Gender Differences in Agricultural Technology Adoption and Crop Productivity: Evidence from Malawi

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Abstract

There is limited evidence of the gender gaps in technology adoption and agricultural productivity after accounting for the differential access to factors of production. This study investigates gender differences in the adoption of improved agricultural technologies and crop productivity using nationally representative data collected from 1600 households and 5238 plots. We use a multivariate probit model to analyze gender differences in the adoption of improved technologies, including intercropping, improved varieties, crop rotation, manure, crop residue retention, and minimum tillage. To analyze gender differences in crop productivity, we use the exogenous switching regression model and recentered influence function decomposition. We find that female plot managers are more likely to adopt intercropping and minimum tillage and less likely to adopt improved varieties and crop rotation compared to male plot managers. Importantly, findings show that female-managed plots are 14.6-23.1% less productive than male-managed plots. The gender productivity gap results also indicate that female plot managers have a slight endowment advantage, yet a much greater structural disadvantage compared to male plot managers. The finding points to the need for policies and agricultural development programs that consider the underlying factors that shape gender productivity gaps, rather than focusing solely on the factors of agricultural production.

Key words: Improved agricultural technologies; Gender productivity gap; Multivariate probit; Exogenous switching regression; Recentered influence function decomposition; Malawi

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1. Introduction

Gendered non-land agricultural input, technology, and extension services gaps create noticeable productivity differences between women and men in lower-income countries (Peterman et al. 2014). Some studies show that the adoption of improved agricultural technologies and practices intended to increase productivity or enhance other agronomic outcomes is gendered, with men more likely to adopt than women (Doss and Morris, 2001; Peterman et al., 2014; Dontsop-Nguezet et al., 2016; Gaya et al., 2017). Other studies highlight the significance of labor shortages explaining women's lower levels of productivity (World Bank, 2014). FAO (2011) argues that women's farm yields could increase by 20 to 30% if they had the same access to productive resources as men do. These estimated gains would increase the total agricultural output by 2.5–4% in lower-income countries. The World Bank (2014), however, concludes that even with equal access to productive resources women would still have lower agricultural productivity given gender norms, institutional constraints, and market failures that impact how these resources are used by women.

In the economics literature, the endowment effect is described as the difference in the factors of agricultural production (or the levels of resources used in production) between women and men that determine the portion of the gender gap in productivity (World Bank, 2014). Factors of production can include, for example, age of the farmer, their use of improved agricultural technologies, their access to land and labor resources or extension services, or the number of years of formal education they obtained. Knowing what portion of the gender gap in productivity is explained by these factors can help to inform policies or interventions that aim to increase access to or ownership of the resources women lack. The structural effect, on the other hand, is the difference between women and men in their returns to a given amount of a factor of production that determines the portion of the gender gap in productivity (World Bank, 2014). Increasing women's access to improved agricultural technologies, for example, may not result in gender-equal productivity levels in this case as the structural effect highlights the underlying factors that shape gender gaps such as unequal formal and informal social institutions at the household, community or state levels that constrain women from using resources to increase their agricultural yields.

To date, various studies exploring the significant contribution of the endowment effect versus the structural effect of the gender gap in productivity have found mixed results. In Malawi, southern Nigeria, Uganda, Tanzania and Kenya, for instance, the endowment effect played a bigger role in explaining the differences in productivity between women and men (Fisher and Kandiwa, 2014; Kilic et al., 2015; Oseni et al., 2015; Ali et al., 2016; Slavchevska, 2015; Alene et al., 2008), while in Ethiopia and northern Nigeria, the structural effect explained more of the variation in the gender gap (Aguilar et al., 2015; Oseni et al., 2015). Likewise, across studies, there are clear differences in the main factors that contribute to the endowment or the structural effect. For instance, access to agricultural tools and the cultivation of high-value export crops were key factors that explained the endowment effect of the gender gap in productivity in Malawi that did not explain the structural effect (Kilic et al., 2015). In Niger, land size contributed significantly to explaining the endowment effect, while child dependency ratio was a key factor explaining the structural effect (Backiny-Yetna and McGee, 2015). In Nigeria, the endowment effect was explained by the number of adult females in the household and herbicide use per hectare, while the structural effect was explained by age and child dependency ratio (Oseni et al., 2015). In Uganda, production of cash crops, use of improved seeds, use of pesticides and assets owned by males contributed to the gap in the endowment effect, while child dependency ratio and number of household members contributed to the gap in the structural effect (Ali et al., 2016).

The majority of these previous studies use the Oaxaca–Blinder decomposition technique (Oaxaca, 1973; Blinder, 1973) to estimate the portion of the endowment and the structural effect to explain the gender gap in productivity. However, the Oaxaca–Blinder decomposition technique has limitations: (1) it is prone to specification errors and lacks a counterfactual; (2) the choice of the reference group may affect the ratio of endowment effect to the structural effect of the gap (Oaxaca, 1973; Sen, 2014); and (3) it overstates the contribution of the endowment effect (Elder et al., 2010). In this study, we use the recentered influence function (RIF) decomposition to account for the limitations of the Oaxaca–Blinder decomposition (Firpo et al., 2018; Rios Avila, 2019). We also use the exogenous switching regression and inverse probability-weighted regression adjustment (IPRWA) models as a robustness check for the results of the RIF decomposition.

This study contributes to the empirical literature in three ways. First, we use a multivariate probit model to assess the differences in the adoption rate of improved agricultural technologies and the determinants of adoption for female and male plot managers. Unlike the univariate probit that is commonly used in other studies, the multivariate probit accounts for the interdependency of the different improved agricultural technologies. Second, we investigate whether controlling for the adoption of improved technologies, which is a proxy for endowment, can significantly reduce the gender gap in agricultural productivity. To the best of our knowledge, there is no study that comprehensively accounts for the adoption of agricultural technologies in analyzing the gender gap in agricultural productivity. Third, we decompose the total gender gap in agricultural productivity using the more robust RIF decomposition and exogenous switching regression (ESR) techniques. Specifically, we use the RIF decomposition method to account for model specification errors and to identify a suitable counterfactual to accurately estimate the gender gap in agricultural productivity.

The rest of the paper is organized as follows. The next section presents survey design and data collection. The third section presents details of the theoretical model and empirical procedure. The fourth section describes the data used in the study. The fifth section presents and discusses the results and the last section concludes with implications for policy.

2. Survey design and data collection

This study uses nationally representative data collected from 1600 households and 5238 plots in six districts of Malawi (Lilongwe, Mchinji, Dedza, Ntchisi, Kasungu, and Mzimba). The data were collected in the 2016/17 cropping season using a standard questionnaire programmed in *Surveybe*[i] software and administered by trained enumerators. The data comprise characteristics of the household members, production and marketing of crops, assets of the household, access to extension and credit services, household expenditure, social capital and networking and general household characteristic (e.g. distance to the main market). The area of cultivated land was measured using a global positioning system (GPS) device.

3. Empirical models and procedures

One of the pathways through which the endowment effect influences productivity is through the adoption of improved technologies. For instance, a study conducted in Ghana showed that gender differences in adoption of modern maize varieties and chemical fertilizers resulted from the differences in access to inputs between women and men such as land, labor and extension services (Doss and Morris, 2001). The study provides evidence that the contribution of the endowment effect on the agricultural productivity gap between women and men farmers can be captured by controlling for the adoption of improved technologies. In this study, therefore, we first analyze gender differences in the adoption of improved technologies using a multivariate probit model that accounts for the interdependence of the decision to adopt improved technologies (Ndiritu et al., 2014). Second, using the ESR model and RIF decomposition technique, we analyze agricultural productivity differences between female- and male-managed plots. We analyze the agricultural productivity gap between female- and male-managed plots after controlling for the adoption of major agricultural technologies, including improved varieties and agronomic practices such as legume-cereal intercropping, crop rotation, residue retention, manure application and minimum tillage, as well as important socio-economic variables.

In this study, we consider six agricultural technologies: legume intercropping (I), improved varieties (S), crop rotation (C), manure (M), residue retention (R) and minimum tillage (Z). The decision to adopt these technologies can be influenced by the demographic and socioeconomic characteristics of households and plot managers and the characteristics of plots, the interdependence of the technologies, and the expected costs and benefits. Farmers adopt technologies if the potential benefits exceed the potential costs.

To be more specific, some or all of the six technologies can be correlated because (1) they can be adopted as complements and substitutes to address specific production constraints such as stresses, low crop productivity, and food needs and (2) the choice of the technologies by smallholder farmers may depend on previous choices. The interdependence in the decision of the adoption of these technologies can lead to a potential correlation among the unobserved disturbance terms in the adoption equations and hence biased estimates may be obtained if analyzed separately using a univariate probit model. Therefore, it is important to analyze using a multivariate probit model to obtain unbiased estimates of the determinants of adoption of multiple technologies.

We assess the gender gap in productivity using the ESR model (Kassie et al., 2014) and the RIF decomposition (Rios Avila, 2019). The ESR model and RIF decomposition take care of the interaction between the sex of the plot manager and other explanatory variables. In addition, the RIF decomposition has a feature that decomposes the productivity gap into a pure endowment and a pure structural effect and gives coefficient estimates for the factors that contribute to the endowment and structural effects.

3.1. Multivariate probit model

Adoption of agricultural technologies by smallholder farmers is effected by access to credit and information, farm size, human capital, mechanization, availability of inputs (e.g., seed, chemicals and water) and appropriate transportation infrastructure, among others (Croppenstedt et al., 2013; Feder et al., 1985). Furthermore, as female and male farmers do not have the same level of access to these resources, there are male-female differences in the extent of adoption of improved technologies (Doss and Morris, 2001). There is also interdependence in the adoption of agricultural technologies that are complementary or substitutes (Dorfman, 1996). We use a multivariate probit (MVP) model to examine the determinants of the gender difference in the adoption of improved technologies. The MVP model uses simultaneous interdependent systems of equations of adoption of different agricultural technologies (Belderbos et al., 2004; Gillespie et al., 2004; Khanna, 2001; Ndiritu et al., 2014; Wu & Babcock, 1998). The MVP model is expressed in two systems of equations (Gillespie et al., 2004; Ndiritu et al., 2014).

The first system of equation is a general one and can be expressed as below:

$$Y^*_{hpj} = \beta'_j x_{hp} + \varepsilon_{hp}, \qquad j = I, S, C, F, M, R, Z \qquad 2.$$

where Y^*_{hpj} is a latent (unobservable) dependent variable representing a level of benefit or utility derived from the adoption of $I, S, C, M, R\ and\ Z$. X_{hp} denotes observed characteristics of the plot manager, h, and plot, p. Plot managers adopt the agricultural technologies if the benefit from adoption exceeds that from non-adoption. The second system of equation expresses an observable binary choice of technologies by plot managers as follows:

$$T_{hpj} = \begin{cases} 1 & if\ Y^*_{hpj} > 0, and \\ 0 & otherwise \end{cases} \qquad 3.$$

where T_{hpj} is the adoption of the j^{th} agricultural technology by the h^{th} plot manager on p^{th} plot.

In this model, we assume the stochastic terms (ε_I, ε_S, ε_C, ε_F, ε_M, ε_R, and ε_Z) to be a jointly distributed multivariate normal random variable ($(MVN(0, \emptyset))$, where $\emptyset$ is a variance-covariance matrix as follows:

$$\emptyset = \begin{bmatrix} 1 & \rho 12 & \dots & \rho 1j \\ \rho 21 & 1 & \dots & \rho 2j \\ \rho 31 & \rho 32 & \dots & \rho 3j \\ \vdots & \vdots & & \vdots \\ \rho j1 & \rho t2 & & 1 \end{bmatrix} \quad 4.$$

The off-diagonal elements represent pairwise error terms correlation $rho(\rho)$ for any two adoption equations in the MVP model. According to Ndiritu et al. (2014), when there is a correlation between the error terms, the off-diagonal elements in the variance-covariance matrix of adoption equations become non-zero and equation 2 becomes a MVP model. A positive correlation shows a complementary relationship, while a negative correlation shows a substitute relationship.

3.2. Exogenous switching regression

We use an ESR model to examine the gender differences in productivity. The ESR model takes into account the interaction between sex of the plot manager and other explanatory variables. Following Kassie et al (2014), the ESR framework can be expressed as:

$$\begin{cases} Y_{hpf} = \delta_f x_{hpf} + u_f & \text{if } g = 1 \\ Y_{hpm} = \delta_m x_{hpm} + u_m & \text{if } g = 0 \end{cases} \quad 5.$$

where subscripts f and m represent the female plot manager and male plot manager, respectively. Y_{hpf} is productivity (MWK/ha) of p^{th} plot managed by a female; and Y_{hpm} is productivity (MWK/ha) of p^{th} plot managed by a male. Productivity is defined as total value per hectare of all crops grown on a plot. It should be noted that maize dominates in Malawi, grown by 97% of farmers on at least 60% to 80% of the total cultivated land (White, 2019; Gumma et al., 2019)[ii]. g is a gender dummy variable that equals 1 for female plot managers and 0 otherwise; x is a vector of plot manager, household, and plot characteristics; σ is a vector that captures how the productivity of female and male plot managers responds to the characteristics of the plot manager, household, and plot; and u represents the error terms with zero mean and constant variance.

We cannot estimate the gender difference in productivity from equation 4 as it is not possible to simultaneously observe one plot manager group in two states. To solve this problem, we estimate the counterfactual productivity of each group and compare the actual and counterfactual productivity estimates using equations 5a to 5d expressed as follows:

$$E(Y_{hpf}|g=1) = \delta_f x_{hpf} \qquad 5a.$$

$$E(Y_{hpm}|g=0) = \delta_m x_{hpm} \qquad 5b.$$

$$E(Y_{hpm}|g=1) = \delta_f x_{hpm} \qquad 5c.$$

$$E(Y_{hpf}|g=0) = \delta_m x_{hpf} \qquad 5d.$$

where E is the expected value operator.

We derive the actual productivity estimates from equation 4a for female plot managers and equation 4b for male plot managers using the observed data. The counterfactual productivity estimates, i.e., the productivity of male (or female) plot managers would have been, if the coefficients on their characteristics had been the same as the coefficients on the female (or male) plot managers, can be derived from equation 5c (or 5d).

The gender gap, the average treatment effect (ATT), i.e., if female plot managers have the same coefficient as male plot managers, is the difference between equations 5a and 5c (Kassie et al., 2014); and can be expressed as follows:

$$ATT = E(Y_{hpf}|g=1) - E(Y_{hpm}|g=1) = x_{hpf}(\delta_f - \delta_m) \qquad 6.$$

3.3. Recentered influence function (RIF) decomposition

RIF decomposition is an improved extension and refinement of the standard Oaxaca (Oaxaca, 1973) and Blinder (Blinder, 1973) techniques, together called OB decomposition (Fortin et al., 2011). RIF gives detailed contributions of individual covariates on aggregate decomposition (Rios Avila, 2019), unlike the ESR model. Following Rios Avila (2019), we assume $f_{Y,X,g}(y_i, x_i G_i)$ is a joint distribution function that describes all relationships between productivity (Y), household, plot managers and plot characteristics (X) and sex of the plot manager (G). The joint probability distribution function and cumulative distribution of Y conditional on (G) can be expressed as:

$$f^g{}_{Y,X}(y,x) = f^g{}_{Y|X}(Y|X) f^g{}_X(X) \qquad 7a.$$

$$F_Y^g(y) = \int F_{Y|X}^g(Y|X) dF_X^g(X) \qquad 7b.$$

where the superscript g represents that the density is conditional on $G = g$ with $g \epsilon [0,1]$. To analyze the difference in agricultural productivity between male plot managers ($g = 0$) and female plot managers ($g = 1$) for a given distributional statistic v, the cumulative conditional distribution of Y can be used to calculate the productivity gap:

$$\Delta v = v_1 - v_0 = v(F_Y^1) - v(F_Y^0) \qquad 8a.$$

$$\Delta v = v\left(\int F_{Y|X}^1(Y|X)dF_X^1\right) - v\left(\int F_{Y|X}^0(Y|X)dF_X^0(X)\right) \qquad 8b.$$

Equation $7b$ shows that the difference in the statistics Δv arises from differences in the distribution of Xs $(dF_X^1(X) \neq dF_X^0(X))$ and differences in the relationship between $Y$and $(dF_{Y|X}^1(Y|X) \neq dF_{Y|X}^0(Y|X))$. To decompose the overall productivity gap (Δv) into the gap due to the endowment effect and the gap due to the structural effect, we obtain the counterfactual using the statistic v_c (Rios Avila, 2019) that can be expressed as:

$$v_c = v(F_Y^c) = v\left(\int F_{Y|X}^0(Y|X)dF_X^1(X)\right) \qquad 9.$$

The gap in distribution statistic v can be disaggregated into two: the endowment (Δv_X) and the structural (Δv_s) effects as follows:

$$\Delta v = \underbrace{(v_1 - v_c)}_{\Delta v_s} + \underbrace{(v_c - v_0)}_{\Delta v_X} \qquad 10.$$

However, as outcomes and characteristics are not observed for the same plot manager group in two states, it is not possible to identify the counterfactual statistic v_c. We use semiparametric reweighting procedure suggested by DiNardo et al. (1996) to identify the counterfactual distribution $F_{Y|X}^0(Y|X)dF_X^1(X)$ based on the observed data. According to Rios Avila (2019), even though we cannot directly observe the distribution of outcomes and characteristics, we can approximate the counterfactual distribution by multiplying the observed distribution of characteristics $dF_X^0(X)$ with a factor $\omega(X)$ so it represents the distribution $dF_X^1(X)$. Therefore, the counterfactual function in equation 8 can be rewritten as:

$$F_Y^C = \int F_{Y|X}^0(Y|X) dF_X^1(X) \cong \int F_{Y|X}^0(Y|X) dF_X^0 (X)\omega(X) \qquad 11.$$

The reweighting factor $\omega(X)$ can be identified using the Bayes rule as follows:

$$\omega(\mathrm{X}) = \frac{\mathrm{dF_X^1(X)}}{\mathrm{dF_X^0(X)}} = \frac{\mathrm{dF_{X|G}(X|G=1)}}{\mathrm{dF_{X|G}(X|G=0)}} = \frac{\mathrm{dF_{X|G}(G=1|X)}}{\mathrm{dF_G(G=1)}} = \frac{\mathrm{dF_G(G=0)}}{\mathrm{dF_{G|X}(G=0|X)}} = \frac{1-\mathrm{P}}{\mathrm{P}} \frac{\mathrm{P(T=1|X)}}{1-\mathrm{P(T=1|X)}} \qquad 12.$$

where p is the proportion of plot managers in group $G = 1$ and $P(G = 1|X)$ is the conditional probability of a plot manager with characteristics X being part of group 1. This means that the counterfactual distribution, $F_{Y|X}^C$, can be identified by estimating the reweighting factor, $\omega(X)$, using parametric methods to estimate the conditional probability $P(G = 1|X)$. Probit or logit models can be used to estimate $P(G = 1|X)$ (Firpo et al., 2018). After obtaining the reweighting factors for the counterfactual statistic v_C, we can estimate a separate RIF regression for each group and the counterfactual as follows:

$$v_1 = E\left(RIF\left(y_i; v(F_Y^1)\right)\right) = \bar{X}^{1'} \hat{\beta}^1 \qquad 13a.$$

$$v_0 = E\left(RIF\left(y_i; v(F_Y^0)\right)\right) = \bar{X}^{0'} \hat{\beta}^0 \qquad 13b.$$

$$v_C = E\left(RIF\left(y_i; v(F_Y^C)\right)\right) = \bar{X}^{C'} \hat{\beta}^C \qquad 13c.$$

Therefore, the final decomposition components are defined as follows:

$$\Delta v = \underbrace{(\bar{X}^c - \bar{X}^m)'\hat{\beta}_m}_{\Delta v_X^p} + \underbrace{\bar{X}^{c`}(\hat{\beta}_c - \hat{\beta}_m)}_{\Delta v_X^e} + \underbrace{\bar{X}^{f`}(\hat{\beta}_f - \hat{\beta}_c)}_{\Delta v_S^p} + \underbrace{(\bar{X}^{f`} - \bar{X}^c)'\hat{\beta}_c}_{\Delta v_S^e} \qquad 14.$$

The components $\Delta v_X^p + \Delta v_X^e$ resemble the OB aggregate endowment effect and $\Delta v_S^p + \Delta v_S^e$ resemble the aggregate structural effect. While Δv_X^p and Δv_S^p represent a pure endowment effect and a pure structural effect, respectively, Δv_X^e and Δv_S^e assess the overall fitness of the model, and Δv_X^e is the specification error and assesses the importance of departure from linearity in the model specification or the RIF approximation (Rios Avila, 2019). A large and significant Δv_X^e shows that the model is mis-specified and the RIF is providing poor approximation to the distributional statistic v. Δv_S^e is the reweighting error and shows the quality of the reweighting strategy. The counterfactual is not well identified if Δv_S^e is large and significant, implying the need for modification of the specification of the logit model.

4. Variable definition and descriptive statistics

The variables included in this study were selected based on economic theory and past empirical work relating to the adoption of agricultural innovations (Croppenstedt et al., 2013; Doss, 2001; Doss et al., 2015; Feder et al., 1985; Kassie et al., 2014; Kristjanson et al., 2017; Ndiritu et al., 2014). Table 1 presents the definitions of the variables and their descriptive statistics disaggregated by sex of the plot manager. The results of the descriptive analysis show that female-managed plots are, on average, 15% less productive than male-managed plots. There are also considerable variations between the female and the male plot managers in their socioeconomic and plot characteristics. Female plot managers are older, less educated and less wealthy (less income and fewer assets), and use less amount of fertilizer, less likely to grow commercial crops such as tobacco and soybean compared to male plot managers. These results are consistent with the results of previous studies (Croppenstedt et al., 2013; UNWomen, 2015). The descriptive results also show that female plot managers have smaller household sizes than male plot managers. This result is also in agreement with World Bank (2014) that reports female farmers in Ethiopia, Malawi, north Nigeria, Tanzania and Uganda tend to live in households with fewer men and thus have fewer household members to provide labor on the farm. Female plot managers also have fewer numbers of relatives and non-relatives to rely on for critical support in times of need, were more reliant on government support, and reside farther away from district markets compared to their male counterparts. A greater percentage of female plot managers reside in households who follow a matrilineal kinship system compared to male plot managers whose households predominately follow a patrilineal system. The matrilineal system is the main kinship system followed in Lilongwe and Dedza districts, where Chewa are the dominate ethnic group (Berge et al., 2014).

We also find a considerable difference in the characteristics of the plots managed by female and male farmers in terms of land size, perceived soil fertility and perceived soil depth. Female plot managers cultivate smaller, less fertile and shallower plots compared to male plot managers. Compared to male-managed plots, higher proportions of female-managed plots are farther away from the residences of their plot managers.

Table 1. Mean socioeconomic and plot characteristics, by sex of the plot manager

Variable	Description	(1) Full sample	(2) Female plot manager	(3) Male plot manager	(4) Diff
Outcome variable					
Ln crop productivity	Log of total value of crop production (MKW/ha)	10.50(1.14)	10.39(1.21)	10.54(1.13)	-0.15***
Crop productivity	Total value of crop production (MWK/ha)	61586(892)	57169(1717)	62980(1041)	5811***
Socioeconomic characteristics					
Age	Age of plot manager (# of years)	44.55(14.79)	47.55(15.85)	43.59(14.32)	3.92***
Education	Education of plot manager (number of years of schooling)	6.59(3.98)	5.86(4.60)	6.82(3.73)	-0.96***
Joint decision	Decision on what to grow on the plot made jointly (1=yes)	0.80(0.40)	0.44(0.50)	0.91(0.29)	-0.47***
Main occupation	Main occupation of the plot manager was farming (1=yes)	0.93(0.25)	0.88(0.33)	0.95(0.22)	-0.07***
Household size	Number of household members	5.29(2.05)	4.87(2.02)	5.42(2.04)	-0.55***
Marriage system	Marriage system of household (1=matrilineal, 0=patrilineal)	0.64(0.48)	0.81(0.39)	0.59(0.49)	0.23***
Marital status (1=married)		0.85(0.36)	0.45(0.50)	0.97(0.15)	-0.53***
Membership	Household head and/or spouse membership in organization (1=yes)	0.37(0.48)	0.30(0.46)	0.39(0.49)	-0.09***
Traders	Number of traders known who can buy product	1.29(2.19)	1.20(1.94)	1.31(2.26)	-0.11
Government support	Reliance on government support if crops fail (1=yes)	0.65(0.48)	0.68(0.47)	0.64(0.48)	0.05***
Kinship	Number of relatives who be relies on in times of need	5.71(6.24)	5.10(4.82)	5.91(6.62)	-0.81***

Variable	Description	(1) Full sample	(2) Female plot manager	(3) Male plot manager	(4) Diff
Non kinship	Number of non-relatives who be relies on in times of need	5.87(9.99)	5.15(7.81)	6.10(10.57)	-0.95***
Labor	Labor used (man-day/ha)	144.97(81.15)	145.01(77.06)	144.96(82.42)	0.05
Fertilizer	Fertilizer used (kg/ha)	93.58(145.43)	81.13(131.02)	97.53(149.51)	-16.40***
Asset	Value of asset (MWK/adult equivalent)	102,869(158,497)	72,488(140,660)	112,548(162,600)	-40,059***
Income	Per capita expenditure (MWK/person/year)	73,688(59,162)	66,369(64,433)	75,998(57,212)	-9,629***
TLU	Total livestock holding in TLU	0.76(4.49)	0.40(2.10)	0.88(5.01)	-0.48***
Tobacco	Plot planted to tobacco (1=yes)	0.024(0.15)	0.005(0.07)	0.030(0.17)	-0.025***
Soybean	Plot planted to soybean (1=yes)	0.229(0.42)	0.195(0.397)	0.240(0.427)	-0.045***
Common beans	Plot intercropped with common beans (1=yes)	0.129(0.34)	0.158(0.37)	0.120(.33)	0.038***
Groundnut	Plot planted to groundnut (1=yes)	0.161(037)	0.173(0.38)	0.157(0.36)	0.016
Extension contact	Number of days of contact with extension personnel	0.59(2.10)	0.64(2.42)	0.58(1.99)	0.06
Credit	Access to credit (1=yes)	0.26(0.44)	0.27(0.44)	0.26(0.44)	0.01
Distance	Distance to the nearest district market (minutes of walking time)	127.03(130.10)	138.24(219.36)	123.49(83.90)	14.75***
Plot characteristics					
Plot area	Area of the plot (ha)	0.34(0.31)	0.28(0.26)	0.36(0.32)	-0.08***
Plot distance	Plot distance from residence (minutes of walking time)	24.98(31.34)	26.56(33.07)	24.49(30.76)	2.07**
Poor fertility	Perceived fertility of the plot was poor (1=yes)	0.23(0.42)	0.27(0.44)	0.22(0.41)	0.05***

Variable	Description	(1) Full sample	(2) Female plot manager	(3) Male plot manager	(4) Diff
Medium fertile	Perceived fertility of the plot was medium fertile (1=yes)	0.52(0.50)	0.51(0.50)	0.53(0.50)	-0.02
Very fertile	Perceived fertility of the plot was very fertile (1=yes)	0.25(0.430)	0.22(0.416)	0.25(0.435)	-0.03**
Shallow	Perceived depth of the soil was shallow (1=yes)	0.19(0.39)	0.22(0.42)	0.17(0.38)	0.05***
Medium deep	Perceived depth of the soil was medium deep (1=yes)	0.51(0.50)	0.47(0.50)	0.53(0.50)	-0.06***
Deep	Perceived depth of the soil of the plot was deep (1=yes)	0.30(0.46)	0.30(0.46)	0.29 (0.46)	0.01
Flat	Perceived slope of the plot was flat (1=yes)	0.60(0.49)	0.59(0.49)	0.61(0.49)	-0.02
Medium	Perceived slope of the plot was medium (1=yes)	0.25(0.43)	0.24(0.43)	0.25(0.44)	-0.01
Steep	Perceived slope of the plot was steep (1=yes)	0.14(0.35)	0.16(0.37)	0.14(0.35)	0.02*
Owner plot	Owner managed plot (1=yes)	0.85(0.36)	0.88(0.33)	0.84(0.37)	0.04***
Location (the plot is in …)					
Lilongwe	1=yes	0.25(0.43)	0.31(0.46)	0.24(0.42)	0.07***
Mchinji	1=yes	0.25(0.43)	0.20(0.40)	0.27(0.44)	-0.07***
Dedza	1=yes	0.20(0.40)	0.27(0.45)	0.17(0.38)	0.10***
Ntchisi	1=yes	0.13(0.34)	0.11(0.31)	0.14(0.35)	-0.04***
Kasungu	1=yes	0.11(0.31)	0.06(0.24)	0.12(0.33)	-0.06***
Mzimba	1=yes	0.05(0.23)	0.05(0.21)	0.06(0.23)	-0.01

Standard deviations are in parenthesis
$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Table 2 presents plot level adoption of agricultural technologies, disaggregated by sex of the plot manager. The results show that crop rotation and improved crop varieties were adopted on 69%

and 61% of female-managed plots and on 80% and 71% of male-managed plots, respectively. Crop residue retention and intercropping were adopted on 47% and 32% of plots managed by females, and 50% and 22% of plots managed by males, respectively. The adoption of minimum tillage was very low at 5% on female-managed plots and 3% on male-managed plots. These results show that intercropping and minimum tillage were practiced more on female-managed plots than on male-managed plots, whereas technologies such as improved varieties, crop rotation and crop residue retention were applied more on male-managed plots than on female-managed plots. Some of these results are in accordance with the results of a study conducted in Malawi that found that the incidence of intercropping was higher in female-managed plots than in male-managed plots (Kilic et al., 2015). There was no significant difference found between female-managed plots and male-managed plots with regards to the use of manure. In Malawi, various input subsidy programs have supplied chemical fertilizers and improved varieties to smallholder farmers since the 1970s (Nkhoma, 2018). The result of the study that used nationally representative data from the 2010/2011 farming season in Malawi [the third integrated household survey (IHS3)] revealed that the farm input subsidy program (FISP) reduced the gap between female and male farmers in the adoption of agricultural technologies (Fisher and Kandiwa, 2014). For manure, our result is consistent with the finding of Holden and Lunduka (2012) who showed limited use of manure in the country.

Table 2. Plot level adoption of agricultural technologies ((1=yes) by sex of the plot manager

	Full sample	Female plot manager	Male plot manager	
Technology	Mean(SD)	Mean(SD)	Mean(SD)	Diff
Intercropping	0.248(0.432)	0.325(0.469)	0.223(0.417)	0.102***
Improved seed	0.686(0.464)	0.607(0.489)	0.712(0.453)	-0.105***
Crop rotation	0.770(0.421)	0.691(0.462)	0.795(0.403)	-0.104***
Manure use	0.157(0.363)	0.153(0.360)	0.158(0.365)	-0.005
Crop residue retention	0.496(0.500)	0.471(0.499)	0.504(0.500)	-0.033**
Minimum tillage	0.035(0.184)	0.052(0.222)	0.030(0.170)	0.022***

$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

5. Empirical results and discussion

The likelihood ratio test results presented in Table 3 show that the null hypothesis of independent error terms is rejected $(chi^2(15) = 116.194, p > chi^2 = 0.00)$. The results of the correlation analysis show significance in 8 out of 15 pairwise correlation coefficients between error terms of adoption equations. These results imply that the probability of adoption of some of the agricultural technologies is not independent of the decision to adopt other technologies and thus justifies our choice of the MVP model. More specifically, the estimates of the correlations between the error terms are negative and significant for improved varieties and intercropping, crop rotation and intercropping, and manure and crop rotation, suggesting substitutability of the technologies. On the other hand, the estimates of the correlations between the error terms are positive and significant for manure and intercropping, residue retention and improved varieties, and minimum tillage and manure, and minimum tillage and residue retention, showing their complementarities.

Table 3. Correlation coefficients of error terms obtained from multivariate probit model estimation

Binary correlation	Correlation coefficient	Robust standard error
rho21: Improved varieties and intercropping	-0.055**	0.026
rho31: Crop rotation and intercropping	-0.060**	0.029
rho41: Manure use and intercropping	0.190***	0.031
rho51: Crop residue retention and intercropping	0.024	0.028
rho61: Minimum tillage and intercropping	-0.023	0.047
rho32: Crop rotation and improved varieties	-0.019	0.025
rho42: Manure use and improved varieties	0.038	0.031
rho52:Crop residue retention and improved varieties	0.061***	0.023
rho62: Minimum tillage and improved varieties	0.030	0.046
rho43: Manure use and crop rotation	-0.086***	0.029
rho53: Crop residue retention and crop rotation	0.100***	0.032
rho63: Minimum tillage and crop rotation	0.012	0.052
rho54: Residue retention and manure use	0.008	0.027
rho64: Minimum tillage and manure use	0.101**	0.049
rho65: Minimum tillage and crop residue retention	0.133***	0.051

Likelihood ratio test of rho21=rho31=rho41=rho51=rho61=rho32=rho42=rho52=rho62=rho43=rho53=rho63=rho54=rho64=rho65=0 chi2 (15)= 16.194 Prob>chi2=0.0000 where rho1=Intercropping; rho2=improved varieties; rho3=crop rotation; rho4=manure application; rho5=crop residue retention; rho6=minimum tillage.

Table 4 presents the results from the MVP regression for all agricultural technologies. The results show that female plot managers are more likely to adopt intercropping and minimum tillage after controlling for other covariates. The adoption of intercropping could be related to female farmers' preferences for the production of diverse crops used for home consumption (Croppenstedt et al., 2013) or a function of their socially-assigned roles as food crop producers. Contrary to the findings of Ndiritu et al. (2014) for Kenya, our results show that female plot managers are more likely to adopt minimum tillage compared to male plot managers. Ndiritu et al. (2014) argue that female farmers may lack the resources such as labor, knowledge, livestock, and credit required for the adoption of minimum tillage and minimum tillage is also relatively new where more time and information are needed to explain the adoption process. However, in Malawi, the greater likelihood of adoption of minimum tillage by female plot managers could be due to seasonal labor constraints that female farmers face and the presence of many NGOs that target female farmers when promoting minimum tillage. Male plot managers are more likely to adopt manure because, as shown in Table 1, they own more livestock than female plot managers.

Table 4. Multivariate probit model estimates of adoption of interrelated agricultural technologies in Malawi

Variable	Intercropping	Improved varieties	Crop rotation	Manure	Residue	Minimum tillage
Plot manager sex (1=female)	0.353***(0.07)	-0.097(0.07)	-0.089(0.10)	-0.133*(0.07)	-0.001(0.10)	0.276**(0.12)
Age	-0.005(0.01)	0.024**(0.01)	0.017(0.01)	-0.004(0.01)	0.005(0.01)	-0.015(0.02)
Age squared	0.000(0.00)	-0.000***(0.00)	-0.000(0.00)	0.000(0.00)	-0.000(0.00)	0.000(0.00)
Education	-0.012**(0.01)	0.015***(0.01)	0.007(0.01)	0.000(0.01)	0.016*(0.01)	0.002(0.01)
Joint decision	0.240***(0.08)	-0.101(0.07)	-0.007(0.10)	-0.054(0.08)	0.563***(0.11)	0.263(0.19)
Adult female labor (man-day/ha)	0.211***(0.06)	-0.041(0.06)	-0.028(0.09)	0.041(0.07)	-0.029(0.10)	0.128(0.12)
Adult male labor (man-day/ha)	0.112*(0.06)	-0.054(0.06)	0.011(0.09)	-0.069(0.07)	-0.220**(0.09)	0.101(0.11)
Child dependency ratio	0.234(0.15)	0.193(0.15)	0.114(0.20)	-0.133(0.17)	-0.023(0.20)	0.008(0.32)
Marriage system	-0.112**(0.06)	0.092*(0.06)	0.163**(0.07)	-0.008(0.06)	-0.067(0.08)	0.057(0.11)
Marital status	-0.015(0.10)	0.158*(0.09)	0.095(0.12)	0.029(0.09)	-0.357***(0.13)	-0.116(0.23)
Membership	0.133**(0.06)	0.039(0.05)	0.232***(0.07)	0.067(0.06)	0.141*(0.08)	0.081(0.09)
Traders	0.010(0.01)	0.013(0.01)	0.009(0.02)	0.010(0.01)	-0.018(0.02)	0.015(0.02)
Government support	-0.056(0.05)	-0.002(0.05)	-0.192***(0.07)	0.065(0.06)	0.127*(0.07)	0.058(0.11)
Kinship	-0.002(0.00)	0.003(0.01)	0.004(0.01)	-0.010*(0.01)	-0.009(0.01)	-0.015(0.01)
Non kinship	0.003(0.00)	-0.000(0.00)	0.004(0.00)	0.002(0.00)	0.002(0.00)	-0.005(0.01)
Ln plot area (ha)	0.581***(0.03)	0.046**(0.02)	-0.105***(0.02)	0.191***(0.03)	0.079***(0.02)	-0.070**(0.03)

Variable	Intercropping	Improved varieties	Crop rotation	Manure	Residue	Minimum tillage
Ln total area (ha)	-0.537***(0.05)	0.095**(0.04)	0.289***(0.06)	-0.184***(0.06)	-0.078(0.05)	0.056(0.09)
Plot distance	-0.002**(0.00)	0.000(0.00)	0.001(0.00)	-0.003***(0.00)	-0.001(0.00)	-0.002(0.00)
Fertile soil (1=yes)	0.008(0.05)	0.104**(0.05)	-0.054(0.06)	0.085(0.06)	0.087(0.07)	0.102(0.09)
Deep soil	-0.133**(0.05)	0.219***(0.05)	-0.070(0.07)	0.117**(0.06)	-0.355***(0.08)	-0.007(0.08)
Flat slope	0.027(0.05)	-0.027(0.04)	0.055(0.06)	0.054(0.05)	0.034(0.06)	-0.328***(0.08)
Ln per capita income	0.113***(0.04)	0.111***(0.04)	0.125**(0.05)	-0.047(0.04)	-0.046(0.05)	0.040(0.08)
Ln TLU	0.010(0.02)	0.001(0.02)	-0.035(0.02)	0.031*(0.02)	0.044**(0.02)	-0.008(0.03)
Extension contact	-0.011(0.01)	0.039***(0.01)	0.010(0.02)	0.003(0.01)	0.017(0.02)	0.044**(0.02)
Credit	0.075(0.06)	-0.048(0.06)	-0.125*(0.07)	0.062(0.06)	-0.129(0.08)	-0.186*(0.10)
Distance	-0.000(0.00)	-0.000(0.00)	-0.001**(0.00)	-0.000(0.00)	-0.000(0.00)	0.000(0.00)
Lilongwe	0.254**(0.10)	-0.199*(0.11)	-0.763***(0.13)	0.744***(0.12)	0.123(0.14)	0.354*(0.20)
Mchinji	-0.231**(0.10)	0.013(0.11)	-0.477***(0.13)	0.527***(0.11)	0.226*(0.14)	0.070(0.19)
Dedza	0.757***(0.10)	-0.333***(0.11)	-0.984***(0.14)	0.840***(0.12)	0.317**(0.14)	-0.157(0.22)
Ntchisi	-0.068(0.11)	-0.005(0.12)	-0.007(0.16)	0.284**(0.11)	0.045(0.17)	-0.067(0.21)
Mzimba	-0.269*(0.15)	0.040(0.14)	-0.080(0.16)	0.110(0.18)	-0.003(0.18)	0.022(0.23)
Constant	-1.335**(0.54)	-1.234**(0.57)	-0.851(0.79)	-0.563(0.62)	0.376(0.75)	-2.101*(1.11)
N	5202					

Log pseudo likelihood = -14320.817
Wald chi2(186) = 3490.92***
Robust standard errors adjusted for 323 clusters at village level and are in parentheses
$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Table 5 presents the estimates of the ESR model. The results show that the conditional productivity gap is 21% in favor of male plot managers. This conditional productivity gap is higher than the unconditional productivity gap indicated in Table 1. The results of the pooled regression show that crop productivity is significantly related to labor, fertilizer, asset ownership, cultivated land, production of tobacco, production of soybean, production of groundnut, soil fertility, the slope of the plot, and district dummies. Crop productivity is also significantly related to the adoption of intercropping, improved varieties, and crop residue retention. These variables with significant coefficient estimates in the pooled regression show the presence of endowment differences between female and male plot managers (see Ali et al., 2016). For some variables, the coefficient estimates for female plot managers are different than those of male plot managers, indicating the superiority of the ESR model compared to the pooled[iii] regression model. The variables with noticeable differences in the size of coefficient estimates between female and male plot managers are child dependency ratio, labor, fertilizer, assets, cultivated land, tobacco production, soybean production, plot characteristics, and adoption of intercropping, improved varieties, crop residue retention, and minimum tillage. A 1% increase in the rate of labor use is associated with a 0.084% and 0.141% increase in crop productivity on female- and male-managed plots, respectively. Likewise, a 1% increase in fertilizer use is associated with a 0.179% increase in crop productivity on female-managed plots and a 0.194% increase on male-managed plots. By contrast, a 1% increase in the size of cultivated land is associated with a 0.627% and 0.482% decrease in crop productivity on plots managed by females and males, respectively, due to the inverse farm size productivity relationship (Ali et al., 2016).

Table 5. Exogenous switching regression (ESR) estimates of crop productivity by sex of the plot manager in Malawi

Variable	(1) Pooled sample	(2) Female managed plot	(3) Male managed plot
Plot manager sex (female=1)	-0.210***(0.03)		
Age (# of years)	0.005(0.01)	-0.006(0.01)	0.006(0.01)
Age squared	-0.000(0.00)	0.000(0.00)	-0.000(0.00)
Education	-0.002(0.00)	-0.001(0.01)	-0.001(0.00)
Marriage system	0.053*(0.03)	0.118(0.08)	0.042(0.03)
Child dependency ratio	-0.089(0.08)	-0.184(0.16)	-0.107(0.09)
Labor used (man-day/ha)	0.129***(0.02)	0.084(0.05)	0.141***(0.03)
Fertilizer used (kg/ha)	0.188***(0.01)	0.179***(0.01)	0.194***(0.01)
Value of asset (MWK/adult equivalent)	0.092***(0.01)	0.087***(0.02)	0.093***(0.01)
Ln total area (ha)	-0.516***(0.02)	-0.627***(0.05)	-0.482***(0.03)
Tobacco	1.032***(0.09)	1.169***(0.45)	1.007***(0.09)
Soybean	0.509***(0.04)	0.366***(0.09)	0.557***(0.05)
Common beans as intercrop (1=yes)	0.110**(0.05)	0.119(0.10)	0.112*(0.06)
Groundnut	0.760***(0.05)	0.778***(0.10)	0.766***(0.05)

Variable	(1) Pooled sample	(2) Female managed plot	(3) Male managed plot
Poor fertility	-0.111***(0.03)	-0.182***(0.07)	-0.094**(0.04)
Steep	-0.076**(0.04)	-0.132*(0.08)	-0.068(0.04)
Shallow	-0.006(0.04)	0.114(0.08)	-0.049(0.04)
Lilongwe	-0.225***(0.05)	-0.246*(0.13)	-0.205***(0.06)
Mchinji	-0.016(0.05)	-0.060(0.13)	-0.006(0.05)
Dedza	-0.333***(0.05)	-0.353***(0.13)	-0.323***(0.06)
Ntchisi	0.198***(0.05)	0.203(0.14)	0.206***(0.06)
Mzimba	-0.315***(0.07)	-0.354**(0.17)	-0.281***(0.08)
Intercropping	0.526***(0.04)	0.626***(0.08)	0.479***(0.05)
Improved variety	0.075**(0.03)	0.084(0.06)	0.076**(0.03)
Crop rotation	0.056*(0.03)	0.038(0.06)	0.072*(0.04)
Manure use	0.074*(0.04)	0.104(0.08)	0.060(0.04)
Crop residue retention	0.074***(0.03)	-0.002(0.06)	0.089***(0.03)
Minimum tillage	0.022(0.07)	-0.209(0.13)	0.162*(0.09)
Constant	8.097***(0.21)	8.484***(0.45)	7.958***(0.25)
N	5238	1256	3982

Standard errors in parentheses
$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Table 6 presents the estimates of the gender crop productivity gap results after running the ESR model. After controlling for the adoption of improved agricultural technologies, we expected no significant productivity differences to emerge between female and male managed plots, but this was not the case. Female-managed plots are less productive by 18.86% compared to plots managed by males. The significant result found could be due to the differences in the characteristics of plots managed by females and males. Our results show that female-managed plots are more likely to be less fertile, steeper and shallower. In our analysis, we used perceived soil fertility, depth and plot slope, which may not be an accurate measure of soil fertility. A study conducted in Kenya showed that farmers' reported soil fertility status does not predict observed soil fertility (Berazneva et al., 2018). Another reason for the persistence of the gender productivity gap after controlling for access to assets and technologies could be a difference in labor productivity. The results of our study also show that the labor, fertilizer, and asset (a proxy for capital) productivities are lower for female plot managers compared to male plot managers. While not a strictly similar comparison, a study conducted in Malawi revealed that agricultural labor productivity on plots managed by female household heads was 44% lower than that on plots managed by male household heads (Palacios-López and López, 2015). Our results are also in agreement with the findings of Karamba and Winters (2015) who found that equal participation of women and men farmers in Malawi in the input subsidy program did not remove the gender gap in agricultural productivity, suggesting that women farmers face additional constraints to productivity apart from access to non-labor agricultural inputs.

Table 6. Estimates of gaps in productivity between female and male plot managers

Sex of plot manager	Observed	Counterfactual	ATT§
Female (n=1,256)	10.3956(0.020)	10.5842(0.018)	-0.1886***(0.006)
Male (n=3,982)	10.5414(0.010)	10.2606(0.011)	0.2808***(0.003)
Base-heterogeneity	-0.1458	0.3236	

Standard errors in parentheses
$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$
§ATT represents the average treatment effect, i.e., if female plot managers have the same coefficient as male plot managers,

However, the ESR model does not decompose the productivity into the endowment effect (difference in distribution) and the structural effect (technical efficiency) and does not provide coefficient estimates for the factors that contribute to the endowment as well as structural effects. These coefficients are very important to estimate as they enable us to make policy recommendations. We use the RIF technique to decompose the gender productivity gaps into an endowment effect and a structural effect and to determine the factors that influence these effects. RIF decomposes the gender productivity gap based on the base-heterogeneity reported in Table 6.

Table 7 presents the results of the RIF decomposition. The main results show that female-managed plots are on average 14.6% less productive than male-managed plots. Besides, the cumulative distribution function for crop productivity on RIF decomposition estimates for male plot managers dominated those of the female plot managers for all productivity levels (Figure 1). The non-parametric Kolmogorov-Smirnov test for first-order stochastic dominance reveals that the cumulative distribution function of male plot managers stochastically dominates (p<0.01) that of the female plot managers for crop productivity, showing that, if randomly chosen, there is a higher probability that male plot managers will on average have higher crop productivity than female plot managers. A decomposition of the total gender productivity gap into a total endowment effect and a total structural effect shows that female plot managers have an overall endowment advantage of 3.8% and an overall structural disadvantage of 18.4%. The results also show nonsignificant specification and reweighting errors, implying that our model is correctly specified and the counterfactual is correctly identified. After correcting for specification and reweighting errors, we found that female plot managers have a pure endowment advantage of 8.2% and a pure structural disadvantage of 23.1%. The pure structural effect of 23.1% is similar to the result of the IPWRA (results will be available on request). The similarity is because RIF decomposition uses reweighting like the IPWRA model. The structural effect can also be identified and interpreted as a treatment effect under the assumption of conditional independence and overlapping support (Rios Avila, 2019).

The main contributor to the endowment advantage for female plot managers is ownership of cultivated land. There is an inverse relationship between cultivated land and productivity for female- and male-managed plots but the relationship is stronger on female-managed plots due to a smaller cultivated area (0.28 vs. 0.36 ha). This finding is consistent with the result found by Ali et al. (2016) in the case of Uganda, where female plot managers face a very strong inverse relationship between productivity and land size. Other factors that contribute to the female plot managers' endowment advantage include groundnut production and cereal-legume intercropping. There are also factors that contributed to the endowment disadvantage of female plot managers. The most notable factors are fertilizer use, amount of capital per adult equivalent, tobacco production, soybean production, and adoption of improved varieties and minimum tillage. Most of these results are intuitive as female farmers in Malawi often have less access to farm inputs due to a shortage of cash (UNWomen, 2015).

Table 7. RIF decomposition estimates of the gaps in productivity between female and male plot managers in Malawi

	Overall ln productivity (MWK/ha)	Total explained difference		Total unexplained difference	
		Pure explained	Specification error	Pure unexplained	Reweight error
Male plot manager	10.541***(0.03)				
Counterfactual	10.357***(0.11)				
Female plot manager	10.396***(0.04)				
Total difference	0.146***(0.05)				

Table 7. RIF decomposition estimates of the gaps in productivity between female and male plot managers in Malawi

	Overall ln productivity (MWK/ha)	Total explained difference		Total unexplained difference	
		Pure explained	Specification error	Pure unexplained	Reweight error
Total explained difference	-0.038(0.10)				
Total unexplained difference	0.184(0.12)				
Corrected differences		-0.082(0.06)	0.044(0.05)	0.231**(0.10)	-0.046(0.09)
Age		0.028(0.03)	0.475(0.65)	0.037(1.12)	0.003(0.02)
Age squared		-0.008(0.02)	-0.320(0.31)	0.122(0.52)	-0.003(0.02)
Education		-0.002(0.00)	0.065(0.08)	-0.061(0.12)	-0.002(0.01)
Marriage system		-0.032***(0.01)	0.055(0.06)	-0.104(0.12)	0.010(0.02)
Child dependency ratio		-0.004(0.00)	0.059(0.08)	-0.042(0.14)	0.001(0.01)
Labor used (man-day/ha)		0.002(0.00)	0.055(0.47)	0.221(0.76)	-0.004(0.01)
Fertilizer used (kg/ha)		0.090**(0.04)	0.040(0.08)	0.000(0.11)	-0.061(0.05)
Value of asset (MWK/adult equivalent)		0.058***(0.01)	0.257(0.49)	-0.189(0.80)	-0.011(0.01)
Ln area (ha)		-0.296***(0.07)	0.002(0.02)	0.023(0.02)	0.054(0.08)
Tobacco		0.065(0.04)	0.014(0.02)	-0.012(0.01)	-0.042(0.05)
Soybean		0.005(0.01)	0.019(0.04)	0.024(0.08)	0.014(0.01)
Common beans as intercrop		-0.002(0.00)	0.005(0.03)	-0.005(0.03)	-0.003(0.01)
Groundnut		-0.022*(0.01)	-0.014(0.02)	0.013(0.04)	0.008(0.01)
Poor fertile		0.015***(0.00)	-0.014(0.02)	0.035(0.04)	-0.009(0.01)
Flat		0.005**(0.00)	0.002(0.02)	0.006(0.03)	-0.001(0.00)
Shallow		-0.009***(0.00)	-0.004(0.02)	-0.024(0.03)	0.003(0.01)
Lilongwe		0.018**(0.01)	-0.029(0.06)	0.038(0.10)	-0.000(0.01)
Mchinji		-0.003(0.00)	-0.015(0.07)	0.031(0.12)	-0.003(0.01)
Dedza		0.035***(0.01)	-0.045(0.05)	0.049(0.08)	0.003(0.02)
Ntchisi		0.012(0.01)	-0.038(0.04)	0.033(0.06)	0.001(0.01)

Table 7. RIF decomposition estimates of the gaps in productivity between female and male plot managers in Malawi

	Overall ln productivity (MWK/ha)	Total explained difference		Total unexplained difference	
		Pure explained	Specification error	Pure unexplained	Reweight error
Mzimba		-0.001(0.00)	-0.007(0.02)	0.012(0.03)	-0.002(0.01)
Intercropping		-0.054***(0.01)	-0.043(0.03)	0.007(0.05)	-0.007(0.01)
Improved varieties		0.011**(0.00)	-0.067(0.07)	0.060(0.12)	0.000(0.00)
Crop rotation		0.002(0.00)	0.074(0.06)	-0.050(0.12)	0.005(0.01)
Manure use		0.001(0.00)	-0.026(0.02)	0.018(0.04)	0.000(0.00)
Crop residue retention		-0.000(0.00)	-0.014(0.05)	0.059(0.08)	0.001(0.00)
Minimum tillage		0.004**(0.00)	-0.002(0.00)	0.013(0.01)	0.000(0.00)
Constant			-0.439(0.77)	-0.087(1.34)	
N			5238	5238	

Standard errors in parentheses
$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

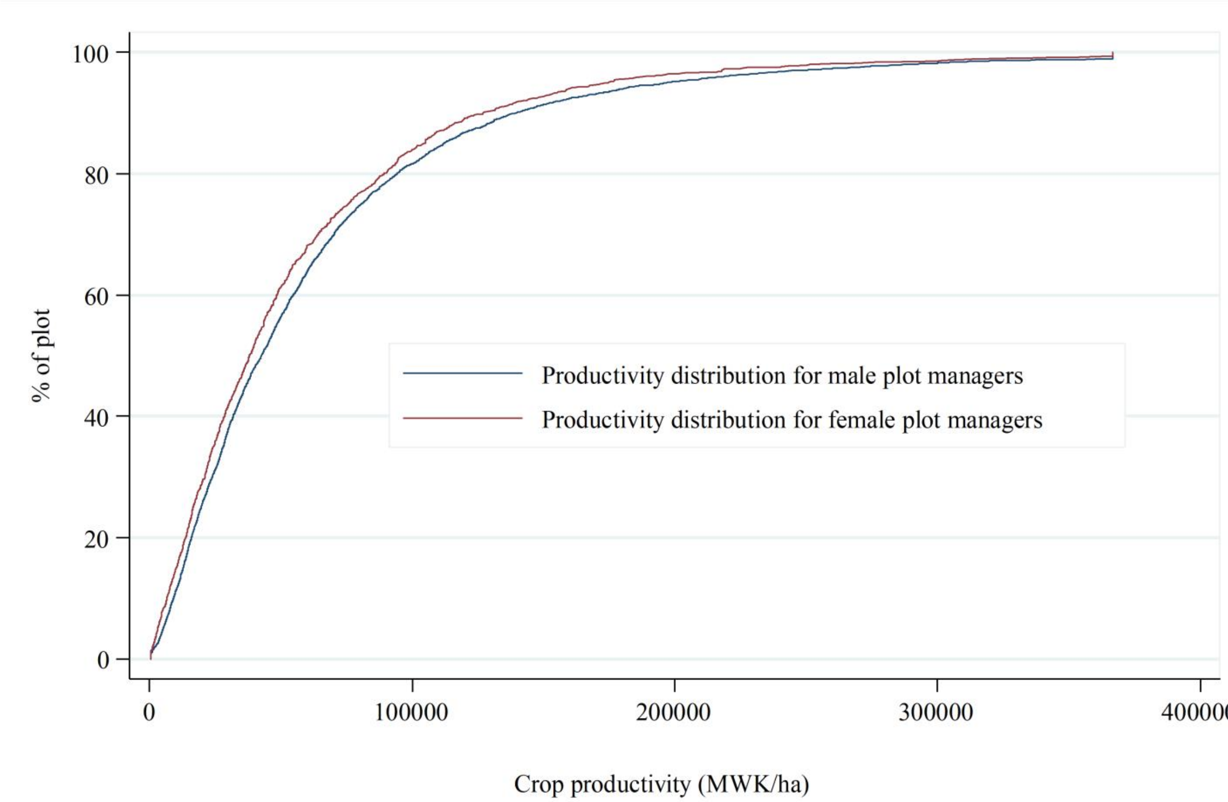

Figure 1. Cumulative distribution of crop productivity for female plot managers and male plot managers

6. Conclusions and implications

This study investigated gender differences in the adoption of improved agricultural technologies and in crop productivity in Malawi using nationally representative data collected from 1600 households and 5238 plots. The results from the MVP model show a gender gap in the adoption of agricultural technologies. More specifically, we find that female plot managers are more likely to adopt technologies beneficial to produce diverse crops, and technologies at the demonstration stages and are less likely to adopt technologies that are cash-intensive such as improved varieties and those that require more land such as crop rotation. Agricultural programs in Malawi aiming to increase diversification and intensification of crop production by smallholder farmers through intercropping would be more successful if they target female farmers. Likewise, programs that aim to increase diversification and intensification of crop production by smallholder farmers through crop rotation should target male farmers for better success.

The results of the gender productivity gap analysis show that female plot managers in Malawi are less productive by 14.6 – 23.1% compared to male plot managers. The gender productivity gap results also indicate that female plot managers have a slight endowment advantage, yet a much greater structural disadvantage compared to male plot managers. Together, these results suggest that policies and agricultural development programs need to consider the underlying factors that shape gender productivity gaps, rather than focusing solely on the factors of agricultural production. The shift in focus requires that policies and programs use gender transformative approaches (see Cole et al., 2014; 2020; Wong et al., 2019) to address the root causes of gender inequalities that constrain women from using resources efficiently to increase their agricultural yields such as unequal formal and informal social institutions at the household, community, market, and state levels (World Bank, 2014).

We have contributed to the literature on improving the way differences in adoption rates of technologies get assessed and how adoption of technologies get accounted for when analyzing the gender productivity gap, and on how the gender gap is decomposed using the more robust RIF decomposition and ESR technique.

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[i] *Surveybe* software is a tool that helps to design electronic computer-assisted personal interview (CAPI) questionnaires and collect and export analysis-ready data (https://surveybe.com/).

[ii] Other key food crops grown in Malawi include cassava, sorghum, sweet potato, rice, beans, groundnuts and potatoes, while tobacco, cotton, sugar, coffee, tea, soybeans, and groundnuts are the main cash and export crops (Gumma et al., 2019).

[iii] Pooled regression model uses sex of the plot managers as a binary variable and estimates a common slope coefficient for female and male plot managers.