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Agricultural productivity, land use intensification and rural household welfare: evidence from Ethiopia

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ABSTRACT

While the role of agricultural productivity in alleviating poverty and enhancing household well-being is widely acknowledged, the micro-level evidence on the relationship between smallholder productivity and rural household welfare remains scarce in sub-Saharan Africa. Utilising three-wave comprehensive panel data from rural Ethiopia, this paper offers valuable insights into the effect of maize productivity on rural household welfare. We use both fixed-effects and correlated random-effects IV estimators to account for unobserved heterogeneity and endogeneity. Our findings reveal that increased maize productivity leads to higher household income, enhanced maize consumption, and greater asset ownership, ultimately reducing rural poverty. Notably, the welfare gains from maize productivity vary among farm households, with the most substantial effects observed among advantaged households, particularly those headed by male farmers and those with a more favourable economic standing in terms of poverty status. These results not only hold promise for poverty reduction through intensified agricultural practices in rural Ethiopia but also emphasise the necessity for targeted interventions to ensure equitable distribution of welfare benefits.

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1. Introduction

A broad consensus exists that agricultural productivity growth is key to achieving poverty reduction through enhancing household welfare. In Sub-Saharan Africa (SSA), where the majority of rural residents rely heavily on agriculture for their livelihoods, agricultural productivity plays a pivotal role in meeting poverty reduction targets (Ariga et al. 2019; Mason-D'Croz et al. 2019). However, despite substantial investment in agricultural research and the advent of innovative agricultural practices, poverty and food insecurity continue to be pervasive challenges in SSA. Addressing these issues remains a priority on the global development agenda, as reflected in initiatives such as the Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs), which aim to eradicate poverty and hunger by 2030 (United Nations 2015, 2019). In line with the SDGs, which emphasise the need to double productivity for small-scale farmers in the lowest-income countries, efforts to combat poverty and food insecurity in SSA have predominantly centred on enhancing the

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productivity of smallholder agriculture (United Nations 2019). However, progress has been slow, with extreme poverty and undernourishment rates showing limited improvement (World Bank 2021).

The persistent challenges of rural poverty and food insecurity in SSA underscore the critical need to accelerate efforts in enhancing agricultural productivity to achieve the SDGs in SSA. While smallholder agriculture is viewed optimistically as a means to alleviate rural poverty, debates persist regarding its effectiveness. Arguments against agricultural-led poverty reduction often point to a lack of supportive institutions and ineffective policy implementation in SSA countries (Collier and Dercon 2014; Timmer 2008). Limited public investment and market barriers further hamper smallholder agriculture's potential to reduce poverty (Timmer 2008; Dzanku 2015; Collier and Dercon 2014). Additionally, low rates of technology adoption, varying widely across countries due to factors like soil quality and market conditions, contribute to the weak link between agricultural productivity and rural poverty reduction (Takahashi, Muraoka, and Otsuka 2019; Sheahan and Barrett 2017). Heterogeneity in the yield response to modern inputs, such as chemical fertiliser, further complicates the situation (Takahashi, Muraoka, and Otsuka 2019). Overall, scholars widely concur that the link between smallholder productivity and rural poverty is context-dependent (Amare, Parvathi, and Nguyen 2023; Gebremedhin, Jaleta, and Hoekstra 2009; Timmer 2008).

This paper contributes to the ongoing debate on the relationship between productivity and poverty in SSA, with a specific focus on Ethiopia – the second most populous country in Africa. In SSA, Ethiopia has been at the forefront of implementing agriculture-led growth policies to address the challenges of food security and poverty. The paper explores the welfare implications of Ethiopia's advancements in smallholder maize productivity, a remarkable success story that holds promise for broader application throughout SSA (see Abate et al. 2015; Bachewe et al. 2018). In recent years, Ethiopia's growing population has led to a rapid decline in farm sizes, making land use intensification a critical element in meeting future food demands (Headey et al., 2014; Holden, 2018). To achieve this, the increased use of modern inputs and improved farming practices have been identified as crucial for sustainable intensification and food security (Assefa et al., 2021; Holden, 2018). Particularly for maize, a staple food in rural Ethiopia, intensification efforts through increased use of inorganic fertiliser, combined with improved farming practices, have been a policy priority (Geffersa 2023; Assefa et al., 2021; Holden, 2018). Despite the notable transformation in maize productivity in Ethiopia, micro-level evidence regarding its impact on household welfare and poverty reduction is still lacking.

Thus far, a growing number of studies examining the relationship between agricultural productivity and welfare highlight the significant positive effect of agricultural productivity on household welfare and rural poverty reduction in developing countries (Breisinger et al. 2011; Datt and Ravallion 1998; De Janvry and Sadoulet 2009; Ravallion 1990; Ravallion and Datt 2002). Nevertheless, the majority of research on the productivity-poverty nexus in SSA focuses on macro-level evidence regarding these relationships (Breisinger et al. 2011; De Janvry and Sadoulet 2009). A few exceptions include studies by Darko et al. (2018), Dzanku (2015), Abro, Alemu, and Hanjra (2014), and Sarris, Savastano, and Christaensen (2006). These studies have investigated the micro-level welfare impacts of agricultural productivity in countries such as Malawi, Ghana, Ethiopia, and Tanzania, respectively.

This paper extends the existing body of research in SSA context by offering crop-specific micro-level evidence regarding the association between agricultural productivity and welfare. By exploring the micro-level impacts of maize productivity on household well-being and rural poverty in Ethiopia, the study aims to contribute valuable insights into the productivity-poverty nexus in SSA. We use comprehensive three-wave household panel data collected from smallholder farm households in three major maize-producing regions in Ethiopia. The use of panel data in this paper allows us to control for unobserved heterogeneity. Given that we have panel data, we establish the relationship between maize productivity and household welfare using both the household fixed-effects and correlated random-effects estimators that account for unobservable household heterogeneity. To test and address potential endogeneity of maize productivity in the welfare models, we applied a control function and two-stage least squares approaches depending on the nature of the welfare outcome variable.

In the context of ongoing discussions concerning rural household well-being and agricultural productivity in SSA, this study enriches our understanding of the effects of agricultural productivity on welfare in three crucial ways. Firstly, our comprehensive analysis includes an asset-based indicator of household welfare, supplementing previous SSA studies that primarily used direct monetary measures of household welfare. By employing a latent-trait modelling, our study establishes a link between agricultural productivity growth and household welfare. This model, drawing insight from Item Response Theory (IRT) models, infers asset ownership based on farm households' access levels to various items. This asset-based approach to measuring household welfare provides a forward-looking perspective, capturing movements in and out of poverty, unlike income or consumption metrics, which are relatively static and backward-looking (Carter & Barrett, 2006). Considering the limited access to banking services in most rural African settings, smallholder farmers often tend to store their wealth as assets (Brockington 2021). Therefore, this asset-based measure serves as a more valid predictor of long-term household wealth resulting from smallholder productivity in a developing country, like Ethiopia, where access to rural saving institutions and banking services is limited. Secondly, utilising comprehensive panel data, we offer robust estimates on the relationship between household welfare outcomes and productivity of maize, a vital staple crop crucial for food security and poverty reduction goals. Thirdly, we provide deeper insights into the productivity-poverty relationship by disaggregating the welfare impacts based on the gender and poverty status of the households. This disaggregation holds significant policy implications, particularly in guiding targeted efforts for optimal outcomes.

The rest of this paper is organised as follows. Section 2 provides background on the agricultural sector and smallholder maize productivity in Ethiopia. Section 3 presents the analytical framework and describes the key variables used for the empirical analyses. Section 4 provides the description of the data utilised for the analyses. Section 5 is devoted to the empirical results and discussion while the final section draws conclusions and policy implications of the results.

2. Smallholder maize production, productivity and land use intensity in Ethiopia

In SSA, Ethiopia stands out as a significant agricultural-dependent nation that has prioritised agricultural-led development policies. It is the second most populous country in SSA and ranks among the top five countries with the highest rural poor population globally (World Bank 2018). Over 83% of Ethiopia's population depends on smallholder agriculture for their livelihoods (CSA 2019). Despite remarkable technological advancements driven by agriculture-led growth policies, Ethiopia, like many other SSA countries, grapples with persistent challenges related to poverty and food security. Official estimates reveal that Ethiopia's poverty rate stands at 23.5%, down from 29.6% in 2011 (World Bank 2020). However, the pace of poverty reduction has been notably slower in rural areas compared to urban areas, emphasising the predominance of poverty in Ethiopia's rural regions. While urban areas have experienced a 10.9% decline in poverty since 2011, rural areas have seen only a 4.8% reduction during the same period. This situation places Ethiopia among the top five countries globally with the largest rural poor population (World Bank 2018). Additionally, Ethiopia faces a widening gap between food production and consumption. Despite increased food production, it struggles to keep up with the rapidly growing population, leading to heightened reliance on foreign food aid. This challenge underscores the pressing need for sustainable agricultural strategies to bridge this gap and ensure food security for the country's populace.

In response, the Ethiopian government has embarked on an agricultural transformation policy since the mid-2000s. The government has implemented agricultural development policies consistent with the country's five-year Growth and Transformation Plans (GTP-I and GTP-II – implemented in 2011 and 2015, respectively), which have a clearly articulated goal for agricultural policies (Ministry of Finance and Economic Development [MoFED] 2012). However, rural poverty and food insecurity remain pervasive in the country. In recent years, the population pressure has also caused a rapid decline in farm sizes, exacerbating the food crisis. For example, the area cultivated for grain crop production decreased by 50.83% in 2015/2016, compared with the production year of 2014/2015, resulting in a dramatic drop in the national grain production (reduced by 113.61%) (CSA 2016). As a result, the Ethiopian government has prioritised enhancing the contribution of smallholder agriculture to food security and rural poverty reduction through intensive farming of major food crops, such as maize.

As part of the GTP-I and GTP-II policy initiatives, the Ethiopian government placed great emphasis on enhancing the productivity of food crops through the introduction of modern inputs and expanded access to extension services. Over the past two decades, the government substantially increased the extension agent-to-farmer ratio (1:476), to improve farmers' access to modern inputs (Cairns and Prasanna 2018). The effect of such policy initiatives has been an increase in agricultural output by more than double in the past two decades (Bachewe et al. 2018). Given the growing importance of maize in household food consumption, and for achieving food security, the Ethiopian government has placed continued efforts to enhance the smallholder maize productivity through improved research-extension linkages and enhanced access to modern inputs.

Consequently, in recent years, maize has emerged as a leading crop, in terms of the scale and volume of production, utilisation of modern inputs, the number of farmers producing it and household consumption (CSA 2016, 2019). Maize is predominately a subsistence food crop in Ethiopia, and household food security is mainly defined in terms of access to maize, as in most SSA countries. Maize is a significant food source in rural Ethiopia, relative to other cereal crops. Maize has the largest share in the country's crop production, next to *teff* (CSA 2016, 2019). For example, in the 2017/2018 cropping season, maize accounted for an estimated 48% of the cropped area and 56% of the volume of crop production (CSA 2019). Compared with other major cereals produced in Ethiopia, maize takes the lion share of the scale of production, accounting for about 30% of the total cereal production and 20% of the total area allocated to the production of cereals in 2017/2018 cropping-season (World Bank 2019). Over the past two decades, the average area allocation for maize production is large, compared with the area allocations for all other major cereals, except *teff* (CSA 2016, 2019). In addition to having the highest volume of total annual production and per hectare yield, maize has recently emerged as the single most important food crop in Ethiopia, in terms of the number of farmers engaged in cultivation. For example, in the Meher (main)

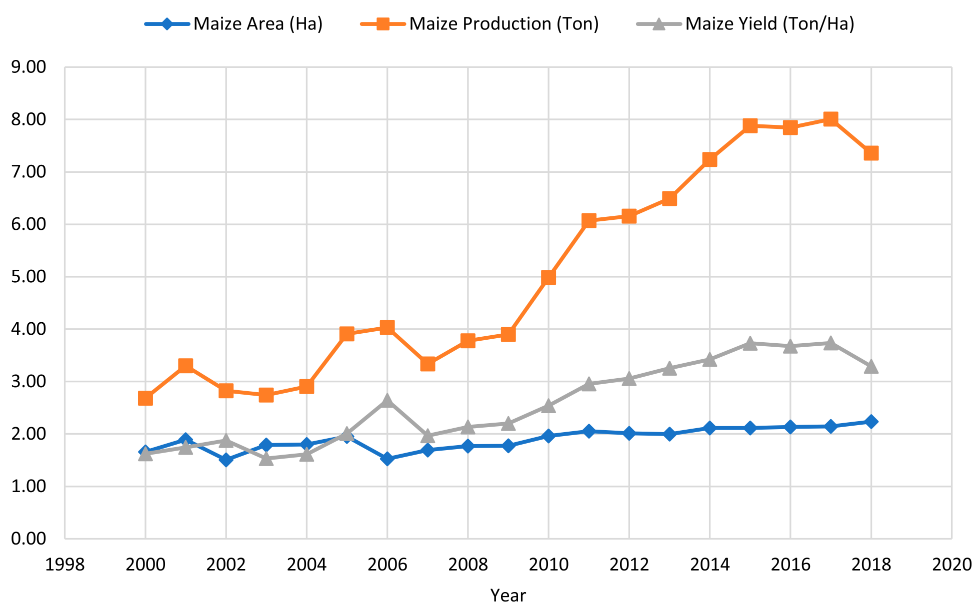

Figure 1. Maize production, productivity, and land allocations in Ethiopia (2000–2020). Source: Author's construction based on FAOSTAT (2020).

2014/2015 cropping-season, about 10% of the country's population produced maize, which accounted for 95% of the national maize production (World Bank 2019).

Recent evidence shows that transforming maize productivity through the increased use of modern inputs has substantially contributed to the rapid agricultural output growth in the country (see Abate et al. 2015; Bachewe et al. 2018). While multiple factors have contributed to the expansion and productivity changes in the maize sector in general, the overall research and development efforts are believed to be the key to the remarkable improvement over the past decades (see Figure 1). According to Abate et al. (2015), the major factors that transformed maize in Ethiopia include better research-extension linkages that enhanced farmer access to, and use of, modern inputs, wider adaptability of the maize crop to the country's agro-ecological environment, low production risks and growing demand for maize. Compared with area expansion, increased use of modern agricultural inputs and improved agricultural practices have contributed more to the enhanced contribution of maize to the country's food production over the last few decades (Abate et al. 2015; Cairns and Prasanna 2018). While Ethiopia's achievement in the maize sector in general is widely perceived as a success story for possible broader implementation elsewhere in SSA, smallholder maize farmers in Ethiopia continue to face high maize yield variability across regions and time. For example, as shown in the descriptive results (Table 2), the observed maize yields for smallholder farmers were less than 2 tons in the survey villages, although the national figure (which includes both smallholder and commercial farms) is more than 3 tons during the same period.

3. Analytical framework

Theoretically, agricultural productivity has the potential to contribute significantly to rural development, primarily by enhancing the well-being of rural households and mitigating poverty, both through direct and indirect mechanisms. Firstly, agricultural productivity can exert a direct positive influence by ameliorating the living standards of rural households and alleviating poverty. This enhancement is attained through an augmentation in food availability and improved income for individuals engaged in agricultural pursuits (De Janvry and Sadoulet 2002; Dzanku 2015). Secondly, it can yield indirect benefits for the agricultural community through broader societal welfare adjustments. These adjustments are manifested in productivity-driven gains, such as reductions in food prices and the stimulation of employment creation via enhancements in real wages for unskilled labourers (De Janvry and Sadoulet 2002; Minten and Barrett 2008; Zeng et al. 2015).

In the context of a farm household, however, the link between agricultural productivity growth and household welfare is not straightforward. One of the issues that complicate the understanding of the welfare impact of productivity in the context of developing countries is the trade-offs between profit-maximisation and utility-maximisation emerging from market imperfections (Feder and Umali 1993). Therefore, the welfare impact pathways of maize productivity have been viewed through the theoretical lens of the non-separable farm household model developed by Singh, Squire, and Strauss (1986). Following Singh et al. (1986), we built a theoretical model to illustrate the expected relationship between maize productivity and household welfare, assuming the production- and consumption-related decision-making of maize farmers to be simultaneously determined.

Agricultural productivity growth is expected to influence household welfare through changes in land productivity (maize yield per hectare). An improvement in maize productivity is expected to enhance household food consumption and to raise household income through selling surplus maize. The increased maize productivity could also indirectly affect household income. First, by releasing land for or taking land away from the production of other food crops. Second, an increase in land productivity could improve rural household welfare by releasing scarce farm labour for other supplementary income-generating activities (Dzanku 2015). Third, it may enhance household income from livestock production through the increased supply of livestock feed. The increase in household income would, in turn, translate to consumption expenditure. Overall, a consistent improvement in maize productivity over the years would result in an accumulation of household assets and raise the households above the poverty line. Therefore, we hypothesise a positive relationship between household welfare and growth in maize productivity.

3.1 The model

Our theoretical household welfare model (W) is specified as a function of maize productivity indicator and a set of variables representing socioeconomic characteristics of a household:

$$W = f(\mathbf{L},\ Z') \tag{1}$$

where W denotes household welfare for a household i at time t; L is a productivity indicator (maize yield/ha); whereas Z' is a vector of variables representing socioeconomic characteristics of a household.

To empirically estimate the extent to which maize productivity affects rural household welfare, we specify an empirical model that directly draws from the theoretical household welfare function in Equation 1. The empirical welfare equation is specified as:

$$W_{it} = \alpha_0 + \beta\mathbf{L}_{it} + \theta P_{it} + \psi H_{it} + \tau E_{it} + \varepsilon_{it} \tag{2}$$

$$\varepsilon_{it} = c_i + \mu_{it}$$

where i indexes household at t; W_{it} represents various measures of household welfare (as defined in Table 1); L_{it} is the agricultural productivity indicator, measured by land productivity (maize yield per hectare); P_{it} represents village level maize price; H is a vector of household characteristics; E denotes a vector of environmental characteristics; β, ψ, and τ are vectors of parameters to be estimated; α_0 is the intercept, while ε_{it} is an error term composed of two components (unobserved time-invariant factors, c_i and unobserved time-variant shocks, μ_{it}) that may affect maize production decisions. Table 1 presents the key variables used in analyses.

3.2 Welfare measures

We used four welfare indicators: *household income, household maize consumption, poverty index,* and *asset-based wealth index*. We estimated a separate equation for each welfare indicator. The two welfare indicators (*household maize consumption* and *household income*) were computed per adult, which was equivalent to adjusting for family size. *Household maize consumption* denotes the sum of household maize consumption (quantities in kg of both green and dry) from the home production of maize in each cropping season. *Household income* includes both farm (crop production as well as livestock production) and non-farm income.

The use of an asset-based approach to welfare measurement is in line with the increasing relevance of household assets as proxies of household well-being in developing countries (Brockington 2021; Filmer and Scott 2012; Vandemoortele 2014). The major advantage of the asset-based approach for measuring household well-being is that it offers a forward-looking dynamic framework and measures movements in and out of poverty compared to standard measures of household well-being such as income or consumption. This stands in contrast to conventional measures like income or consumption, which are static and backward-looking (Brockington 2021; Carter & Barrett, 2006). Consequently, asset-based measures serve as indicators of whether households are likely to remain impoverished in the future (Brockington 2021). Moreover, as argued by Sahn and Stifel (2003) in rural contexts, an asset index proves to be a more reliable predictor of long-term household welfare changes as it encompasses the child health and nutrition dimension of rural poverty.

However, one major challenge faced in empirical research involving asset-based methods is the significant disparity in asset ownership among households. Commonly employed strategies to address this issue include assigning weights based on subjective qualitative judgments, generating

Table 1. Description of variables used in the welfare models.

Variables	Variable description
Dependent variables: *Welfare indicators* ($\boldsymbol{W_{it}}$)	
Household income	Household income (real per capita per year, constant 2010 USD PPP)
Own maize consumption	Households' maize consumption from own production (per capita per year, kg)
Poverty index	Foster – Greer – Thorbecke (FGT) poverty index (defined using the international poverty line < 1.90 US$ PPP/day)
Asset index	Asset-based wealth index (generated using an IRT model)
Agricultural productivity indicator:	
Maize productivity ($\boldsymbol{L_{it}}$)	Maize yield (kg/ha)
Control variables:	
Maize output prices (P_{it}):	Village level maize price prior to planting season
Household characteristics ($\boldsymbol{H_{it}}$):	
Age	Age of the head of the household (in years)
Gender	1 = for a male household head head; zero otherwise
Education level	Number of years of schooling of the household head
Family size	Family size in adult-equivalent units (AEU)
Livestock ownership	Household's livestock ownership (in tropical livestock units: TLU)
Landholding	Total land size owned (in hectares)
Off-farm employment	1 = if the household participated in off-farm income-generating activities; zero otherwise
Environmental characteristics ($\boldsymbol{E_{it}}$):	
Land quality	Average land quality index
Regions:	1 = for a household in Oromia region
Oromia	
SNNP	1 = for households in SNNP region
Benishangul-Gumuz	1 = for households in Benishangul-Gumuz region
Time dummies:	1 = for production season 2009/10; zero otherwise
The year 2010	
The year 2013	1 = for production season 2012/13; zero otherwise
The year 2015	1 = for production season 2014/15; zero otherwise
Instrumental variables (IV) in reduced form equation:	
IV1	A dummy variable if maize farm was affected by drought in previous production season
IV2	Frequency of oxen ploughing
Household item used to asset-based wealth index (*j*)	
TV	1 = if the household owns a TV and 0 otherwise
Radio	1 = if the household owns a radio, and 0 otherwise
Mobile	1 = if the household has a mobile phone and 0 otherwise
Bicycle	1 = if the household has a bicycle and 0 otherwise
Motorbike	1 = if the household owns a motorbike and 0 otherwise
Electricity	1 = if the household has access to electricity and 0 otherwise
Donkey cart	1 = if the household owns a donkey cart and 0 otherwise
Horse cart	1 = if the household owns a horse cart and 0 otherwise
Pushcart	1 = if the household owns a pushcart and 0 otherwise
Iron-roofed house	1 = if the household owns an iron-roofed house and 0 otherwise
Toilet facility	1 = if the household owns a cemented private toilet and 0 otherwise

a set of weights derived from a common factor, or applying principal component analysis (PCA) to mathematically determine the weights (Filmer & Pritchett, 1999). However, there is a growing recognition of the advantages of treating asset ownership as a latent variable to circumvent measurement problems arising from the vast differences in assets among farm households in developing nations (Filmer and Scott 2012; Vandemoortele 2014). For instance, Vandemoortele (2014) demonstrated that utilising a Latent Trait Model (LTM) for measuring asset ownership yields statistically superior results in assessing household wealth, compared to more commonly used methods such as PCA.

We, therefore, use the LTM technique to generate a composite variable for an asset-based wealth index. LTM draws on item response theory (IRT), making it to be referred to as an IRT model (*henceforth*, we use IRT to maintain consistency). The IRT model generates a latent variable that captures asset ownership of a given household by allowing for the interaction between different items. IRT model has a long history of use in education and psychology fields and has recently been adopted in economics and other social sciences to generate indices such as household deprivation, wealth, social capital, access to information, and labour quality (Filmer and Scott 2012; Geffersa, Agbola, and Mahmood 2022; Vandemoortele 2014). The IRT model infers the asset ownership of the farm households using their levels of access to various household items or assets.

We follow Birnbaum (1968) to specify the IRT logistic model. We generate a latent variable for the asset-based wealth index using a range of household items (in Table 1):

$$\mu_{it,j} = \frac{exp\{a_j(\theta_{it} - b_j)\}}{1 + exp\{a_j(\theta_{it} - b_j)\}};\ \ \theta_{it} \sim N(0, 1) \tag{3}$$

where $\mu_{it,j}$ is the estimated probability that household i has access to household item j at time t; θ_{it} is a latent variable that captures household $i's$ asset ownership at time t; a_j and b_j are the estimated level of "discrimination" and the level of "difficulty" of item j, respectively.

The income poverty in our sample was estimated using the Foster–Greer–Thorbecke (FGT) index (Foster, Greer, & Thorbecke, 1984), defined as:

$$p_a = \frac{1}{N}\sum_{i=1}^{q}\left[\frac{z - W_i}{z}\right]^a \tag{4}$$

where N is the total number of sample households; q denotes the number of poor households; W_i is a measure of the household welfare (in our case real household income per capita per day); a is a parameter of inequality aversion; z is the international poverty line. We used the international poverty line of US$1.90/day at 2011 purchasing power parity (PPP) values. Ferreira et al. (2016) provide details on how this poverty line was constructed.

3.3 Control variables

The choice of control variables in the welfare equations was informed by previous studies (see, for example, Abro, et al., 2014; Darko et al. 2018; Dzanku 2015). We used village-level maize output prices to control for spatial output prices (P) alongside a set of variables representing the socio-economic characteristics of a household (H). In addition, given that smallholder farming is characterised by environmental disturbances that could adversely affect household welfare, we included variables representing environmental variations (E) such as soil quality and region dummies. Following Adamie, et al. (2018) and Abro et al. (2014), we generate a composite variable for land quality index using a subjective index based on farmers' observations. Initially, we assigned numerical values to specific land attributes. Specifically, we designated a value of 1 to denote flat slopes, 2 for medium slopes, and 3 for steep slopes for each plot under consideration. In a similar fashion, for soil fertility evaluations, we allocated a value of 1 to indicate good fertility, 2 for medium fertility, and 3 for poor fertility. Subsequently, we formulated a quality indicator by multiplying the slope and fertility indicators. This multiplication process was designed in such a way that a plot with a value of 1 represented the highest land quality, whereas a plot with the lowest quality received a value of 9. Therefore, a higher numerical value indicates lower land quality. Table 1 presents all variables.

3.4 Choice of estimators and estimation issues

3.4.1 Controlling for unobserved heterogeneity (c_i)

A key estimation issue that would affect the welfare analysis is an issue stemming from an endogeneity problem due to unobservable household heterogeneity (c_i in Equation (2)). Such an estimation issue may arise because both household welfare and maize productivity are likely influenced by unmeasurable farm household characteristics such as skills, risk behaviour, etc., which could potentially correlate with the idiosyncratic error terms. For instance, some farm households may adopt superior maize technology as a consequence of unobservable characteristics, such as skill, risk-taking tendencies, or individual perceptions about the production technology, despite having higher welfare levels *ex-ante*. We controlled for unobservable heterogeneity using a household fixed-effects (FE) estimator when the welfare measure was continuous (i.e., measured by per capita maize consumption: *Model 1* and per capita household income: *Model 2*).

However, as argued by Wooldridge (2013), applying a FE estimator for nonlinear models (e.g., in the situation where the welfare measures are non-linear) is difficult because of a potential incidental parameters problem. We estimated the poverty equation using a probit model while the welfare equation with a *latent wealth index* using the Tobit estimator because the latent index is censored. Therefore, we apply the CRE approach to control for unobservable heterogeneity in the estimation of the two nonlinear models (*Model 3* and *Model 4*). The CRE framework, first proposed by Mundlak (1978) and relaxed by Chamberlain (1982), is a parametric approach that addresses the incidental parameter problem of a FE model by allowing dependence between exogenous variables and time-invariant, unobserved factors (Wooldridge 2013). Following Wooldridge (2013), we implement the CRE strategy by adding the time-average values of the time-varying explanatory variables as additional controls.

3.4.2 Addressing potential endogeneity of maize productivity

As indicated above, the productivity effect can be estimated consistently using the FE estimator or CRE estimator if endogeneity of maize productivity arises through the household-specific effect (c_i). However, this may not suffice because endogeneity could emerge from a potential correlation between L_{it} and μ_i. Maize productivity variable can be considered endogenous in the welfare equations for several reasons. For example, the rate of adoption of modern technologies is likely to vary with farm households' access to various household endowments that could determine maize yield. To test and account for the potential endogeneity of maize productivity in the welfare models, we applied Two-Stage Least Squares (2SLS) estimation procedure and a control function (CF) approach depending on the nature of the welfare outcome variable. We use FE-2SLS estimator when the welfare outcome variables are continuous (*Model 1* and *Model 2*) while the CF approach (Smith and Blundell 1986; Wooldridge 2015) was used for the two non-linear welfare models (measured by *latent wealth index: Model 3* and *poverty index: Model 4*).

While the CF procedure is technically similar to the standard 2SLS, the CF is more efficient than standard 2SLS in estimations involving non-linear models (Papke and Wooldridge 2008; Wooldridge 2015). We followed Wooldridge (2015) to implement a two-stage endogeneity test using the CF approach. First, we estimate the reduced form equation for maize productivity (L_{it}) as a function of exogenous variables that include the control variables used in the second-stage estimations (welfare equations) alongside two additional variables used as instruments. Second, we obtain the generalised residual from the reduced form equation and include that as an additional regressor in the welfare equations (i.e., structural model) along with the observed values of the agricultural productivity indicator (maize productivity). According to Wooldridge (2015), the significance of the generalised residual in the structural model suggests the presence of endogeneity. This approach to test and control for endogeneity in estimations involving non-linear models is consistent with earlier empirical studies (Bezu et al. 2014; Geffersa, Agbola, and Mahmood 2022; Ricker-Gilbert and Jones 2015; Verkaart et al. 2017).

Both the 2SLS and CF approaches necessitate the selection of appropriate instrumental variables (IV) to address potential endogeneity concerning maize productivity. In our case, the chosen IVs must exhibit correlation with the agricultural productivity indicator (L_{it}) while remaining uncorrelated with the welfare outcome variables. However, identifying theoretically sound household-level instruments in the context of smallholder production, where information is limited, often proves challenging. To tackle this issue, we employed a pair of variables as instruments for maize productivity in our welfare models. The first instrumental variable (IV1) used was a dummy variable indicating whether the maize farm was affected by drought in the previous cropping season. The choice of this variable as an instrumental variable was informed by previous SSA studies (e.g., Abro, et al., 2014 and Amare et al. 2018) that used similar weather-related shocks from the previous year as instruments for agricultural productivity. Our second instrumental variable (IV2) measured the frequency of oxen ploughing. We do not anticipate these variables, when used as IVs, to directly influence the welfare outcome variables, particularly after accounting for other crucial institutional, access-related variables, and constant unobserved heterogeneity over time. Given that maize productivity is assessed through land productivity, we expect these variables to impact household welfare solely through their effect on land productivity. To validate our instruments, we conducted rigorous statistical tests and additional analyses. The results suggested that the exclusion restriction was satisfied, as detailed in section 5.1.

4. Data and descriptive statistics

To explore the relationship between agricultural productivity and the welfare of rural households, we utilised data from a comprehensive three-wave panel farm household survey conducted in Ethiopia. This survey spanned three crucial maize-producing regions: Oromia, the Southern Nations, Nationalities, and Peoples (SNNP), and the Benishangul-Gumuz regions. The surveys, carried out during the 2009/2010, 2012/2013, and 2014/2015 cropping seasons, were a collaborative effort between the Ethiopian Institute of Agricultural Research (EIAR) and the International Maize and Wheat Improvement Centre (CIMMYT). The data collection employed a multi-stage sampling technique, as detailed by Marenya et al. (2016).

In the initial stage, nine districts were purposefully chosen – five from Oromia, three from SNNP, and one from Benishangul regions – based on maize production potential and agro-ecological suitability. In the subsequent stage, a total sample of 69 *kebeles*[1] were selected using the probability proportional to size sampling technique. Finally, in the selected *kebele*, the probability to proportional size sampling was also used to identify total sample households to increase the odds of households in high population *kebeles* being sampled.

The baseline survey, conducted in 2011 and covering the 2009/2010 production season, encompassed 898 sample households. The second round, conducted in 2014 for the 2012/2013 production season, gathered information from 874 farm households, achieving a success rate of 97.3%. However, by the third round in 2016 (encompassing the 2014/2015 production season), the number of interviewed sample households had decreased to 798. This reduction was due to factors such as households relocating or members passing away, resulting in an attrition rate of 8.7%. To maintain consistency and align with the methodology of prior studies utilising farm household panel data (Verkaart et al. 2017), our analysis focused exclusively on sample households that were interviewed across all three survey rounds.

Before estimating our empirical models, we standardised household income and other essential variables measured in Ethiopian Birr (ETB) to real values, allowing for meaningful comparisons over time. This process involved deflating nominal values using regional consumer price indices provided by the Central Statistics Agency (CSA) of Ethiopia, with the year 2010 as the base. Understanding that national poverty assessments vary due to differences in purchasing power across countries, we converted the 2010 constant prices from ETB to US dollars (USD) at purchasing power parity (PPP) values. To achieve this, we utilised the World Bank's 2011 International Comparison Program (ICP) estimates, extrapolated from the 2011 benchmark. Additionally, in preparation for our econometric analysis, we applied natural logarithmic transformations to the two continuous welfare outcome variables, namely household income and maize consumption. This transformation was necessary due to the skewed nature of their distributions. Following Bellemare and Wichman (2020), we also apply the inverse hyperbolic sine transformation when taking the logarithm to address the zero-observation problem. Table 2 provides detailed descriptive statistics.

Table 2. Descriptive statistics of variables used in welfare equations, by year.

Variables	2009/10 Mean (Std. Dev.)	2012/13 Mean (Std. Dev.)	2014/15 Mean (Std. Dev.)
Welfare indicators			
Household Income (per capita, USD PPP) [a]	699.2 (1841.4)	1394.5 (4472.7)	1000.1 (1605.3)
Own Maize Consumption (per capita, kg) [a]	63.18 (83.72)	414.9 (263.4)	423.8 (304.3)
Asset ownership index (*latent variable*)	−0.20 (0.68)	0.05 (0.74)	0.15 (0.76)
Poverty status (Poor = 1 for < 1.90 US$ PPP/day)	0.85 (0.35)	0.57 (0.49)	0.66 (0.48)
Maize Productivity (kg/ha)	1659.38 (2546.97)	1370.00 (1362.61)	1684.68 (1927.81)
Control variables:			
Age of the head (years)	41.25 (13.19)	43.87 (13.13)	46.71 (13.11)
Gender of the head (male = 1)	0.91 (0.28)	0.92 (0.27)	0.92 (0.28)
Education level of the head (years)	3.26 (3.39)	3.16 (3.38)	3.04 (3.34)
Family size (AEU)	4.94 (2.25)	5.04 (2.22)	4.93 (2.01)
Livestock ownership (TLU)	4.16 (4.61)	5.92 (6.39)	6.02 (6.32)
Landholding (ha)	2.25 (1.95)	1.72 (1.46)	2.17 (1.77)
Off-farm employment (yes = 1)	0.62 (0.49)	0.57 (0.50)	0.52 (0.50)
Maize price (ETB/kg) [b]	3.11 (3.34)	8.83 (8.75)	5.58 (5.08)
Land quality (1 = best,..,9 = worst)	2.41 (1.46)	2.07 (1.41)	2.12 (1.16)
IV in reduced form equation			
A dummy if maize farm was affected by drought	0.00 (0.00)	0.26 (0.44)	0.21 (0.41)
Frequency of oxen ploughing	6.52 (3.91)	6.19 (3.69)	6.06 (3.63)

Notes: [a] We used AEU, instead of the number of households, to convert the variables into per capita terms.
[b]Ethiopian-Birr (ETB) is a local currency, where 1 USD was equivalent to 17.01 ETB in 2009/10, 20.50 ETB in 2012/13 & 20.68 ETB in 2014/15 cropping seasons.

5. Results and discussion

This section presents the empirical results of the welfare model specified in Equation 2. Before estimating our empirical model, we estimated the IRT model (specified in Equation [3]) to quantify the underlying latent variable for household asset ownership. Table A1 (in Appendix A) presents the IRT model results. Following, we proceed to test potential endogeneity resulting from the endogenous nature of maize productivity in our welfare models (as discussed in section 3.4.2).

5.1 Endogeneity test

First, we test for the endogeneity of maize productivity in the two linear welfare equations estimated using FE-2SLS estimator. The test results for the IV estimates reported at the bottom of Table 3 support the choice of the instruments. The pair of instruments strongly predicts maize productivity and the over-identification tests fail to reject the null hypotheses that the instruments are statistically valid. The Stock and Yogo test for weak identification suggests rejection of the null hypothesis that a given group of instruments is weak. To verify the validity of the IVs, we conduct two additional analyses. First, we ran a correlation analysis between the two IVs and other explanatory variables employed in the analyses to validate our instruments. The results (reported in Table A3 in Appendix

Table 3. Welfare Effects of Maize Productivity using FE-IV regression.

Explanatory variables	Welfare indicators [a]			
	(1) Ln per capita maize consumption		(2) Ln per capita real income	
	FE-2SLS	FE	FE-2SLS	FE
Ln maize yield (kg/ha)	0.798***	0.511***	0.373**	0.048*
	(0.236)	(0.053)	(0.181)	(0.028)
Gender (1 = Male)	−0.314	−0.337	0.077	0.040
	(0.522)	(0.576)	(0.368)	(0.324)
Age of the household head (years)	0.009	0.005	0.004	−0.001
	(0.010)	(0.010)	(0.008)	(0.007)
Education of the household head (years)	0.003	0.007	−0.013	−0.011
	(0.037)	(0.037)	(0.027)	(0.027)
Family size (AEU)	−0.301***	−0.296***	−0.118***	−0.113***
	(0.036)	(0.034)	(0.028)	(0.026)
Landholding (ha)	0.018	0.051	0.040	0.089**
	(0.071)	(0.065)	(0.053)	(0.044)
Livestock ownership (TLU)	0.042**	0.043**	0.016	0.016
	(0.018)	(0.018)	(0.014)	(0.013)
Off-farm employment (1/0)	0.214	0.167	0.913***	0.813***
	(0.132)	(0.122)	(0.111)	(0.088)
Maize price (ETB/kg)	−0.032**	−0.017**	0.055***	0.073***
	(0.016)	(0.007)	(0.012)	(0.006)
Land quality (1 = best, … ,9 = worst)	0.035	0.010	−0.082*	−0.113***
	(0.052)	(0.048)	(0.042)	(0.033)
Endogeneity and IV tests				
Hansen's *J* statistic	1.888		1.308	
Test statistic of exogeneity	2.047		4.028**	
LM statistic for underidentification test	28.052***		18.946***	
Stock-Yogo (Cragg-Donald Wald F statistic)	13.237***		10.992**	
Model summary				
F statistic	182.51***	170.68***	35.96***	
Number of observations	1,876	1,876	1,876	
Number of households	677	677	677	
Log likelihood	−3363.951		−1973.094	

Note: significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (standard errors in parentheses).
[a]All regressions include year dummies in addition to household fixed-effects.

A) indicated weak correlations between the IVs and other variables used in the analyses. Second, we included our IV as additional explanatory variables in the welfare models (structural equations) and found that our IVs were insignificant in welfare equations, indicating that the exclusion restriction was met.

While the null hypothesis that maize productivity is exogenous is rejected in *Model 2*, we fail to reject the null in *Model 1*. This indicates that maize productivity is exogenous when the welfare equation is measured by per capita household maize consumption. Performing an IV estimation in the absence of endogeneity could mislead statistical inference as it inflates the asymptotic variance of the estimators (Wooldridge 2010). Therefore, for Model 1, we used the results of non-IV estimation (FE estimates) presented alongside the FE-2SLS (in Table 3).

To test and account for the endogeneity of maize productivity in the two non-linear welfare models (*Model 3* and *Model 4*), we used a CF approach. We follow Wooldridge (2015) to test the presence of endogeneity checking the statistical significance of the generalised residual in the second-stage regressions. Both variables used as instruments are statistically significant in the first-stage model results shown in Table A2 (in Appendix A), indicating the statistical validity of the instruments we used. The statistically significant coefficient for the *generalised residual* in our non-linear welfare equations (*Model 2* and *Model 3*) suggests that we can reject the null hypothesis of maize productivity being exogenous in these two welfare equations. This suggests that maize productivity is endogenous in these two welfare models.

5.2 The effect of maize productivity on household welfare

Table 3 and Table 4 present results for the welfare effects of maize productivity. The coefficient on the maize productivity indicator was positive and statistically significant for all four welfare models (*Model 1* to *Model 4*). In line with our prior expectation, the results indicate that maize productivity has welfare-improving effects through increasing maize consumption, raising household income, enhancing household asset ownership, and reducing income poverty. Controlling for other factors, a 10% increase in maize yield per hectare led to about 5.11% increase in per capita maize consumption (Table 3). A 10% increase in maize yield is associated with about 3.73% increase in per capita household income. Considering the impact on asset ownership and poverty, the results confirmed that maize productivity has enhanced farmers' ability to accumulate household assets while also reducing household poverty. As the results in Table 4 show, a 10% increase in maize yield increased the household's ability to accumulate assets by about 0.38%. The coefficient on maize yield for poverty estimate is negative and highly significant. All things being equal, a 10%

Table 4. Welfare effects of maize productivity using a control function approach.[a]

	Welfare model estimates	
	(3) Asset index (latent)	(4) Poor household (<$1.90)
Ln maize yield (kg/ha)	0.038***	−0.141***
	(0.013)	(0.038)
Generalised Residual [b]	0.004***	−0.010**
	(0.001)	(0.004)
Gender (1 = Male)	0.017	−0.091
	(0.066)	(0.167)
Age of the household head (years)	−0.003	0.006
	(0.003)	(0.010)
Education of the household head (years)	0.022**	0.040
	(0.010)	(0.035)
Family size (AEU)	0.013	0.175***
	(0.010)	(0.038)
Landholding (ha)	0.015	−0.085**
	(0.012)	(0.042)
Livestock ownership (TLU)	0.015***	−0.038**
	(0.004)	(0.017)
Off-farm employment (1/0)	0.066**	−0.961***
	(0.032)	(0.123)
Maize price (ETB/kg)	0.003	−0.083***
	(0.002)	(0.010)
Land quality (1 = best, … ,9 = worst)	−0.035***	0.091***
	(0.010)	(0.034)
Year dummy (2010)	−0.332***	0.647***
	(0.033)	(0.125)
Year dummy (2013)	−0.130***	−0.099
	(0.028)	(0.100)
Time averages (CRE) [c]	Yes	Yes
Model summary		
Constant	−0.985***	2.273
	(0.146)	(0.366)
F statistic		
Wald Chi^2	615.03***	263.45***
Number of observations	1,876	1,876
Number of households	677	677
Log likelihood	−764.244	−1246.285

Note: significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include year and region dummies.
[a]Reduced form equation of maize productivity (first stage estimation) was estimated using fixed-effects regression.
[b]*Generalised residual* from the reduced form equation of maize productivity was used to test and correct for the endogeneity of maize productivity in the two welfare equations.
[c]CRE framework: time averages of all time-varying explanatory variables were used as additional regressors.

increase in the maize yield is associated with a reduction of the probability of being below the \$1.9 poverty line by 1.41%.

The results are in line with the prediction of our conceptual model that an improvement in maize productivity could have a direct food consumption effect and household income effect through direct and indirect pathways that would ultimately reduce income poverty. The overall result provides evidence that maize productivity enhanced the welfare of maize farmers in rural Ethiopia by increasing household's income to such a degree that it can raise households above the \$1.9 poverty line.

Overall, our findings are encouraging for achieving poverty-reduction through intensive farming in rural Ethiopia. The direction of the welfare effect generally supports the widely held notion that agricultural productivity growth could be an effective channel for improving the welfare of rural farm households. The findings are largely consistent with earlier studies that observed similar significant effects of agricultural productivity on household welfare in Ethiopia (Abro, et al., 2014) and in other parts of SSA (Amarea et al. 2015; Darko et al. 2018; Dzanku 2015). Abro, et al. (2014) estimate that a 50% rise in agricultural productivity (measured by labour productivity) reduces rural poverty by less than 10% in Ethiopia. In Nigeria, Dzanku (2015) observed that a percentage increase in agricultural productivity (measured by the value of output per ha) increased per capita household consumption by 0.207%. In particular to maize productivity, most recently, Darko et al. (2018) estimated similar significant effects of agricultural productivity on rural poverty in Malawi. Darko et al. (2018) observed that a percentage increase in maize yield per hectare increases the probability of being poor by 0.057% in Malawi.

Additional findings of this study indicate that there are other important determinants of the welfare of rural farm households. The statistically significant positive effect of *education* on asset ownership suggests that an increased level of the household-head education improves farm household welfare through enhancing the ability to accumulate assets. Except for asset ownership, *family size* has an adverse welfare effect. In particular, the significant positive association between *family size* and income poverty appears counter-intuitive. This may be because the production effects might be offset by possible consumption effects for extended households as large families often put additional pressure on the farm production for immediate household consumption.

Our findings on the determinants of the welfare of rural farm households are supported by previous studies in SSA, such as Darko et al. (2018), Verkaart et al. (2017), and Bezu et al. (2014). As has been demonstrated by previous studies in other developing countries, a higher level of key household resources, such as *land* and *livestock* has significantly enhanced household welfare (e.g., Amarea et al. 2015; Darko et al. 2018).

Participation in off-farm income-generating activities also has welfare-enhancing effects, except for maize consumption. While higher maize price has consistently significant welfare-enhancing effects through increased household income and poverty reduction, it has a statistically significant negative effect on maize consumption. This is not unexpected because of the possible trade-offs between maize consumption and marketing. When facing higher maize prices, farmers may tend to sell more of their maize production rather than consumption.

The results for the land quality index indicate that poor land quality has adverse welfare consequences through increasing income poverty, reducing household income, and deterring households' ability to accumulate assets. This suggests that in addition to directly enhancing maize productivity, there is a possibility of enhancing the welfare and reducing rural poverty by improving the quality of the land.

5.3 Impact heterogeneity of maize productivity

In this section, we examine the potential heterogeneous effect of maize productivity on household welfare by disaggregating the welfare estimations. To do so, we allow β which is our coefficient of interest corresponding to the maize productivity indicator (L_{it} in Equation [2]) to vary with the household heads gender and the poverty status. The results (Table 5) suggest that, although maize productivity has the capacity to enhance household welfare, its welfare impact is weak on the disadvantaged households – such as those headed by female farmers and less-endowed farm households. The results (Table 5) indicate that maize productivity has a statistically significant welfare-enhancing effect for households headed by male households. However, except for maize consumption, the welfare impact of maize productivity is statistically insignificant for households headed by female farmers. This could be because female farmers in Ethiopia have limited access to key farm resources and productivity-enhancing technologies. The significant impact of maize productivity on household consumption irrespective of the gender of the household head highlights the importance of maize to the food security of maize farming households in Ethiopia.

To test whether maize productivity affects the poor differently than non-poor households, we disaggregate the analysis by distinguishing sample households as poor *versus* better-off households using the FGT income poverty index. The results (Table 5) indicate a significant and positive effect of maize productivity on household maize consumption for poor households. This suggests that, in terms of the impact on maize consumption, maize productivity favours the poor farm households compared to the better-off households. In contrast, the statistically significant effect of maize productivity only for better-off households suggests that maize productivity is not pro-poor in terms of its impact on household income. This may be because poor smallholder farmers in Ethiopia face several constraints hindering their productivity – such as, for example, limited access to and information about improved production techniques, particularly for modern productivity-enhancing agricultural inputs.

5.4 Robustness check

To check the robustness of our main results, we have undertaken supplementary analyses (Table 6). First, we re-estimated the welfare models using the expected (predicted) values of our productivity indicator as an alternative instrument for maize productivity. Second, we used labour productivity (kg/man-equivalent) instead of land productivity (kg/ha) as an alternative measure of maize productivity. The results presented in Table 6 show similar estimates both in terms of sign, magnitudes, and statistical significance with the main regressions. These confirms the robustness of our findings to alternative specifications and different outcome proxies.

Table 5. Welfare impact of maize productivity disaggregated by groups.

Different specifications [a]	Welfare indicators		
	(1) Ln per capita own maize consumption	(2) Ln per capita real income	(3) *Poverty status (poor<$1.90/ day)*
Welfare impact by gender			
Male * Ln maize productivity	0.355***	0.386**	−0.059***
	(0.054)	(0.199)	0.022
Female * Ln maize productivity	0.168*	0.023	−0.020
	(0.099)	(0.038)	0.024
Welfare impact by poverty status			
Poor * Ln maize productivity	0.114***	0.099	-
	(0.027)	(0.014)	
Better-off * Ln maize productivity	0.015	0.298***	-
	(0.019)	(0.098)	
Number of households	677	677	677

Note: significance levels; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Robust standard errors in parentheses.
[a]The results are similar to the results from the primary results presented in Tables 3 and 4, except our measure of maize productivity now interacts with indicators of groups the sample households belonged. All regressions include explanatory variables from Tables 3 and 4 but not reported here because the main interest is to investigate the welfare effect of maize productivity.

Table 6. Robustness check of welfare impacts of maize productivity.

Different specifications	Welfare indicators [a]			
	Ln per capita maize consumption	Ln per capita real income	Asset index	Poor household (< \$1.90)
Original Model: Primary results [b]	0.513***	0.373**	0.038***	−0.141***
	(0.038)	(0.188)	(0.013)	(0.038)
(a) Predicted values as an alternative IV	0.742***	0.387**	0.035**	−0.706***
	(0.269)	(0.169)	(0.055)	(0.170)
(b) Labour productivity as productivity indicator	0.119	0.105**	0.038**	−0.148**
	(0.076)	(0.049)	(0.017)	(0.054)
Number of observations	1,876	1,876	1,876	1,876
Number of households	677	677	677	677

Note**:** Significance levels; * p<0.1, ** p<0.05, ***p<0.01. Robust standard errors in parentheses.
[a]All regressions include explanatory variables from Tables 3 and 4.
[b]Original model results are reported here for comparison.

6. Conclusion and policy implications

There is growing recognition that agricultural productivity growth significantly reduces poverty, exemplified by the success of the Green Revolution in parts of Asia and Latin America. However, the relationship between agricultural productivity and the welfare of rural households remains unclear, particularly in Sub-Saharan Africa (SSA). In this study, we examine the micro-level welfare impacts of maize productivity in rural Ethiopia. Using three-wave comprehensive panel data, we assess the welfare effects of maize productivity through fixed-effects regression and correlated random-effects framework. To address potential endogeneity of maize productivity in the welfare models, we employ an IV estimation procedure and a control function approach. Our analysis provides deeper insights into the productivity-welfare relationship. We go beyond traditional monetary measures and employ an asset-based approach, considering household welfare alongside income, maize consumption, and poverty index.

The results demonstrate that increased maize productivity leads to higher household income, enhanced maize consumption, and greater asset ownership, ultimately reducing poverty. Specifically, a 10% rise in maize productivity is associated with a 1.41% decrease in the probability of falling below the \$1.9 poverty line. Additionally, our study reveals heterogeneous effects across households. Advantaged households, particularly those headed by male farmers or with better income poverty status, experience more substantial benefits. This highlights the need to recognise and accommodate the diverse circumstances of farm households, emphasising tailored strategies rather than one-size-fits-all interventions to improve welfare of maize farmers. While enhanced maize productivity overall shows promise for poverty reduction in rural Ethiopia, achieving sustained progress is vital given the constraints posed by population pressure. It is crucial to continue improving maize productivity, but policies aimed at reducing rural poverty should extend beyond merely increasing agricultural productivity. As our additional findings suggest, enhancing household welfare requires policy options addressing non-agricultural measures that ensure improved level of education, optimum family size, enhanced ownership of physical resources such as land.

While our results are consistent with prior expectations and existing research, two important considerations arise. Firstly, it is vital to recognise the significance of investigating the impact of land use intensification on soil quality, particularly concerning potential soil mining that could compromise long-term land productivity. However, it is imperative to acknowledge the data limitations we faced in our study, a common challenge in developing countries like Ethiopia where obtaining detailed micro-level data on quantitative soil quality metrics proves challenging. This scarcity of comprehensive data underscores the need for further studies shedding light on the interactions between agricultural productivity, land use practices, and soil quality dynamics in the Ethiopian context and beyond. Secondly, we acknowledge indirect effects on both maize producers and non-producers, such as growth linkages, reduced food prices, and employment opportunities. While our study primarily focuses on partial-equilibrium welfare analysis, future research exploring comprehensive general equilibrium effects will enhance the generalisability of our findings.

Note

1. A *kebele* is the smallest administrative unit in Ethiopia that is smaller than a *woreda* (or district), but larger than a village.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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