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Gender differences in technology adoption and agricultural productivity: Evidence from Malawi

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ABSTRACT

It is widely recognized that female farmers have considerably less access to productive assets and support services than male farmers. There is limited evidence of gender gaps in technology adoption and agricultural productivity after accounting for the differential access to factors of production between males and females. This study investigates the gender differences in the adoption of improved technologies and agricultural productivity in Malawi using nationally representative data collected from 1600 households and 5238 plots. We used a multivariate probit model to analyze the gender differences in the adoption of improved technologies, including intercropping, use of improved varieties, crop rotation and residue retention, manure use, and minimum tillage. To analyze gender differences in agricultural productivity, we used an exogenous switching regression (ESR) model and recentered influence function decomposition. We found that female plot managers were more likely to adopt intercropping and minimum tillage but less likely to adopt crop rotation and use improved varieties than male plot managers. The ESR model estimation results showed that female-managed plots were 14.6–23.1% less productive than male-managed plots. The gender productivity gaps also indicated that female plot managers had an 8.2% endowment advantage but a 23.1% structural disadvantage than male plot managers. The importance of structural effects in accounting for the gender productivity gap highlights the need for policies and agricultural development programs that consider the underlying factors shaping gender productivity gaps rather than focusing solely on agricultural production factors.

1. Introduction

There is growing recognition of the important contribution of women to agricultural production in low-income countries (Ashby et al., 2008; Doss et al., 2018). Globally, the agricultural labor force comprises 43% women ((Food and Agricultural Organization of the United Nations (FAO), 2011)). The participation of women in the agricultural labor force has gradually increased since 1980, ranging from approximately 20% in Latin America and the Caribbean to approximately 50% in sub-Saharan Africa (SSA). The time that women contribute to agricultural activities varies considerably between and within regions and is dependent on factors such as the crop, production cycle phase, activity type, and also the woman's age and ethnicity (FAO, 2011). However, a major factor limiting agricultural development and broad economic growth in SSA is the wide and pervasive gender gap in agricultural productivity (World Bank, 2014).

Udry et al. (1995) showed intra-household differences in farm productivity between women and men in Burkina Faso, where women cultivating the same crop as men within their households, but on different plots, had markedly lower yields. Subsequent studies in SSA have shown that the yield gaps between women and men continue to persist (World Bank, 2014). For example, plots managed by women were found to be less productive on average than those managed by men, by 28% in Nigeria (Oseni et al., 2015), 25% in Malawi (Kilic et al., 2015), 23% in Ethiopia (Aguilar et al., 2015), 19% in Niger (Backiny-Yetna & McGee, 2015), 17.5% in Uganda (Ali et al., 2016), and 8.1% in Tanzania (Slavchevska, 2015).

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Gender gaps in access to non-land agricultural input, technology, and extension services create noticeable differences in productivity between women and men in low-income countries (Peterman et al., 2014). Some studies have shown that the gender gap in the adoption of agricultural technologies and practices increases agronomic outcomes such as productivity, with men being more likely to adopt them than women (Peterman et al., 2014; Dontsop-Nguezet et al., 2016; Gaya et al., 2017). Other studies highlight the importance of labor shortages in explaining women's low levels of productivity (World Bank, 2014). FAO (2011) outlines that women's farm yields could increase by 20–30% if they had the same access to the same productive resources as men. These estimated gains could increase total agricultural output by 2.5–4% in low-income countries. However, the World Bank (2014) concludes that even with equal access to productive resources, women would still have lower agricultural productivity than men, given gender norms, institutional constraints, and market failures that impact how effectively they use these resources.

In the economic development literature, the gender gap in agricultural productivity (hereafter, productivity) resulting from differential individual characteristics (e.g., age of the farmer, number of years of formal education) and access to factors of agricultural production (e.g., land, labor, capital, use of improved technologies) is referred to as the endowment effect (World Bank, 2014). The portion of the gender gap in productivity resulting from the difference in returns to individual characteristics and factors of production is referred to as the structural effect (World Bank, 2014). The decomposition of the gender gap into endowment and structural effects is helpful because it provides an order of magnitude of the gap in productivity can be linked to, for instance, the education level and age of the plot manager and their differential use of inputs (organic or inorganic fertilizer, and improved seeds), with some of these factors being influenced by policies (Singbo et al., 2020).

Studies exploring the relevant contributions of the endowment effect versus the structural effect of the gender gap in productivity outline mixed results. In Malawi, southern Nigeria, Uganda, Tanzania, and Kenya, the endowment effect plays a big role in explaining the differences in productivity between women and men (Fisher & Kandiwa, 2014; Kilic et al., 2015; Oseni et al., 2015; Ali et al., 2016; Slavchevska, 2015; Alene et al., 2008), and in Ethiopia, northern Nigeria and South West Nigeria, the structural effect explains a considerable proportion of the variation in the gender productivity gap (Aguilar et al., 2015; Oseni et al., 2015; Bello et al., 2021). Similarly, there are apparent differences in the main factors contributing to the endowment or structural effects. For instance, in Malawi, access to agricultural tools and the cultivation of high-value export crops explained the endowment effect but not the structural effect of the gender gap in productivity (Kilic et al., 2015). In Nigeria, land size contributed substantially to explaining the endowment effect; the child dependency ratio was a key factor in explaining the structural effect (Backiny-Yetna & McGee, 2015). The endowment effect was explained by the number of adult females in the household and also by herbicide use per hectare, whereas the structural effect was explained by the farmer's age and child dependency ratio in Nigeria (Oseni et al., 2015). In Uganda, the production of cash crops, use of improved seeds and pesticides, and assets owned by men helps explain the endowment effect, whereas the child dependency ratio and number of household members helps explain the structural effect (Ali et al., 2016).

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

This study contributes to empirical literature in three ways. First, we used a multivariate probit (MVP) model to assess the differences in the adoption rate of improved agricultural technologies (hereafter, technologies) and the determinants of adoption for female and male plot managers. Unlike the univariate probit model commonly used in other studies, the MVP model accounts for the interdependency of different technologies. Second, we investigate whether controlling for technology adoption, which is a proxy for endowment, can markedly reduce the gender gap in productivity. Third, we isolate the impact of being a female or male plot manager on productivity using ESR techniques and decompose the total gender gap in productivity using a more robust RIF decomposition procedure. Specifically, we use RIF decomposition to account for model specification and reweighting errors and to identify a suitable counterfactual to accurately estimate the gender gap in productivity. We also isolated ATT endowments and structural effects (Rios Avila, 2019; Bose, 2022). Previous studies have mostly focused on the aggregate decomposition of gender productivity gaps into endowment and structural effects. Fourth, we untangled the sources of gender differences in productivity using RIF regression, an area that has not been widely explored to date. Thus, the findings can aid development actors and policymakers in making gender-aware decisions to enhance productivity.

The remainder of this paper is organized as follows. The following section provides an overview of the survey design and data collection. The third section presents the details of the theoretical model and empirical procedure; the fourth section describes the data used in the study. The fifth and sixth sections present and discuss the results, respectively. The final section concludes the study with policy implications.

2. Survey design and data collection

This study used nationally representative data collected from 1600 households and 5238 plots in six districts of Malawi (Lilongwe, Mchinji, Dedza, Ntchisi, Kasungu, and Mzimba). Stratified random sampling was used to select households in 20 extension planning areas (EPAs), 80 sections, and 320 villages. Six districts were selected based on total crop production in the first stage. In the second stage, 20 EPAs were selected from a list of all EPAs in the six districts using a probability proportional to size technique based on the 2015/16 total crop production area. The six districts selected accounted for over 75% of the country's total soybean production. In the third and subsequent stages, a random sampling technique was used to select samples of predetermined sizes, such as four sections per EPA, two blocks per section, two villages per block, and five households per village. The sample size[2], n, was determined using the following formula:

$$n = \frac{\left(p(1-P)\left(\frac{z}{c}\right)^2 * d * s\right)}{r} \tag{1}$$

[2] The sample size was determined using a confidence level of 95% (z statistics of 1.96), a confidence interval or error margin of 0.05, a sample proportion of 0.5, design effect of 2, a response rate of 95%, and group value of 2 (female and male plot managers).

where p is the percentage of selecting a choice or sample proportion, c is the confidence interval or error margin, d is the design effect, s is the group value, and r is the response rate.

Data were collected during the 2016/17 cropping season using a standard questionnaire programmed in the *Surveybe*[3] Version 4.2 software and administered by trained enumerators. The data comprise the characteristics of the household members, production and marketing of crops, household assets, access to extension and credit services, household expenditure, social capital and networking, and general household characteristics (e.g., distance to the main market). The area of cultivated land was measured using a global positioning system device.

3. Empirical models and procedures

One pathway by which the endowment effect influences productivity is the adoption of technologies. For instance, a study conducted in Ghana showed that gender differences in the adoption of modern maize varieties and chemical fertilizers resulted from differences in access to inputs between women and men, such as land, labor, and extension services (Doss & Morris, 2001). The study provides evidence that the contribution of the endowment effect on the gender productivity gap can be captured by controlling for the adoption of technologies. Therefore, in this study, we first analyzed gender differences in the adoption of technologies using an MVP model that accounts for the interdependence of the decision to adopt technologies (Ndiritu et al., 2014). Second, we analyzed the productivity differences between female- and male-managed plots using ESR and RIF decomposition techniques. We analyzed the productivity gap between female- and male-managed plots after controlling for the adoption of major technologies, including using improved varieties, adopting agronomic practices, and accounting for important socioeconomic variables.

This study considered six technologies: cereal-legume intercropping, improved varieties, crop rotation, manure, residue retention, and minimum tillage. Intercropping, crop rotation, residue retention, and minimum tillage are components of conservation agriculture that address soil degradation in the maize-based farming system in Malawi (Giller et al., 2009). Intercropping and crop rotation of maize with grain legumes, such as common beans, soybean, pigeon pea, and groundnuts, enhances soil fertility through biological nitrogen fixation and the addition of soil organic matter, thus improving crop yields (Bezner Kerr et al., 2019; Komarek et al., 2018; Ngwira et al., 2020; Njira et al., 2021). Minimum tillage, or minimum soil disturbance, is a land preparation method that uses rip lines, planting basins, and holes at planting stations, leaving the remaining part of the land undisturbed. The most commonly used minimum tillage methods in Malawi are planting basins and holes (dibble-stick planting on permanent ridges) (Andersson & D'Souza, 2014). Compared to that of traditional farming practices, the use of planting basins increases maize yields where there is moisture stress, whereas using dibble-stick planting on permanent ridges increases maize yields under high rainfall conditions (Nyagumbo et al., 2016). The use of rip lines and planting basins increases productivity by improving the efficiency of water and fertilizer use (Baudron et al., 2015). However, minimum tillage must be combined with crop residue cover to obtain better yields (Thierfelder et al., 2013). Organic manure used by smallholder farmers in Malawi to enhance soil fertility includes farmyard manure, compost and green manure, crop residues, and household refuse (Holden & Lunduka, 2012; Holden et al., 2018; Komarek & Msangi, 2019).

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

The decision to adopt these technologies can be influenced by the demographic and socioeconomic characteristics of households and plot managers, of plot characteristics, interdependence of technologies, and expected costs and benefits. Farmers often adopt technologies if their potential benefits exceed the potential costs.

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 productivity, and food needs. Furthermore, (2) the choice of technologies by smallholder farmers may depend on previous choices. The interdependence in the decision to adopt these technologies can lead to a potential correlation among the unobserved disturbance terms in the adoption equations; hence, biased estimates may be obtained if analyzed separately using a univariate probit model. Therefore, it is important to use an MVP model to obtain unbiased estimates of the determinants of the adoption of multiple technologies.

We assessed the gender gap in productivity using the ESR model (Kassie et al., 2014) and RIF decomposition (Rios Avila, 2019; Nchanji et al., 2021). The ESR model and RIF decomposition considered the interaction between the sex of the plot manager and other explanatory variables. In addition, the RIF decomposition decomposes the productivity gap into a pure endowment effect (the effect after removing model specification errors) and a pure structural effect (the effect after removing the effect of reweighting errors) and provides coefficient estimates for the factors that contribute to the endowment and structural effects (Rios Avila, 2019).

3.1. MVP

The adoption of technologies by smallholder farmers is affected by their access to credit and information, farm size, human capital, mechanization, availability of inputs, and appropriate transportation infrastructure, among other factors (Croppenstedt et al., 2013). Furthermore, as female and male farmers do not have the same level of access to these resources, there are differences between these groups in the extent of their adoption of technologies (Doss & Morris, 2001). We use an MVP model to examine the determinants of gender differences in technology adoption. The MVP model uses simultaneous interdependent systems of equations of adoption of different technologies (Belderbos et al., 2004; Gillespie et al., 2004; Khanna, 2001; Ndiritu et al., 2014). The MVP model is expressed by two systems of equations (Gillespie et al., 2004; Ndiritu et al., 2014).

The first system of equations is general and can be expressed as follows:

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

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

$$T_{hpj} = \begin{cases} 1\ if\ Y^{*}_{hpj} > 0 \\ 0\ otherwise \end{cases} \tag{3}$$

where T_{hpj} is the adoption of the j^{th} agricultural technology by the h^{th} plot manager on the 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 (($MVN(0, \varnothing)$), where $\varnothing$ is a variance–covariance matrix as follows:

$$\varnothing = \begin{bmatrix} 1 & \rho 12 \cdots & \rho 1j \\ \rho 21 & 1 \cdots & \rho 2j \\ \rho 31 & \rho 32 \cdots & \rho 3j \\ \vdots & \vdots & \vdots \\ \rho j1 & \rho t2 & 1 \end{bmatrix} \quad (4)$$

The off-diagonal elements represent pairwise error term 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 the adoption equations become nonzero, and Eq. (2) becomes an MVP model. A positive correlation indicates a complementary relationship, whereas a negative correlation indicates a substitute relationship.

3.2. ESR

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

$$\begin{cases} Y_{pf} = \delta_f x_{pf} + u_f \text{ if } g = 1 \\ Y_{pm} = \delta_m x_{pm} + u_m \text{ if } g = 0 \end{cases} \quad (5)$$

where the subscripts f and m represent female and male plot managers, respectively. Y_{pf} is the productivity (MWK/ha) of p^{th} plot managed by a female, and Y_{pm} is the productivity (MWK/ha) of p^{th} plot managed by a male. Productivity was defined as the total production per hectare of all crops grown on a plot. It should be noted that maize dominates Malawi, grown by 97% of farmers on at least 60 to 80% of the total cultivated land (White, 2019; Gumma et al., 2019)[4]. g is a gender dummy variable that equals 1 for female plot managers and 0 otherwise; x is a vector of characteristics of the plot manager, household, and plots; δ is a vector of parameters that capture how the productivity of female and male plot managers respond 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 Eq. (5), as it is impossible to observe one plot manager group in two states simultaneously. To solve this problem, we estimated the counterfactual productivity of each group and compared the actual and counterfactual productivity estimates using equations 5a to 5d, expressed as follows:

$$E(Y_{pf}|g = 1) = \delta_f x_{pf} \quad (5a)$$

$$E(Y_{pm}|g = 0) = \delta_m x_{pm} \quad (5b)$$

$$E(Y_{pm}|g = 1) = \delta_m x_{pf} \quad (5c)$$

$$E(Y_{pf}|g = 0) = \delta_f x_{pm} \quad (5d)$$

where E is the expected value operator.

Using the observed data, we derived the actual productivity estimates from Equation 5a for female plot managers and Equation 5b for male plot managers. The counterfactual productivity estimates, that is, what the productivity of male (or female) plot managers would have been if the coefficients of their characteristics were the same as the coefficients of the female (or male) plot managers, can be derived from Equation 5c (or 5d).

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

The average treatment effect on the treated (ATT) (i.e., if female plot managers had the same coefficients as male plot managers) is the difference between equations 5a and 5c (Kassie et al., 2014) and is expressed as follows:

$$ATT = E(Y_{pf}|g = 1) - E(Y_{pm}|g = 1) = x_{pf}(\delta_f - \delta_m) \quad (6)$$

3.3. RIF decomposition

RIF decomposition is an improved extension and refinement of the standard Oaxaca (Oaxaca, 1973) and Blinder (Blinder, 1973) techniques, together called the Oaxaca–Blinder decomposition (Fortin et al., 2011). RIF provides the detailed contributions of individual covariates to aggregate decomposition (Rios Avila, 2019). 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 characteristics (X), and the sex of the plot manager (G). The joint probability distribution function and cumulative distribution of Y conditional on (G) can be expressed as

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

$$F^g_Y(y) = \int F^g_{Y|X}(Y|X) dF^g_X(X) \quad (7b)$$

where superscript g indicates that the density is conditional on $G = g$ with $g\epsilon[0, 1]$. To analyze the difference in 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:

$$\Delta v = v_1 - v_0 = v\left(F^1_Y\right) - v\left(F^0_Y\right) \quad (8a)$$

$$\Delta v = v\left(\int F^1_{Y|X}(Y|X) dF^1_X\right) - v\left(\int F^0_{Y|X}(Y|X) dF^0_X(X)\right) \quad (8b)$$

Equation 8b shows that the difference in the statistics Δv arises from the differences in the distribution of Xs $\left(dF^1_X(X) \neq dF^0_X(X)\right)$ and differences in the relationship between $Y$and $\left(dF^1_{Y|X}(Y|X) \neq dF^0_{Y|X}(Y|X)\right)$. To decompose the overall productivity gap (Δv) into the gap caused by the endowment effect and the gap caused by the structural effect, we obtain the counterfactual using the statistic v_c (Rios Avila, 2019), which can be expressed as.

$$v_c = v(F^c_Y) = v\left(\int F^0_{Y|X}(Y|X) dF^1_X(X)\right) \quad (9)$$

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

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

However, as outcomes and characteristics are not observed for the same plot manager group in the two states, it is not possible to identify the counterfactual statistic, v_c. We use the semiparametric reweighting procedure suggested by DiNardo et al. (1996) to identify the counterfactual distribution $F^0_{Y|X}(Y|X) dF^1_X(X)$ based on the observed data. According to Rios Avila (2019), although we cannot directly observe the distribution of outcomes and characteristics, we can approximate the counterfactual distribution by multiplying the observed distribution of characteristics $dF^0_X(X)$

with a factor $\omega(X)$, thus representing the distribution $dF_X^1(X)$. Therefore, the counterfactual function in Equation 8b can be rewritten as:

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

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

$$\begin{aligned}\omega(X) &= \frac{dF_X^1(X)}{dF_X^0(X)} = \frac{dF_{X|G}(X|G=1)}{dF_{X|G}(X|G=0)} = \frac{dF_{X|G}(G=1|X)}{dF_G(G=1)} \\ &= \frac{dF_G(G=0)}{dF_{G|X}(G=0|X)} = \frac{1-P}{P}\,\frac{P(T=1|X)}{1-P(T=1|X)}\end{aligned} \tag{12}$$

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 implies 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 υ_C, we estimated a separate RIF regression for each group and the counterfactual as follows:

$$\upsilon_1 = E\left(RIF\left(y_i; \upsilon\left(F_Y^1\right)\right)\right) = \bar{X}^{1'}\hat{\beta}^1 \tag{13a}$$

$$\upsilon_0 = E\left(RIF\left(y_i; \upsilon\left(F_Y^0\right)\right)\right) = \bar{X}^{0'}\hat{\beta}^0 \tag{13b}$$

$$\upsilon_C = E\left(RIF\left(y_i; \upsilon\left(F_Y^C\right)\right)\right) = \bar{X}^{C'}\hat{\beta}^C \tag{13c}$$

Therefore, the final decomposition components were defined as follows:

$$\Delta\upsilon = \underbrace{\left(\bar{X}^c - \bar{X}^m\right)^{\prime\hat{\beta}_m}}_{\Delta\upsilon_X^p} + \underbrace{\bar{X}^{c'}\left(\hat{\beta}_c - \hat{\beta}_m\right)}_{\Delta\upsilon_X^e} + \underbrace{\bar{X}^{f'}\left(\hat{\beta}_f - \hat{\beta}_c\right)}_{\Delta\upsilon_S^p} + \underbrace{\left(\bar{X}^{f'} - \bar{X}^c\right)'\hat{\beta}_c}_{\Delta\upsilon_S^e} \tag{14}$$

The components$\Delta\upsilon_X^p + \Delta\upsilon_X^e$ resemble the Oaxaca–Blinder aggregate endowment effect, and $\Delta\upsilon_S^p + \Delta\upsilon_S^e$ resemble the aggregate structural effect. $\Delta\upsilon_X^p$ and $\Delta\upsilon_S^p$ represent a pure endowment effect and a pure structural effect, respectively; $\Delta\upsilon_X^e$ and $\Delta\upsilon_S^e$ assess the overall fitness of the model; and $\Delta\upsilon_X^e$ 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 substantial $\Delta\upsilon_X^e$ indicates that the model is misspecified, and the RIF provides a poor approximation of the distributional statistic υ. $\Delta\upsilon_S^e$ is the reweighting error and indicates the quality of the reweighting strategy. The counterfactual is not well identified if $\Delta\upsilon_S^e$ is large and significant, implying the need to modify 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 previous empirical work related to the adoption of agricultural innovations (Croppenstedt et al., 2013; Doss, 2001; Doss et al., 2015; 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 the sex of the plot manager. The results of the descriptive analysis showed that female-managed plots were on average 15% less productive than male-managed plots. There were also considerable variations between female and male plot managers in their socioeconomic and plot characteristics. Female plot managers were older, less educated and wealthy (less income and fewer assets), and used less fertilizer than male plot managers. A relatively small proportion of female plot managers grew commercial crops such as tobacco and soybean than male plot managers. The descriptive results also showed that female plot managers had smaller household sizes than male plot managers. Female plot managers had fewer relatives and non-relatives to rely on for critical support in times of need, were more reliant on government support, and resided farther away from district markets than their male counterparts. A greater percentage of female plot managers resided in households that followed matrilocality than male plot managers, whose households predominately followed patrilocality[5].

We also found considerable differences 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 cultivated smaller, less fertile, and shallower plots than did male plot managers. Compared with those of male-managed plots, a greater proportion of female-managed plots were farther away from the residences of their plot managers.

Table 2 presents the adoption rates of technologies at the plot level disaggregated by the sex of the plot manager. Regardless of the sex of the plot manager, crop rotation was the most adopted technology, followed by use of improved variety, crop residue retention, intercropping, manure use, and minimum tillage. Crop rotation and improved varieties were utilized in 69 and 61% of the female-managed plots and 80 and 71% of the male-managed plots, respectively. Crop residue retention and intercropping were adopted in 47 and 32% of plots managed by women, and 50 and 22% of plots managed by men, respectively. The adoption of minimum tillage was very low, at 5% for female-managed plots and 3% for male-managed plots. Intercropping and minimum tillage were practiced more in female-managed plots than in male-managed plots, whereas improved varieties, crop rotation, and crop residue retention were applied more in male-managed plots than in female-managed plots. There were statistically significant differences between female- and male-managed plots in the adoption of all technologies, except for manure use. Female plot managers had 10.2 and 2.2% higher adoption rates for intercropping and minimum tillage, respectively, than male plot managers. In contrast, male plot managers had 10.4, 3.3, and 10.5% higher adoption rates for crop rotation, residue retention, and use of improved varieties, respectively, than female plot managers.

5. Empirical results

Consistent with the expected interdependence of adoption decisions by farmers facing multiple technologies, the likelihood ratio test results presented in Table 3 show that the null hypothesis of independent error terms for the MVP model of adoption was rejected $\left(chi^2(15) = 116.194,\ p > chi^2 = 0.00\right)$. This finding suggests mutual interdependence among the adoption decisions of the technologies, confirming the appropriateness of using a multivariate framework in our adoption study. The results of the correlation analysis showed statistical significance in eight out of 15 pairwise correlation coefficients between the error terms of the adoption equations. More specifically, the estimates of the correlations between the error terms were negative and significant for use

[5] Matrilocality dictates that a man relocate to his wife's village when married, while patrilocality requires that a woman relocates to her husband's village (Peters, 1997). Matrilineal ethnic groups such as Chewa are predominant in the study districts of Lilongwe and Dedza (Berge et al., 2014).

Table 1
Mean differences in 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 [(2) – (3)]§
Outcome variable					
Ln productivity	Log of total value of crop production (MWK/ha)	10.50	10.39	10.54	−0.15***
Productivity	Total value of crop production (MWK/ha)	61,586	57,169	62,980	5811***
Socioeconomic characteristics					
Age	Age of plot manager (# of years)	44.55	47.55	43.59	3.92***
Education	Education of plot manager (# of years of schooling)	6.59	5.86	6.82	−0.96***
Joint decision	Decision on what to grow on the plot made jointly (1 = yes)	0.80	0.44	0.91	−0.47***
Main occupation	Main occupation of the plot manager was farming (1 = yes)	0.93	0.88	0.95	−0.07***
Household size	Number of household members	5.29	4.87	5.42	−0.55***
Residence practice – all districts	Residence practice of household (matrilocality = 1, patrilocality = 0)	0.64	0.81	0.59	0.23***
Residence practice in Lilongwe	Residence practice of household (matrilocality = 1, patrilocality = 0)	0.79	0.91	0.74	0.17**
Residence practice in Dedza	Residence practice of household (matrilocality = 1, patrilocality = 0)	0.86	0.91	0.83	0.08**
Residence practice in Mchinji	Residence practice of household (matrilocality = 1, patrilocality = 0)	0.58	0.79	0.53	0.26**
Residence practice in Ntchisi	Residence practice of household (matrilocality = 1, patrilocality = 0)	0.54	0.79	0.49	0.30***
Residence practice in Kasungu	Residence practice of household (matrilocality = 1, patrilocality = 0)	0.37	0.44	0.36	0.08*
Residence practice in Mzimba	Residence practice of household (matrilocality = 1, patrilocality = 0)	0.23	0.23	0.22	0.01
Marital status	Marital status (married = 1)	0.85	0.45	0.97	−0.53***
Membership	Household head and/or spouse membership in organization (1 = yes)	0.37	0.30	0.39	−0.09***
Number of traders	Number of traders that you know who can buy agricultural produce	1.29	1.20	1.31	−0.11
Government support	Reliance on government support if crops fail (1 = yes)	0.65	0.68	0.64	0.05***
Kinship	Number of relatives to rely on in times of need	5.71	5.10	5.91	−0.81***
Non-kinship	Number of non-relatives to rely on in times of need	5.87	5.15	6.10	−0.95***
Labor	Labor used (man-day/ha)	144.97	145.01	144.96	0.05
Fertilizer	Fertilizer used (kg/ha)	93.58	81.13	97.53	−16.40***
Asset	Value of asset (MWK/adult equivalent)	102,869	72,488	112,548	−40,059***
Income	Per capita expenditure (MWK/person/year)	73,688	66,369	75,998	−9,629***
Livestock	Total livestock holding in TLU	0.76	0.40	0.88	−0.48***
Tobacco	Plot planted to tobacco (1 = yes)	0.024	0.005	0.030	−0.025***
Soybean	Plot planted to soybean (1 = yes)	0.229	0.195	0.240	−0.045***
Common beans	Plot intercropped with common beans (1 = yes)	0.129	0.158	0.120	0.038***
Groundnut	Plot planted to groundnut (1 = yes)	0.161	0.173	0.157	0.016
Extension contact	Number of days of contact with extension personnel	0.59	0.64	0.58	0.06
Credit	Access to credit (1 = yes)	0.26	0.27	0.26	0.01
Distance to district	Distance to the nearest district market (minutes of walking time)	127.03	138.24	123.49	14.75***
Plot characteristics					
Plot area	Area of the plot (ha)	0.34	0.28	0.36	−0.08***
Plot distance	Plot distance from residence (minutes of walking time)	24.98	26.56	24.49	2.07**
Poor fertility	Perceived fertility of the plot was poor (1 = yes)	0.23	0.27	0.22	0.05***
Medium fertile	Perceived fertility of the plot was medium fertile (1 = yes)	0.52	0.51	0.53	−0.02
Very fertile	Perceived fertility of the plot was very fertile (1 = yes)	0.25	0.22	0.25	−0.03**
Shallow	Perceived depth of the soil was shallow (1 = yes)	0.19	0.22	0.17	0.05***
Medium deep	Perceived depth of the soil was medium deep (1 = yes)	0.51	0.47	0.53	−0.06***
Deep	Perceived depth of the soil of the plot was deep (1 = yes)	0.30	0.30	0.29	0.01
Flat	Perceived slope of the plot was flat (1 = yes)	0.60	0.59	0.61	−0.02
Medium	Perceived slope of the plot was medium (1 = yes)	0.25	0.24	0.25	−0.01
Steep	Perceived slope of the plot was steep (1 = yes)	0.14	0.16	0.14	0.02*

Table 1 (*continued*)

Variable	Description	(1) Full sample	(2) Female plot manager	(3) Male plot manager	(4) Diff [(2) – (3)]§
Owner plot	Owner managed plot (1 = yes)	0.85	0.88	0.84	0.04***
Location					
Lilongwe	The plot is in Lilongwe (1 = yes)	0.25	0.31	0.24	0.07***
Mchinji	The plot is in Mchinji (1 = yes)	0.25	0.20	0.27	−0.07***
Dedza	The plot is in Dedza (1 = yes)	0.20	0.27	0.17	0.10***
Ntchisi	The plot is in Ntchisi (1 = yes)	0.13	0.11	0.14	−0.04***
Kasungu	The plot is in Kasungu (1 = yes)	0.11	0.06	0.12	−0.06***
Mzimba	The plot is in Mzimba (1 = yes)	0.05	0.05	0.06	−0.01

Standard deviations are in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
§t-test.

Table 2
Mean plot level adoption of technologies by sex of the plot manager.

Technologies	Full sample (n = 5238)	Female plot manager (n = 1256)	Male plot manager (n = 3982)	p-value§
Intercropping				52.31***
Adopter (1 = yes)	1299 (24.80)	408 (32.48)	891 (22.38)	
Non-adopter (0 = No)	3939	848	3091	
Improved varieties				48.93***
Adopter (1 = yes)	3596 (68.65)	762 (60.67)	2834 (71.17)	
Non-adopter (0 = No)	1642	494	1148	
Crop rotation				58.97***
Adopter (1 = yes)	4036 (77.05)	868 (69.11)	3168 (79.56)	
Non-adopter (0 = No)	1202	388	814	
Manure use				0.21
Adopter (1 = yes)	822 (15.69)	192 (15.29)	630 (15.82)	
Non-adopter (0 = No)	4416	1064	3352	
Crop residue retention				4.14**
Adopter (1 = yes)	2600 (49.64)	592 (47.13)	2008 (50.43)	
Non-adopter (0 = No)	2638	664	1974	
Minimum tillage				12.72***
Adopter (1 = yes)	186 (3.55)	65 (5.18)	121 (3.04)	
Non-adopter (0 = No)	5052	1191	3861	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
§Pearson chi2 test.
Percent adoption in the parenthesis.

of improved varieties and intercropping, crop rotation and intercropping, and manure use and crop rotation, suggesting substitutability between the technologies. The estimates of the pairwise correlations between the error terms were positive and significant for manure and intercropping, residue retention and use of improved varieties, minimum tillage and manure use, and minimum tillage and residue retention, showing their complementarity. This implies that the adoption of a given technology is conditional on the adoption of the other.

Table 4 presents the results of the MVP regression for all the technologies. The results showed that female plot managers were more likely to adopt intercropping and minimum tillage but less likely to adopt manure after controlling for other covariates. Households that made joint decisions on what to plant on a plot, who had more female adult labor, larger plot sizes, higher per capita income, and whose members participated in farmer organizations, were more likely to adopt intercropping. In contrast, households who follow matrilocality and those who have more educated plot managers, larger areas of total cultivated land, and plots farther away from their residences were less likely to adopt intercropping. The adoption of improved varieties was positively related to the age of the plot manager, education level of the plot manager, size of the plot, size of the total cultivated land, fertility of the plot, soil depth of the plot, per capita income, and number of extension contacts. Households that follow matrilocality residence practices, whose members participate in farmer organizations and have larger sizes of total cultivated land and higher per capita income were more likely to adopt crop rotation. Households that rely on government support, have smaller plot sizes, and less access to credit are less likely to adopt crop rotation. Manure use was positively related to plot size, soil depth, and total livestock holdings, but negatively associated with the size of total cultivated land and distance of the plot from the residence.

There was a considerable likelihood of adoption of crop residue among households where decisions on what to plant on a plot are made jointly, whose members are better educated and have a household head or spouse in a farmer organization, and who cultivate larger plots than others. There was a lower likelihood of crop residue adoption among households with more adult male labor and deeper soil than others. The likelihood of adopting minimum tillage increased with the number of extension contacts.

Table 5 presents the estimates of the pooled regression and ESR models. The pooled regression and ESR results showed that productivity was significantly related to labor, fertilizer, asset ownership, cultivated land, tobacco, soybean and groundnut production, soil fertility, plot slope, and district dummy variables. Productivity was also significantly related to intercropping, improved varieties, and crop residue retention. However, there were some noticeable differences in the effects of covariates between the female- and male-managed plots. For example, a 1% increase in the rate of labor

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

Binary correlation	Correlation coefficient	Significance level	Robust standard error	z-value
rho21: Improved varieties and intercropping	−0.055	**	0.026	−2.06
rho31: Crop rotation and intercropping	−0.060	**	0.029	−2.09
rho41: Manure use and intercropping	0.190	***	0.031	6.16
rho51: Crop residue retention and intercropping	0.024		0.028	0.86
rho61: Minimum tillage and intercropping	−0.023		0.047	−0.48
rho32: Crop rotation and improved varieties	−0.019		0.025	−0.76
rho42: Manure use and improved varieties	0.038		0.031	1.20
rho52:Crop residue retention and improved varieties	0.061	***	0.023	2.62
rho62: Minimum tillage and improved varieties	0.030		0.046	0.65
rho43: Manure use and crop rotation	−0.086	***	0.029	−3.00
rho53: Crop residue retention and crop rotation	0.100	***	0.032	3.04
rho63: Minimum tillage and crop rotation	0.012		0.052	0.22
rho54: Crop residue retention and manure use	0.008		0.027	0.28
rho64: Minimum tillage and manure use	0.101	**	0.049	2.07
rho65: Minimum tillage and crop residue retention	0.133	***	0.051	2.61

Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho61 = rho32 = rho42 = rho52 = rho62 = rho43 = rho53 = rho63 = rho54 = rho64 = rho65 = 0 chi2 (15) = 116.194 Prob > chi2 = 0.000 where rho1 = Intercropping; rho2 = improved varieties; rho3 = crop rotation; rho4 = manure application; rho5 = crop residue retention; rho6 = minimum tillage.

use was associated with 0.08 and 0.14% increases in productivity on female- and male-managed plots, respectively. Similarly, a 1% increase in fertilizer use was associated with a 0.18% increase in productivity in female-managed plots and a 0.19% increase in male-managed plots. In contrast, 1% increase in the size of cultivated land was associated with a 0.63 and 0.48% decreases in productivity on female- and male-managed plots, respectively.

The pooled regression results showed that the conditional productivity gap was 21% in favor of male plot managers. This is higher than the unconditional productivity gap (15%), as indicated in Table 1. As the covariates in the pooled regression did not interact with the sex of the plot manager, there was only an intercept shift; in other words, the covariates exerted the same effect on productivity in the female- and male-managed plots. To isolate the causal effect of the plot manager's sex on productivity, we estimated two models for female and male plot managers.

Table 6 presents the estimates of the gender productivity gap results of the ESR model estimation. Female-managed plots were 18.86% less productive than male-managed plots. The results suggest that female plot managers would have been more productive if they had the same observed resources and characteristics and returns to the resources as male plot managers. In other words, the difference in productivity between the female- and male-managed plots could have been caused by endowment and structural effects. However, the ESR model does not decompose the productivity gap into the endowment effect and structural effect and does not provide coefficient estimates for the factors that contribute to these effects. The coefficients are important to estimate because they enable us to make policy recommendations. We used the RIF technique to decompose gender productivity gaps into an endowment effect and structural effect and to determine the factors that influence these effects. RIF decomposes the gender productivity gap based on base heterogeneity, as reported in Table 6.

Table 7 presents the results of RIF decomposition. The main results showed that female-managed plots were, on average, 14.60% less productive than male-managed plots, confirming the results of ESR estimation. In addition, the cumulative distribution function for productivity on the RIF decomposition estimates for male plot managers dominated that of female plot managers for all productivity levels (Fig. 1). The non-parametric Kolmogorov-Smirnov test for first-order stochastic dominance revealed that the cumulative distribution function of male plot managers stochastically dominated ($p < 0.01$) that of female plot managers for crop productivity, showing that, if randomly chosen, there was a higher probability that male plot managers will, on average, have higher productivity than female plot managers. Decomposition of the total gender productivity gap into a total endowment effect and a total structural effect showed that female plot managers had an overall endowment advantage of 3.80% and an overall structural disadvantage of 18.40%. The results also showed non-significant specification and reweighting errors, implying that our model was correctly specified, and the counterfactual was 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% was similar to that of the IPWRA (see Appendix Table 1). This similarity was because RIF decomposition uses reweighting, similar to the IPWRA model.

6. Discussion

This study showed that female plot managers were more likely to adopt intercropping and minimum tillage after controlling for other covariates. Plausible explanations for the adoption of intercropping by women could be related to their preferences for producing diverse crops used for home consumption (Croppenstedt et al., 2013) or a function of their socially assigned role as food crop producers. However, intercropping can increase or decrease the need for labor for weeding under different conditions (see Dahlin & Rusinamhodzi, 2019). Given women's substantial contributions to carrying out other productive work and performing multiple domestic and caregiving tasks, intercropping reduces the need for weed control and seems to be an attractive technology for uptake by women in Malawi. Women's adoption of intercropping and minimum tillage could also simply be because of the presence of many NGOs in Malawi that target female farmers when promoting these technologies. This study also found that male plot managers are more likely to use manure. This finding can be explained by the greater number of livestock owned by male plot managers than their female counterparts (see Table 1).

The results of the pooled regression (Table 5) show a 21% gender productivity gap, disfavoring female plot managers. When estimating the ESR model, this study found that female-managed plots were 18.86% less productive than male-managed plots, and this difference was significant. These results are consistent with past studies that showed the presence of endowment differences between female and male plot managers (e.g., see Ali et al., 2016; Singbo et al., 2020; Slavchevska, 2015), including studies conducted in Malawi (Fisher and Kandiwa, 2014; Kilic et al.,

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

Variable	Intercropping	Improved varieties	Crop rotation	Manure use	Crop residue retention	Minimum tillage
Plot manager sex (1 = female)	0.353***	−0.097	−0.089	−0.133*	−0.001	0.276**
	(0.07)	(0.07)	(0.10)	(0.07)	(0.10)	(0.12)
Plot manager age (# of years)	−0.005	0.024**	0.017	−0.004	0.005	−0.015
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Plot manager age squared	0.000	−0.000***	−0.000	0.000	−0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Plot manager Education (# of years)	−0.012**	0.015***	0.007	0.000	0.016*	0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Joint decision (1 = yes)	0.240***	−0.101	−0.007	−0.054	0.563***	0.263
	(0.08)	(0.07)	(0.10)	(0.08)	(0.11)	(0.19)
Adult female labor (man-day/ha)	0.211***	−0.041	−0.028	0.041	−0.029	0.128
	(0.06)	(0.06)	(0.09)	(0.07)	(0.10)	(0.12)
Adult male labor (man-day/ha)	0.112*	−0.054	0.011	−0.069	−0.220**	0.101
	(0.06)	(0.06)	(0.09)	(0.07)	(0.09)	(0.11)
Child dependency ratio	0.234	0.193	0.114	−0.133	−0.023	0.008
	(0.15)	(0.15)	(0.20)	(0.17)	(0.20)	(0.32)
Residence practice (1 = matrilocality)	−0.112**	0.092*	0.163**	−0.008	−0.067	0.057
	(0.06)	(0.06)	(0.07)	(0.06)	(0.08)	(0.11)
Marital status (1 = married)	−0.015	0.158*	0.095	0.029	−0.357***	−0.116
	(0.10)	(0.09)	(0.12)	(0.09)	(0.13)	(0.23)
Membership in organization (1 = yes)	0.133**	0.039	0.232***	0.067	0.141*	0.081
	(0.06)	(0.05)	(0.07)	(0.06)	(0.08)	(0.09)
Number of traders	0.010	0.013	0.009	0.010	−0.018	0.015
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Government support (1 = yes)	−0.056	−0.002	−0.192***	0.065	0.127*	0.058
	(0.05)	(0.05)	(0.07)	(0.06)	(0.07)	(0.11)
Kinship (# of relatives)	−0.002	0.003	0.004	−0.010*	−0.009	−0.015
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Non kinship (# of non-relatives)	0.003	−0.000	0.004	0.002	0.002	−0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Ln plot area (ha)	0.581***	0.046**	−0.105***	0.191***	0.079***	−0.070**
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Ln total area (ha)	−0.537***	0.095**	0.289***	−0.184***	−0.078	0.056
	(0.05)	(0.04)	(0.06)	(0.06)	(0.05)	(0.09)
Plot distance (minutes of walking time)	−0.002**	0.000	0.001	−0.003***	−0.001	−0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fertile soil (1 = yes)	0.008	0.104**	−0.054	0.085	0.087	0.102
	(0.05)	(0.05)	(0.06)	(0.06)	(0.07)	(0.09)
Deep soil (1 = yes)	−0.133**	0.219***	−0.070	0.117**	−0.355***	−0.007
	(0.05)	(0.05)	(0.07)	(0.06)	(0.08)	(0.08)
Flat slope (1 = yes)	0.027	−0.027	0.055	0.054	0.034	−0.328***
	(0.05)	(0.04)	(0.06)	(0.05)	(0.06)	(0.08)
Ln per capita income (MWK/person/year)	0.113***	0.111***	0.125**	−0.047	−0.046	0.040
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.08)
Ln TLU (natural logarithm of total livestock holding in TLU)	0.010	0.001	−0.035	0.031*	0.044**	−0.008
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Extension contact (# of days per year)	−0.011	0.039***	0.010	0.003	0.017	0.044**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Access to credit (1 = yes)	0.075	−0.048	−0.125*	0.062	−0.129	−0.186*
	(0.06)	(0.06)	(0.07)	(0.06)	(0.08)	(0.10)
Distance to district markets (minutes of walking time)	−0.000	−0.000	−0.001**	−0.000	−0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lilongwe (1 = yes)	0.254**	−0.199*	−0.763***	0.744***	0.123	0.354*
	(0.10)	(0.11)	(0.13)	(0.12)	(0.14)	(0.20)
Mchinji (1 = yes)	−0.231**	0.013	−0.477***	0.527***	0.226*	0.070
	(0.10)	(0.11)	(0.13)	(0.11)	(0.14)	(0.19)
Dedza (1 = yes)	0.757***	−0.333***	−0.984***	0.840***	0.317**	−0.157
	(0.10)	(0.11)	(0.14)	(0.12)	(0.14)	(0.22)
Ntchisi (1 = yes)	−0.068	−0.005	−0.007	0.284**	0.045	−0.067
	(0.11)	(0.12)	(0.16)	(0.11)	(0.17)	(0.21)
Mzimba (1 = yes)	−0.269*	0.040	−0.080	0.110	−0.003	0.022
	(0.15)	(0.14)	(0.16)	(0.18)	(0.18)	(0.23)
Constant	−1.335**	−1.234**	−0.851	−0.563	0.376	−2.101*
	(0.54)	(0.57)	(0.79)	(0.62)	(0.75)	(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
Exogenous switching regression (ESR) estimates of crop productivity (ln MWK/ha) 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)		
Plot manager age (# of years)	0.005	−0.006	0.006
	(0.01)	(0.01)	(0.01)
Plot manager age squared	−0.000	0.000	−0.000
	(0.00)	(0.00)	(0.00)
Plot manager education (# of years)	−0.002	−0.001	−0.001
	(0.00)	(0.01)	(0.00)
Residence practice (1 = matrilocality)	0.053*	0.118	0.042
	(0.03)	(0.08)	(0.03)
Child dependency ratio	−0.089	−0.184	−0.107
	(0.08)	(0.16)	(0.09)
Labor used (man-day/ha)	0.129***	0.084	0.141***
	(0.02)	(0.05)	(0.03)
Fertilizer used (kg/ha)	0.188***	0.179***	0.194***
	(0.01)	(0.01)	(0.01)
Value of asset (MWK/adult equivalent)	0.092***	0.087***	0.093***
	(0.01)	(0.02)	(0.01)
Ln total area (ha)	−0.516***	−0.627***	−0.482***
	(0.02)	(0.05)	(0.03)
Grew tobacco (1 = yes)	1.032***	1.169***	1.007***
	(0.09)	(0.45)	(0.09)
Grew soybean (1 = yes)	0.509***	0.366***	0.557***
	(0.04)	(0.09)	(0.05)
Grew common beans as intercrop (1 = yes)	0.110**	0.119	0.112*
	(0.05)	(0.10)	(0.06)
Grew groundnut (1 = yes)	0.760***	0.778***	0.766***
	(0.05)	(0.10)	(0.05)
Poor fertile (1 = yes)	−0.111***	−0.182***	−0.094**
	(0.03)	(0.07)	(0.04)
Steep slope (1 = yes)	−0.076**	−0.132*	−0.068
	(0.04)	(0.08)	(0.04)
Shallow soil (1 = yes)	−0.006	0.114	−0.049
	(0.04)	(0.08)	(0.04)
Lilongwe (1 = yes)	−0.225***	−0.246*	−0.205***
	(0.05)	(0.13)	(0.06)
Mchinji (1 = yes)	−0.016	−0.060	−0.006
	(0.05)	(0.13)	(0.05)
Dedza (1 = yes)	−0.333***	−0.353***	−0.323***
	(0.05)	(0.13)	(0.06)
Ntchisi (1 = yes)	0.198***	0.203	0.206***
	(0.05)	(0.14)	(0.06)
Mzimba (1 = yes)	−0.315***	−0.354**	−0.281***
	(0.07)	(0.17)	(0.08)
Intercropping (1 = yes)	0.526***	0.626***	0.479***
	(0.04)	(0.08)	(0.05)
Improved variety (1 = yes)	0.075**	0.084	0.076**
	(0.03)	(0.06)	(0.03)
Crop rotation (1 = yes)	0.056*	0.038	0.072*
	(0.03)	(0.06)	(0.04)
Manure use (1 = yes)	0.074*	0.104	0.060
	(0.04)	(0.08)	(0.04)
Crop residue retention (1 = yes)	0.074***	−0.002	0.089***
	(0.03)	(0.06)	(0.03)
Minimum tillage (1 = yes)	0.022	−0.209	0.162*
	(0.07)	(0.13)	(0.09)
Constant	8.097***	8.484***	7.958***
	(0.21)	(0.45)	(0.25)
N	5238	1256	3982

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2015). Differences in endowment can lead to productivity gaps between female and male plot managers, which was evident in the differences in the coefficient estimates between the two samples of female and male plot managers. These differences clearly indicate the interaction between resource-use efficiency and the sex of the plot manager. The variables with noticeable differences in the size of the coefficient estimates between female and male plot managers were child dependency ratio, labor, fertilizer, assets, cultivated land, tobacco production, soybean production, plot characteristics, adoption of intercropping, improved varieties, crop residue retention, and minimum tillage.

Table 6
Estimates of gaps in productivity between female and male plot managers based on the ESR model.

Sex of plot manager	Observed	Counterfactual	ATT§
Female (n = 1,256)	10.3956	10.5842	−0.1886***
	(0.020)	(0.018)	(0.006)
Male (n = 3,982)	10.5414	10.2606	0.2808***
	(0.010)	(0.011)	(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 on the treated, i.e., if female plot managers had the same coefficient as male plot managers.

The significant productivity difference between female- and male-managed plots could also be because of differences in the unmeasured characteristics of plots managed by women and men. Our results showed that female-managed plots were more likely to be less fertile, steeper, and shallower than plots managed by men. Our analysis used perceived soil fertility, soil depth, and plot slope, which may not be an accurate measure of soil fertility. A study conducted in Kenya showed that farmer-reported soil fertility status did not adequately predict the 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 the difference in labor productivity. The results also show that labor, fertilizer, and asset (a proxy for capital) productivity were lower for female plot managers than for 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 female and male farmers in Malawi in the input subsidy program did not remove the gender gap in productivity, suggesting that female farmers face additional constraints on productivity apart from access to non-labor agricultural inputs.

The gender productivity gap results from the ESR model suggest that even if female and male plot managers have the same amount of resources, there are still unmeasured differences that inhibit women from making the best use of their resources. This finding implies that efforts to close the gender productivity gap should go beyond attempting to create equal access to the observed resources to facilitate the empowerment of women and overcome the underlying causes of gender inequalities in productivity outcomes. Such efforts could entail, for instance, using gender transformative approaches that aim to enhance women's decision-making and negotiation skills while also addressing the gender norms and power relations that restrict women from utilizing and benefiting from the resources they have (or do not have) access to (see Cole et al., 2014; Cole et al., 2020).

Concerning the RIF decomposition results on the endowment and structural effects and the set of covariates contributing to the gender differences in productivity, the results showed that female plot managers have some endowment advantages but face significant structural disadvantages. The main contributor to

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 (endowment effect)	Specification error	Pure unexplained (structural effect)	Reweight error
Male plot manager	10.541***				
	(0.03)				
Counterfactual	10.357***				
	(0.11)				
Female plot manager	10.396***				
	(0.04)				
Total difference (gender productivity gap)	0.146***				
	(0.05)				
Total explained difference (total endowment effect)	−0.038				
	(0.10)				
Total unexplained difference (total structural effect)	0.184				
	(0.12)				
Corrected differences		−**0.082**	**0.044**	**0.231****	−**0.046**
		(0.06)	(0.05)	(0.10)	(0.09)
Plot manager age (# of years)		0.028	0.475	0.037	0.003
		(0.03)	(0.65)	(1.12)	(0.02)
Plot manager age squared		−0.008	−0.320	0.122	−0.003
		(0.02)	(0.31)	(0.52)	(0.02)
Plot manager education (# of years)		−0.002	0.065	−0.061	−0.002
		(0.00)	(0.08)	(0.12)	(0.01)
Residence practice (1 = matrilocality)		−0.032***	0.055	−0.104	0.010
		(0.01)	(0.06)	(0.12)	(0.02)
Child dependency ratio		−0.004	0.059	−0.042	0.001
		(0.00)	(0.08)	(0.14)	(0.01)
Labor used (man-day/ha)		0.002	0.055	0.221	−0.004
		(0.00)	(0.47)	(0.76)	(0.01)
Fertilizer used (kg/ha)		0.090**	0.040	0.000	−0.061
		(0.04)	(0.08)	(0.11)	(0.05)
Value of asset (MWK/adult equivalent)		0.058***	0.257	−0.189	−0.011
		(0.01)	(0.49)	(0.80)	(0.01)
Ln area (ha)		−0.296***	0.002	0.023	0.054
		(0.07)	(0.02)	(0.02)	(0.08)
Grew tobacco (1 = yes)		0.065	0.014	−0.012	−0.042
		(0.04)	(0.02)	(0.01)	(0.05)
Grew soybean (1 = yes)		0.005	0.019	0.024	0.014
		(0.01)	(0.04)	(0.08)	(0.01)
Grew common beans as intercrop (1 = yes)		−0.002	0.005	−0.005	−0.003
		(0.00)	(0.03)	(0.03)	(0.01)
Grew groundnut (1 = yes)		−0.022*	−0.014	0.013	0.008
		(0.01)	(0.02)	(0.04)	(0.01)
Poor fertile (1 = yes)		0.015***	−0.014	0.035	−0.009
		(0.00)	(0.02)	(0.04)	(0.01)
Flat slope (1 = yes)		0.005**	0.002	0.006	−0.001
		(0.00)	(0.02)	(0.03)	(0.00)
Shallow soil (1 = yes)		−0.009***	−0.004	−0.024	0.003
		(0.00)	(0.02)	(0.03)	(0.01)
Lilongwe (1 = yes)		0.018**	−0.029	0.038	−0.000
		(0.01)	(0.06)	(0.10)	(0.01)
Mchinji (1 = yes)		−0.003	−0.015	0.031	−0.003
		(0.00)	(0.07)	(0.12)	(0.01)
Dedza (1 = yes)		0.035***	−0.045	0.049	0.003
		(0.01)	(0.05)	(0.08)	(0.02)
Ntchisi (1 = yes)		0.012	−0.038	0.033	0.001
		(0.01)	(0.04)	(0.06)	(0.01)
Mzimba (1 = yes)		−0.001	−0.007	0.012	−0.002
		(0.00)	(0.02)	(0.03)	(0.01)
Intercropping (1 = yes)		−0.054***	−0.043	0.007	−0.007
		(0.01)	(0.03)	(0.05)	(0.01)
Improved varieties (1 = yes)		0.011**	−0.067	0.060	0.000
		(0.00)	(0.07)	(0.12)	(0.00)
Crop rotation (1 = yes)		0.002	0.074	−0.050	0.005
		(0.00)	(0.06)	(0.12)	(0.01)
Manure use (1 = yes)		0.001	−0.026	0.018	0.000
		(0.00)	(0.02)	(0.04)	(0.00)
Crop residue retention (1 = yes)		−0.000	−0.014	0.059	0.001
		(0.00)	(0.05)	(0.08)	(0.00)
Minimum tillage (1 = yes)		0.004**	−0.002	0.013	0.000

(*continued on next page*)

Table 7 (*continued*)

	Overall ln productivity (MWK/ha)	Total explained difference		Total unexplained difference	
		Pure explained (endowment effect)	Specification error	Pure unexplained (structural effect)	Reweight error
		(0.00)	(0.00)	(0.01)	(0.00)
Constant			−0.439	−0.087	
			(0.77)	(1.34)	
N			5238	5238	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

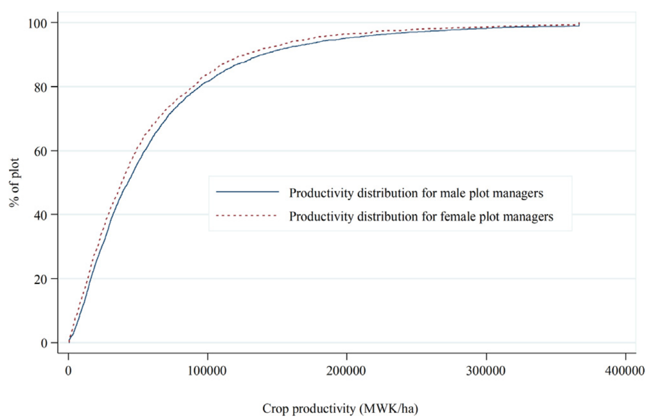

Fig. 1. Cumulative distribution of crop productivity for female plot managers and male plot managers.

endowment advantage for female plot managers was the ownership of cultivated land. There was an inverse relationship between cultivated land and productivity for female- and male-managed plots, but the relationship was stronger for female-managed plots because of a smaller area of cultivated land compared to that for male-managed plots (0.28 vs. 0.36 ha). We also found a similar result from the ESR model, where a decrease in productivity was associated with a 1% increase in cultivated land for female-managed plots (0.63%) compared with that for male-managed plots (0.48%). This finding is consistent with that of Ali et al. (2016) in the case of Uganda, where female plot managers faced a stronger inverse relationship between productivity and land size than that of male plot managers. Other major factors that contributed to the endowment advantage of female plot managers included their involvement in groundnut production and intercropping. Groundnut production is a gendered activity carried out mostly by women in rural Malawi on smaller plots of land, as is the case with intercropping, given its potential to reduce labor contributions to weed control and enhance productivity (Dahlin and Rusinamhodzi, 2019; Ngwira et al., 2020). In contrast, some factors contribute to the endowment disadvantage of female plot managers. The most notable factors were fertilizer use, amount of capital per adult equivalent, and adoption of improved varieties. Most of these results are intuitive, as female farmers in Malawi often have less access to farm inputs because of a shortage of cash (UNWomen, 2015).

The larger magnitude of the unexplained component (structural effect) relative to the explained component (endowment effect) indicates the increased importance of the returns on women's and men's resources and characteristics than the level of resources. This study did not reveal the source of the structural effect as the coefficients of the observed resources and characteristics represented by the covariates included in the RIF regression model were not statistically significant. However, by simply considering the magnitude of the coefficients of the covariates used to explain the structural effects, we can argue that the return on labor matters the most as it accounts for the major portion of the gender gap in productivity.

7. Conclusions and implications

This study investigated the gender differences in the adoption of technologies and 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 technologies. Specifically, we found that female plot managers were more likely to adopt technologies such as intercropping. In contrast, male plot managers were more likely to use improved varieties and adopt crop rotation and crop residue retention than female plot managers. Agricultural programs in Malawi aiming to increase the diversification and intensification of crop production by smallholder farmers via intercropping might be more successful if they target female farmers than male farmers. Similarly, programs that aim to increase diversification and intensification of crop production by smallholder farmers through crop rotation could target male farmers for better success.

The RIF decomposition results of the gender productivity gap analysis show that female plot managers in Malawi were 14.6% less productive than male plot managers. The gender productivity gap results also indicated that female plot managers have a relatively low endowment advantage (8.2%) yet a much greater structural disadvantage (23.1%) than male plot managers. Together, these results suggest that policies and agricultural development programs should consider the underlying factors that shape gender productivity gaps rather than focusing solely on agricultural production factors. The shift in focus requires policies and programs to use gender transformative approaches 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. Finally, as the study did not reveal the source of the structural effects, further research is warranted to investigate the underlying factors responsible for the structural effects.

CRediT authorship contribution statement

Adane Hirpa Tufa: Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Writing – original draft. **Arega D. Alene:** Conceptualization, Methodology, Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition. **Steven M. Cole:** Conceptualization, Writing – review & editing. **Julius Manda:** Writing – review & editing. **Shiferaw Feleke:** Writing – review & editing. **Tahirou Abdoulaye:**

Writing – review & editing. **David Chikoye:** Supervision, Funding acquisition. **Victor Manyong:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
Ln productivity gap between female and male plot managers – estimates of exogenous switching regression model using IPWRA†.

Variable	ATE	Population mean	Female plot managers	Male plot managers
Ln productivity difference	0.231***			
	(0.04)			
Ln productivity for female plot managers		10.311***		
		(0.04)		
Plot manager age (# of years)			0.005	0.006
			(0.01)	(0.01)
Plot manager age squared			−0.000	−0.000
			(0.00)	(0.00)
Plot manager education (# of years)			0.008	−0.001
			(0.01)	(0.00)
Residence practice (1 = matrilocality)			0.219**	0.042
			(0.09)	(0.03)
Child dependency ratio			0.045	−0.107
			(0.20)	(0.09)
Labor used (man-day/ha)			0.096	0.141***
			(0.07)	(0.03)
Fertilizer used (kg/ha)			0.194***	0.194***
			(0.02)	(0.01)
Value of asset (MWK/adult equivalent)			0.111***	0.093***
			(0.03)	(0.01)
Ln total area (ha)			−0.619***	−0.482***
			(0.06)	(0.03)
Grew tobacco (1 = yes)			1.396***	1.007***
			(0.28)	(0.08)
Grew soybean (1 = yes)			0.457***	0.557***
			(0.13)	(0.05)
Grew common beans as intercrop (1 = yes)			0.156	0.112**
			(0.12)	(0.05)
Grew groundnut (1 = yes)			0.680***	0.766***
			(0.13)	(0.06)
Poor fertile soil (1 = yes)			−0.255***	−0.094**
			(0.08)	(0.04)
Steep slope plot (1 = yes)			−0.112	−0.068
			(0.10)	(0.04)
Shallow soil plot (1 = yes)			0.089	−0.049
			(0.08)	(0.04)
Lilongwe (1 = yes)			−0.369**	−0.205***
			(0.17)	(0.06)
Mchinji (1 = yes)			−0.123	−0.006
			(0.17)	(0.05)
Dedza (1 = yes)			−0.606***	−0.323***
			(0.18)	(0.06)
Ntchisi (1 = yes)			−0.026	0.206***
			(0.19)	(0.06)
Mzimba (1 = yes)			−0.497**	−0.281***
			(0.25)	(0.08)
Intercropping (1 = yes)			0.445***	0.479***
			(0.10)	(0.04)
Improved variety (1 = yes)			−0.008	0.076**
			(0.08)	(0.03)
Crop rotation (1 = yes)			0.135	0.072*
			(0.08)	(0.04)
Manure use (1 = yes)			−0.054	0.060
			(0.11)	(0.04)
Crop residue retention (1 = yes)			−0.028	0.089***
			(0.08)	(0.03)
Minimum tillage (1 = yes)			−0.271**	0.162**
			(0.13)	(0.07)
Constant			8.045***	7.958***
			(0.55)	(0.26)
N	5238			

Standard errors in parentheses.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
†Inverse probability weighted regression adjustment.

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