Sustainable Land Management Practices and Gender Differentials in Agricultural Productivity

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Abstract

This paper examines the heterogeneous effects of sustainable land management practices (SLMPs) on productivity and productivity gap among female and male farm managers. It uses data from a number of districts in northern Ethiopia where some of the most important SLMPs–soil and water conservation, crop-legume diversification, and agroforestry are commonly practiced. Heterogeneous effect analysis and decomposition methods were primarily used to estimate productivity differences and gender gap in productivity. Overall, we find that female managers had 15.2% lower productivity; and this gap increased with the use of SLMPs. After controlling for labor, non-labor inputs and other characteristics, we find that subsamples of SLMPs generated higher productivity gaps, asserting their important role in enhancing productivity. While earlier studies documented the dominant effect of differences in access to inputs, we find in contrast that unequal returns to inputs or unobserved heterogeneity largely explains not only mean productivity but also productivity differences at various percentiles. This result is consistent with documentation in the wider literature that unequal access to inputs does not fully explain productivity differences, indicating the important role of unequal returns to inputs in widening or closing the gender gap in productivity. Assessment of the gender gap from different perspectives in this paper points to not only promoting the use of SLMPs but also emphasize the need for policy to focus on bridging unequal returns to productive inputs.

Keywords*:* SLMPs, gender gap, agricultural productivity, decomposition, Ethiopia.

1 Introduction

Mainstream production theories underline the role of inputs or resources in enhancing productivity. The bulk of literature (e.g., Gilbert et al., 2002; Alene et al., 2008; Kilic et al., 2015; Vargas Hill and Vigneri, 2014) in this regard documents that the majority of productivity differences among farmers in developing countries is attributed to differences in the endowment of production inputs (mainly land, labor, capital and innovations such as fertilizer, etc.). While the plethora of evidence supports such assertions, the role of enhancing the productivity of land resources (such as land and water) for boosting agricultural productivity cannot be emphasized enough. Enhancing the productivity of land resources is especially crucial given the low labor and land productivity in rural areas of developing countries. In this regard, Kaczan et al. (2013), Kassie et al. (2013), Teklewold et al. (2013), and Abdulai and Huffman (2014) emphasize the importance of innovations such as sustainable agricultural practices for enhancing the productivity of land resources.

Empirical evidence further supports the role of sustainable agricultural practices in enhancing agricultural production and subsequently welfare improvement. For instance, Mohammad et al. (2012) report cereal-legume rotational practices in Pakistan increased crop production by 36%. Abdulai and Huffman (2014) report a 24% increment in rice yield of Ghanaian farmers as a result of soil and water conservation practices. Gebremariam and Wünscher (2018) report that the sole adoption of cereal-legume diversification increased income by 4%; but when it is combined with improved maize varieties, income increased by 16%. Moreover, they report that net crop revenue per acre increased by 20% when farmers adopted a package consisting of improved maize varieties, soil &

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water conservation and cereal-legume diversification. Amadu et al. (2020) report participation in agroforestry by Malawian farmers brought them a 2% increase in maize yield per acre from the use of agroforestry (they note the small but positive increment). More broadly, the literature documents the contribution of sustainable agricultural practices to poverty reduction (Issahaku and Abdulai, 2020), nutrition improvement (Teklewold, 2019), income and consumption (Gebremariam and Wünscher, 2018) and enhancing agricultural productivity (Mohammad et al., 2012; Abdulai and Huffman, 2014; Amadu et al., 2020). But the evidence also shows that these increments in productivity and the other welfare indicators are not the same across farmers (such as male and female farmers).

Tekelewold et al. (2019) examined the impact of sustainable agricultural practices on gender-differentiated nutrition. While insightful, their study was not directly related to productivity, and moreover, the unit of analysis was the gender of the household head. Earlier studies on gender-differentiated productivity analysis (such as Kilic et al., 2015; Aguilar et al., 2015; Oseni et al., 2015; Slavchevska, 2015) presented pioneering insights about gender differentials in agricultural productivity emanating from differences in inputs and unequal returns to productive inputs. This study builds upon these earlier studies to contribute to our understanding of the gender-differentiated impact of sustainable land management practices (SLMPs). While earlier studies present ample evidence on gender-differentiated productivity, disaggregated analysis of SLMPs and the way they derive gender differences in productivity is limited. By dwelling into this knowledge gap, this study contributes to the literature in three ways. One, to our knowledge, we have not come across a similar study that attempted to examine the heterogeneous effects of SLMPs on agricultural productivity. Also, we use decomposition methods to assess gender gap in productivity for different SLMPs. Second, we build upon the work of Aguilar et al. (2015), Oseni et al. (2015) and Slavchevska (2015) by considering multi-crop data and analyzing gender differentials in productivity at the mean and various points of the productivity distributions for different SLMPs. Third, we also attempted to explore the heterogeneity in productivity by female marital status and geographical location, which helps give additional perspective as to how productivity varies in response to important female-centered institutions–such as marriage.

We also present results on a crop-level basis where monetary values are disentangled from actual yield. We believe using the value of yield as an outcome variable entangles actual crop productivity with crop prices that are exogenous to gender differences in agricultural productivity. Crop prices that female and male managers bargain may vary based on prevailing (and fluctuating) supply and demand conditions. These crop prices are exogenous in the sense that they rarely have anything to do with the productive capability of female and male managers. Moreover, it is documented in the literature (see Tadesse, 2012; Oseni et al., 2015) that poorly-functioning markets in many developing countries influence crop prices even when there are no production (productivity) differences among plot managers. This analysis paints a different picture on its own as to what the productivity difference was like for different crops.

2 Data

The data for the study come from districts in the Regional State of Tigray in northern Ethiopia, covering a wide range of agro-ecologies and cropping systems. The districts considered also constitute some of the notable areas in Tigray that implement SLMPs, including soil and water conservation, agroforestry and crop-legume diversification. Sample farm households were visited after harvest, where data related to plot and manager-level and household as well as community-level characteristics were collected. Since the objective was to identify gender differentials in agricultural productivity vis-à-vis the use of SLMPs, the survey questionnaire was designed in such a way that it allows identifying the gender and respective characteristics of each plot manager instead of using household head data. The plot manager was identified as the decision maker who had decided about what crops to grow and what types of land management practices to implement in each plot. Moreover, this plot manager was the one who decided about labor allocation and the use of important inputs (such as chemicals and fertilizer) on each plot.

Data were collected in a disaggregated manner at crop, plot and household levels. Data about important features such as plot manager's characteristics, crops grown, land and labor endowments and allocation, production, use of external inputs, plot level attributes and household demographic and socioeconomic characteristics were collected. Data related to agricultural production were collected at crop level and were later aggregated at plot level to record production levels and values from each plot (i.e., different crops' harvest values were aggregated at the plot level). In the end, productivity was operationalized as aggregated harvest value of all crops per hectare of land[2]. While this operational definition was used to estimate gender differentials in productivity, manager's characteristics, labor and non-labor inputs, plot characteristics, household and community characteristics that might explain heterogeneity in agricultural productivity were also incorporated in the decomposition analysis.

Table 1: Summary statistics of variables by plot manager and pooled sample

	Pooled sample	**Male manager**	**Female manager**	**Difference**
Outcome variable				
Value of total harvest (log)	10.75	10.80	10.70	–0.099**
Manager characteristics				
Age (years)	49.65	52.33	46.77	–5.57***
Education level (years of schooling)	0.201	0.193	0.209	0.017
Marital status (1=married)	0.984	0.990	0.979	–0.011
Membership in social groups (1=yes)	0.235	0.215	0.257	0.042
Manager's plot characteristics				
Plot size (hectares)	0.229	0.243	0.214	–0.029***
Plot fertility (1=highly fertility)	0.353	0.395	0.308	–0.087**
Plot fertility (medium fertility)	0.281	0.317	0.241	–0.076**
Plot slope (steep=1)	0.136	0.175	0.094	–0.081***
Plot slope (medium slope=1)	0.245	0.265	0.223	–0.043
Plot distance from home (km)	1.389	1.462	1.310	–0.152*
Tenure security (1=yes)	0.843	0.867	0.818	–0.049*
Access to services				
Access to credit (1=yes)	0.303	0.300	0.306	0.006
Access to extension (1=yes)	0.876	0.888	0.863	–0.024
Access to training (1=yes)	0.367	0.447	0.282	–0.166***
Access to irrigation (1=yes)	0.105	0.115	0.095	–0.019
Market information (1=yes)	0.906	0.955	0.853	–0.102***
Access to mobile (1=yes)	0.294	0.265	0.324	0.059*
Use of inputs in manager's plots				
Fertilizer (kg)	21.92	23.28	20.46	–2.83**
Chemicals (kg)	1.072	1.159	0.979	–0.178***
Use of fertilizer (1=yes)	0.792	0.880	0.697	–0.183***
Use of improved seeds (1=yes)	0.714	0.810	0.611	–0.199***
No use of organic manure (1=yes)	0.217	0.235	0.198	–0.037
Use of herbicides (1=yes)	0.631	0.750	0.504	–0.246***
Use of pesticides (1=yes)	0.625	0.765	0.475	–0.290***
Use of irrigation in plots (1=yes)	0.097	0.115	0.078	–0.037*
Never practice fallowing (1=yes)	0.103	0.117	0.089	–0.029
Use of SLMP in manager's plots				
Soil and water conservation (1=yes)	0.894	0.937	0.847	–0.090***
Agroforestry (1=yes)	0.351	0.387	0.311	–0.077**

2 Each plot manager was asked about total production of each crop. Self-reported production measured in kilograms for each crop was then aggregated at the manager level using reported median prices to calculate total values. Management of several plots by many farmers meant that analysis had to be done at manager-level (Aguilar et al., 2015).

	Pooled sample	Male manager	Female manager	Difference
Cereal legume diversification (1=yes)	0.213	0.263	0.161	–0.102***
Household characteristics				
Livestock ownership (TLU)	0.294	0.372	0.211	–0.161***
Household size (number)	4.404	4.852	3.922	–0.930***
Male members (adult number)	0.938	1.088	0.777	–0.310***
Female members (adult number)	0.541	0.532	0.550	0.017
Labor input for production				
Female family labor (labor man days)	50.91	52.27	49.45	–2.82**
Male family labor (labor man days)	42.17	43.29	40.96	–2.34**
Hired labor (labor man days)	13.15	13.31	12.98	–0.334
Community characteristics				
Distance to all-weather roads (km)	14.58	16.30	12.75	–3.551***
Distance to dry-weather roads (km)	8.477	9.661	7.207	–2.454***
Distance to markets (km)	8.173	9.504	6.746	–2.759***
Distance to seed distribution center (km)	8.010	9.199	6.735	–2.465***
Distance to cooperative (km)	7.851	9.109	6.503	–2.607***
Distance to financial institution (km)	7.977	9.284	6.575	–2.709***
Distance to farmer training center (km)	12.03	13.79	10.15	–3.633***

Unconditional mean values presented in Table 1 indicate that female managers achieved lower productivity (value of output per hectare). This productivity gap could be due to their apparent disadvantages in terms of access to key resources such as land, labor and physical inputs, technical knowledge and information, and SLMPs. Unconditional mean differences of plot characteristics need to be highlighted. Resource-wise, female managers owned significantly smaller land size (0.21 hectares compared to 0.24 hectares for male managers) and irrigated land of 0.023 hectares (compared to 0.032 hectares for male managers). Moreover, labor supply for agricultural activities (both male and female labor) is significantly lower in female-managed plots. Equally important, plots owned by female managers are less fertile and less secure. In addition, female managers used significantly smaller productivity-enhancing inputs such as fertilizer and chemicals (such as pesticides and herbicides). This, coupled with the significant disparity in resource ownership (land and labor), could be key for differences in agricultural productivity among male and female-managed plots.

As far as the use of SLMPs is concerned, significantly fewer female managers practiced sustainable land management strategies on their plots. Household-wise, households of female managers had significantly smaller livestock size, household size, and male numbers, all of which could directly influence agricultural productivity through either labor supply or draught power. Interestingly, however, female managers were situated closer to important agricultural institutions (seed distribution centers, cooperatives, and farmer training centers) and infrastructural services (roads, markets, and financial institutions). Overall, with the significant disadvantage in resource ownership and quality, the use of productivity-enhancing inputs, use of SLMPs, and comparatively lower access to technical training, female managers would struggle to scale up agricultural production and close the gender gap in productivity.

3 Empirical strategy

Following Peterman et al. (2011), agricultural productivity is often estimated through an *a priori* defined production function, which gives rise to expected output produced using a set of inputs, given production technology. This production technology (function) can be specified as:

$$y_{pm} = f\left(\mathbf{W}_{pm}, \mathbf{F}_{pm}, \mathbf{L}_{p}, \mathbf{K}_{m}, \mathbf{Z}_{m}\right) \quad (1)$$

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where y is a measure of agricultural productivity from plot p managed by plot manger m. $\mathbf{W}$ represents the vector of characteristics of the plot manager; the aggregate vector of production inputs used in the production process (for each plot p managed by plot manger m), including land, labor, etc. are represented by the vector $\mathbf{F}$; $\mathbf{L}$ denotes plot characteristics; $\mathbf{K}$ represents the vector of SLMPs, and $\mathbf{Z}$ aggregates the vector of household socioeconomic characteristics, access to some services and infrastructure that influence production.

SLMPs constitute one of the different forms of human and physical capital that play key roles in production. These land management practices are part of sustainable agriculture implemented using locally available resources and knowledge and skills that are used to increase productivity. Teklewold et al. (2013) and Manda et al. (2016) document that SLMPs include, among others, cropping systems, agroforestry, soil and water conservation measures, and crop diversification. Of these various forms of SLMPs, we examine the impact of soil and water conservation, agroforestry practices, and crop-legume diversification on agricultural productivity.

Gender differences in agricultural productivity could arise due to a number of reasons. Even if male and female farmers face the same production technology, Slavchevska (2015) argues that differences in the use of inputs manifested in differences in initial endowments, quality of factors of production (such as land), skill and knowledge, risk preferences, and choices (such as using and cultivating different crops) can lead to productivity differences. Not only these but also differences in access to services such as credit, extension, and training can also define productivity differences among male and female farmers, where female farmers are often reported to have lower access to these important services (Peterman et al., 2010; Oseni et al., 2015). Moreover, the lack of knowledge and skills in the effective use of productivity-enhancing land management practices (such as crop-legume diversification and agroforestry (Amadu et al., 2020)) could lead to lower returns for women due to the inadequate practicing of these SLMPs. Therefore, while access to these and other production technologies is important for enhancing productivity, access by women to these sustainable agricultural practices alone may not materialize if the returns do not match those of men (Slavchevska, 2015). Studying how these SLMPs influence productivity differences and singling out their contribution to productivity can thus help identify the underlining endowment and structural differences (Aguilar et al., 2015; Oseni et al., 2015) and shed some light to help bridge the potential gap in agricultural productivity among male and female farmers.

3.1 Assessment of gender differentials

Given the data allow the use of the plot manager's characteristics; we estimate Eq. (2) that accounts for manager's own characteristics. Moreover, even though the variable of interest is the manager's gender, the model is expanded to include other factors that explain productivity differences.

$$\ln\left(y_{pm}\right) = \alpha + \delta g_{pm} + \sum_{w=1}^{\mathrm{W}} \beta_w c_{pm} + \sum_{l=1}^{\mathrm{L}} \pi_l d_p + \ln\left(\sum_{f=1}^{\mathrm{F}} \eta_f l_{pf}\right) + \sum_{k=1}^{\mathrm{K}} \theta_k r_{pm} + \sum_{z=1}^{\mathrm{Z}} \lambda_z h_{pm} + \varepsilon_{pm} \tag{2}$$

where y is the log of the value of harvest per hectare by plot manager m from plot p; α is the constant term; g is manager's gender; c is the vector of W characteristics of the plot manager m; d is the vector of L characteristics of each plot p; l is log of the vector of F characteristics of production inputs used in each plot p; r is the vector of K cropping strategies by plot manager m in each plot p, including the use of sustainable land management strategies; h is the vector of Z household and community characteristics related to managers and plots; and ε was assumed to be independently and identically distributed as $N\left(0,\sigma^2\right)$.

In estimating Eq. (2), we follow Oseni et al. (2015) and use a step-wise approach of adding a set of control variables in order to explore their influence on the conditional gender differential. In doing so, we start with a very parsimonious model that controls for only the manager's gender. Then, we re-estimate the model by controlling for location fixed effects. Since the interest is to estimate mean gender differentials in productivity, we control for manager's characteristics, plot characteristics, labor use, non-labor inputs, and use of SLMPs, among others, which define (differentials in) agricultural productivity. In the process, we include these control variables in estimating Eq. (2) containing different specifications. Results related to these specifications are reported in table 2[3].

One main analysis is testing the hypothesis that $\delta = 0,$ which sheds light on whether the value of total harvest varies with gender. In testing this hypothesis, we follow the approach proposed by Battese (1997)[4], also applied in Slavchevska (2015), to make log transformation of important control variables including labor and non-labor inputs. Many observations reported zero values of these inputs. To maintain plots with zero values for these inputs in the analysis, we re-specify Eq. (2) by adding a dummy variable equal to one for plots with zero reported values as follows:

$$y_{pm} = \alpha + \delta g_{pm} + D_{pf} + \sum_{f=1}^{F} \eta_f l_{pf}^* + f(.) + \varepsilon_{pm}$$

where, $f(.)$ is the specification containing the other control variables in Eq. (2), and

$$D_{pf} = \begin{cases} 1 & \text{if} \quad l_{pf} = 0 \\ 0 & \text{if} \quad l_{pf} > 0 \end{cases}, \text{ and } l_{pf}^* = Max(l_{pf}, D_{pf}) \quad (3)$$

By using Eq. (3), the full data was used to obtain estimates that are efficient and unbiased (Battese, 1997).

[3] For lack of space, the full results of the models for each SLMP based on Eq. (2) could not be included. But, summarized results are presented in table 4. The full results are available on request.

[4] Battese (1997) argues that adding arbitrary values (such as the value 1 or any small number) to make log transformation is invariant to the unit of measurement of the variable under consideration.

Table 2: OLS regression underlying the mean decomposition

	(1)	(2)	(3)	(4)	(5)	(6)	Male plot manager	Female plot manager
Female plot manager	–0.0990**	–0.00883	–0.0541	–0.0774	–0.111**	–0.152***		
	(0.0471)	(0.0552)	(0.0498)	(0.0483)	(0.0457)	(0.0468)		
Age		–0.0067***	–0.0064***	–0.0061***	–0.0053***	–0.0052**	–0.0083***	–0.000494
		(0.00219)	(0.00203)	(0.00200)	(0.0020)	(0.0021)	(0.00252)	(0.00315)
Years of schooling		–0.0454*	–0.0381	–0.0391*	–0.0389*	–0.0358	–0.0868**	0.0126
		(0.0275)	(0.0242)	(0.0233)	(0.0214)	(0.0219)	(0.0349)	(0.0171)
Membership in cooperatives		0.0280	–0.119**	–0.174***	–0.170***	–0.135**	–0.0864	–0.222***
		(0.0588)	(0.0596)	(0.0568)	(0.0575)	(0.0594)	(0.0944)	(0.0809)
Land size (*ln*)		–0.703***	–0.842***	–0.818***	–0.834***	–0.836***	–0.678***	–1.009***
		(0.0726)	(0.0636)	(0.0643)	(0.0628)	(0.0618)	(0.113)	(0.0601)
High plot fertility		0.216***	0.206***	0.167***	0.131***	0.140***	0.126*	0.168***
		(0.0563)	(0.0495)	(0.0490)	(0.0466)	(0.0467)	(0.0688)	(0.0612)
Medium plot fertility		0.0621	0.0902*	0.0627	0.0796*	0.0736*	0.0369	0.0699
		(0.0530)	(0.0460)	(0.0452)	(0.0436)	(0.0443)	(0.0660)	(0.0577)
Steep plot slope		0.0192	–0.0143	–0.000348	–0.0116	–0.0342	–0.0375	0.00561
		(0.0713)	(0.0579)	(0.0572)	(0.0554)	(0.0553)	(0.0752)	(0.0750)
Medium plot slope		0.0330	0.0568	0.0587	0.0634	0.0439	0.0305	0.108*
		(0.0488)	(0.0435)	(0.0420)	(0.0410)	(0.0409)	(0.0635)	(0.0553)
Do not use organic manure		0.0541	–0.0854	–0.125*	–0.110*	–0.103*	–0.160*	–0.0400
		(0.0685)	(0.0638)	(0.0650)	(0.0580)	(0.0596)	(0.0906)	(0.0746)
Plot distance from home		0.117***	0.0934***	0.0823***	0.0698***	0.0553***	0.0644**	0.0558***
		(0.0195)	(0.0163)	(0.0163)	(0.0166)	(0.0171)	(0.0269)	(0.0208)
Plot tenure security		0.112*	0.0276	0.0338	0.0646	0.0947*	0.0693	0.00553
		(0.0635)	(0.0549)	(0.0550)	(0.0513)	(0.0525)	(0.0803)	(0.0680)
Female family labor (*ln*)			0.165***	0.149***	0.151***	0.149***	0.328**	0.143***
			(0.0465)	(0.0454)	(0.0421)	(0.0424)	(0.148)	(0.0362)
Male family labor (*ln*)			0.0607	0.0476	0.0410	0.0317	0.0356	0.0353
			(0.0449)	(0.0464)	(0.0386)	(0.0374)	(0.0699)	(0.0365)
Hired labor (*ln*)			0.613***	0.493***	0.468***	0.465***	0.671***	0.170**
			(0.102)	(0.0975)	(0.0914)	(0.0950)	(0.132)	(0.0782)
Fertilizer amount (*ln*)				0.0754***	0.0488***	0.0446***	0.0304	0.0420**
				(0.0154)	(0.0161)	(0.0165)	(0.0306)	(0.0189)
Pesticide amount (*ln*)				0.172***	0.132**	0.118**	0.153*	0.111
				(0.0598)	(0.0574)	(0.0594)	(0.0792)	(0.0866)

	(1)	(2)	(3)	(4)	(5)	(6)	Male plot manager	Female plot manager
Soil & water conservation					0.191***	0.154**	0.112	0.162**
					(0.0587)	(0.0672)	(0.136)	(0.0771)
Agroforestry					–0.0941*	–0.0916*	–0.146**	–0.0234
					(0.0504)	(0.0519)	(0.0733)	(0.0647)
Crop-legume diversification					0.337***	0.323***	0.251***	0.343***
					(0.0559)	(0.0543)	(0.0751)	(0.0814)
Livestock size						0.00872	–0.0858	0.139**
						(0.0445)	(0.0557)	(0.0612)
Household size						0.0296*	0.0330	0.0297
						(0.0176)	(0.0245)	(0.0263)
Male number						–0.00565	0.0395	–0.0100
						(0.0206)	(0.0283)	(0.0316)
Female number						0.0178	0.0125	0.0319
						(0.0265)	(0.0404)	(0.0398)
Distance to all-weather roads						–0.00320	–0.00367	–0.00573
						(0.00490)	(0.00592)	(0.00866)
Distance to markets						0.00459	0.00463	0.0513**
						(0.00899)	(0.00939)	(0.0199)
Access to credit						–0.105*	–0.0751	0.00403
						(0.0549)	(0.0896)	(0.0723)
Access to extension						0.0179	0.0200	–0.0227
						(0.0441)	(0.0686)	(0.0559)
Access to training						0.0799**	0.117**	0.0304
						(0.0383)	(0.0528)	(0.0636)
Constant	10.80***	9.348***	6.954***	7.315***	7.350***	7.397***	6.955***	7.216***
	(0.0346)	(0.230)	(0.320)	(0.325)	(0.318)	(0.350)	(0.651)	(0.439)
Location fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	773	773	773	773	773	773	400	373
R-squared	0.006	0.243	0.401	0.428	0.474	0.485	0.458	0.631

Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.2 Decomposing mean productivity differentials

An important aspect of analyzing gender productivity gap involves a decomposition method that helps determine the extent to which differences in levels and returns to productivity explain the overall gender differential in agricultural productivity (Aguilar et al., 2015). Eq. (2) enables us to identify the factors that explain the productivity difference among male and female managed plots. However, it does not help isolate the relative importance of the different factors (Oseni et al., 2015). We use the Oaxaca-Blinder decomposition method to explore the relative importance of different factors, as it allows quantification of the contributions of different factors to the gender gap in productivity.

We follow Kilic et al. (2015) derivation of the Oaxaca-Blinder decomposition for the gender gap in agricultural productivity. Since this decomposition method aims at partitioning the overall difference of a given distribution's statistic of interest between two groups (such as male and female plot managers), we can start by presenting the expected harvest value per hectare of plots managed by either males (m) or females (f) as follows:

$$\mathrm{E}(y_g) = \delta g + \mathrm{E}(\mathbf{X}_g)'\boldsymbol{\theta}_g \tag{4}$$

where $\mathbf{X}$ represents the vector of the different productivity explaining factors specified in Eq. (2), i.e., $\mathbf{X} = (\mathrm{W}, \mathrm{L}, \mathrm{F}, \mathrm{K}, \mathrm{Z}),$, $\boldsymbol{\theta}$ is the corresponding vector of coefficients, i.e., $\boldsymbol{\theta} = (\beta, \pi, \eta, \theta, \lambda),$ and $g = (m, f).$ The mean difference in productivity (i.e., the gender gap) among male and female plot managers can then be expressed as the difference in the expected value of harvest from male and female managed plots:

$$\mathrm{R} = \mathrm{E}(y_m) - \mathrm{E}(y_f) = \delta_m + \mathrm{E}(\mathbf{X}_m)'\boldsymbol{\theta}_m - \left(\delta_f + \mathrm{E}(\mathbf{X}_f)'\boldsymbol{\theta}_f\right) \tag{5}$$

where $\mathrm{E}(\varepsilon) = 0.$

An important aspect of the analysis is identifying the source of the gap in productivity. Oaxaca (2007) states that the gap typically emanates from differences in the levels of the characteristics, i.e., $\mathbf{X} = (\mathrm{W}, \mathrm{L}, \mathrm{F}, \mathrm{K}, \mathrm{Z}),$ including gender; and a part of it is attributable to differences in coefficients or 'discrimination' as Fortin et al. (2011) termed it when the difference is linked to permanent characteristics such as gender. Given this, if we assume that there is some nondiscriminatory vector of coefficients, $\boldsymbol{\theta}^*$ by which the difference in the factors is weighted; Eq. (5) can then be re-specified as:

$$\mathrm{R} = \left(\mathrm{E}(\mathbf{X}_m) - \mathrm{E}(\mathbf{X}_f)\right)'\boldsymbol{\theta}^* + \left(\mathrm{E}(\mathbf{X}_m)'(\boldsymbol{\theta}_m - \boldsymbol{\theta}^*) + \mathrm{E}(\mathbf{X}_f)'(\boldsymbol{\theta}^* - \boldsymbol{\theta}_f)\right) \tag{6}$$

Eq. (6) is made up of two-fold decomposition components, which can be stated as $\mathrm{R} = \mathrm{Q} + \mathrm{U}.$

where

$$\mathrm{Q} = \left(\mathrm{E}(\mathbf{X}_m) - \mathrm{E}(\mathbf{X}_f)\right)'\boldsymbol{\theta}^*, \text{ and}$$
$$\mathrm{U} = \left(\mathrm{E}(\mathbf{X}_m)'(\boldsymbol{\theta}_m - \boldsymbol{\theta}^*) + \mathrm{E}(\mathbf{X}_f)'(\boldsymbol{\theta}^* - \boldsymbol{\theta}_f)\right)$$

Jann (2008) refers to Q as part of the mean difference 'explained' by group differences in the predictors and shows the proportion of the gender productivity gap that results from gender differences in the explanatory variables. This part of the source of the gender gap is referred to as endowment or factor effect. The other part (U) is the 'unexplained' part or residual, which is attributed to discrimination or unequal returns to the predictors (Oaxaca, 2007). This residual is termed as structure effect (Fortin et al., 2011), which can be re-specified as:

$$\mathrm{U} = (\delta_m - \delta) + \mathrm{E}(\mathbf{X}_m)'(\boldsymbol{\theta}_m - \boldsymbol{\theta}^*) + (\delta - \delta_f) + \mathrm{E}(\mathbf{X}_f)'(\boldsymbol{\theta}^* - \boldsymbol{\theta}_f) \tag{7}$$

When there is no advantage to any particular group, the expectation of the vector of coefficients for each group is equal. In this case, the only source for observed differences in productivity between male and female-managed plots should be based on differences in factors and characteristics. However, as Jann (2008) argues, since the 'unexplained' part is associated not only with discrimination but also differences in unobserved features, such sources of difference may lower the returns to one group (females, in our case) and increase the returns to the other group (males). In such cases, Eq. (7) can be further simplified into two distinct parts. While one part quantifies the discrimination in favor of one group (males) showing structural advantage, the other part quantifies the discrimination against (i.e., the structural disadvantage) the other group (females), which can be presented as (see Kilic et al., 2015):

$$\mathrm{U}_m = (\delta_m - \delta) + \mathrm{E}(\mathbf{X}_m)'(\boldsymbol{\theta}_m - \boldsymbol{\theta}^*) \tag{7a}$$

$$\mathrm{U}_f = (\delta - \delta_f) + \mathrm{E}(\mathbf{X}_f)'(\boldsymbol{\theta}^* - \boldsymbol{\theta}_f) \tag{7b}$$

where δ_m and δ_f denote group-specific discrimination coefficients for male and female plot managers, respectively. This overall approach then helps differentiate the proportion of the gap that may arise from differences in inputs and characteristics (endowment effect), and discrimination or differences in unobserved characteristics (structural effect). Furthermore, the structural effect permits analysis of the disaggregation of a possible advantage for male managers and a possible disadvantage for female managers.[5]

3.3 Decomposition by productivity percentiles

The Oaxaca-Blinder decomposition helps shed light on the factors that influence mean productivity differences among male and female plot managers. While this provides useful insight for the average manager, it is also important to explore how productivity differences vary for some distributional statistics other than the mean. In this regard, Slavchevska (2015) holds that some distinct aspects may explain gender differentials for farmers with different productivity records and adds that gender differences in inputs and outputs may be more observable at the extreme ends of the productivity distribution (than at the mean). Exploring productivity differences at these extreme ends and other percentiles of the productivity distribution can give a different perspective of the gender gap in productivity.

We used the Recentered influence function (RIF) regression method developed by Firpo et al. (2009), which builds upon the Oaxaca-Blinder decomposition to identify productivity differences at various percentiles of the productivity distribution. This method works by substituting the dependent variable y with the statistic (percentile) of interest, and is defined as:

$$\mathrm{RIF}(y;v) = v(F_y) + \mathrm{I\,F}(y;v) \tag{8}$$

where y is the dependent variable of interest (ln of the value of harvest per hectare) and $v(F_y)$ is the distributional statistic of interest (such as percentiles). The second term on the right, $\mathrm{I\,F}(y;v)$ is the influence function associated with the observed agricultural productivity y for the distributional statistics $v(F_y)$, which is given by:

$$\mathrm{I\,F}(y;v) = \frac{\tau - 1\{y \le v(F_y)\}}{f_y(v(F_y))} \tag{9}$$

where τ is the $\tau'th$ percentile of $v(F_y)$ and $f_y(v(F_y))$ is the density of the marginal distribution of the dependent variable, y. Based on the methodology developed by Firpo et al. (2009), the RIF is computed using the calculated sample percentile and the estimated density at the point utilizing kernel density methods, separately for each gender. After obtaining the RIF estimates, the Oaxaca-Blinder decomposition can be run by using the RIF estimate as the dependent variable on the same set of predictors as the OB decomposition.

[5] Decomposition methods work based on the assumption of conditional independence and overlapping support. Despite these strong assumptions, Fortin et al. (2011) and Oseni et al. (2015) state that the methods are nonetheless useful to identify the factors or characteristics that are important determinants of productivity difference.

4 Results and Discussion

4.1 Factors that Explain Productivity Difference

We begin by presenting results of the base OLS regression in Table 2 to identify factors that explain productivity differences among male and female-managed plots. Table 2 displays part of the step-wise regression results obtained by controlling for a set of variables in different model specifications. While table 2 presents selected results, the full results of the step-wise regression are presented in Table A.1. In column (1), the unconditional gender gap shows female plot managers were 9.9% less productive than male managers. In the next 5 columns, results from different model specifications by controlling for factors that influence productivity including labor and non-labor inputs and SLMPs are reported. The results show that the gender gap in productivity persists, with the conditional gender gap estimated to be 15.2% in the full model (column 6). Age is negatively correlated with productivity, which may be explained by the depreciation of human and physical capital with age. Years of schooling was negatively associated with agricultural productivity for male managers. With education, male farmers are thought to exhibit dissatisfaction with agricultural activities, which may negatively affect their productivity.

Plot characteristics such as land size, plot fertility, and tenure security constitute key productivity shifters. We find that productivity decreases with land size, both in female and male-managed plots, which is consistent with other findings (such as Aguilar et al., 2015; Oseni et al., 2015; Slavchevska, 2015) in the literature that document diminishing returns in productivity with land (i.e., inverse relationship between productivity and land size). High plot fertility positively affected productivity. This was observed in both male and female-managed plots. Tenure security, in addition, affected productivity positively. Important agricultural practices such as the use of organic manure also influence productivity. We find lower productivity on plots where application of organic manure was not practiced. While the use of organic manure improves soil health (nutrient content) and contribute to productivity, Aguilar et al. (2015) find a contrasting result that organic manure dampens productivity on female-managed plots. On the other hand, closer plots were expected to allow more time for better management; however, we find that plot distance positively influenced productivity. The literature documents mixed results in this case as Aguilar et al. (2015) report negative effect in a study in Ethiopia, while Slavchevska (2015) and Oseni et al. (2015) report positive effects from their studies in Tanzania and southern Nigeria, respectively (for female-managed plots only in the study in southern Nigeria).

Key production inputs, such as labor and non-labor inputs, affected productivity positively. Both female family labor and hired labor[6] were associated with higher levels of productivity. Moreover, returns to hired labor were comparatively higher, as shown by the marginal effect of the returns to hired and female family labor (1% increase in hired labor and female family labor increased productivity by 0.465% and 0.149%, respectively). More interestingly, however, the productivity effects of these labor inputs are significantly lower on female-managed plots. Female family laborers on female-managed plots had significantly lower productivity (0.328% on male-managed plots and 0.143% on female-managed plots for a 1% increase in female family labor). This effect on productivity gap even got wider for hired labor, where a 1% increase in hired labor resulted in a 0.671% increase in productivity on male-managed plots, compared to an increment of only 0.170% on female-managed plots. These contrasting effects of labor on productivity shed some light on the prevailing gap in productivity among female and male-managed plots. Slavchevska (2015: 346) points out that such observed differences in returns to family and hired labor may be associated with heterogeneous effort levels and monitoring capability of male and female managers. It is to be noted as well that the observed differences in returns to labor may also be masked by heterogeneous differences in unobservable factors. On the other hand, fertilizer and pesticides positively affected productivity. The positive role of inorganic fertilizer in agricultural productivity is also documented in the literature (Aguilar et al., 2015; Oseni et al., 2015; Slavchevska, 2015).

SLMPs such as soil and water conservation and crop-legume diversification increase productivity. These land management practices are important in maintaining and increasing soil fertility (health), which in turn boost productivity. However, their effect is heterogeneous. Interestingly, the effect of these practices is more

[6] Regrettably, only aggregated data about female, male and hired labor were available. This may mask some of the effects on productivity that could otherwise have been discerned from and unmask the effects if disaggregated data about labor types were available.

pronounced on male-managed plots, as shown by the higher marginal effects (coefficients). Male-managed plots on which crop-legume diversification was practiced had 34.3% higher productivity, as compared to the 25.1% increment in productivity on female-managed plots. On the other hand, while soil and water conservation on male-managed plots increased productivity by 16.2%, the effect appears insignificant on female-managed plots. It appears in general that crop-legume diversification was more important to productivity. Not only was the returns to crop-legume diversification lower on female-managed plots, but its relative returns was also higher than the returns to practicing soil and water conservation.

4.2 Overall Mean Decomposition

It is to be noted that unobserved heterogeneity may mask productivity differences among female and male-managed plots. The analysis in the previous section permits only identification of the factors that explain productivity differences among male and female-managed plots. However, these results do not show whether the productivity gap is solely due to differences in productive inputs or differences in returns to these inputs. In this and subsequent sections, we report results that help isolate the relative importance of productive inputs and examine the gender gap by decomposing the productivity difference into a part that is attributed to productive inputs (observables) and a part that may be due to unobservable factors (or differences in returns to inputs.

Table 3 summarizes the aggregate and detailed Oaxaca–Blinder decomposition results for the pooled sample. The estimated mean difference in productivity among male and female-managed plots was about 10% (9.9%), in favor of male-managed plots. The portion of this gender gap in productivity due to differences in productive inputs was 22.2%, which is not statistically significant. The portion of the unexplained gender gap that is further disaggregated into male structural advantage and female structural disadvantage was 122.2%, which may be attributed to differences in returns to inputs or unobserved heterogeneity.

Table 3: Decomposition of gender differentials in agricultural productivity

Mean gender differential in agricultural productivity		0.099** (0.0471)	
A. Aggregate decomposition	**Endowment effect**	**Male structural advantage**	**Female structural disadvantage**
Total	–0.0220	0	0.121***
	(0.0414)	(0.0118)	(0.0389)
Share of gender differential	22.2%	0%	122.2%
B. Detailed decomposition	**Endowment effect**	**Male structural advantage**	**Female structural disadvantage**
Age	0.0286**	0.209	0.166**
	(0.0120)	(0.134)	(0.0662)
Years of schooling	–0.000642	0.00899*	0.00768
	(0.00320)	(0.00509)	(0.00491)
Membership in cooperatives	–0.00753	–0.0152	–0.00965
	(0.00516)	(0.0120)	(0.0152)
Land size (*ln*)	–0.131***	0.275***	0.251**
	(0.0259)	(0.0907)	(0.110)
Plot distance from home	–0.00868	0.0185	–0.0186
	(0.00555)	(0.0225)	(0.0260)
High plot fertility	–0.0118*	0.00589	–0.00162
	(0.00604)	(0.0135)	(0.0190)
Medium plot fertility	–0.00602	–0.00179	0.00998
	(0.00420)	(0.0111)	(0.0141)
Plot tenure security	–0.00517	–0.0502	–0.0166
	(0.00372)	(0.0407)	(0.0508)
Do not use organic manure	0.00381	0.0172	0.0101
	(0.00376)	(0.0124)	(0.0142)
Female family labor (*ln*)	–0.0234**	–0.0615	–0.556

	(0.00933)	(0.101)	(0.502)
Male family labor (*ln*)	–0.00493	–0.00355	0.0571
	(0.00581)	(0.0965)	(0.219)
Hired labor (*ln*)	–0.0145	–0.763***	–0.492*
	(0.0128)	(0.195)	(0.289)
Fertilizer amount (*ln*)	–0.0157**	–0.00921	–0.0119
	(0.00675)	(0.0321)	(0.0605)
Pesticide amount (*ln*)	–0.00158	–0.00550	–0.000407
	(0.00286)	(0.0136)	(0.0126)
Soil and water conservation	–0.0132**	0.00858	0.121
	(0.00672)	(0.0483)	(0.0991)
Agroforestry	0.00718	0.0218	0.0165
	(0.00505)	(0.0166)	(0.0201)
Crop-legume diversification	–0.0324***	0.00376	0.0175
	(0.0107)	(0.0105)	(0.0126)
Livestock size	–0.00121	0.0266**	–0.0287**
	(0.00703)	(0.0121)	(0.0139)
Household size	–0.0266	0.0323	–0.00737
	(0.0164)	(0.0863)	(0.0755)
Male number	0.00229	–0.00807	–0.0520**
	(0.00626)	(0.0212)	(0.0206)
Female number	0.000264	0.00622	0.00287
	(0.000826)	(0.0164)	(0.0154)
Distance to all-weather roads	0.000473	–0.0724	–0.0451
	(0.0120)	(0.0487)	(0.0534)
Distance to markets	–0.00851	0.0384	0.0338
	(0.0109)	(0.0315)	(0.0343)
Access to credit	–0.000575	0.0281*	0.00317
	(0.00340)	(0.0161)	(0.0207)
Access to extension	–0.000323	–0.0424	–0.00643
	(0.00109)	(0.0379)	(0.0435)
Access to training	–0.0127*	–0.0161	–0.0157
	(0.00652)	(0.0139)	(0.0162)
Observations	773		

Robust standard errors are reported in parentheses.
***p<0.01, ** p<0.05, * p<0.1.

Land stands out as the single most important productive input (as shown by the higher coefficient of 13.1%) that explains gender gap in agricultural productivity. As shown in table 1, females manage plots that are on average 13.6% smaller in size. As also documented in previous research (Aguilar et al., 2015; Oseni et al., 2015; Slavchevska, 2015), diminishing returns in productivity with land size then means that land negatively contributes to the endowment effect (accounting for 13.1%) and reduces the gender gap in productivity. In this regard, Oseni et al. (2015) and Slavchevska (2015) point out that gender differences in productivity are often masked due to the fact that women on average are more productive despite possessing smaller plot sizes. On the flip side, land size was found to increase the productivity gap by increasing returns to inputs on male managed plots while decreasing the returns on female-managed plots. Earlier studies document that land size increases the gap by increasing the returns to male managers (Slavchevska, 2015) and decreasing the returns to female managers (Aguilar et al., 2015). Another productive input that was found to contribute to the endowment effect is female family labor (accounting for 2.3% of the endowment effect), where productivity decreased with the quantity of female family labor. Among the physical inputs, quantity of fertilizer was found to negatively contribute to the endowment effect, suggesting its role in reducing the gender gap in productivity.

Crop-legume diversification and soil and water conservation contributed negatively to the endowment effect (3.2% and 1.3% respectively). In fact, crop-legume diversification was the second most important factor that explained gender difference in productivity. While observations show significant differences in practicing crop-legume diversification on male and female-managed plots, results nonetheless indicate that this important SLMP reduces the gender gap. In addition, soil and water conservation also helped reduce the productivity gap (the third most important factor) by negatively contributing to the endowment effect. Moreover, both high plot fertility and access to training were shown to reduce the gap, as both help boost productivity.

The main factors that explained the structural effect were age, years of schooling, land, and hired labor. Results related to age (of both male and female managers) suggest that female managers face substantial disadvantage. The positive coefficients of age (in column 3 of table 3) indicate that older female managers obtain lower returns than average. This implies age widens the returns to factors of production. We find that schooling contributes positively to male structural advantage, suggesting that education enables male managers to obtain higher returns (relative to female managers). The log of size of land contributes 27.5% to male structural advantage and 25.1% to female structural disadvantage. These relative contributions suggest that while land increases returns to inputs for male managers, it decreases returns to female managers. In this regard, Slavchevska (2015) emphasizes the fact that women possess smaller plots is an important source of gender inequality that plays a big role in widening the productivity gap. On the other hand, hired labor contributed 49% in closing the gap through the female structural disadvantage component. The negative coefficient of hired labor on the male structural advantage component also indicates male managers obtain lower returns from hired labor. Overall, hired labor reduces the gap by not only lowering the returns to male managers but also increasing the returns to female managers. Livestock resources are traditionally key agricultural inputs in Ethiopia. They define production in an important way, as especially oxen are used not only for traction but also harvesting and women are less endowed with these critical factors. In this regard, despite the result showing livestock size contributed to widening the gap through increasing the returns to male managers (26.6%), its effect was countered by the higher percentage on the female structural disadvantage component (28.7%), which in the end indicates, on aggregate, livestock size helped reduce the gap.

4.3 Decomposition by SLMPs

First, we report results related to productivity differences presented in table 4. These results were obtained using Eq. (2) based on the use of SLMPs on male and female-managed plots. The results in Table 4 show the varying but yet important role SLMPs play in agricultural productivity. As reported in table 1, female managers used SLMPs less frequently on their plots. These differences in the application of SLMPs manifest themselves in higher productivity differences among male and female-managed plots. The productivity effect of using SLMPs varied between 11.5% (for soil and water conservation) and 47.5% (for the combined use of agroforestry and crop-legume diversification), which shows the difference that investment in land management practices can make to enhancing productivity.

Table 4: Gender differences in agricultural productivity by SLMPs, dependent variable: ln (value of harvest per hectare)

	Pooled sample	**AGF**	**CLD**	**SWC**	**AGF plus CLD**	**AGF plus SWC**	**CLD plus SWC**
Female plot manager	–0.152*** (0.047)	–0.200** (0.092)	–0.176* (0.104)	–0.115** (0.051)	–0.475*** (0.164)	–0.197* (0.116)	–0.235** (0.090)
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	773	271	165	691	177	158	247
R-squared	0.485	0.519	0.628	0.436	0.710	0.627	0.528

Robust standard errors are reported in parentheses.

All regressions for the different models of the use of sustainable land management practices include control variables related to manager characteristics, plot attributes, labor and non-labor inputs, access to agricultural services, household and community characteristics.

AGF: agroforestry; SWC: soil and water conservation; CLD: crop-legume diversification.

***p<0.01, ** p<0.05, * p<0.1.

Mean gender differentials in Table 5 show that the gap in productivity got even wider with different uses of SLMPs. Combinations of SLMPs appear to result in higher productivity gaps of 36.2% (AGF–CLD) and 31.9% (AGF–SWC). Individually, subsamples of crop-legume diversification (26.9%) and soil and water conservation (12.2%) showed higher productivity gaps than the whole sample. The use of more than one SLMPs could have multiplier effect in exacerbating productivity gaps. The data show female managers tended to practice these SLMPs less frequently, which may drive the gap as shown by the significant differences in yield per hectare and value of harvest per hectare (in favor of male managers). The unexplained part of the aggregate decomposition results in Table 5 in addition show that female managers face significant disadvantages in that they received lower returns. This can be discerned from the share of gender differentials (Table 5, last column) and associated positive coefficients, which show the varying levels of lower returns to inputs that female managers received. The implication from the results in Table 5 is that the use of individual and combinations SLMPs tended to widen the productivity gap, as female managers practiced them less often on their plots. In the end, we advise readers to take heed with the interpretation of these results as they were generated from reduced subsamples. Nevertheless, the results shed light on the potential that SLMPs have in increasing the gap as female managers tended to practices them on significantly fewer plots.

Table 5: Mean gender gap in productivity and aggregate decomposition

Types of SLMPs	Productivity gap (mean)			Aggregate decomposition			
	Mean productivity of plots managed by males	Mean productivity of plots managed by females	Gender gap in productivity	Endowment effect		Female structural disadvantage	
				Total	Differential share (%)	Total	Differential share (%)
All the SLMPs	10.8***	10.7***	0.099**	–0.0220	22.2	0.121***	122.2
	(0.0346)	(0.0320)	(0.0471)	(0.0414)		(0.0389)	
AGF	10.78***	10.68***	0.0962	–0.0634	65.9	0.160**	166.3
	(0.0585)	(0.0529)	(0.0789)	(0.0774)		(0.0743)	
SWC	10.86***	10.74)***	0.122**	0.0464	38	0.0752*	62
	(0.0395)	(0.0312)	(0.0503)	(0.0451)		(0.0456)	
CLD	11.27***	11.00***	0.269***	0.168*	62.5	0.100	37.4
	(0.0833)	(0.0595)	(0.102)	(0.0962)		(0.0862)	
SWC and CLD	10.75***	10.66***	0.0849	–0.0969	114	0.182**	214
	(0.0607)	(0.0538)	(0.0811)	(0.0767)		(0.0752)	
SWC and AGF	11.34***	11.02***	0.319***	0.159*	49.8	0.161*	50.2
	(0.0845)	(0.0607)	(0.104)	(0.0964)		(0.0917)	
AGF and CLD	11.35***	10.98***	0.362***	0.0967	26.7	0.265**	73.2
	(0.0981)	(0.0861)	(0.131)	(0.129)		(0.110)	

Robust standard errors are reported in parentheses.
AGF: agroforestry; SWC: soil and water conservation; CLD: crop-legume diversification.
Male structural advantage is not reported as it is not the issue of interest.
*** p<0.01, ** p<0.05, * p<0.1.

Table 6 presents additional decomposition results for female managers based on their use of SLMPs. Female managers that did not practice crop-legume diversification had 34.4% lower productivity than male managers. After controlling for inputs and characteristics, the differences only marginally reduced to 33.6%, suggesting that most of the productivity difference was due to differences in returns to factors of production (structural effect). In contrast, female managers that practiced crop-legume diversification appeared to have 43.2% higher productivity than male managers. However, after controlling for inputs and characteristics and accounting for location fixed effects, this difference vanished, indicating productivity difference may be masked by factors other than practicing crop-legume diversification. On the other hand, while no significant productivity difference was observed among female managers who practiced agroforestry and male managers, female managers who did not practice agroforestry were found to have 17.8% lower productivity than male managers. The fact that this productivity difference is only marginally lower than 18.9% (obtained from a model with no control variables and no location

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fixed effects) indicates that the difference was largely due to the structural effect. Importantly, these overall results indicate that female managers that did not practice the SLMPs had significantly lower productivity.

4.4 Decomposition by marital status and geographic location

Table 6 reports results related to heterogeneity in productivity by marital status and geographic location. Estimates show that married female managers had 9.6% lower productivity than male managers. After controlling for inputs and characteristics and location fixed effects, this difference increased to 17.7%. While a part of this difference is attributable to differences in productive inputs (endowment effect), it is likely that a part of the difference may also be masked by unobserved heterogeneity (or differences in returns to factors). Perhaps married female managers' productivity could be negatively affected by time constraints that come with the additional household responsibilities after marriage. On the other hand, non-married female managers had a lot lower productivity of 43.4%. Interestingly, we find that this difference in productivity vanishes once we control for inputs as well as characteristics and location fixed effects. In contrast, Aguilar et al. (2015) found that non-married female managers were less productive while they find at the same time no productivity difference among married female managers and male managers. We want to make a note of the small sample size of the non-married subsample of our data for which the small sample properties estimators may not hold. So, we advise readers to take heed with the interpretation of these results.

Table 6: Heterogeneity in productivity by female marital status, use of SLMPs and location

	1	2	3	4
By marital status				
Female × married	–0.0956** (0.0473)	–0.0672 (0.0594)	–0.1469*** (0.0394)	–0.1773*** (0.0471)
Female × unmarried	–0.4339** (0.0823)	–0.4423** (0.1067)	0.2412 (0.1728)	0.1683 (0.1852)
R-squared	0.007	0.019	0.513	0.515
By use of SLMPs				
Female × AGF	–0.3458** (0.1213)	–0.3750*** (0.1290)	0.0586 (0.1123)	0.0.210 (0.1175)
Female × no–AGF	–0.1899* (0.1063)	–0.2450** (0.1117)	–0.2185** (0.1021)	–0.1777* (0.1070)
Female × CLD	0.4316*** (0.0725)	0.4913*** (0.0749)	–0.0352 (0.0874)	–0.0281 (0.0866)
Female × no–CLD	–0.3435*** (0.0808)	–0.3262*** (0.0805)	–0.3397*** (0.0633)	–0.3362** (0.0632)
R-squared	0.052	0.064	0.500	0.501
By geographic location				
Female × Aregen	–0.1296* (0.0666)	0.0385 (0.0925)	–0.1348** (0.0655)	–0.1145 (0.0774)
Female × Selam	–0.0981 (0.0871)	–0.2439** (0.0968)	–0.1996*** (0.0704)	–0.2275*** (0.0763)
Female × Embarufael	–0.0541 (0.1348)	–0.0480 (0.1423)	–0.2307*** (0.0888)	–0.2079** (0.0936)
Female × Lemlem	–0.0712 (0.0533)	0.1387 (0.1208)	–0.0899* (0.0500)	–0.1962** (0.0829)
R-squared	0.007	0.027	0.513	0.515
Control variables	No	No	Yes	Yes
Location fixed effects	No	Yes	No	Yes
Observations	773	773	773	773

Robust standard errors are reported in parentheses.

Control variables include manager characteristics, plot attributes, labor and non-labor inputs, access to agricultural services, sustainable land management practices and household and community characteristics.

There was no sufficient variation in the use of some of the interest SLMPs (such as SWC) for which results could not be generated.
AGF: agroforestry; CLD: crop-legume diversification.
***p<0.01, ** p<0.05, * p<0.1.

Also reported in Table 6 are results related to spatial differences in productivity among male and female-managed plots of the four districts. The results from different specifications that account for location fixed effects and control for inputs and characteristics show that female managers had lower productivity than male managers in most areas. In Aregen, we find that female managers were circa 13% less productive than male managers. After controlling for baseline covariates, the gap slightly increases to 13.5% before becoming statistically insignificant in the full model that accounts for location fixed effects. Elsewhere, the results show the presence of gender gap in productivity. However, the margin of gender gap in productivity appears to be narrow ranging from 19.6% in Lemlem to 22.7% in Selam. A clear indication from these results, however, is that female managers appeared to be less productive than male managers (with gap ranging from 19.6% to 22.7%). Slavchevska (2015) pointed out that female farmers were highly likely to be more disadvantaged in areas where agricultural conditions are harsher. Our results conform to such observations as two of the areas (Selam and Lemlem) are generally known to be low agricultural potential areas. As a support to this observation, data show female managers in these areas had significantly lower yield per hectare compared to male managers.

4.5 Decomposition by percentiles

Except at the lower end of the distribution, we find the female structural disadvantage dominated the endowment effect in explaining the gap (i.e., accounted for the largest share of the gap). The effect of the female structural disadvantage component is highest at the 40th percentile, and is generally higher for the upper half of the productivity distribution. This in turn suggests that among the more productive female managers, differences in returns to factors (or unobserved heterogeneity) explained the productivity gap in a more important manner than access to inputs. As far as the explanatory power on productivity gap is concerned, Kilic et al. (2015), Oseni et al. (2015) and Slavchevska (2015), in contrast found that the endowment effect dominated the female structural disadvantage component in explaining the greatest portion of the gap in several points of the productivity distribution. While it is well documented in the literature (example Alene et al., 2008; Kilic et al., 2015; Vargas Hill and Vigneri, 2014; Oseni et al., 2015) that differences in access to factors of production largely explain productivity differences, returns to productive inputs and unobserved heterogeneity also constitute important aspects that contribute to productivity differences among male and female managers. These results in turn show that reducing unequal returns to these inputs (as shown by the dominant effect of the female structural disadvantage component) is equally important in reducing the productivity gap at different levels of the productivity distribution (see also Slavchevska, 2015).

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Table 7: RIF aggregate decomposition of gender differentials at various distribution points

	Mean	**10th percentile**	**20th percentile**	**30th percentile**	**40th percentile**	**50th percentile**	**60th percentile**	**70th percentile**	**80th percentile**	**90th percentile**
Gender differentials										
Male managers	10.8***	10.05***	10.28***	10.49***	10.65***	10.75***	10.96***	11.16***	11.35***	11.70***
	(0.0346)	(0.0568)	(0.0586)	(0.0436)	(0.0748)	(0.0734)	(0.112)	(0.0842)	(0.0951)	(0.0711)
Female managers	10.7***	10.09***	10.27***	10.42***	10.50***	10.70***	10.83***	11.02***	11.25***	11.53***
	(0.0320)	(0.0859)	(0.0378)	(0.0310)	(0.0313)	(0.0159)	(0.0349)	(0.0419)	(0.0212)	(0.0243)
Gender differentials	0.099**	–0.0382	0.0068	0.0738**	0.151**	0.0488	0.127	0.146*	0.0972	0.174**
	(0.0471)	(0.0770)	(0.0492)	(0.0356)	(0.0758)	(0.0685)	(0.120)	(0.0879)	(0.0868)	(0.0828)
Aggregate decomposition										
Endowment effect	–0.0220	0.0041	–0.0216	–0.0383	–0.0734	–0.0562	–0.0455	–0.0308	–0.0072	–0.0258
	(0.0414)	(0.0447)	(0.0355)	(0.0415)	(0.0483)	(0.0567)	(0.0839)	(0.0921)	(0.103)	(0.0892)
Share of differential	22.2%	10.7%	317%	51.9%	49%	115%	35.7%	21%	7%	14.8%
Male structural advantage	0	0	0	–0	0	0	0	0	–0	0
	(0.0118)	(0.0131)	(0.0112)	(0.0274)	(0.0277)	(0.0109)	(0.0294)	(0.0121)	(0.0291)	(0.0199)
Share of differential	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Female structural disadvantage	0.121***	–0.0423	0.0283	0.112*	0.225***	0.105***	0.172***	0.177***	0.104*	0.200***
	(0.0389)	(0.0409)	(0.0191)	(0.0586)	(0.0737)	(0.0266)	(0.0534)	(0.0377)	(0.0553)	(0.0614)
Share of differential	122.2%	110.7%	416%	151.8%	149%	215%	135.6%	121%	107%	114.9%
Observations	773	773	773	773	773	773	773	773	773	773

Robust standard errors are reported in parentheses.

Control variables include manager characteristics, plot attributes, labor and non-labor inputs, access to agricultural services, sustainable land management practices and household and community characteristics.

***p<0.01, ** p<0.05, * p<0.1.

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Disaggregated analysis of decomposition results by SLMPs (reported in Table 8) shows the presence of productivity gaps across various points of the productivity distribution. Other than depicting productivity differences at various percentiles, these results are consistent with the mean decomposition results reported in Table 5. For the crop-legume diversification subsample, the results show that the endowment effect dominates the female structural disadvantage component for female managers with lower productivity, suggesting that differences in inputs largely explain the gap when productivity is low. For the most productive women (80th and 90th percentiles) on the other hand, the results show returns to inputs (or unobserved heterogeneity) largely explain the difference in productivity. For the most productive, this in effect means that productivity gap may be largely due to differences in returns to inputs (or unobserved factors) instead of access to productive inputs. Moreover, among the more productive farm managers, the positive coefficients imply crop-legume diversification widens the gap in productivity.

Soil and water conservation (SWC) and combined use of soil and water conservation and crop-legume diversification (CLD plus SWC) tended to widen the gap in the upper half of the distribution. As can be discerned from the positive coefficients of the female disadvantage components in this half, SWC and combined use of CLD and SWC tended to widen the gap among the higher-than-average productive female managers. On the other hand, SWC tended to close the gap at the lower end of the distribution, suggesting it reduced the gap among female managers with lower productivity. For the combined use of AGF and CLD, the female structural disadvantage component dominated the endowment effect at different percentiles and contributed to increasing the gap. [7] Overall, these results suggest that unequal returns to inputs and unobserved factors outweigh the effect by productive inputs in widening or narrowing the gender gap in productivity. Earlier studies (such as Quisumbing et al., 2001; Peterman et al., 2011; Slavchevska, 2015) document that productivity differences may not be fully explained by differences in access to inputs, and bridging such differences (in access to inputs) may not necessarily close the gender gap in productivity due to unequal returns to productive inputs or unobserved heterogeneity.

[7] These are only part of the detailed RIF decomposition results. All the related results can be made available on request.

Table 8: RIF aggregate decomposition of gender differentials at various distribution points by SLMPs

	10th percentile	20th percentile	30th percentile	40th percentile	50th percentile	60th percentile	70th percentile	80th percentile	90th percentile
Agroforestry (AGF)									
Gender differentials	0.0035	–0.0057	0.0582	0.0525	0.0347	0.0956	0.0436	0.0488	0.0711
	(0.0111)	(0.107)	(0.0623)	(0.0544)	(0.0867)	(0.0965)	(0.0689)	(0.116)	(0.0948)
Endowment effect	0.0845	0.0372	0.0003	–0.0104	–0.106	–0.202	–0.187	–0.128	–0.148*
	(0.0738)	(0.106)	(0.0607)	(0.0435)	(0.118)	(0.124)	(0.120)	(0.158)	(0.0901)
Female structural	–0.081**	–0.0429	0.058***	0.0629**	0.141**	0.298***	0.230***	0.177***	0.220***
disadvantage	(0.0321)	(0.0738)	(0.0217)	(0.0312)	(0.0463)	(0.0537)	(0.0619)	(0.0486)	(0.0846)
Crop-legume diversification (CLD)									
Gender differentials	0.194*	0.283**	0.287***	0.150**	0.151***	0.114**	0.166**	0.265**	0.527***
	(0.114)	(0.141)	(0.0833)	(0.0618)	(0.0419)	(0.0576)	(0.0795)	(0.114)	(0.108)
Endowment effect	0.150	–0.265*	–0.186**	–0.0961**	–0.105*	0.0861	0.184	0.0187	0.0947
	(0.126)	(0.258)	(0.0847)	(0.0367)	(0.0546)	(0.0667)	(0.115)	(0.0769)	(0.0972)
Female structural	0.0442	0.0187	0.100	0.0354	0.0461	0.0283	–0.0184	0.276**	0.432***
disadvantage	(0.0748)	(0.149)	(0.147)	(0.0535)	(0.0549)	(0.0701)	(0.116)	(0.138)	(0.0674)
Soil and water conservation (SWC)									
Gender differentials	0.0633	0.0906**	0.0298	0.0674	0.0952	0.131*	0.156**	0.116	0.243**
	(0.0551)	(0.0425)	(0.0484)	(0.0720)	(0.101)	(0.0804)	(0.0786)	(0.164)	(0.0942)
Endowment effect	–0.0675*	–0.114*	–0.0193	–0.0138	0.0151	–0.0057	–0.0021	0.0430	0.0144
	(0.0368)	(0.0675)	(0.0588)	(0.0696)	(0.101)	(0.0904)	(0.100)	(0.146)	(0.0991)
Female structural	0.0042	0.0237	0.0492	0.0812	0.080***	0.137***	0.158***	0.0730	0.228***
disadvantage	(0.0542)	(0.0624)	(0.0712)	(0.0740)	(0.0255)	(0.0392)	(0.0414)	(0.0912)	(0.0545)
Agroforestry plus crop-legume diversification (AGF plus CLD)									
Gender differentials	0.498***	0.454**	0.388**	0.248***	0.234**	0.335**	0.439**	0.246	0.302
	(0.174)	(0.156)	(0.126)	(0.0558)	(0.110)	(0.170)	(0.212)	(0.210)	(0.220)
Endowment effect	0.215	–0.0237	0.0190	0.0591	0.102	0.0260	0.193*	0.130	0.185
	(0.190)	(0.128)	(0.127)	(0.0948)	(0.121)	(0.0914)	(0.109)	(0.134)	(0.187)
Female structural	0.283	0.478***	0.370*	0.189*	0.132	0.309	0.245	0.115	0.117*
disadvantage	(0.238)	(0.101)	(0.216)	(0.0981)	(0.167)	(0.223)	(0.160)	(0.171)	(0.0611)
Agroforestry plus soil and water conservation (AGF plus SWC)									

	10th percentile	20th percentile	30th percentile	40th percentile	50th percentile	60th percentile	70th percentile	80th percentile	90th percentile
Gender differentials	0.358**	0.411***	0.364***	0.216**	0.200***	0.347***	0.277**	0.354***	0.570***
	(0.159)	(0.135)	(0.0969)	(0.0929)	(0.0677)	(0.109)	(0.0925)	(0.0959)	(0.111)
Endowment effect	0.387**	0.291	0.166*	0.0910	0.126	0.189*	0.223	0.0885	0.101
	(0.195)	(0.188)	(0.0932)	(0.0882)	(0.0771)	(0.102)	(0.163)	(0.215)	(0.0922)
Female structural disadvantage	–0.0289	0.120	0.198**	0.125***	0.0739	0.158***	0.0549	0.266	0.469***
	(0.105)	(0.143)	(0.0788)	(0.0284)	(0.0509)	(0.0191)	(0.0879)	(0.246)	(0.0455)
Crop-legume diversification plus soil and water conservation (CLD plus SWC)									
Gender differentials	0.0073	–0.0128	–0.0219	0.0338	0.0433	0.135	0.116	0.0634	0.143
	(0.0992)	(0.112)	(0.100)	(0.0741)	(0.112)	(0.171)	(0.118)	(0.188)	(0.123)
Endowment effect	0.0379	–0.0193	–0.0269	–0.0444	–0.207	–0.233	–0.215	–0.214	–0.123
	(0.0849)	(0.0981)	(0.122)	(0.0843)	(0.129)	(0.185)	(0.138)	(0.173)	(0.130)
Female structural disadvantage	–0.0307	0.0065	0.0049	0.0782	0.251**	0.368***	0.331***	0.278***	0.267*
	(0.0361)	(0.0804)	(0.0757)	(0.0592)	(0.104)	(0.0538)	(0.107)	(0.0803)	(0.137)

Robust standard errors are reported in parentheses.

Control variables include manager characteristics, plot attributes, labor and non-labor inputs, access to agricultural services, sustainable land management practices and household and community characteristics.

Male structural advantage is not reported to save space as well as its limited relevance to the discussion.

***p<0.01, ** p<0.05, * p<0.1.

4.6 Robustness Checks

An important assumption for both the base OLS and decomposition results to remain unbiased is the absence of omitted variable bias. This is especially important for studies that use observational data. In such studies, unobserved heterogeneity or selection on unobservables can bias estimates. The concern is that some unobservable characteristics may jointly determine productivity and the probability of being a plot manager by either gender. For lack of relevant and valid instruments, we first performed the standard omitted variables test for the base OLS and followed Aguilar et al. (2015) and Oseni et al. (2015) in using the approach proposed by Altonji et al. (2005) to explore the presence of omitted variable bias.

Table 9: Assessment of robustness of the base OLS model for omitted variables

		Additional groups of control variables			
	Base OLS	**Manager characteristics**	**Plot attributes**	**Other infrastructure**	**Crop fixed effects**
Female plot manager	–0.152***	–0.159***	–0.157***	–0.1569**	–0.156***
	(0.0468)	(0.0467)	(0.0466)	(0.0476)	(0.0414)
Age	–0.0052**	–0.00441**	–0.00480**	–0.00433**	–0.00381**
	(0.0021)	(0.00204)	(0.00206)	(0.00205)	(0.00169)
Years of schooling	–0.0358	–0.0296	–0.0333	–0.0328	–0.0165
	(0.0219)	(0.0199)	(0.0210)	(0.0209)	(0.0199)
Marital status	–0.0918	–0.0260	–0.0904	–0.0547	–0.0237
	(0.110)	(0.113)	(0.112)	(0.107)	(0.0762)
Membership in cooperatives	–0.135**	–0.147	–0.126**	–0.118**	–0.161
	(0.0594)	(0.143)	(0.0586)	(0.0586)	(0.139)
Land size (*ln*)	–0.836***	–0.819***	–0.829***	–0.840***	–0.829***
	(0.0618)	(0.0595)	(0.0622)	(0.0608)	(0.0506)
High plot fertility	0.140***	0.179***	0.152***	0.155***	0.0842**
	(0.0467)	(0.0460)	(0.0464)	(0.0462)	(0.0405)
Medium plot fertility	0.0736*	0.0645	0.0746*	0.0730	0.00984
	(0.0443)	(0.0439)	(0.0444)	(0.0446)	(0.0385)
Steep plot slope	–0.0342	–0.00200	–0.0202	–0.0314	–0.0189
	(0.0553)	(0.0550)	(0.0560)	(0.0558)	(0.0474)
Medium plot slope	0.0439	0.0503	0.0474	0.0439	–0.0199
	(0.0409)	(0.0394)	(0.0401)	(0.0397)	(0.0310)
Do not use organic manure	–0.103*	–0.121**	–0.0884	–0.0887	–0.0626
	(0.0596)	(0.0605)	(0.0592)	(0.0591)	(0.0515)
Plot distance from home	0.0553***	0.0423**	0.0583***	0.0572***	–0.0185
	(0.0171)	(0.0176)	(0.0172)	(0.0172)	(0.0148)
Plot tenure security	0.0947*	0.142***	0.0873*	0.0841	0.143***
	(0.0525)	(0.0532)	(0.0516)	(0.0527)	(0.0452)
Female family labor (*ln*)	0.149***	0.137***	0.145***	0.140***	0.150***
	(0.0424)	(0.0415)	(0.0417)	(0.0412)	(0.0382)
Male family labor (*ln*)	0.0317	0.0477	0.0340	0.0381	0.0119
	(0.0374)	(0.0370)	(0.0370)	(0.0363)	(0.0290)
Hired labor (*ln*)	0.465***	0.462***	0.460***	0.470***	0.497***
	(0.0950)	(0.0948)	(0.0921)	(0.0926)	(0.0949)
Fertilizer amount (*ln*)	0.0446***	0.0291*	0.0464***	0.0457***	0.0320**
	(0.0165)	(0.0161)	(0.0163)	(0.0163)	(0.0144)

		Additional groups of control variables			
	Base OLS	**Manager characteristics**	**Plot attributes**	**Other infrastructure**	**Crop fixed effects**
Pesticide amount (*ln*)	0.118**	0.117**	0.110*	0.118**	0.0432
	(0.0594)	(0.0579)	(0.0578)	(0.0585)	(0.0495)
Soil & water conservation	0.154**	0.106	0.154**	0.156**	0.133**
	(0.0672)	(0.0647)	(0.0655)	(0.0655)	(0.0517)
Agroforestry	–0.0916*	–0.0274	–0.0823	–0.0881*	0.0518
	(0.0519)	(0.0490)	(0.0518)	(0.0510)	(0.0440)
Crop-legume diversification	0.323***	0.327***	0.339***	0.334***	0.285***
	(0.0543)	(0.0511)	(0.0514)	(0.0513)	(0.0489)
Livestock size	0.00872	0.0415	0.0106	0.0175	0.0462
	(0.0445)	(0.0427)	(0.0422)	(0.0419)	(0.0395)
Household size	0.0296*	0.00907	0.0326*	0.0296*	–0.0209
	(0.0176)	(0.0177)	(0.0178)	(0.0175)	(0.0153)
Male number	–0.00565	–0.00724	–0.00746	–0.00464	–0.0100
	(0.0206)	(0.0198)	(0.0205)	(0.0202)	(0.0170)
Female number	0.0178	0.0157	0.0173	0.0216	0.0180
	(0.0265)	(0.0262)	(0.0269)	(0.0267)	(0.0212)
Distance to all-weather roads	–0.00320	–0.00880*	–0.00369	–0.00802	–0.00494
	(0.00490)	(0.00522)	(0.00493)	(0.00540)	(0.00443)
Distance to markets	0.00459	–0.0165	0.00465	–0.0169	–0.00801
	(0.00899)	(0.0121)	(0.00894)	(0.0120)	(0.00992)
Access to credit	–0.105*	–0.0192	0.00785	0.00641	–0.0534
	(0.0549)	(0.0432)	(0.0447)	(0.0441)	(0.0350)
Access to extension	0.0179	0.0111	–0.104*	–0.111**	–0.0397
	(0.0441)	(0.0610)	(0.0545)	(0.0544)	(0.0557)
Access to training	0.0799**	0.0873**	0.0963**	0.0906**	0.0319
	(0.0383)	(0.0364)	(0.0374)	(0.0373)	(0.0291)
Observations	773	773	773	773	773
R-squared	0.485	0.520	0.495	0.502	0.663

The standard omitted variable test (Ramsey test) generated a test statistic against the rejection of the null hypothesis of no omitted variables ($F(3, 736) = 0.85$; p–value=0.4662) indicating the base OLS model (full model) had no omitted variables. To further explore the sensitivity of the base coefficients, we estimated different models with different specifications by sequentially adding groups of variables based on the approach proposed by Altonji et al. (2005). Among the groups of variables added include manager characteristics (mobile access, access to market, membership in social groups), plot characteristics (fallowing and access to irrigation), household and community characteristics (rainfall condition, distance to dry-weather roads, distance to finance centers, distance to FTCs), and crop fixed effects. The hypothesis is selection on unobservables (i.e., omitted variable bias) would not be a concern should the coefficients from the base OLS model (including the gender variable) remain robust (not sensitive) to the re-specifications. Table 9 presents the base OLS results from table 2 and the results of different model specifications. We find that the coefficients for the main variables were largely not sensitive to the re-specifications and remained robust in terms of statistical significance and sign. A few coefficients were sensitive in the model with crop fixed effects. Crop choices among male and female farmers may explain this variation due to differences in risk preferences and cultural norms (Slavchevska, 2015) or self-selection into cultivating certain crops (Aguilar et al., 2015) whereby male farmers comparatively cultivate cash crops. Moreover, while agro-climatic conditions dictate what is grown (i.e., crop choice) in some localities, the small micro-climate variation around the study areas may still have some effect, leading to some variation in the coefficients.

5 Conclusion

This paper presented results related to the analysis and decomposition of productivity gap among female and male farm managers who exhibited heterogeneous use of sustainable land management practices. The bulk of literature documents the productivity gap among female and male farmers is largely due to differences in access to inputs and resources. This study adds to the stock of knowledge by examining this issue through parsing the decomposition analysis vis-à-vis the use of SLMPs. First, we estimated a baseline regression to identify factors that explain productivity differences among male and female-managed plots. Since such approaches do not help isolate the relative importance of the different factors, we use decomposition methods to distinguish the source and quantify the proportion the productivity difference that emanates from differences in productivity enhancing factors and differences in returns to factors.

The estimated gender gap (15.2%) is substantially smaller than productivity gaps reported by earlier studies such as Peterman et al. (2011, 27%) in Uganda, Kilic et al. (2014, 25%) in Malawi, Aguilar et al. (2015, 23.4%) in Ethiopia, Oseni et al. (2015, 27.5%) in northern Nigeria, and Slavchevska (2015, 21%) in Tanzania. While such variations may be due to several factors, it is important to note that our study was based on selected districts in northern Ethiopia whereas earlier studies were based on nationally representative data. Nevertheless, this overall productivity gap is significant on its own and the gap increased with the use of SLMPs. As could be discerned from the data, male managers implemented significantly higher SLMPs on their plots. Analysis of productivity gap based on the use of SLMPs showed that the gap as a result increased significantly. Estimated higher productivity gaps included 36.2% (for the combined use of agroforestry and crop-legume diversification), 31.9% (combined use of agroforestry and soil and water conservation), and 26.9% (for crop-legume diversification). We reckon that the significant differences among male and female managers in the use of these SLMPs could explain the higher gaps in productivity. However, we still need to point out that unobserved heterogeneity could explain some of the gap despite the robustness analysis showing results remained insensitive to omitted variables bias. Moreover, analysis of the soil and water conservation subsample showed a 12.2% productivity difference among male and female plot managers. This relatively smaller productivity difference may be due to the larger number of female managers who implemented soil and water conservation on their plots (compared to the other SLMPs).

Overall, SLMPs tended to widen the productivity gap as female managers practiced them less often on their plots. Moreover, it was shown that female managers face significant disadvantages due to the low returns they received to productive inputs. In another analysis, decomposition of productivity differentials vis-à-vis SLMPs showed that the share of gender differentials was largely explained by varying levels of lower returns to inputs that female managers received. This could mean that unobserved factors related to SLMPs may contribute to the differences in returns to these inputs, as shown by the results further widening the productivity gap. Moreover, we find that SLMPs could increase or close the gap in productivity based on the productivity level (deciles) of female managers. For example, crop-legume diversification helped reduce the gap among the less-than-average productive female managers. In contrast, it increased the gap among the more productive female managers (upper end of the distribution). On the other hand, soil and water conservation increased the gap among the higher-than-average productive female managers. In contrast, soil and water conservation had contributed to closing the gap for female managers with lower productivity (lower end of the distribution). In general, however, differences in returns to SLMPs appear to explain the increase in productivity gap between male and female managers at various distribution points.

In lieu of the contribution of female family and hired labor, policies that reduce female time constraints and increase access to affordable labor markets could help reduce productivity gaps. Aguilar et al. (2015), for example, suggest the use of labor-saving technologies that women can get more out of limited time for farming towards reducing the gap. Increasing women's access to non-labor inputs such as fertilizer and livestock were also found to not only increase productivity but also reduce the gap. On the other hand, both soil and water conservation and crop-legume diversification helped increase productivity and weighed negatively on the endowment effect, showing their importance as 'productive inputs' that help reduce the productivity gap. Policies that promote implementation of these SLMPs on female-managed plots could therefore bridge and compensate for some of the constraints female farmers have in accessing inputs for enhancing productivity. Again, analysis of the gender gap along productivity distribution reflects the need for devising tailor-made strategies for different productivity classes. For instance, soil and water conservation could be more important for low productivity females while cop-legume diversification could play a more important role among the more productive female farmers.

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