.1. Measuring efficiency with the stochastic frontier approach

The concepts of efficiency and productivity are sometimes confused, although there is an important distinction between the two. Productivity can be defined as a measure of the amount of output obtained per the amount of input used (for instance, how much maize is produced with a given amount of seed, fertilizer and labour). By contrast, efficiency refers to measuring the actual amount produced when comparison to how much *could* be produced with the same amount of resources (input). Efficiency therefore examines how much actual output differs from the maximal output with a given set of inputs (Coelli, Rao, O'Donnell, & Battese, 2005).

The most common method for measuring efficiency is SFA. A stochastic approach is suitable for work on agriculture, as agriculture involves a lot of variability. SFA is a parametric method where the frontier function is estimated by using statistical methods. Literature on the stochastic frontier approach originates from the work of Aigner Lovell and Schmidt as well as Meeusen and Van Den Broeck, two groups of researchers who simultaneously came up with the theoretical approach in 1977 (Kumbhakar & Lovell, 2000). SFA models allow for technical inefficiency, but they also recognize that random shocks outside the control of producers, such as weather, luck or variation in machinery performance, affect the output. SFA models try to separate the contribution of random factors from the contribution of variation in TE. In a stochastic frontier model, the compound error term consists of a two-sided noise component, which is independent and identically distributed and symmetric, and of the non-negative technical inefficiency component, as illustrated in Equation (3)..

SFA requires using quantitative data including information on input quantity. Parametric approaches require the functional form of the frontier to be defined prior to the estimation, by specifying a particular function relating output to input. However, tests to select the best specification exist and are used here prior to selecting the final model. Robust efficiency estimations require the method to allow for random shocks as well as measurement errors which may occur in field data. The data also need to be sufficiently large and robust. Our data include information collected from 1400 farms.

The production functions most commonly used in SFA are Cobb–Douglas, quadratic or the translog function. They are linear in parameters and can be estimated using least squares methods that allow multi-output and multi-input distance functions. The advantage of the Cobb–Douglas function is its simplicity; however, it is less flexible than the models including second-order- and cross-terms. The alternative functional forms can be tested against each other through a nested test. Choosing the right model should be based on the data and on the model providing the best fit, as well as on the focus of the study, as different models may give slightly different results (Kuosmanen, Saastamoinen, & Sipiläinen, 2013).

An alternative approach to assess efficiency of a decision-making unit would have been data envelopment analysis (DEA), which is suitable for analysing cross-sectional data particularly in smaller datasets. In a non-parametric approach such as DEA, there is no need to specify the functional form of the frontier as it is determined by the most efficient producers. However, the best specification cannot be tested and the number of efficient firms on the frontier tends to increase with the number of input and output variables (Berg, 2010). Non-parametric approaches have the advantage of low specification error, but they do not allow for measurement error or random shocks. As these factors are attributed to (in)efficiency, this leads to potential estimation errors.

Efficiency is estimated using a production function that usually incorporates a model for assessing the factors influencing the inefficiency. This can be done in two steps or a single-step approach. In the two-step approach, the efficiency scores from the first stage are regressed on a set of variables that are assumed to influence efficiency, while in the case of the single-step procedure, the estimation of efficiency and the factors influencing efficiency are done simultaneously. The two-step model has been criticized for its inconsistency relating to the assumptions regarding the independence of the error component (Battese & Coelli, 1995). Although there are ways around this inconsistency (Madau, 2011), most scientists rely on the single-step approach developed by Battese and Coelli (1995).

Battese and Coelli agree that there is no formal econometric model to describe TE (Battese & Coelli, 1995; Battese, Malik, & Gill, 1996). It will be up to each scientist to make an informed choice on which parameters will be relevant for the specific research question. This implies a certain degree of arbitrariness in the definition of the inefficiency effect variables (Irz & Thirtle, 2004). This also provides the opportunity to create a number of behavioural variables relating to issues such as farmers' goals and preferences and analyse how these affect efficiency (Berkhout, Shipper, Kuyvenhoven, & Coulibaly, 2010). Depending on the available data and the focus of the study, the variables to explain efficiency may include issues such as family size, number of working adults, education or experience of family members, area of cultivated land and land quality, land tenancy, share of non-agricultural income and extension contact, to name a few.

3. Data and methods

Our data are from a household survey conducted in Uganda in collaboration with International Food Policy Research Institute, as part of the Finnish-funded FoodAfrica Programme (2012–2018). Uganda has a predominantly rural population (72%), relying heavily on agriculture for their livelihoods (Uganda Bureau of Statistics [UBOS], 2014). There are different climatic zones in the country, which means the varying conditions are factors influencing productivity. The climate is generally stable and mostly suitable for agriculture even though climate change is predicted to have severe impact on productivity over time (James, 2010). We have chosen to focus on one of the most central crops in Ugandan agriculture, namely maize. Maize is one of the most important staple crops in Uganda, together with matoke (cooking banana), cassava and beans. Studies show that maize yields in Uganda will be severely impacted by climate change, reducing yields by 5% by 2050, compared to yields in 2000 (Kikoyo & Norbert, 2016). Identifying ways to increase production is therefore essential. Maize is also interesting as it is a central crop in East Africa, grown by a large majority of households. Comparisons to other African countries may therefore be possible.

As part of the study in Uganda, a baseline household survey was conducted in December 2012–January 2013, in eight districts of the country as shown in the map in Figure 1. The survey covered approximately 1400 households and generated a large amount of information on households' production systems. After deleting observations with missing values and outliers, we ended up with 896 observations of maize-growing households for the efficiency analysis.

The data were sex-disaggregated, specifying if the plot was managed by male farmers, female farmers or jointly. The way management was defined in this study is in line with other studies with similar objective (e.g. Aguilar et al., 2015). For management, the enumerator manual stated: "Ask who in the household has primary responsibility for the decisions related to the production of the crop in this plot in this season". The management responsibility was coded either to the individual person or as jointly managed. The focus was on decision-making and it does not necessarily imply actual labour use by the responsible person on the plot in question. As the data did not include information on the amount of household labour allocated to specific plots, we could not determine a traditional production function.

However, the data did allow comparison of output, in relation to input, including land, seed, fertilizer and pesticides, by the different management systems. In addition, the survey data included a range of variables that describe both the household and the individuals in the household, such as age, educational level and possible non-farm activity. Household characteristics included number of household members, the crops grown and the share of the yield sold in the market, as well as other assets owned by the household, such as animals. This gave us an overview of a typical small-scale farming household in rural Uganda and allowed us to identify the most important constraints for women farmers.

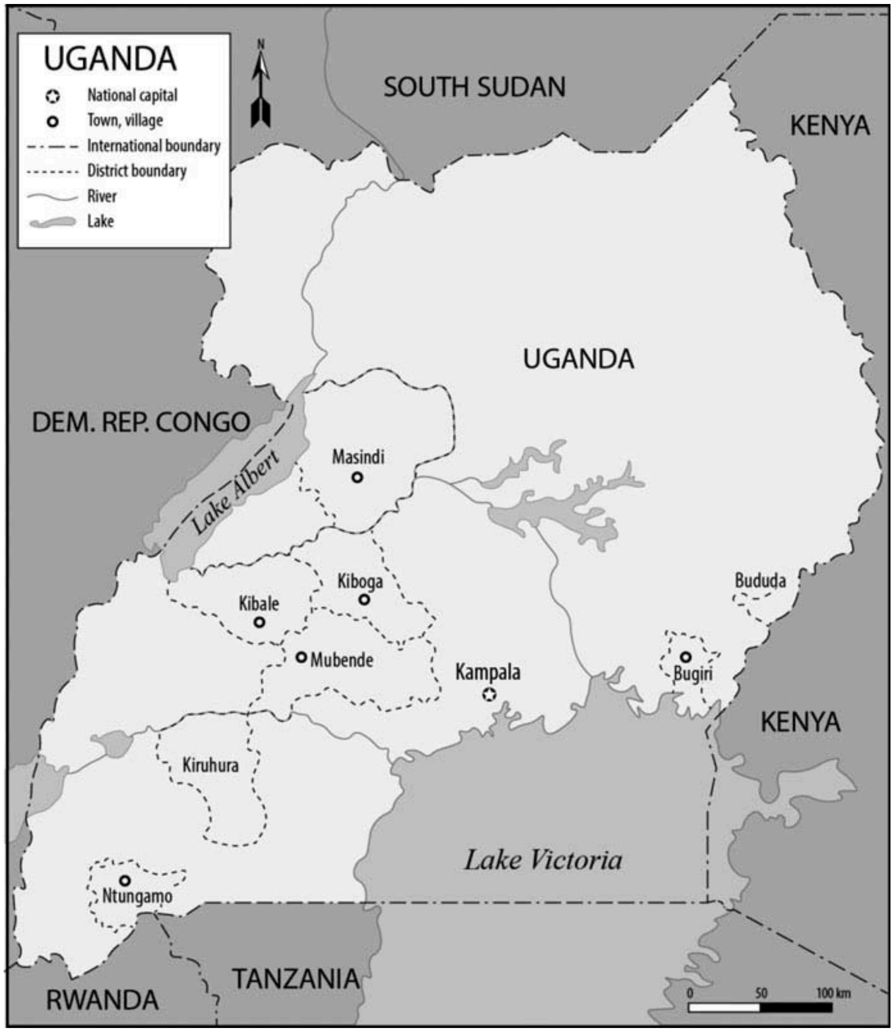

Figure 1. Map of Uganda highlighting study districts (©Magdalena Lindberg).

The survey also included a time-use module, based on the women empowerment in agriculture index. Both a female and a male household member responded to a 24-h recall study, reporting what he or she had done as primary and secondary activity for each hour between four in the morning the previous day until four in the morning of the survey.

It was not possible to integrate this information directly into the production function as it was based on a 24-h recall. However, it gave us useful background information on the differences in time-use of men and women in the study. In Table 1, the mean hours used by men and women for key activities are reported, grouped into five categories. The most significant difference can be seen in relation to domestic work. Women use on average close to 5 h doing domestic work, while men use on average only one and half hours. The amount of sleep of men and women are very similar. Women use slightly less time than men on all other activities apart from sleep or domestic work, including agricultural work, other employment or leisure. However, no other category has such a large difference between men and women, as does domestic work.

3.1. Conceptual framework and empirical specification

Based on the literature, our hypothesis is that female-managed plots are less productive and one of the reasons for this is lower efficiency of female farmers. We, therefore, test the difference in efficiency between the groups and identify the causes of inefficiency. We are interested in whether

Table 1. Time-use among male and female household members

Activity (24-h recall)	Male (h)	Female (h)
Sleep	11.12	11.22
School/Employment/Business*	1.58	0.64
Agricultural work	3.93	2.64
Domestic work**	1.56	4.99
Leisure***	5.82	4.52

*School, employment and business include going to school or doing homework, working as employed of engaged in one's own business work.

**Domestic work includes cooking, caring for children, adults or elderly, domestic work, such as cleaning and fetching wood, also activities such as shopping and getting services, including health series and weaving, sewing and other textile work.

***Leisure includes such activities as watching TV, listening to radio or reading, exercising, social- and religious activities and others.

the major determinants of efficiency are related to inputs, human capital such as education, or other individual, household or community-related factors, and whether these differences are attributed to gender inequalities related to access or perhaps other structural and institutional causes?

Maize is widely grown by all groups, that is by women, by men and on jointly managed plots. However, within the household, it is not common to grow maize under different management types, even when grown on several plots. Only 7% report different management types for maize plots. We can therefore use a household as our unit of analysis, but not to make inference about intra-household distributions or difference in efficiency.

The data provide information on inputs at the crop, rather than the plot level. For the sake of the analysis, we have included the small group of households with maize under several management types in the joint management group, leaving us with three distinct management types to compare. We utilize Battese and Coelli's (1995) single-step approach to stochastic frontier modelling, estimating the parameters associated with TE. This is based on a production function where we look at yield, that is, output per hectare, and inputs including land, seed, and equipment, as well as their quadratic terms. The use of fertilizers and pesticides has been combined into a chemical inputs dummy variable, which is also included in the production function.

We have not included labour in our production function, because the data do not include information on household working hours allocated to specific plots. Because the majority of the respondents were small-scale farm households, using hired labour was uncommon. Overall, any form of hired labour was used only for 15% of plots. Hired labour used specifically for maize was higher, 33%; however, even for those using hired labour, it was usually only for a few working hours, which means it has no impact for the model.

Information on household labour was included in the data through the specification of main and secondary activity of each household member, as well as through the 24-h recall time-use model, as described above. Because farms are often small and family labour has a very low opportunity cost, there is evidence that household labour is often overused (Oladeebo & Fajuyigbe, 2007). In rural areas, people also face disguised unemployment, which leads family members to participate in farm work as little opportunity for off-farm work is available (Coelli, Rahman, & Thirtle, 2002).

The stochastic frontier function used in the study is defined as

$$Y_i = f(X_i;\beta)\,\exp(\varepsilon_i) = f(X_i;\beta)\,\exp(V_i - U_i), \qquad i = 1, 2 \ldots N \tag{1}$$

where Y_i is the log of output in kg/ha for the ith farm, $f(X_i;\beta)$ is the production function, X_i is a vector of inputs in a logarithm-transformed form and ε_i is the error term. The error term is a two-way error component, where V_i is random error and U_i is management-related efficiency component. V_i is assumed to be independently $N(0,\sigma_v)$ distributed. U_i is assumed to be independently half-normal and takes values between zero and one, where one indicates full efficiency.

Empirically our model is presented as

$$\ln y_i = \beta_0 + \sum_{k=1}^{m} \beta_k \ln x_{ki} + \frac{1}{2}\sum_{k=1}^{m}\sum_{j=1}^{m} \beta_{kj} \ln x_{kji} + v_i - u_i \tag{2}$$

where $\ln$ is the natural logarithm and y_i is the output measured in kg/ha, x_{kj} is the vector of input variables for k different parameters, including land area, seed and their quadratic terms, based on the quadratic function, β_k are the vectors of parameters to be estimated, u_i is vector of random error and u is a vector of management-related efficiency component. We include the following Battese and Coelli (1995) model specifying the inefficiency effect:

$$\mu_i = \delta_0 + Z_i\delta_i \tag{3}$$

where Z_i is a vector of explanatory variables associated with TE effects and δ are vectors of unknown parameters.

All variables were normalized before calculating the logarithms.

Information on all household assets and numbers owned at the time of the survey was collected. The variable representing agricultural assets is calculated as the sum of the value of each asset. The value used is the price of a new item in 2012, because the exact current value of each asset was unavailable. For the seed variable, we have not differentiated between the sources of seed used by the household, which in the collected data is separated into bought, saved and donated. The input variable for seed combines all seed use into one value which is expressed in kilograms rather than in monetary value.

The inefficiency effect is a vector of both household and individual level characteristics. The vector includes household size and number of members in different age groups, location of farm in terms of distance to paved road, describing how remote a given household is, and the share of the yield that is sold on the market.

Individual information includes age and years of education of the household head and spouse as well as participating in non-farm income generating activity. Age is often used as a proxy for experience, although the literature is mixed on whether it influences TE in a positive or a negative way (Rahman, 2010). We consider all three individual variables to be relevant in terms of experience and likely to influence efficiency.

In addition to the household and individual vectors, we include the study districts as dummy variables. Data were collected in all of the eight districts seen in the map (Figure 1). However, the number of observations in some districts was quite limited, so we have combined the district of Bugiri and Bududa into a variable called *East*, and the districts of Kiruhura and Ntungamo into a variable called *Southwest*.

Our production function describes the yield in quantity. In the context of our data, this is more intuitive than using the value of output as only small shares of the yield are sold. Similarly, seeds are measured in quantity as substantial proportion of seed originates from the household's previous harvest or are acquired as donated seed.

3.2. Model specification

Several specifications of equations and models were estimated to identify the best fit for the data at hand. In order to select the best-fitting functional form, log-likelihood ratio test, utilising chi-square values,[1] was used to test the Cobb–Douglas, quadratic and translog forms. In all of the models, we assume a half-normal distribution of the error term. We found that the quadratic form was the most-suited model for our data, both for specification of the overall model and the female model. The test results indicated that the quadratic model performed significantly better at 5% risk level than translog specification. Based on this result, we implemented both models using the quadratic functional form.

To evaluate the joint effect of the district variables, we ran our models with and without the districts and then tested the results with the likelihood ratio test. The test result for the joint effect of the districts suggest the model including the districts performed significantly better at the 5% risk level compared to the model without districts in our joint model. However, for the female model, the districts are not significant even at the 5% level, and therefore not included.

We use Stata 14 for all our estimations.

4. Results

4.1. Descriptive statistics

After the largest 1% of farms was dropped from the sample as outliers, the mean farm size is 2.2 ha. The largest outlier farm was 606 ha, which was not considered representative of the farmers in the area. Eighty-seven per cent of households allocate less than 1 ha to maize production. The mean size of male-managed plots was 0.605 ha, while for jointly managed, it was 0.468, and for female-managed plots, it was only 0.293 ha (Table 2). Among the study households, 77% grew maize, 84 beans, 68 matoke and 60 cassava. The largest share of land was allocated to maize, on average 28% of all household land, compared to 18 for beans, 15 for cassava and 17% for matoke.

Most farms in Uganda are small-scale and use very little inputs. Apart from plot size, there are few significant differences in characteristics between households where maize plots are managed by men, women or jointly. There seems to be a difference between districts in which proportion of maize plots are under each management type. In most areas, the distribution is quite even, but some stand out. In Southwest Uganda, 60% of the maize plots in our data are managed by women, whereas in Masindi, 60% were managed jointly. Masindi is also the only district that is significantly associated with higher levels of efficiency, according to the overall model (Model 1; explained in more detail below). There were insufficient data on other cultural factors of the different districts, to make deeper inference on the reasons behind this.

Only 19% of households used agrochemicals (either fertilizer or pesticides) on their maize plots. Only minor differences between the groups using and not using chemicals were noticed. On average, female farmers were using less agrochemicals than male farmers, as shown in Table 3. Only 10% of all female-managed plots used agrochemicals, compared to 28% of male-managed plots. Out of all plots using agrochemicals, 44% were male managed, 40% jointly managed, while only 16% were female managed, suggesting a gender gap.

Although agrochemicals were not found to be statistically significant as an explanatory variable for TE, we included it as a dummy variable in the production function. In the overall model, it was significantly associated with increased yield but had no significant effect in the female model. This could be an indication that supports the assumptions of Aguilar et al. regarding future developments. However, considering the very low number of users among the female group, no such conclusions can be made.

Table 2. Descriptive statistics of survey data

Management type	Male managed *N* = 268 Mean (SD)	Female managed *N* = 260 Mean (SD)	Jointly managed *N* = 368 Mean (SD)
Hectares of land allocated to maize	0.577 (0.687)	0.235 (0.31)	0.477 (0.587)
Kilograms of input seed per hectare	51.9 (67.4)	60.5 (78.9)	57.1 (79)
Number of household members	6.2 (3.0)	6.4 (3.0)	6.7 (2.8)
Members 5 years and under	1.3 (1.1)	1.1 (1.2)	1.5 (1.2)
Members 6–15 years	2.1 (1.9)	2.3 (1.7	2.2 (1.9)
Members 16–19 years	0.6 (0.7)	0.6 (0.8)	0.6 (0.8)
Member 20–60 years	2.1 (1.1)	2.1 (1.3)	2.2 (1.0)
Members over 60 years	0.2 (0.5)	0.2 (0.5)	0.2 (0.5)
Education in years of highest educated female in household	6.1 (3.1)	6.5 (3.4)	5.8 (3.3)
Age of head of household	42 (15)	48 (14)	43 (16)
Education in years of head of household	5.7 (3.3)	4.9 (4)	5.7 (3.4)
Percentage of household heads involved in non-farm activity	38	42	38
Percentage of household spouses involved in non-farm activity	9	9	6
Mean time in minutes to paved road	86 (148)	71 (204)	71 (181)
Percentage of households in Kiboga district under different management types	44	29	27
Percentage of households in Mubende district	44	23	34
Percentage of households in Southwest Uganda	22	60	19
Percentage of households in East Uganda	26	27	47
Percentage of households in Kibaale district	31	24	46
Percentage of households in Masindi district	22	18	60
Percentage of households using agrochemicals	28	10	18
Mean marketed percentage of yield	49 (28)	32 (27)	43 (28)

Source: Data from IFPRI Household Survey 2012/13.

4.2. SFA

We start the analysis by running a quadratic model of the whole data to identify the most important factors related to efficiency (Model 1). Management type was included as explanatory variable, leaving out female management as the reference. The analysis shows that both male management and joint management stand out as very significantly associated with higher efficiency, compared to

Table 3. Use of fertilisers and pesticides under different management types

Management	Use of agrochemicals —No	Use of agrochemicals —Yes	Total
Male	193	75	268
	72%	28%	100%
Female	234	26	260
	90%	10%	100%
Joint	303	65	368
	82%	18%	100%
Total	773	181	954
	81%	19%	100%

Source: Data from IFPRI Household Survey 2012/13.

female management. This is the most important factor influencing efficiency in our model. The age of the head of household is also associated with lower efficiency, but only at the 10% risk level.

The share of the yield sold by the household, rather than used for own consumption, was a variable significant at the 1% level. However, again the actual effect on the coefficient was very low. A statistically significant relationship was found between a higher efficiency on the plots and the spouse of the household (in 98% of cases a female) being involved in income-generating activity outside of the farm household. This may suggest that providing women with off-farm opportunities for income-generating activity may have positive effects on the farm household. This is in line with the literature, according to which personal access to income improves women's empowerment, and thereby household well-being outcomes, such as child nutrition (Sraboni, Malapit, Quisumbing, & Ahmed, 2014; Wouterse, 2016). Therefore, it is an interesting result to explore further in future studies. Share of crop yield sold was another variable significantly associated with higher efficiency, both for the overall and for the female model, although the significance level is much higher for the overall model. This suggests that commercial plots are managed more efficiently.

Farms located in Masindi district achieved higher levels of efficiency than farms in other areas. There are differences between districts, in relation to climatic and cultural factors. Future studies or programmes should take geographical and cultural factors into consideration in the design phase. Although there was a difference in the mean size of plots managed by men, by women and jointly, women having much smaller plots, we didn't see evidence on the inverse effect on efficiency (Table 4), presented in the literature (see e.g. Ali et al., 2016; Slavchevska, 2015). We also tested including self-reported soil quality dummy variables in the model. In contrast to our expectations, soil quality was not found to be significantly associated with efficiency and was therefore left out of the final model. Possibly this is due to self-reported information being too subjective and thus not reliable.

After confirming our assumption that efficiency of female-managed plots was significantly lower than that of the other management styles, we continued to identify the specific factors associated with efficiency of the female group (Model 2). Several variables found to be significant in this model were related to household composition. Increased number of household members was associated with lower efficiency. Women tend to carry the brunt of the burden of household work, including childcare, cooking and in many cases producing food for home consumption in small-scale household gardens. This workload seems to influence the efficiency of production negatively. As the results suggest, the larger the family, the greater the time burden.

The number of older children, aged 6–15, was however associated with higher efficiency. This was interpreted to suggest that older children provide labour input on the plots, thereby helping to improve efficiency. Also, time to weekly market and share of yield sold are significant variables in

Table 4. Estimated parameters (z-value) of Stochastic frontier models for the (1) overall and (2) female model

		(1) Overall model	(2) Female model
ln yield (kg/ha)	Ln of area	0.062	0.077
		(1.76)*	(0.70)
	Ln of area squared	0.041	0.016
		(2.27)**	(0.33)
	Ln of seed (kg/ha)	0.399	0.431
		(10.48)***	(5.76)***
	Ln of seed (kg/ha) squared	−0.012	−0.050
		(0.64)	(1.40)
	Ln of value of equipment	0.059	−0.015
		(2.47)**	(0.26)
	Ln of value of equipment squared	0.002	−0.001
		(1.23)	(0.21)
	Chemical Input (dummy variable,1 = true)	0.149	−0.036
		(2.03)**	(0.20)
	Intercept	0.645	−0.273
		(8.07)***	(2.00)**
lnsig2v	Intercept	−1.159	−0.297
		(8.09)***	(3.21)***
lnsig2u	Male management (dummy variable, 1 = true)	−0.538	–
		(3.08)***	–
	Joint management (dummy variable, 1 = true)	−0.469	–
		(2.79)***	–
	Household size (persons)	−0.044	0.664
		(0.70)	(2.23)**
	Number of members 5 years and under	−0.025	−1.045
		(0.26)	(1.54)
	Number of members 6–15 years old	0.044	−1.189
		(0.61)	(2.45)**
	Number of members 16–19 years old	0.117	−0.667
		(1.10)	(1.11)
	Number of members over 60 years	−0.035	−3.883
		(0.21)	–
	Age of head (years)	0.012	–
		(1.95)*	–
	Highest level of education of household member	−0.028	–
		(1.15)	(0.85)

(Continued)

		(1) Overall model	**(2) Female model**
	Highest education level in years of female in household	–	−0.082
		–	(0.67)
	Head involved in non-farm activity (dummy variable, 1 = true)	0.117	−0.468
		(0.80)	(0.50)
	Spouse involved in non-farm activity (dummy variable, 1 = true)	−0.572	–
		(2.02)**	–
	Time to weekly market (h)	0.000	0.021
		(1.02)	(2.32)**
	Share of crop yield sold (%)	−0.014	−0.089
		(5.24)***	(1.87)*
	East (dummy variable,1 = true)	0.213	–
		(0.93)	–
	Southwest (dummy variable,1 = true)	0.323	–
		(1.25)	–
	Mubende (dummy variable,1 = true)	−0.129	–
		(0.50)	–
	Kibaale (dummy variable,1 = true)	−0.210	–
		(0.78)	–
	Masindi (dummy variable,1 = true)	−0.844	–
		(2.96)***	–
	Intercept (dummy variable,1 = true)	0.804	−1.406
		(1.88)*	(1.00)
N		896	259

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
Source: Data from IFPRI Household Survey 2012/13.

the female model. However, the effect of these variables was considered low, so not much inference can be made based on this.

4.3. Elasticities

We calculated the input elasticities for the overall model and for the female model. There are no clear differences between the groups, as can be seen in Table 5. For both models, seed is the input with the highest elasticity (0.38 for the overall model and 0.33 for the female model). The elasticity suggests that for the female model if you increase the seed input by 1%, maize output will increase by 0.3%. Area elasticity has the value of 0.11 (female model) and 0.15 (overall model), which implies that increasing land area by 1%, maize output increases by only 0.11% for female-managed farms.

Table 5. Input elasticities

Overall model	**Elasticity**
Area	0.15
Seed	0.38
Equipment	0.06
Female model	**Elasticity**
Area	0.11
Seed	0.33
Equipment	−0.15

Source: Data from IFPRI Household Survey 2012/13.

4.4. Efficiency scores of the different groups

To get a better understanding of the levels of efficiency, we calculate the TE for each observation. The TE represents the distance of a given observation from the potential maximum, that is, the frontier, and has a value between zero and one, one indicating perfect efficiency. For Model 1, the overall model, the frontier is predicted based on the full data. We calculated the TE of the different groups, in relation to this frontier (Table 6), and found that there are significant differences, the mean TE of the male group being the highest.

We group the efficiencies into five categorise, based on the scores, ranging from lowest efficiency, 0.0–0.2, up to highest efficiency, 0.81–1.0 (Table 7). Around 50% of male and jointly managed plots reach the two highest efficiency categories (although only 5% respectively is actually in the highest score group), whereas over 70% of women are in the three lowest categories.

Table 6. Mean technical efficiency of different management types

Management	***N***	**Mean**	**SD**	**Min**	**Max**
Male	268	0.57	0.18	0.03	0.87
Female	260	0.43	0.21	0.02	0.82
Joint	368	0.56	0.19	0.06	0.84
All	896	0.52	0.20	0.02	0.87

Source: Data from IFPRI Household Survey 2012/13.

Table 7. Number (*N*) and proportion (%) of farmers in each technical efficiency category according to management type (actual values of technical efficiency)

Efficiency category	**Male**		**Female**		**Joint**	
	N	**%**	***N***	**%**	***N***	**%**
Lowest efficiency	10	4	47	18	24	7
Second efficiency	37	14	71	27	52	14
Third efficiency	84	31	73	28	99	27
Fourth efficiency	124	46	65	25	178	48
Highest efficiency	13	5	4	2	15	4
Total	268	100	260	100	368	100

Source: Data from IFPRI Household Survey 2012/13.

Table 8. Technical efficiency of women managed plots in relation to own frontier (Model 2)

Efficiency category	*N*	%
Lowest efficiency	2	1
Second efficiency	5	2
Third efficiency	9	3
Fourth efficiency	33	13
Highest efficiency	211	81
Total	260	100

Source: Data from IFPRI Household Survey 2012/13.

However, when the TE is calculated separately for the female model alone, we find that women are in fact very efficient in relation to their own frontier (Table 8). In this model, 81% of the women reach the highest efficiency category, while only 1% is in the lowest category. Mean TE of women in this model is 0.88 (standard deviation 0.16, min 0.1, max 0.999). This suggests that women have the capacity to be efficient within their boundary conditions.

5. Discussion and conclusion

In this paper, we looked at whether a difference in efficiency in maize production on plots managed by men, women or jointly can be found. We tried to identify the factors associated with efficiency, both in general and on female-managed plots specifically. We used SFA to analyse the determinants of efficiency. Each model predicts a frontier based on the input and output data of the group and identifies which efficiency parameters are significantly associated with higher or lower levels of efficiency. Each individual observation is then given a predicted TE score between 0 and 1 in relation to the frontier.

When looking at the overall model, we find a significant difference between the TE of female-managed plots in comparison to that of male or jointly managed plots, the male being the most efficient. However, looking at the efficiency scores of only the female group, in relation to their own frontier, we found on average even higher efficiency scores than those of the men in the overall model. Over 80% were in the highest efficiency category, between 0.8 and 1. This suggests that there are underlying factors negatively affecting the efficiency of women.

When looking at the determinants of efficiency, women were faced with gender-specific constraints. For the female-managed plots, we identified household-level factors associated with inefficiency. The most important variables were related to household size and composition. A high number of household members was associated with lower efficiency, suggesting that time burden is a constraint for women. Women commonly allocate more of their time towards taking care of other family members, including housework, cooking and other household activates, at the expense of working efficiently on their own plots. This is in line with other studies, which have found that women in Africa contribute time towards domestic work to a much higher degree than their male counterparts, already at a very young age (Addison et al., 2016). For example, Slavchevska found that time burden relating to child care responsibility negatively affected women's productivity (2015). These constraints also limit women's access to other economic opportunities outside the household.

The data used for the analysis are cross-sectional. The results show that women are very efficient in their group but are faced with gender-specific constraints that reduce their efficiency indirectly. The results suggest that the joint model may not be able to fully identify all characteristics, such as differences in land quality, which may be associated with female-farmers and which may influence their efficiency indirectly. In other words, in the joint group, the efficiency of female farmers may be limited by household-related constraints and (the quality of) inputs that they have at their disposal. Our results show that efficiency is higher if the household produces higher shares for the market. Women tend to have smaller plots, use fewer inputs and are less likely than men to produce for the market (Hill & Vigneri, 2009). This reinforces the gap in access to markets, between men and women. Although overall efficiency is not directly affected by issues such as access to markets, some factors may still be important. The results suggest that women's efficiency could be improved if they were more market-oriented. However, the fact that women are more limited by their household burden will likely affect their readiness to do so.

At the same time, the overall model suggested that female spouses involved in income-generating activity outside the household was a factor that positively influenced efficiency. Policies to support women's involvement in non-farm income-generating activity may therefore be relevant as an alternative, or in addition to, supporting their active involvement in market-oriented agriculture.

Interestingly education was not significantly correlated with efficiency. This may confirm what Aguilar et al. (2015) found in their study, suggesting that education was only relevant at higher levels of productivity. For small-scale farmers with only marginal yields sold to market, even higher levels of education may not significantly help them to improve their efficiency, due to the many other constraints they are faced with.

There are regional variations influencing efficiency, related either to cultural or possibly climatic factors. Therefore, support mechanisms need to be developed that take the specific needs of women in their given contexts and reality into consideration. These mechanisms may include factors that decrease women's time burden within the household and improves their access to resources. It would for example be useful to study the influence of extension and other forms of informal training on the efficiency of women, although previous studies have not always found access to extension associated with increased efficiency (Muoh, Sukoya, Kwame, & Yangari, 2015).

The fact that agrochemicals was not found to be significantly associated with TE is in line with findings of Aguilar et al. (2015). They, however, argue that if and when the use of agrochemicals starts to increase, it may lead to the productivity gap between men and women increasing again. The gender effects of any intervention promoting agrochemical use need to be carefully considered.

Based on our study, it seems that in most cases women are unable to fill their full potential and may not be contributing to productivity as much as they could. Many of the reasons behind this are linked to structural issues. However, also local issues relating to women's access can play a role in improving the situation. Finding ways of developing livelihood opportunities for women is central. One step is empowering women to take a more active role, whether as farmers or in other income generating activities. This should therefore be a central policy goal.

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Note

1. The model used for the log-likelihood ratio test is: LR = −2 × {log[likelihood (H_0)] − log[likelihood (H_1)]} (Battese & Coelli, 1995).

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