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Market production and productivity: The effects of cash cropping on technical efficiency in staple crop production

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To meet increasing food demand, most developing countries cannot rely on expanding the crop area, but will need to stimulate yield growth arising from increased factor productivity. This can be achieved through more efficient utilization of inputs to produce maximum output given existing technologies. Low productivity arising from technical inefficiency negatively impacts on household income and food security by reducing food availability as well as economic access. It has been hypothesized that market-oriented production enhances productivity of staple crops through increased use of quality inputs and management technologies. This hypothesis was tested using household survey data from western Uganda. Using a stochastic production frontier model, technical efficiency of the major cash crop and staple crops was estimated. A propensity score matching approach was used to compare the technical efficiency of market-oriented and subsistence households in production of selected staple crops. Results show higher technical inefficiency in staple crops compared to the cash crop among the market-oriented households. A significant negative relationship was also found between cash crop production and technical efficiency in staple crops production. The negative association was attributed to withdrawal of critical resources particularly labor from staple crops to cash crops during peak periods of labor demand.

Key words: Crop productivity, food security, market production, stochastic production frontier.

INTRODUCTION

Developing countries face the challenge of feeding their rapidly increasing population on limited productive land. To meet increasing food demand most countries cannot rely on expanding the crop area, but will need to stimulate yield growth arising from increased factor productivity. This can be achieved in different ways. First, through increased access to and use of non-land inputs such as fertilizers and better technologies, for example high

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yielding varieties to boost crop yields thus shifting to a higher production frontier (Mekonnen et al., 2015). Second, through more efficient utilization of inputs to produce maximum output given existing technologies. The latter approach is known as increasing technical efficiency. Technical efficiency is a prerequisite for economic efficiency, which in turn may be necessary for economic viability and sustainability of farms. Recent studies, however, show that technical efficiency is typically not achieved in African agriculture, as most households do not operate along the best practice frontier (Mugera and Ojede, 2014). Most farms produce at levels below potential for their biophysical environment, implying that more agricultural output can be produced using existing resources (Thiam et al., 2001).

Important to policy makers and farmers is that inefficiencies in agricultural production undermines poverty reduction and food security. Technical inefficiency directly decreases food availability by reducing supply. Indirectly it creates a demand problem by denying producers sufficient income to access what they do not produce themselves. Persistent technical inefficiency in sub-Saharan Africa is often attributed to limited access to information, extension services (Asante et al., 2014) and high-quality inputs especially clean seed (Poulton et al., 2010). A study by Mekonnen et al. (2015) reveals that developing countries have a sizable potential of improving agricultural production from the same level of inputs if they invest in efficiency enhancing technologies including knowledge and information transfer technologies (e.g. radios).

In recent years, most African countries have made an effort to invest in transforming agriculture from subsistence farming (often characterized by low productivity) to market-oriented farming in order to overcome poverty and food insecurity (Carletto et al., 2016). Farmers have received support from governments and non-governmental organizations in form of extension services, training and inputs such as high-quality seeds to produce highly marketable crops such as rice. Prospects of getting high crop income induced farmers to invest in the production of marketable crops and adopt the recommended technologies.

This paper seeks to better understand the changes in technical efficiency in food crop production as farmers increasingly become more market-oriented. How market-oriented crop production affects technical efficiency in the production of staple crops was investigated. Promoting market production in a farming system dominated by subsistence production may positively or negatively affect technical efficiency of staple crops. Positive effects may arise through income generation that can facilitate households' timely access to quality inputs, information, extension services and improved technologies. For instance, access to technologies such as radio programs and mobile phone subscriptions facilitates the transfer of knowledge and information expected to influence technical efficiency in agricultural production (Mekonnen et al., 2015). Farmers may also easily access improved technologies and information by participating in market-oriented government-supported programs. For instance, in Uganda market-oriented households have benefited from government support through the commodity-based extension services approach aimed to transform low input subsistence agriculture into commercial market-oriented agriculture (Mwaura, 2014). In Zimbabwe, Govereh and Jayne (2003) found that cash crop production enhances food crop productivity as food crops benefit from extension services that households obtain through cash crop production programs. Similarly, semi-subsistence farms are found to have a higher technical efficiency in rice production than subsistence farmers in Thailand as a result of extension programs (Athipanyakul et al., 2014).

Moreover, income from production may facilitate market-oriented households to carry out timely field operations, the key to achieving technical efficiency. For example, they can supplement family labor with hired labor-reducing competition for labor between cash and staple crops during peak periods. Evidence from rice farmers in Nigeria shows that hired labor can have a positive impact on technical efficiency (Ogundele and Okoruwa, 2006). This positive path, however, requires households to invest income from the cash crop into efficiency enhancing technologies and inputs for the food crop.

In contrast, if poor households choose not to invest their income in production of staple crops, introduction of a cash crop may have a negative impact on technical efficiency of staple crops. This may come as a result of seasonal competition for critical inputs especially labor. Households that mainly depend on family labor are likely to prioritize the cash crop in terms of labor allocation and management such that activities in staple crops may be affected later in the cropping season hence affecting technical efficiency. Further, for households with different plots of land there is likely to be competition for good quality plots between the cash crop and staples, which may result in low yields of staple crops on low quality plots (Binam et al., 2004).

This study contributes to existing literature, by answering the questions whether market-oriented production enhances technical efficiency of staple crops, and whether market-oriented households are more technically efficient in cash crops than in staples. It is important that we understand how market production affects efficiency in staple crop production in order to inform policy interventions designed to enhance resource use to support market production as well as household food security. While a few studies have assessed the impact of cash cropping on food crop productivity (Govereh and Jayne, 2003; Strasberg et al., 1999), both studies focus on the effect of commercialization on food crop yields which may be due to technological change or technical efficiency. To the best of our knowledge none has explicitly studied the effect of market-oriented production on technical efficiency in staple crop production. Other related studies have assessed the effect of market interventions such as agricultural cooperatives (typically formed to aggregate small holders and link them to input and output markets) on technical efficiency in crop production. Using a stochastic frontier model and propensity score matching, Abate et al. (2014) for example found that farmers in cooperatives are more technically efficient than non-members in Ethiopia. They attribute this to increased access to productive inputs and extension linkages provided by agricultural cooperatives.

To answer these questions, we analyze technical efficiency in production of a major food cash crop (food crop grown for sale) and staples among market-oriented and subsistence households. The case of rice market production in western Uganda was used and resource use efficiency in production of staple crops among two groups of farmers-farmers benefitting from an intervention that aimed to promote market production and farmers from control areas that did not were compared. Rice was chosen because it is a crop that has been extensively promoted for market production with the aim of increasing household income and food security. Overall, low technical efficiency in production of both the food cash crop and the staple crops was found. Technical inefficiency for market-oriented households is higher in staple crops compared to the food cash crop. In addition, evidence was found for significant higher technical inefficiency in staple crops production for market-oriented households compared to subsistence households. It was conjectured that this result is associated with competition for critical resources in peak periods between the staple and cash crops.

Market-oriented food crop production in Southwestern Uganda

Market-based crop production in Uganda has increased remarkably in the past years. This is partly the result of the government's efforts to promote selected food crops as cash crops. Market production is motivated by market liberalization and urbanization which have resulted in increased demand for food both in the domestic and international market, especially in the neighboring countries of Rwanda, Kenya and South Sudan. FAO statistics for example, indicate that cereal exports increased from 7.6 tons in 2000 to 299.4 tons in 2013, this is more than a ten-fold increase. Equally, pulses exports have increased by 988.5% from 3.5 tons in 2000 to 38.1 tons in 2013. For this study we consider the case of rice production in Southwestern Uganda, where rice has been highly promoted as a cash crop. Rice is interesting in that it is a marketable crop traded both domestically and internationally.

Through the commodity-based agricultural extension approach under the National Agricultural Advisory Services (NAADS) program, rice is one of the few food crops that has received a lot of support from the government and other agencies, such as the Japan International Cooperation Agency (JICA). Market-oriented rice production in Kanungu district, Southwestern Uganda, started with the introduction of upland rice varieties commonly known as NERICA by IFAD in 2003 (CARD, 2014). The aim of the project was to increase income and food security for small holder households (IFAD, 2012). The project started in two sub counties of Nyamirama and Kihihi, considered to be relatively fertile as they lie along the Rift Valley. Subsequently, with government support under the National Agricultural Advisory Services (NAADS) program, upland rice production has been extended to other sub counties. It is now a major food cash crop in five out of twelve sub counties in the study area, and one of the priority commodities at national level (MAAIF, 2010). Rice production has increased significantly from 150,000 tons on 80,000 ha in 2004 to 280,000 tons on 140,000 ha in 2012 (MAAIF, 2010; Reda et al., 2012). This reflects the results of training programs providing farmers with information on modern farming technologies and marketing. Farmers' capacity to access the market has been enhanced through training in business development, creating market linkages and providing support to value addition initiatives. Twelve rice hulling machines have been established in the study area, including one that does sort and packaging.

METHODOLOGY

Data

The data used are extracted from a household survey on market production and food security conducted in Kanungu district in 2014. The survey used a multi-stage sampling procedure to select households. A total of 1137 households were sampled; 592 were randomly selected from five sub counties exposed to promotion of commercial rice production and the associated extension services-(treatment). These are considered as market-oriented households. Moreover, we surveyed 545 households randomly selected from two sub counties that did not receive this project. These households consequently do not grow rice. The sub counties were purposively selected considering factors that may drive selection of the area for implementing a market-oriented crop production program. In the present case, sub counties with similar socio-economic and agro ecological conditions were considered. Negligible 'contamination'/ spillover effects in the sub counties used as control were observed. This could reflect an information gap, because farmers in our control area lack the capacity or enthusiasm to search for information on rice production for commercial markets by themselves. It is believed that if a similar program would be introduced in the non-rice growing area, households would equally participate in market production, as subsequently discussed. This study uses data on household demographics and socioeconomic characteristics, inputs and outputs for production of key crops; rice as a cash crop; and beans and sweet potatoes as major staples.

Inputs and output for the food-cash crop (rice) and the staple crops (beans and sweet potatoes) were considered during the main

Table 1. Descriptive statistics for variables included in the study.

Variable	Mean			t-test
	Pooled sample (N = 967)	Market-oriented households (N = 342)	Subsistence households (N= 625)	
Bean output (kg)	112.0	97.0	120.0	4.33***
Labour (man-days)	46.4	44.1	47.6	1.619*
Seed (kg)	16.8	16.1	17.3	1.748**
Area (acres)	0.21	0.19	0.22	1.328*
Sweet potato output (kg)	407.0	356.7	421.3	1.79**
Labour (man-days)	27.1	33.0	25.3	-3.462***
Seed (kg)	318.9	400.8	295	-4.872***
Area (acres)	0.2	0.2	0.2	0.844
Rice output (kg)	-	517.3	-	-
Labour (man-days)	-	160.4	-	-
Seed (Kgs)	-	55.8	-	-
Area (acres)	-	0.43	-	-
Age of household head	42.7	42.5	42.7	-0.27
Education of household head (years)	6.2	6.3	6.1	0.79
Education of heads spouse (years)	4.3	4.5	4.1	1.49
Household size	6.3	6.8	6.0	4.21**
Size of land owned (acres)	1.9	2.4	1.5	4.15**
Distance to main road (km)	2.4	1.8	1.3	3.64**
Distance to main market (km)	5.6	4.6	2.6	13.86***
Distance to sub county headquarters (km)	4.7	5.2	4.5	4.2**
Main occupation agriculture = 1	0.9	1.0	0.9	2.76**
No secondary occupation = 1	0.5	0.5	0 .6	-2.00**
Member of farmer group =1	0.5	0.7	0.4	6.71***
Member of savings and credit group =1	0.8	0.8	0.8	-1.61
Market Production Index (MPI)	46.3	54.1	41.0	8.72***
Rice growing households (%)	40.8	-	-	-

*, ** and ***, significant at 10, 5 and 1%.

cropping season (August-February). Output for rice and beans is the measure of threshed dry crop. Three inputs: land, labor and seed were used. Land is the total area covered by the crop during the main season including own and rented land. Labor is the total number of person days, both from the family and hired, spent on all activities for a particular crop. Seed is the quantity of seed used (both retained from the previous harvest and purchased in the market). Only three inputs were considered because fertilizers and pesticides are not used on the crops in this study, and the use of other inputs such as herbicides is negligible. Capital items such as machinery and buildings were not included in the production function as all households use hand hoes and store the produce in residential houses.

Earlier caveat was mentioned that the measurement error is an issue. Crops such as sweet potatoes are harvested in piece meal, which makes it difficult to estimate accurate output levels. We therefore, rely on estimates of participants regarding harvest levels as if the entire garden were harvested at once. The planting material for sweet potatoes is not tradable in the study area and therefore it is difficult to estimate the quantity of seed used. Another limitation is that land is not adjusted for quality differences at plot level as such data is not available. In case a farmer knowingly allocates a better plot to either of the crops (cash or staple), this could bias our comparative analysis of technical efficiency in cash and staple crop production. One could argue that perhaps the farmer gets the potential optimal output from the low productive plot. However, it is important to note that 'poor' land quality may be partly as a result of poor soil management practices which reflect technical inefficiency (Ahmed et al., 2015; Binam et al., 2004).

Descriptive analysis

Table 1 presents a summary of household and farm characteristics. Our sample reduced from 1,137 to 967 after households were dropped with missing observations on variables of interest. Not surprisingly, but important to note, is a significantly higher market production index for the market-oriented households. This indicates that these households are indeed more market-oriented, as they sell on average 54% of their output value compared to only 41% for the control households. A majority of household heads and their spouses have only primary level education. A larger land size was observed for market-oriented households. However, an average farm size of 2.4 acres (with a standard deviation of 1.9) suggests that a majority of the households are still to be considered small holders.

Empirical approach

Stochastic frontier model

Technical efficiency is a measure of the ability to obtain maximum output from a set of inputs given the best available technology. Different approaches are used to estimate technical efficiency. These include stochastic frontier models, parametric deterministic frontier models and non-parametric deterministic models (Bravo-Ureta et al., 2007). The choice for a specific model depends on the data and the context of the study. A stochastic production frontier model was used to estimate technical efficiency in rice production and two major staple crops; sweet potatoes and beans. The stochastic frontier model has an advantage over the deterministic model in that it incorporates a composed error structure with a two-sided symmetric error term that captures the random effects outside the control of the famer and a one-sided component reflecting inefficiency (Bravo-Ureta et al., 2007).

Following Wang and Schmidt (2002), we estimate a 'one-step' model that specifies the stochastic frontier for each crop j (rice, beans and sweet potatoes) on farm i and estimates how technical inefficiency depends on farm characteristics. A Cobb-Douglas functional form was assumed. The model is specified as follows:

$$lny_{ij} = \beta_0 + \beta_1 lnx_{ij} + v_{ij} - u_{ij}, \quad (1)$$

where; y is output and x_{ij} denotes a vector of inputs (seed, labour and land). β is the parameter vector associated with x variables for the stochastic frontier; *v* is a two-sided normally distributed random error - $v \sim N(0,\sigma_V^2)$ that captures the stochastic effects outside the farmer's control (e.g., weather, natural disasters, and luck), measurement errors, and other statistical noise. The term *u* is a one-sided (*u* ≥ 0) efficiency component that captures the technical inefficiency of the farmer. In other words, *u* measures the shortfall in output y from its maximum value given by the stochastic frontier $f(x_i;\beta)+v$. This one-sided term can follow such distributions as half-normal, exponential, and gamma (Greene, 2008). This study assumes that *u* follows a truncated normal distribution $[u{\sim}N(\mu,\sigma_u^2)]$ which allows the inefficiency distribution to have a non-zero mean μ. The two components *v* and *u* are assumed to be statistically independent of each other.

To analyze the effects of exogenous variables (z_m) on farms' levels of technical efficiency, we defined the technical inefficiency model as follows:

$$\mu_{ij} = \delta_0 + \delta_1(\, cashcrop_i) + \delta_m z_{mij} + \varepsilon_{ij} \quad (2)$$

where μ_i is the mean of the inefficiency term assumed to follow a truncated normal distribution. $cashcrop_i$ represents a dummy for market-oriented rice production (the key variable), and δ_m is a vector of unknown parameters to be estimated.

The control variables used in the efficiency model include: sex, age and education of household head, household size, size of land owned, access to extension services, type of seed, secondary occupation, source of labor (takes the value of 1 if the household mainly uses family labor, zero otherwise), distance to market and sub-county headquarters, membership to farmer groups and savings and credit associations. These factors are often reported to explain variation in technical inefficiency in agricultural production. Sex of household head is likely to affect technical efficiency as it influences access to productive resources such as land and inputs (Peterman et al., 2011). Age reflects experience, as most farmers have grown up in agricultural households. Education and access to extension services are likely to influence uptake of technologies which in turn affect technical efficiency (Kitila and Alemu, 2014). In Ethiopia, engagement in non-farm activities and, land holding are reported to influence technical efficiency of small holder maize farmers (Kitila and Alemu, 2014). There is mixed evidence on the relationship between farm size and productivity, while some studies report a positive relationship (Chirwa, 2007; Tan et al., 2010), others show an inverse relationship (Carletto et al., 2013). Membership of farmer associations and extension services facilitate timely access to inputs, information and technical assistance which are critical for technical efficiency (Chepng'etich et al., 2015). Access to credit facilitates timely usage of inputs including hired labor thus minimizing inefficiency.

Estimating market production effects on technical efficiency

Comparing technical efficiency between the market-oriented and subsistence households presents some methodological challenges. First, market-oriented rice production is a government supported program and such programs are typically not offered at random. It is therefore important to consider the factors that are likely to drive the selection of the area (sub county) in which the program is promoted. In this case for example, rice production may have been first promoted in sub counties that have more favorable weather and geographical conditions for the crop, or in sub counties with few other development programs. Regrettably sub-county specific data is lacking so we are unable to provide statistical information. The available information, however, indicates that sub counties are simply demarcated for administrative purposes and not geographical differences (Kanungu District Local Government, 2013). Arguably we may not completely rule out regional differences that may cause biased estimates. We therefore, include regional dummies in the inefficiency model to control for potential regional variation.

Second, participating in market production is not randomly assigned, but voluntary. Households self-select into market production. It is reasonable therefore, to expect that individual households who participate in market production are different from those that do not. While any household can engage in market production to increase its income, those with more resources such as capital and land are perhaps more likely to engage in it. Moreover, other factors such as entrepreneurship capability are not observable but may influence participation in market production (as well as efficiency in farming). We therefore, face a common problem of selection bias due to un-observables. To overcome the problem of self-selection requires a counterfactual or control group that has the same characteristics as the treated group. Common approaches are instrumental variables, difference in differences and matching methods (Blundell and Costa, 2000). This study employs propensity score matching to construct an appropriate control group.

Matching tries to eliminate selection bias due to observable factors by comparing treated households with control households that have similar observable characteristics. The propensity score is the conditional probability of receiving treatment; in the present case, the conditional probability that a household participates in market-oriented rice production given its geographic location, demographic and household characteristics. Propensity score matching provides unbiased estimates in case self-selection can be explained by observables and reduce dimensionality of the matching problem (Becker and Ichino, 2002). Within subpopulations with the same value for the propensity score, covariates are independent of the treatment indicator and thus cannot lead to biases (Imbens and Wooldridge, 2008). The weakness of propensity score matching is its inability to deal with hidden bias due to unobserved heterogeneity between the treated and control groups which my lead to overestimation of market production effects. This problem was addressed by using Rosenbaum bounds approach to determine how strongly the unobservable must affect selection into treatment in order to undermine our conclusion on market production effects (DiPrete and Gangl, 2004).

In the present analysis, the effect of market-oriented production on technical efficiency in staple crops production is determined by the difference in technical efficiency levels for the market-oriented (rice growing) households and the comparison group (non-rice growing).

It was assumed that participation in market-oriented rice production is a function of a range of observable characteristics at household and individual level. Formally it is expressed as follows:

$$d_i = \beta(w_i) + \tau_i \qquad (3)$$

where; $\mathrm{d} = 1$ for households growing rice and $\mathrm{d} = 0$ for the comparison group, w_i is a set of observed variables that influence the decision to participate in market-oriented production. Other unobserved household-specific factors are summarized by the random variable τ_i.

A logit regression model was used to estimate the propensity scores for the treated and control groups. In a counterfactual framework, our interest is to estimate the average treatment effect on the treated (ATT)[1] (Heckman et al., 1997; Smith and Todd, 2005), where the treatment is participation in market production (in this case rice production) and the outcome variable is technical efficiency. Propensity score matching balances distribution of observed covariates between treatment and control group based on similarity of their predicted probabilities of participating in market production. Thus, using different matching methods (kernel and radius) we are able to estimate the effect of market-oriented production on technical efficiency.

RESULTS

Stochastic frontier analysis

The production frontier and technical inefficiency models for beans, sweet potatoes and rice were estimated using the maximum likelihood estimator. Results are presented in Table 2. In the models for beans and sweet potatoes, we assume that both market-oriented and subsistence households have the same production technology. We then predict technical efficiency levels which we use as our outcome variable in the propensity score matching analysis.

As expected, parameter estimates of the stochastic frontier models indicate that inputs elasticities apart from sweet-potato seed are positive and statistically significant. This implies that households can achieve higher levels of output by increasing input use. The insignificant effect of sweet potato seed is not surprising since the seed is vegetative and the optimum plant density depends on the cultivar. Land input has the largest elasticities ranging from 0.32 for sweet potato to 1.2 for rice. This suggests land is the most critical input in crop production, which is logical given that agrochemicals and fertilizers are hardly used. Increasing cultivated land by 1% will increase sweet potato and rice output by more than 1%. The sum of the coefficients on discretionary inputs in the models for beans and rice is greater than one, signifying increasing returns to scale. This means that the farmers are still operating in the first stage of the production process. This is contrary to the general impression that smallholder agriculture is characterized by decreasing returns to scale. Similar findings have been reported elsewhere, for example in small scale rice production in Nigeria (Oniah et al., 2008). While output is highly responsive to changes in land size cultivated, further increasing productive land is presumably not sustainable given that 71.9% of arable land is under cultivation and arable land per person has declined from 0.45 in 1961 to 0.19 ha per person in 2013 (data.wordbank.org/indicators). The likelihood-ratio test for all models indicates presence of significant technical inefficiency at the 1% level. The value of gamma indicates that about 86% of the variation in beans output; 99% of the variation in sweet potatoes output and 77% of the variation in rice output is due to differences in their technical efficiency. These estimates compare well with those in other studies such as Binam et al. (2004) and Anang et al. (2017) reported in literature.

Does market production enhance technical efficiency of staple crops?

Generally, there are high levels of technical inefficiency in food crop production for farmers in both market-oriented and subsistence production. Table 3 presents a summary of technical efficiency scores.

On average, subsistence households have relatively higher technical efficiency in staple crops than market-oriented households. Compared to subsistence households, a larger proportion of market-oriented households have a technical efficiency below the pooled sample's mean. The highest inefficiency is observed in sweet potato production with a mean technical efficiency of 53%. Considering the pooled sample, there is potential for households to increase their beans and sweet potato output by 37 and 36%, respectively, through efficient use of the present technology. A similar message is presented in Figures 1 and 2, where we observe higher technical efficiency (in beans and sweet potato production), for the non-rice growing households. The mean comparison t-test of no difference in technical efficiency for both crops is rejected at 1% significance level. The inefficiency regression results confirm these differences (Table 2). Estimates of the technical inefficiency models show a positive significant relationship between the dummy for rice production and technical inefficiency in staple crop production even after controlling for regional, social economic and farm characteristics. The coefficients for both the beans (0.667) and sweet potatoes (0.679) models are relatively high suggesting that market-oriented production has a strong efficiency decreasing effect on staple crop production. High coefficients could also mean that inefficiency effects are overestimated due

[1]Details on ATT estimation see Heckman, Becker and Ichino (2002), Smith and Todd (2005)

Table 2. Estimates of the stochastic production frontier function and determinants of technical inefficiency.

Variable	Pooled sample		Market-oriented households
	Beans	Sweet potatoes	Rice
Lnoutput	Coefficients (Std. errors)	Coefficients (Std. errors)	Coefficients (Std. errors)
Production frontier			
Constant	3.056*** (0.164)	6.321*** (0.121)	4.293*** (0.382)
Lnlabour (person days)	0.259*** (0.034)	0.036* (0.020)	0.297*** (0.071)
Lnseed (kg)	0.326*** (0.041)	0.014 (0.010)	0.169*** (0.051)
Lnfieldsize (Acres)	0.544** (0.210)	0.324** (0.131)	1.216*** (0.288)
Technical inefficiency model			
Constant	0.539 (0.977)	1.867*** (0.686)	-0.874 (1.13)
Household grows rice =1, 0 otherwise	0.667** (0.262)	0.679*** (0.139)	-
Sex of household head	0.177 (0.192)	-0.052 (0.140)	0.136 (0.219)
Ln age of household head	-0.146 (0.234)	-0.295* (0.173)	0.855*** (0.282)
Ln education of household head (years)	0.005* (0.086)	0.055 (0.070)	0.030 (0.090)
Ln education of heads spouse (years)	-0.170 (0.096)	-0.007 (0.065)	0.012 (0.085)
Ln size of land owned (Acres)	-0.612** (0.242)	-0.323*** (0.121)	-0.246* (0.132)
Ln Distance to main market (km)	-0.181 (0.199)	0.153 (0.135)	-0.549*** (0.193)
Ln Distance to sub county headquarters (km)	0.105 (0.199)	-0.138 (0.145)	0.036 (0.163)
Seed type; improved seed =1; 0 otherwise	-	-	-0.094 (0.133)
Access to extension services	0.084 (0.153)	0.019 (0.116)	0.134 (0.155)
Source of labour; family =1: 0 otherwise	0.553** (0.220)	-0.130 (0.106)	0.478*** (0.143)
Household has no secondary occupation	-0.047 (0.124)	0.052 (0.092)	-0.035 (0.1259)
Member of farmer group =1; otherwise =0	-0.020 (0.150)	-0.192 (0.120)	0.074 (0.143)
Member of saving & credit group = 1; otherwise = 0	-0.073 (0.148)	-0.203* (0.119)	-0.041 (0.150)
Area dummy 1 (Kihihi)	0.027 (0.167)	-0.501** (0.177)	-0.167 (0.142)
Area dummy 2 (Nyamirama)	-0.487* (0.266)	-0.547** (0.168)	-0.523*** (0.188)
Area dummy 3 (Kambuga)	-0.454** (0.220)	-0.240** (0.119)	-
No. of observations	883	518	359
Diagnostic statistics			
$\sigma_s^2 = \sigma_v^2 + \sigma_u^2$	0.75	0.77	0.63
Gamma ($\gamma = \sigma_u^2/\sigma_s^2$)	0.86	0.99	0.77
Log-likelihood	-683.321	-269.64	-356.501
LR statistic	254.86***	7.33*	25.54***
Prob > chi2	0.000	0.000	0.000

*, ** and ***, significant at 10, 5 and 1%. Ln denotes logarithm; pooled sample comprises all market-oriented and subsistence households that grow beans and sweet potatoes.

to endogeneity of participating in rice production. Propensity score matching was used to derive the effects of market-oriented production on technical efficiency in staple crop production.

Propensity score matching analysis

Propensity scores were estimated using the logistic regression and the results are presented in Table 4. Large households, with large size land, distant from the market and are members in farmer groups are more likely to participate in market-oriented production. This is logical in that a household requires a rather large farm to produce for the market and such land is likely to be distant from the market. Farmer groups are likely to be a source of information and inputs which are important for market production.

Market production effects on technical efficiency (ATT) were estimated using kernel and radius matching methods. We impose a common support condition and Chi^2 test results (Table 1 Appendix) show very low pseudo

Table 3. A summary of technical efficiency scores for staple crops.

Efficiency level	Market-oriented households		Subsistence households		Pooled sample		t-values	
	Beans	Sweet potatoes	Beans	Sweet potatoes	Beans	Sweet potatoes	Beans	Sweet potatoes
Mean	0.58	0.53	0.65	0.67	0.63	0.64	4.9667***	6.0206***
Minimum	0.11	0.11	0.13	0.05	0.07	0.05	-	-
Maximum	0.87	0.90	0.91	0.94	0.91	0.94	-	-
Proportion of households < mean	41.6	50.7	36.1	38.2	41.9	44.1	-	-
Number of observations	336	138	493	390	829	626	-	-

*, ** and ***, significant at 10, 5 and 1%.

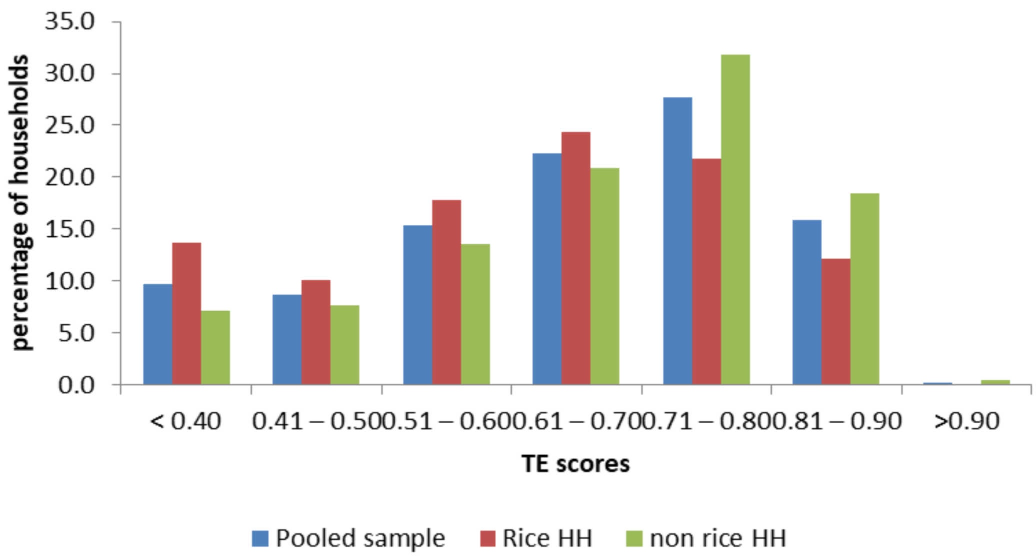

Figure 1. Distribution of technical efficiency scores in beans production.
Source: Survey conducted by the authors.

R2 not statistically significant after matching, and the covariate balancing test results show that all covariates are balanced (Table 2 Appendix). The distribution of propensity scores using kernel and radius matching are shown in Appendix Figure 1. The results are presented in Table 5. Consistent with descriptive statistics and the inefficiency coefficients we find that technical efficiency in staple crops is significantly lower for market-oriented households than for subsistence households. Results reveal that technical inefficiency in bean production is higher by 8.3%

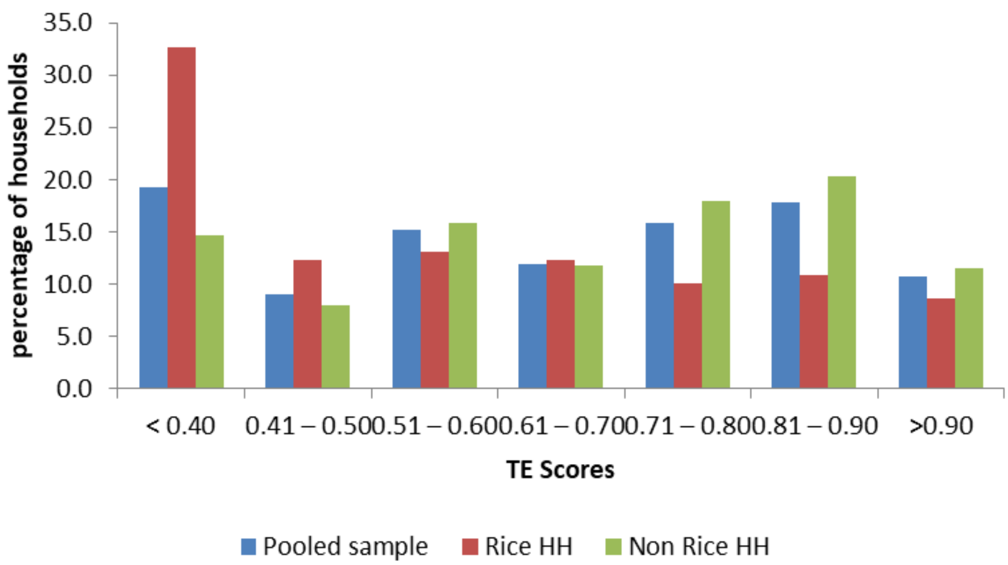

Figure 2. Distribution of technical efficiency scores for sweet potatoes.
Source: Survey conducted by the authors.

Table 4. Logistic regression for participating in rice market production.

Variable	Coefficient	Std. Err.	z
Age of household head	0.0416	0.0422	0.98
Age of household head^2	-0.001*	0.0005	-1.76
Education of household head (years)	-0.0370	0.0258	-1.43
Education of heads spouse (years)	-0.0122	0.0302	-0.4
Household size (no. Persons)	0.0525*	0.0316	1.66
size of land owned (ha)	0.4814***	0.0827	5.82
Size of land owned^2 (ha)	-0.0195***	0.0042	-4.65
Distance to road (km)	-0.0356	0.0519	-0.68
Distance to main market (km)	0.6089***	0.0600	10.14
Agriculture as main occupation=1, otherwise =0	0.5514	0.3876	1.42
Household has no secondary occupation	-0.2878	0.1855	-1.55
Member of farmer group =1; otherwise =0	1.0181***	0.1890	5.39
Constant	-4.2335***	0.9649	-4.39
Number of observations	816	-	-
Prob>chi^2	0.000	-	-
Pseudo R^2	0.268	-	-

*, ** and ***, significant at 10, 5 and 1%.

for market-oriented households compared to subsistence households. Similarly, in sweet potato production, technical inefficiency for market- oriented households is higher by 14.0%. The results are consistent for both kernel and radius matching. Sensitivity analysis using Rosenbaum bounds (Table 3 Appendix) shows that doubts on statistical significance of estimated results can occur if confounding factors cause the odds ratio of participating in market production to differ by a factor above 3.0 (DiPrete and Gangl, 2004). Thus, our results are robust.

The negative significant effects on technical efficiency may supposedly be attributed to withdrawal of critical labor inputs from staple foods when a household is producing a cash crop. A majority (61.2%) of households rely heavily on family labor for production of both staple and cash crop. This means that during peak periods of labor demand, family labor is constrained thus affecting timely field operations and consequently technical efficiency. This is affirmed by the significant positive

Table 5. Effects of market production on technical efficiency in production of staple crops.

Outcome	Matching algorithm	Number of treated	Number of controls	Mean TE treated	ATT (Std. error)	Critical level of hidden bias (Γ)
TE scores for beans	Kernel matching (band width = 0.05)	304	484	0.58	-0.083*** (0.0207)	Above 3
	Radius matching (caliper =0.05)	304	484	0.58	-0.082*** (0.0200)	Above 3
TE scores for sweet potatoes	Kernel matching (band width = 0.05)	134	463	0.54	-0.139*** (0.0247)	Above 3
	Radius matching (caliper =0.05)	134	463	0.54	-0.141*** (0.0258)	Above 3

*, ** and ***, significant at 10, 5 and 1%.

relationship of family as the main source of labor with technical inefficiency. Given the seasonality of the food crops combined with constant changes in weather conditions (e.g. sudden rainfall), management decisions on resource allocation hinge on priorities and the risks effects of timing actions (land preparation, planting, weeding and harvesting) on output of a particular crop. In such situations market-oriented households are more likely to prioritize the cash crop. It is also important to note that subsistence crops are mainly managed by women who are already burdened with other activities (Nakazi et al., 2017). Moreover, market-oriented households are likely to allocate the most productive land to the cash crop leaving marginal land for the staple crops hence affecting their technical efficiency. This argument is in line with the findings of Savadogo et al. (1998) in Burkina Faso. As pointed out by Neumann et al. (2010) inefficiency due to soil fertility constraints can be reduced by an effective land management. In situations where the farmer cannot improve the land quality through better soil management practices, allocating high quality land to the cash crop may seem to be a rational decision if the farmer gets higher utility from the cash crop. However, we are not able to establish whether market-oriented households are economically efficient, as this study did not measure allocative efficiency.

Are market-oriented households more technically efficient in cash crops than staples?

Considering the subsample of market-oriented households, we predict technical efficiency of their major food cash crop and staples. Table 6 presents a summary of the frequency distribution of technical efficiency scores.

Results show that on average market-oriented households could raise output of rice their main cash crop by 40% using the same inputs. However, it is possible that this would imply further delaying operations in staple crops and compromising technical efficiency in these crops. The estimated technical efficiency in rice production ranges from 0.25 to 0.87 and about 42.5% of the households have their technical efficiency score below the mean. Figure 3 shows that in the short run, over 70% of market-oriented households can increase their output in rice and bean production by adopting existing technologies and farming practices used by the best practice producers. While the highest technical efficiency score is recorded in sweet potato production, over 30% of market-oriented households scored less than 40% technical efficiency. A comparison of mean technical efficiency of the cash crop (rice) and the staple crops using a t-test reveals that market-oriented households are more technically efficient (p-value = 0.001) in production of rice compared to the staple crops. The result is consistent with our conjecture that market-oriented households may concentrate their management on production of the cash crop. This result contrasts the findings by Binam et al. (2004) who found no significant differences in technical efficiency among maize and groundnut cropping system.

Other factors influencing technical inefficiency

Other factors that influence technical inefficiency in food crops production include age of household head, education of the spouse of household head, the size of land owned and source of labor. The age of household head has a mixed relationship with technical inefficiency. While it decreases technical inefficiency in sweet potatoes, it increases technical inefficiency in rice production. This might be explained by the fact that older

Table 6. A summary of technical efficiency scores for the cash and staple crops.

Efficiency level	Market-oriented household		
	Rice	Beans	Sweet potatoes
Mean	0.60	0.58	0.53
Minimum	0.25	0.11	0.11
Maximum	0.87	0.87	0.90
Proportion of households < mean (%)	42.5	41.6	50.7
Number of observations	345	336	138

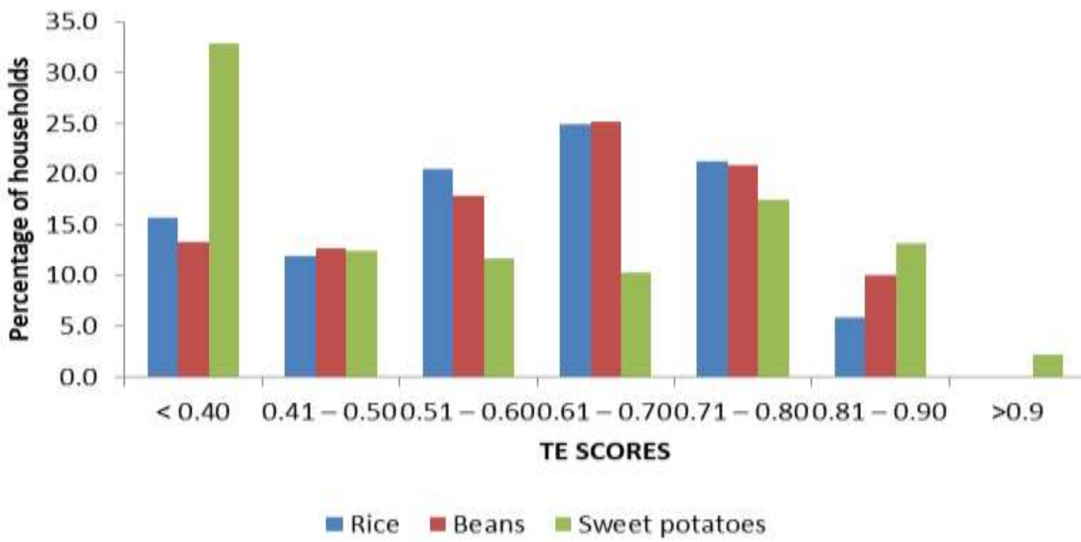

Figure 3. Distribution of technical efficiency scores for market-oriented households.
Source: Survey conducted by the authors.

household heads care more about the 'food security' staple crop (as sweet potato is commonly referred to) than the cash crop. It is likely that older household heads have bigger families to feed and therefore will tend to be efficient in staple crop production. A positive correlation between age and technical inefficiency in rice production seems to suggest that younger farmers are likely to be more technically efficient in production of a cash crop. This is perhaps due to physiological changes that affect managerial capability as well as strength and in turn labor productivity. Given that cash crops are usually managed by household heads, the aged are relatively less active, they may not easily source for information and therefore, they are likely to be inefficient in management of the cash crop hence increased technical inefficiency. The result is consistent with findings of Coelli and Fleming (2004) that age of household head increases technical inefficiency in the small holder mixed food and cash cropping system in Papua New Guinea due to increased difficulty in managing multiple tasks.

Technical inefficiency in beans production decreases with education of the household head's spouse. This result underscores the importance of formal education in agriculture (Reimers and Klasen, 2013). Farmers who are educated are more likely to access, process and use information relevant to crop production including ease of access to inputs and adoption of best practices/ technologies that increase technical efficiency. Moreover, education helps farmers become better managers of limited resources by enhancing their decision-making skills.

Contrary to what is commonly reported, that smaller farms tend to be more efficient, our results show a negative association between land size and technical inefficiency. This might be explained by the possibility that, households with bigger farms could be practicing land management practices such as crop rotation and fallowing that improve land productivity. Similar findings have been reported in Bangladesh (Wadud and White, 2000). It is also probable that some of the plots used by households owning very small land are rented. Such plots may not be very productive as many households will not rent out their best plots. Households who use mainly family labor are less technically efficient, presumably because they have limited time to manage all activities of their different crops at the same time. A negative relationship between membership in a savings and credit group and technical inefficiency may be associated with easy access to credit that may enable households timely access to inputs particularly seed and labor. A negative coefficient of distance to the market in rice production implies that efficiency increases as market-oriented farmers are further away from the market. This can be attributed to relatively easy access to labor and perhaps better plots as average land holdings tend to increase with distance from the market. Further, we observe significant effects on technical inefficiency associated with spatial dummy variables and this could be related to different soils.

Conclusion

The association between market production and technical efficiency in food crop production was explored empirically based on the hypothesis that market-oriented production increases technical efficiency in staple crop production. Technical efficiency of one major food cash crop and two staple crops was estimated and attempt was made to isolate the effects of the cash crop on technical efficiency of the staple crops using propensity score matching approach. We find high technical inefficiency in the selected crops across the household categories. We also find that technical inefficiency in staple crops is significantly higher in market-oriented households compared to subsistence households. We argue that market-oriented households are more likely to withdraw resources from staples to cash crop production and seem not to invest their income in crop production. We offer two possible explanations. The first relates to the timing of operations and therefore the effectiveness of labor. Market-oriented households may give precedence to their commercial crops, which in combination with seasonality of operations, would delay operations in staple crops, thereby compromising staple output. The second explanation is that, market-oriented households may allocate marginal land to staple crops, which would also lower output for staples. The implication is that, they may be getting optimal output from such land and therefore, the model overestimates market production effects. Including data on quality of plots allocated to the different crops in the frontier estimates would allow us to test for land quality effects. Regrettably we did not have the data. The present results should be interpreted with caution; we do not claim that market production causes inefficiency but rather, we show evidence that income from production may not be spent for efficiency enhancement in production of staple crops.

Despite the limitations, the findings show that, there is significant potential for households to increase output in both cash and staple crops by increasing technical efficiency. However, for market-oriented households, increasing staple crop production may partly require withdrawing some inputs from the cash crop. This decision can be driven by the utility the household gains from production of either the food or the cash crop. Extending this study to establish the allocative and economic efficiency of market-oriented households may be necessary. The results suggest that public policies aimed at enhancing market production should support innovations that increase technical efficiency. Supporting formal education for example in form of tailored adult literacy programs particularly for women who provide the bulk of agricultural labor might help farmers improve their management skills and hence improve technical efficiency of food crops. Accelerating the pace of adoption of better farming practices and labor-saving technologies may be necessary to facilitate timely operations and subsequently improve technical efficiency in the long run. Given the increasing demand for critical inputs, the agricultural economy in Uganda and generally sub-Saharan Africa will rely on the growth of total factor productivity other than growth of inputs. Considering the African agrarian economies, this study raises new questions for further research: Does farmer specialization in production of one or two crops increase technical efficiency? What are the risks and benefits?

CONFLICT OF INTERESTS

The authors have not declared any conflict of interest.

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Appendix

Table 1. Chi-square test for significance of variable before and after matching.

Outcome	Matching algorithm	Pseudo R2 Before matching	Pseudo R2 after matching	p>Chi^2 Before matching	p>Chi^2 after matching
TE scores for beans	Kernel matching (band width = 0.05)	0.262	0.010	0.000	0.719
	Radius matching (caliper =0.05)	0.269	0.010	0.000	0.724
TE scores for sweet potatoes	Kernel matching (band width = 0.05)	0.218	0.007	0.000	0.997
	Radius matching (caliper =0.05)	0.218	0.007	0.000	0.996

Table 2. Propensity score matching and covariate balancing test.

Variable		Mean		t-test	p>t
		Treated	Control		
Age of household head	Unmatched	42.461	42.715	-0.27	0.789
	Matched	42.424	43.98	-1.51	0.130
Square of age of household head	Unmatched	1951.8	2022.1	-0.80	0.426
	Matched	1953	2100.7	-1.51	0.131
Education of household head (years)	Unmatched	6.2952	6.0702	0.79	0.430
	Matched	6.3257	6.5617	-0.74	0.459
Education of heads spouse (years)	Unmatched	4.494	4.124	1.49	0.136
	Matched	4.5099	4.4231	0.32	0.752
Household size	Unmatched	6.8464	5.9731	4.21	0.000
	Matched	6.8059	6.7717	0.14	0.888
Size of land owned (ha)	Unmatched	2.3769	1.5366	4.15	0.000
	Matched	2.2309	2.6948	-1.94	0.052
Square of land size owned (ha)	Unmatched	13.074	11.609	0.28	0.783
	Matched	12.092	17.013	-1.31	0.190
Household distance to main road	Unmatched	1.7937	1.2684	3.64	0.000
	Matched	1.668	1.685	-0.11	0.916
Household distance to main market	Unmatched	4.6233	2.5513	13.86	0.000
	Matched	4.0877	3.8922	1.30	0.193
Main occupation agriculture = 1	Unmatched	0.95482	0.90289	2.76	0.006
	Matched	0.95724	0 .96833	-0.72	0.471
No secondary occupation = 1	Unmatched	0.49096	0 .56198	-2.00	0.046
	Matched	0.49671	0.53107	-0.85	0.397
Member of farmer group =1	Unmatched	0.66867	0.43595	6.71	0.000
	Matched	0.66118	0.70169	-1.07	0.285

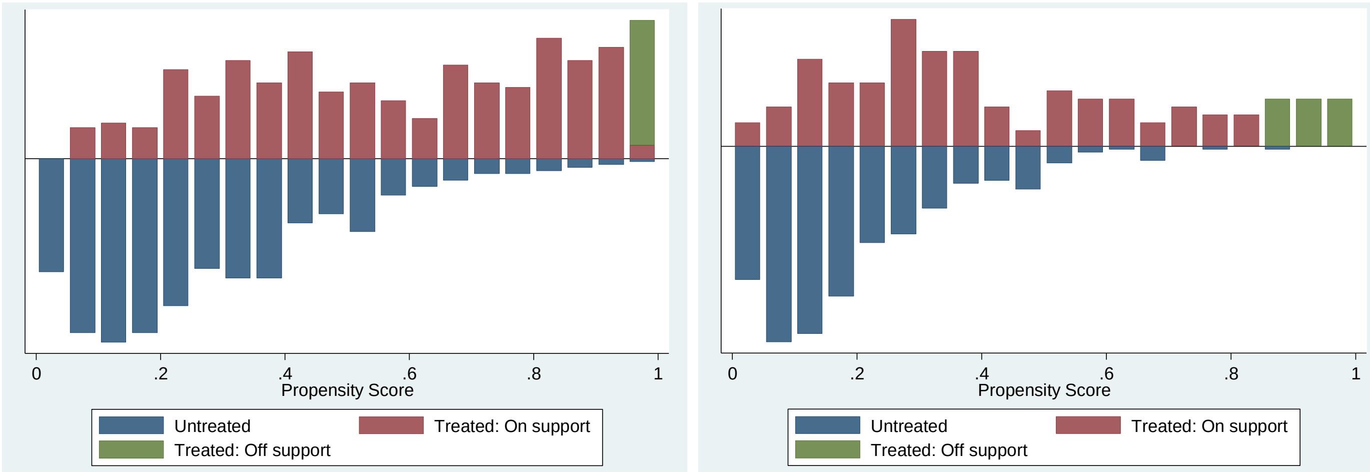

Figure 1. Distribution of propensity scores and the region of common support for beans and sweet potatoes (kernel matching).

Table 3. Sensitivity analysis: Rosenbaum bounds.

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	3.80E-11	3.80E-11	-0.0672	-0.0672	-0.08881	-0.04674
1.1	2.30E-13	3.40E-09	-0.07513	-0.05985	-0.09715	-0.03937
1.2	1.20E-15	1.30E-07	-0.08222	-0.05277	-0.10473	-0.03292
1.3	0	2.40E-06	-0.0889	-0.04661	-0.11201	-0.02707
1.4	0	0.000026	-0.09531	-0.04088	-0.11856	-0.02145
1.5	0	0.000187	-0.10119	-0.03585	-0.12482	-0.01649
1.6	0	0.000952	-0.10675	-0.03126	-0.13068	-0.01162
1.7	0	0.003658	-0.11207	-0.02704	-0.1365	-0.00751
1.8	0	0.01113	-0.11703	-0.02285	-0.1416	-0.00322
1.9	0	0.027883	-0.12161	-0.01897	-0.14651	0.00057
2	0	0.059352	-0.12606	-0.01545	-0.15127	0.004174
2.1	0	0.110141	-0.13039	-0.01195	-0.15581	0.007337
2.2	0	0.182054	-0.13442	-0.00878	-0.16016	0.010609
2.3	0	0.272935	-0.1383	-0.0059	-0.16471	0.013546
2.4	0	0.376928	-0.14201	-0.00293	-0.1686	0.016227
2.5	0	0.48598	-0.14553	-0.00032	-0.17229	0.01868
2.6	0	0.591856	-0.14894	0.002365	-0.17608	0.021614
2.7	0	0.687856	-0.15213	0.004793	-0.17992	0.024032
2.8	0	0.769755	-0.15528	0.00701	-0.18334	0.02653
2.9	0	0.835918	-0.15808	0.009207	-0.18688	0.028908
3	0	0.886813	-0.16134	0.011392	-0.19013	0.031171

gamma - log odds of differential assignment due to unobserved factors; sig+ - upper bound significance level; sig- - lower bound significance level; t-hat+ - upper bound Hodges-Lehmann point estimate; t-hat- - lower bound Hodges-Lehmann point estimate; CI+ - upper bound confidence interval (a= 0.95); CI- - lower bound confidence interval (a= 0.95).