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ORIGINAL ARTICLE

Improved maize adoption and impacts on farm household welfare: Evidence from rural Ethiopia

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Abstract

The use of improved crop varieties can increase agricultural productivity and enhance the welfare of farmers. This study examined whether the adoption of improved maize varieties (IMV) is associated with the increased welfare of farmers in rural Ethiopia. A panel data set with 1886 observations collected in three waves from 2009/10 to 2014/15 were used for the analysis. The adoption decision was modelled using a double-hurdle model, and the welfare effect of IMV adoption was estimated using a fixed-effects instrumental variable approach. Our findings reveal that IMV affects the welfare of farmers. Specifically, we found that IMV adoption increases households' income, asset ownership and maize consumption while also reducing income poverty. The poverty estimates indicate that a 10% increase in the area allocated to IMV was associated with a 4.79% reduction in the probability of being below the $1.90 poverty line. However, the poverty-reducing effect of IMV adoption was heterogeneous across households, with the most pronounced effect experienced by households with extensive landholdings. Our findings suggest that facilitating access to IMV and land under cultivation can effectively improve farmers' welfare and reduce poverty in rural Ethiopia.

KEYWORDS
Ethiopia, household welfare, improved maize, rural poverty, technology adoption

JEL CLASSIFICATION
C33; I32; O13; Q1

1 | INTRODUCTION

Despite growing recognition that agricultural innovation can help achieve food security and reduce poverty, the link between agricultural technology adoption and rural household welfare remains complex and unresolved (Manda et al., 2019; Ogundari & Bolarinwa, 2018a). The Green Revolution, which offered farmers higher-yielding crop varieties (HYV), has significantly increased agricultural productivity and crop yields of major food grains, mainly in Asia and Latin America (De Janvry & Sadoulet, 2002; Evenson & Gollin, 2003; Pingali, 2012). In Sub-Saharan Africa (SSA), despite efforts by various governments to promote the adoption of HYV, as has featured prominently in policy debates, food insecurity and poverty continue to rise, remaining a significant social and economic issue (De Janvry & Sadoulet, 2009; Dercon, 2009). Despite achieving the millennium development goals to reduce extreme poverty by half between 1990 and 2015, extreme poverty has decreased only marginally in SSA compared with other regions (United Nations, 2015). In recent times, poverty incidence has been rising in SSA, particularly in rural areas, which account for nearly 80% of the population still living in extreme poverty (World Bank, 2018).

Enhancing agricultural productivity can contribute to rural development, either directly or indirectly. The direct effect of increased agricultural productivity is the increase in agricultural production and, consequently, income, resulting in an improvement in the welfare of farm households (De Janvry & Sadoulet, 2002). The indirect effects of increased agricultural productivity are induced gains, such as lower food prices and growth linkage effects that create employment by adjusting real wages for unskilled workers (Minten & Barrett, 2008; Zeng et al., 2017). There is growing empirical evidence for developing countries to suggest that the direct and indirect effects of HYV adoption have led to substantial welfare gains (Becerril & Abdulai, 2010; Minten & Barrett, 2008; Ogundari & Bolarinwa, 2018b). However, a recent meta-analysis by Ogundari and Bolarinwa (2018a) revealed that the association between agricultural technology adoption and rural poverty remains complex within the context of SSA. While the dissemination of IMV crops remains an overarching policy in many SSA countries, debate on the role of IMV in rural poverty reduction in SSA has featured prominently in policy discourse (Geffersa et al., 2019a; Ogundari & Bolarinwa, 2018a).

This paper explores whether the adoption of HYV improves the welfare of farm households. We used a sample consisting of 1886 household-level panel data from three waves of surveys (2009/10 to 2014/15) conducted under the Sustainable Intensification of Maize–Legume Cropping Systems for Food Security in Eastern and Southern Africa (SIMLESA) project. We specified improved maize varieties (IMV) adoption using a double-hurdle model and estimated it as a correlated random-effects regression to correct unobservable heterogeneity. We apply a control function approach to control endogeneity resulting from nonrandom access to improved seeds. We establish a link between technology adoption and household wealth by introducing a novel way to construct an asset-based welfare index using latent trait modelling drawing insights from Item Response Theory (IRT) models. The welfare effect of IMV adoption was estimated using an instrumental variable regression approach where predicted values from the double-hurdle model were used as an instrument for IMV adoption.

The paper provides new empirical evidence about the relationship between technology adoption and the welfare of the farmers in SSA. Three arguments are advanced in the agricultural technology adoption literature to explain the weak relationship between the adoption of HYV and the welfare of rural households in SSA. First, the contentious relationship between HYV and welfare is due to the disproportionate access of farm households to physical resources (Dercon & Christiaensen, 2011; Manda et al., 2019; Verkaart et al., 2017), wealth status of farm households (Bezu et al., 2014) and size of landholdings (Alwang et al., 2019; Zeng et al., 2015). Second, the disparity arises from the failure to adequately account for randomness arising from the heterogeneity of households' ability to cultivate HYV (Abay et al., 2018; Verkaart et al., 2017). Third is the unobservable differences due to varying skills, risk-taking inclinations and perceptions of farmers about the benefits of adopting HYV compared with traditional varieties (Abay et al., 2018; Michler et al., 2018; Suri, 2011). For example, Michler et al. (2018) and Suri (2011) have argued that failure to account adequately for household heterogeneity and endogeneity in modelling farmer adoption may bias the effect of adoption of HYV on the welfare of farm households.

A growing number of theoretical and empirical studies have emerged examining the effect of HYV adoption on the welfare of households (see Ahmed et al., 2017; Jaleta et al., 2018; Zeng et al., 2015, 2017). In SSA, adoption studies have focussed on examining the effect of HYV adoption on crop yield and basiceconomic returns of farmers (Jaleta et al., 2018; Manda et al., 2019; Michler et al., 2018), household income (Kassie et al., 2017; Verkaart et al., 2017), child nutrition (Manda et al., 2019; Zeng et al., 2017), food security (Jaleta et al., 2018; Shiferaw et al., 2014), household consumption (Asfaw et al., 2012; Bezu et al., 2014) and household wealth (Manda et al., 2019; Mathenge et al., 2014; Verkaart et al., 2017). Notwithstanding the contribution of these previous studies, the findings are mixed (see Ogundari & Bolarinwa, 2018a). Earlier SSA studies have relied on cross-sectional data (see Ahmed et al., 2017; Jaleta et al., 2018; Zeng et al., 2015, 2017). A major criticism of these studies is that the use of cross-sectional data prevents undertaking a comprehensive analysis and accounting adequately for unobservable household heterogeneity. This could thus bias the inferences from the empirical results and the generalisability of the findings (see Abay et al., 2018; Michler et al., 2018; Suri, 2011). Furthermore, these previous studies fail to account for the long-term welfare outcomes of HYV adoption. There are a few exceptions, such as the studies by Bezu et al. (2014), Mathenge et al. (2014) and Kassie et al. (2017). However, these studies fail to account for the differences in access to technology, which is critical for technology adoption decision-making (Verkaart et al., 2017).

This paper contributes to the agricultural technology adoption literature by analysing the heterogeneous effect of IMV adoption on smallholder household welfare and poverty in rural Ethiopia. Using a composite household welfare measure based on latent-trait modelling, our results complement the policy implications of earlier SSA studies that mainly used direct monetary measures of household welfare. We show that IMV adoption enhances the welfare of maize farmers by increasing household maize consumption, income and asset ownership, while also reducing poverty. We find a heterogeneous effect of IMV adoption on welfare. Although the adoption of IMV raises household income above the $1.90 poverty line, its impact is more pronounced for farmers with large landholdings. This finding provides strong empirical evidence to highlight that ignoring the heterogeneous nature of farm households may bias the effect of IMV adoption on welfare estimates.

The remainder of this paper is outlined as follows. Section 2 presents the background of maize production in Ethiopia, while Section 3 introduces the analytical framework, highlighting the theoretical and empirical models and presents the data and descriptive statistics. Section 4 reports and discusses the observed results. Finally, Section 5 concludes and draws some policy implications of the empirical findings.

2 | OVERVIEW OF MAIZE PRODUCTION IN ETHIOPIA

In SSA, Ethiopia's economy reflects the general dependence on agriculture. More than 83% of the country's population derives livelihood from smallholder agriculture (CSA, 2019). Despite the immense potential of the country's agricultural sector, poverty in Ethiopia is widespread. Recent official estimates indicate that the poverty rate in Ethiopia is 23.5%, which declined from 29.6% in 2011 (World Bank, 2020). However, the reduction has been substantially slower in rural areas than in urban areas, indicating that poverty is still a predominantly rural phenomenon in Ethiopia. Compared with urban areas, where there has been a 10.9% poverty decline since 2011, the reduction has been substantially slower in rural areas, with only a 4.8% decline in the same period (World Bank, 2020). Furthermore, the gap between food production and consumption continues to widen in Ethiopia.

Maize is predominately a subsistence food crop in Ethiopia, and household food security is mainly defined by access to maize, as in most SSA countries. In recent years, maize has emerged as a leading crop in Ethiopia in terms of scale and volume of production, number of farmers producing maize and household consumption (CSA, 2016, 2019). This positions maize as 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 2017/18 cropping season, maize accounted for an estimated 48% of the cropped area and 56% of crop production volume (CSA, 2019). Compared with other significant cereals produced in Ethiopia, maize comprises the majority of the production scale, accounting for about 30% of the total cereal production and 20% of the total area allocated to the production of cereals in the 2017/18 cropping season (World Bank, 2019).

In addition to having the highest volume of total annual production and per hectare yield, maize 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 2014/15 cropping season, about nine million smallholder farmers (about 60–70% of the total farming households) produced maize, which accounted for 95% of the national maize production (World Bank, 2019). Over the past two decades, the share of maize in total cereal consumption in Ethiopia has rapidly increased. For example, in the 2015/16 cropping season, household consumption accounted for 76% of total maize production, and the share of maize supplied to the market was about 11% (CSA, 2016). Compared with other major cereal grains produced in Ethiopia, maize provides the highest caloric intake for consumers in Ethiopia—accounting for 17 to 20% of per-capita calorie intake (World Bank, 2018). As such, maize is crucial for rural poor households. For example, in 2014, it was estimated that maize dominated rural consumption, with 436 per-capita calories—more than four times the per-capita calories in urban areas (Food and Agriculture Organization of the United States [FAO], 2014). Relative to other cereals, maize is also a cheaper source of protein (FAO, 2014).

Given the growing importance of maize in household food consumption and food security, the Ethiopian government has continued efforts to enhance smallholder maize productivity (Assefa et al., 2020; Geffersa et al., 2022). To enhance maize productivity, over the past few decades, the government of Ethiopia has substantially increased the extension agent to farmer ratio (1:476) to improve farmers' access to modern inputs (Geffersa et al., 2022). Since the early 1970s, over 60 IMVs have been released by the national system (Abate et al., 2015). These include the first locally developed, early maturing hybrid maize variety (BH140) that was introduced in 1988, followed by BH660 (a late-maturing hybrid), BH540 and PHB3253 (the Pioneer hybrid) (Abate et al., 2015). Among smallholder farmers in Ethiopia, commonly grown maize varieties are grouped into hybrid varieties, improved open-pollinated varieties (OPV) and local OPV (Abate et al., 2015; Zeng et al., 2015). As a result, the use of modern agricultural inputs more than doubled in the past decade, leading to a substantial improvement in maize productivity in Ethiopia (see Abate et al., 2015; Bachewe et al., 2018). Although the contribution of maize to household well-being remains the policy priority in Ethiopia, rigorous microlevel evidence concerning the constraints on IMV adoption and its effects on household welfare and poverty reduction is scarce in Ethiopia.

3 | ANALYTICAL FRAMEWORK

3.1 | Theoretical model

In developing countries such as Ethiopia, farm households make production and consumption decisions simultaneously because of the prevalence of market imperfections that result in trade-offs between profit-maximisation and utility-maximisation (Bezu et al., 2014; De Janvry et al., 1991). As a result, the assumption of separability between production and consumption decisions is unlikely to hold. Therefore, we viewed the welfare effect pathways of IMV adoption through the theoretical lens of Singh et al.'s (1986) nonseparable farm household model that assumes, in an economic environment with market failures; family members organise their labour to maximise utility over consumption goods and leisure. Following Singh et al. (1986), we assume that farm households produce goods for consumption or sale, and cash constraints are relaxed primarily through farm sales of surplus products where production and consumption-related decision-making of maize farmers is determined simultaneously (Smale et al., 1994; Verkaart et al., 2017).

We consider household welfare in a utility framework such that a household (i) maximises utility, U, subject to resource constraints. While producing maize for home consumption and sale, a household drives utility from the returns of land allocation for IMV. We assume that a household i adopts IMV if the expected utility from adopting is higher than the utility from disadopting. Following Feder et al. (1985), the returns from IMV adoption were assumed to be a function of the area allocated, where the total land allocated to IMV production (A) is a function of output prices (P). Under imperfect factor markets, farmers may not rely solely on market prices in production decisions. Thus, we assumed IMV production to likewise be a function of a set of other factors, denoted by five vectors of variables:

$$\boldsymbol{A} = f(P; \text{ɭ}, H, E, V) \tag{1}$$

where ɭ denotes family labour endowment; H represents farm household characteristics; V represents village-level factors that capture access-related variables, such as the availability/accessibility of IMV seeds and other institutional and village covariates; and E represents variables affecting environmental characteristics.

The adoption of IMV is expected to influence household welfare through changes in maize yield. To conceptualise this, we specify the farm household welfare function (W) as a function of IMV adoption (A):

$$W = f\left(\boldsymbol{A}, Z'\right) \tag{2}$$

where Z denotes a vector of a set of variables representing the socio-economic characteristics of a household. Other variables are as defined above.

Increasing maize yield is expected to enhance household food consumption and raise household income by allowing households to sell surplus maize. In addition, the increased use of IMV could indirectly affect household income in three main ways. First, by releasing land for or taking land away from the production of other food crops. Second, via livestock production through the increased supply of straw for livestock feed. Third, through the effect on household energy and construction (e.g. fences and beehives), enhanced maize production would save cash spent on fuel and construction materials. If farmers used IMV successfully over the years, we would expect that the resulting increase in income could be capitalised to an accumulation of household assets and raise their households above the poverty line (Mathenge et al., 2014; Verkaart et al., 2017). The increase in household income would, in turn, translate to consumption expenditure. We, therefore, hypothesised a positive relationship between household welfare and IMV adoption.

3.2 | An empirical model for estimating IMV adoption decision

Before empirically estimating the welfare function, we first modelled the adoption decision of the farm households. The empirical IMV adoption model was guided by the theoretical model specified in Equation (1). The adoption decision is often quantified as a binary choice variable by identifying growers and nongrowers of improved varieties. However, for divisible technologies, this variable does not refer to the degree (intensity) of the use of new technology as a quantitative measure of the extent of adoption (Smale et al., 1994; Verkaart et al., 2017). The plausible empirical approach for divisible innovations is to define the adoption decision as a rate or a continuum of the land share using censoring methods (Bezu et al., 2014; Smale et al., 1994; Verkaart et al., 2017). Thus, we defined the adoption decision as a rate or a continuum of the land share using a censored regression framework after distinguishing between IMV adopters and nonadopters. We used the area allocated to IMV production as a measure of adoption:

$$A_{it} = \mathrm{Max}\left(0, L_{it}^{*}\right) \tag{3}$$

$$A_{it}^{*} = \alpha + \rho P_{it} + \tau l_{it} + \delta H_{it} + \nu V_{it} + \eta E_{it} + \varepsilon_{it} \tag{4}$$

where A_{it}^{*} is a latent variable for IMV adoption; $\varepsilon_{it}\ \left(= k_i + \mu_{it}\right)$ is an error term composed of two components (unobserved time-invariant factors, k_i, and unobserved time-variant shocks, μ_{it}) that could affect adoption decisions; and ρ, τ, δ, ν and η are vectors of coefficients to be estimated.

Given that the outcome variable in Equation (4) is truncated above zero, the model can be estimated using the standard Tobit model that assumes ε_{it} as normally distributed (Wooldridge, 2010). However, the existence of a significant number of nonadopters in the context of developing countries makes the Tobit model inappropriate because it assumes the adoption decision and the degree of adoption (adoption intensity) to be determined by the same process (Ricker-Gilbert et al., 2011; Verkaart et al., 2017). Thus, a non-linear corner solution framework expresses the model in Equation (4) more appropriately. Therefore, we estimated our adoption model employing Cragg's (1971) flexible double-hurdle model that relaxes the restrictions of the Tobit estimator. Our double-hurdle model had two steps. In the first step (or hurdle), farmers decide whether to use IMV, estimated using a binary choice (probit/logit) model. Once the first hurdle has been crossed, the farmers decide on the amount to adopt (or the intensity of adoption), referred to as hurdle two (or the second hurdle).

Recently, Burke et al. (2015) introduced a triple hurdle approach that uses the third dimension to extend the double-hurdle model. The first stage integrates whether a farmer produced a particular crop (maize in our case). However, in the context of our study, the empirical model in the first stage did not involve whether to produce maize as a choice to be made by the farmer because all sample households targeted by the surveys were maize producers from the selected maize-based farming system in Ethiopia. Therefore, our empirical adoption modelling relied on Cragg's (1971) flexible double-hurdle model. We estimated the first hurdle using a probit model, while we used a truncated normal regression model for hurdle two.

We included the determinants of IMV adoption in both hurdles, which were identified based on the theoretical and empirical adoption literature (P, ɭ, H, V, E in Table 1). We expected that a higher maize price observed in a previous period could stimulate adoption by encouraging farmers to allocate more areas for maize cultivation. Therefore, we hypothesised a positive effect of *maize price* on the adoption of IMV. The influence of *teff price* and *wheat price* could extend in either direction, depending on whether a farmer was a net seller or buyer of maize outputs.

We used family labour to capture the influence of household labour endowment in the adoption decision. According to Feder et al. (1985), adopting input-intensive improved crop varieties may be less attractive for those with limited family labour or those operating in areas with less access to labour markets because it may increase the seasonal demand for labour. As documented by previous studies from developing countries, such as those by Langyintuo and Mungoma (2008), Asfaw et al. (2012) and Ghimire and Huang (2015), the availability of an active labour force positively affects the adoption of HYV. Therefore, we hypothesised a positive influence of household labour endowment on IMV adoption.

Age, which captures the aspects of the farming experience that could increase the likelihood of investing in innovations, was expected to affect IMV adoption positively. The *gender* of the household head, often included in adoption modelling to capture fixed social bias (Langyintuo & Mungoma, 2008), was expected to positively affect IMV adoption decisions because male farmers in Ethiopia have better access to crucial farm resources. The *education level* of the household's head was included to capture the human capital effect in farm production (Geffersa et al., 2019a). Given that educated maize farmers are more likely to have better access to information and managerial skills, we expected that households led by more educated farmers would be more likely to use improved technologies. *Family size* was expected to positively affect IMV adoption because a large household would have more access to a labour force for farming operations.

Landholding and *initial level of asset ownership* were included to capture the effects of access to physical capital endowments. We used the *initial level of asset ownership*, measured in terms of the monetary values of all household assets, including livestock,[1] to control for the initial difference in asset endowments (Verkaart et al., 2017). In Ethiopia, livestock is an essential asset for rural households that could influence maize production by crowding in/out of the land. Using organic amendments, such as livestock manure, could improve soil fertility and enhance maize production. However, maize and maize straw could be fed to livestock, limiting the use of maize stock as organic manure to improve soil fertility. We expect that *landholding* and *initial level of asset ownership* to influence IMV adoption positively because a better position with physical capital endowments would encourage farmers to grow IMV. We anticipated adverse effects from off-farm employment on IMV adoption; *off-farm involvement* could decrease the adoption of IMV, as farming may be less critical to farmers who allocate more time to off-farm work.

Village-level factors (V) included a wide range of variables that represented access to improved seed, institutional services and technical supports. These variables were hypothesised to affect IMV adoption positively because the pattern of technology uptake is significantly determined by the availability (accessibility) of a given technology and institutional supports (Feder et al., 1985; Verkaart et al., 2017). Smallholder farming is characterised by environmental disturbances, and accounting for environmental variations (E) helps to control covariate shocks that could result in adverse welfare consequences. However, in developing countries such as Ethiopia, obtaining microlevel data on environmental factors, such as weather shocks and soil quality, is difficult (Adamie et al., 2018). Adamie et al. (2018) noted that the second-best solution is to use farmers' observations in the absence of reliable data on such variables. Thus, we used subjective measures, such as farmers' observations on

[1] It is worth noting that other important variables related to household wealth, such as livestock ownership, could also influence IMV adoption decisions. However, we excluded the variable from our final model, as it is arguably endogenous to the technology adoption decision.

TABLE 1 Description of variables used for modelling IMV adoption and welfare impacts.

Variables	Variable description	Exp. sign
Adoption outcome variables		
Binary adoption variable	Equals 1 for IMV adopters	
Area under IMV	The total area allocated for IMV cultivation	
Welfare indicators (W)		
Household income	Household income (real per capita/year, constant 2010 USD PPP)	
Household maize consumption	Households' consumption of maize from their 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	An asset-based wealth index generated using an IRT model	
Determinants of IMV adoption ($P, \mathfrak{l}, H, S; V, E$)		
Market-level factors: Output prices (P)		
Maize price	Village-level maize price prior to planting season	+
teff price	Village-level *teff* price prior to planting season	−/+
Wheat price	Village-level wheat price prior to planting season	−/+
Labour endowment ($\mathfrak{l}$): Family labour	Family members working on maize farm (man-equivalent)	+
Household and farm characteristics (H)		
Age	Age of the household head (years)	+
Gender	Male household head (1 = yes)	+
Education level	Years of schooling of the household head	+
Family size	Total family size (in adult-equivalent)	+
Asset ownership	The initial value of assets owned by the household (in ETB)	+
Landholding	Total land size owned (in hectares)	+
Off-farm employment	Equal to 1 if the household participated in off-farm income-generating activities; zero otherwise	−
Village-level factors (V):	Institutional services, technical supports and village-level covariates	
Access to improved seed	Equal to 1 if the household has access to IMV seed in the village; zero otherwise	+
Extension service	Waking minutes to the nearest agricultural extension office	−
Credit access	Equal to 1 if the village has farm credit institutions	+
Farmer group	Equal to 1 if the head is a member of farmer groups	+
Market access	Equal to 1 if a village has access to the primary market	+
Environmental and Agro-ecologic characteristics (E)		
Land quality	Land quality index (1= best, …, 9 = worst)	−
Pest occurrence	Equal to 1 if pest occurred in maize farm in the previous season; zero otherwise	−
Rainfall shortage	Equal to 1 if the household experienced rainfall shortage in previous production season; zero otherwise	−

(Continues)

TABLE 1 (Continued)

Variables	Variable description	Exp. sign
Region dummies		
Oromia	Equal to 1 for farm household in Oromia region; zero otherwise	−/+
SNNP	Equal to 1 for farm households in the SNNP region; zero otherwise	−/+
Benishangul-Gumuz	Equal to 1 for farm households in the Benishangul-Gumuz region; zero otherwise	−/+
Time dummies: The Year 2010	Equal to 1 for production season 2009/10; zero otherwise	−/+
The year 2013	Equal to 1 for production season 2012/13; zero otherwise	−/+
The year 2015	Equal to 1 for production season 2014/15; zero otherwise	−/+
Reduced-form Instrumental Variable	Number of years household head has lived in the village	−/+

rainfall availability, pest incidences and soil quality, to measure environmental disturbances (see Table 1). A composite variable for the land quality index (*land quality*) that captured differences in plot quality was developed following Adamie et al. (2018) and Abro et al. (2014). A higher value indicated lower land quality, according to our coding.[2]

3.3 | An empirical model for estimating the welfare effects of IMV adoption

Following our theoretical household welfare function (in Equation 2), we specified the empirical model as:

$$W_{it} = \psi_0 + \Phi A_{it} + \psi Z'_{it} + e_{it} \tag{5}$$

where W_{it} is a welfare outcome variable for household i at time t; A_{it} is an IMV adoption indicator (as defined earlier); Z'_{it} is a vector of control variables (presented in Table 1); Φ *and* ψ are the vectors of the parameters to be estimated; and ψ_0 *and* e_{it} are the intercept and disturbance terms, respectively.

We used four welfare indicators: *household income*, *household maize consumption*, *poverty index* and *asset-based welfare index*. Earlier studies have explored several other welfare measures, such as child nutrition (Manda et al., 2019; Zeng et al., 2017), food security (Jaleta et al., 2018; Shiferaw et al., 2014), household consumption expenditure (Asfaw et al., 2012; Bezu et al., 2014) and household wealth (Manda et al., 2019; Mathenge et al., 2014; Verkaart et al., 2017). Although using such variables as additional welfare indicators would offer deeper insights into the multidimensional effect of IMV adoption on household welfare, the choice was limited by data availability. In particular, household consumption expenditure would have been an appropriate measure to reflect actual increases in household welfare, as it is closely related to changing economic opportunities (Bezu et al., 2014; Dercon & Christiaensen, 2011).

[2]Prior to indexing, values of one for a flat slope, two for a medium slope, and three for a steep slope were assigned to every plot. Similarly, if soil fertility was good, we assigned a value of one; if medium, we assigned a value of two; and if bad, we assigned a value of three. Finally, a quality indicator was developed by multiplying the slope and fertility indicators in such a way that a plot with a value of one had the best land quality, while a plot with the lowest quality had a value of nine. Furthermore, we used region dummies to control for regional differences among farmers and for other environmental variations.

Unfortunately, we could not use consumption expenditure in our analysis because of several missing values.

However, an asset-based approach to measuring household welfare can provide an alternative to incomplete, unavailable or unreliable expenditure data (Filmer & Scott, 2012; Langyintuo & Mungoma, 2008; Vandemoortele, 2014). According to Vandemoortele (2014), an asset-based approach offers the added advantage of measuring a household's material well-being, which is often distinct from income or expenditure because economies in developing countries are primarily informal. Sahn and Stifel (2003) argued that, in rural settings, an asset index is a more valid predictor of long-term household welfare changes because it captures the child health and nutrition dimension of rural poverty. Similarly, Langyintuo and Mungoma (2008) argued that asset-based measures are expected to contribute to household wealth directly and could serve as a more accurate indicator of households' economic well-being. For Moser (2006), asset-based approaches for measuring household well-being offer a forward-looking, dynamic framework for measuring movements in and out of poverty.

To date, there is an increasing awareness that using asset ownership as a latent variable can avoid measurement issues stemming from the existence of tremendous asset ownership variations among households (Abdul-Salam & Phimister, 2017; Faye et al., 2011; Filmer & Scott, 2012; Vandemoortele, 2014). Therefore, we construct the asset-based welfare index using latent trait modelling (LMT). Given that LTM draws on item response theory (IRT), it is also referred to as the IRT model (henceforth, we use IRT to maintain consistency). The IRT model infers the asset ownership of farm households using their levels of access to various household items or assets. Following Birnbaum (1968), we specified the IRT logistic model (Equation 6) to generate a latent variable for the asset-based wealth index using a range of household items, presented in the Appendix S1 (Table S2):

$$\pi_{it,j} = \frac{\exp\{a_j(\theta_{it} - b_j)\}}{1 + \exp\{a_j(\theta_{it} - b_j)\}}; \theta_{it} \sim N(0,1) \tag{6}$$

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

We estimated poverty in our sample using the Foster–Greer–Thorbecke (FGT) indices (Foster et al., 1984), defined as:

$$p_a = \frac{1}{N} \sum_{i=1}^{q} \left[\frac{z - w_i}{z}\right]^a \tag{7}$$

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); $\subsetneq$ is a parameter of inequality aversion; and z is the international poverty line.

We used the revised current international poverty line of US$1.90/day at 2011 purchasing power parity (PPP) values (Ferreira et al., 2016). Table 1 presents all the variables used in welfare analysis. We estimated a separate equation for each welfare indicator. The two welfare indicators (*household maize consumption* and *household income*) were computed per adult, equivalent to family size adjustment. *Household maize consumption* connotes the sum of household maize consumption (quantities in kilogrammes of both green and dry) from the home production of maize in a given cropping season. *Household income* includes both farm (crop and livestock) and nonfarm income.

Finally, household income and other key variables measured in Ethiopian birr (ETB) were converted to real values. We used regional consumer price indices created and published by the

Central Statistical Agency of Ethiopia (CSA) to deflate nominal values, using 2010 as a base. According to the 2011 International Comparison Program (ICP) of the World Bank (2015), national poverty assessments differ across countries because of differences in national currencies. Therefore, we converted the constant 2010 prices in ETB values to US dollar PPPs. We used the World Bank's (2015) estimates of PPPs extrapolated from the 2011 ICP benchmark.

3.4 | Choice of estimators and econometric issues

3.4.1 | Controlling for unobserved heterogeneity

Failure to control unobserved time-invariant household heterogeneity (k_i in Equation 4) that could correlate with adoption and welfare indicators could lead to a selection bias. For instance, some farm households may adopt maize technology because of unobservable characteristics, such as skill, risk-taking tendencies or individual perceptions about the technology, despite having higher welfare levels before adoption. Although a household fixed-effects model can help control unobservable heterogeneity, as Wooldridge (2013) argued, applying fixed-effects to a nonlinear model is difficult because of the potential incidental parameters problem. Therefore, we adopted the correlated random-effects (CRE) framework to control unobservable heterogeneity when estimating our double-hurdle model (Equation 4). The CRE approach proposed by Chamberlain (1982) and Mundlak (1978) is a parametric approach that addresses the incidental parameter problem of a fixed-effects model by allowing dependence between exogenous variables and time-invariant, unobserved factors (see Wooldridge, 2013). Following Wooldridge (2013), we implemented the CRE strategy by augmenting the time-average values ($\overline{T}_i$) of the time-varying explanatory variables:

$$k_i = \overline{T}_i \pi_i + u_i \tag{8}$$

In our specification of household welfare (Equation 5), we controlled for unobservable heterogeneity using a household fixed-effects estimator, depending on whether the welfare measure was linear. The household fixed-effects estimator is used when welfare is measured by per-capita household income and maize consumption. Given that the variable measuring the poverty status was binary, we estimated the poverty equation using a probit model. Given the non-linearity of the equation, we used a CRE framework to control for unobserved heterogeneity in the probit model for poverty estimation. We used a similar approach (as in Equation 8) to implement the CRE strategy by augmenting the time-average values ($\overline{T}_i$) of the time-varying control variables used in the welfare equation.

3.4.2 | Addressing potential endogeneity issues

Our adoption model's first potential endogeneity issue could arise from nonrandom household access to IMV seed (S_{it}). This is because S_{it} is likely to correlate with unobserved, time-varying factors (μ_{it}), leading to an endogeneity problem. We addressed this by applying a control function (CF) approach (Smith & Blundell, 1986; Wooldridge, 2015). While the CF approach is technically similar to the standard two-stage least squares (2SLS) method, the CF method is more efficient than the standard 2SLS technique when estimations involve a nonlinear corner solution (as in our adoption equation) (Verkaart et al., 2017; Wooldridge, 2015).

We followed Wooldridge (2015) to implement a two-stage endogeneity test using the CF approach. First, we used the probit model to estimate the reduced-form equation for access to improved seed (S_{it}) as a function of exogenous variables that included the control variables used in the second-stage estimation (adoption equation) alongside a variable used as an instrumental variable (IV). Second, we obtained the generalised residual, which we included in our structural equation (i.e. the double-hurdle adoption model), along with observed access to the improved seed variable to test and control endogeneity (Wooldridge, 2015). The reduced-form equation for access to improved seed was specified as:

$$S_{it} = \varpi \mathrm{IV}_{it} + \beta X_{it} + \varsigma_{it} \tag{9}$$

where S_{it} is a dummy variable representing access to improved maize seed; IV_{it} is an appropriate instrument; X_{it} denotes a vector of the variables used in the adoption equation; ϖ is a vector of the parameters to be estimated; and ς_{it} is the error term.

In estimating Equation (9), we applied the CRE approach (i.e. we included the means of the time-varying exogenous variables) to control for unobserved heterogeneity. Finally, following Wooldridge (2015), we tested the null hypothesis that access to seed is exogenous by using the generalised residual from the reduced-form model (first-stage estimation of access to seed) that was included as an additional regressor in the structural model (second-stage estimation: the double-hurdle adoption model). This approach to test and control endogeneity is consistent with earlier empirical technology adoption studies in SSA (see Bezu et al., 2014; Ricker-Gilbert et al., 2011; Verkaart et al., 2017).

The CF approach requires an IV to be used in the reduced-form equation (Equation 9). An appropriate IV for our model should be correlated with access to the IMV seed variable (S_{it}), yet uncorrelated with the variable measuring adoption (i.e., land allocated to IMV production). We used a variable denoting the number of years that the household head had lived in the village as an IV for our model. There are no theoretically sound household-level instruments used to capture smallholder production in the existing literature because of a lack of reliable data. Hence, we followed earlier studies (Bezu et al., 2014; Ricker-Gilbert et al., 2011), and used the number of years a household head had lived in a village as an instrument for access to improved seed.[3] We expected that the variable we used as an instrument could be justified because the number of years a household head lives in a village cannot directly affect a household's land allocation for IMV production, other than through access to improved seed.

We expected that the more years farmers had lived in the village, the more access to improved seed they would have, at least in these three different ways. First, they would be more familiar to neighbours in their village, which may increase access to seeds as a gift from neighbours. Second, they would likely be more familiar with the village market, which would help them purchase improved seeds. Third, the more years a farmer lives in a village, the more acquainted that farmer becomes with community leaders, who often allocate improved seed through borrowing from a revolving seed fund. Until recently, there have been regulations in Ethiopia restricting improved seed sales by private companies to government-designated areas or parastatals (Abate et al., 2015). The selection of this IV was also consistent with the argument of earlier studies by Bezu et al. (2014) and Ricker-Gilbert et al. (2011) that this variable is a measure of socio-political capital that could influence households' access to modern inputs.

Concerning instrument validity, we could not implement standard testing for weak instruments in linear IV regression, such as that by Stock and Yogo (2005), because our adoption model was a non-linear corner solution model. Therefore, we followed the approach of Ricker-Gilbert et al. (2011), who argued that the presence of non-linearity in adoption decision-making

[3]Recent studies suggested incorporating insights into the importance of social networks and peer effects in technology adoption to construct an IV (see Verkaart et al., 2017; Zeng et al., 2017). Unfortunately, we could not apply social interactions or networks in technology adoption to construct our IV because such information was not available in our data.

models has meant that the best instrument validity test is the use of partial correlation of the IV with a potentially endogenous variable in the reduced-form model. Additionally, we ran a correlation analysis between the IV and other explanatory variables used in the analyses. Furthermore, we followed Mason and Smale (2013) to include our IV as an additional explanatory variable in the structural equation.

Another potential endogeneity issue may stem from the endogenous nature of the adoption indicator (the area allocated to IMV) in welfare equations. Previous adoption literature (see Bezu et al., 2014; Verkaart et al., 2017) has suggested using the unconditional expected values of the adoption equation as an instrument for observed adoption in the welfare equation. According to Wooldridge (2015), this approach is more efficient in linear models than other standardised methods used to address endogeneity, such as 2SLS and the CF approach discussed above. Following that literature, we used the predicted value from the double-hurdle model (Equation 4) as an instrument for A_{it} in the welfare equation (Equation 5). The exclusion restriction in the welfare equations was satisfied by the improved maize equation variables yet excluded from the welfare equations. The excluded variables that provided the exogenous variation necessary for identification included distance to the extension office, access to market, pest occurrence in a previous cropping season and access to seed. These variables were not expected to directly affect the welfare outcome equations after controlling for improved maize planted.

3.5 | Data and descriptive statistics

This study used comprehensive three-wave farm household survey data collected from smallholder maize farmers in Ethiopia as part of the SIMLESA programme led by the International Maize and Wheat Improvement Center (CIMMYT) (Marenya et al., 2016). The SIMLESA surveys were conducted in collaboration with the Adoption Pathways regional project implemented by the Ethiopian Institute of Agricultural Research in close collaboration with CIMMYT. The SIMLESA surveys covering 2009/10, 2012/13 and 2014/15 cropping seasons were undertaken on selected maize-producing areas from the SIMLESA project intervention districts in Ethiopia's three regional states: Oromia; Southern Nations, Nationalities and Peoples' Region; and Benishangul-Gumuz (Marenya et al., 2016). The SIMLESA surveys generated rich information at the household, farm and village levels. We relied on the SIMLESA surveys because the surveys exclusively focussed on areas that have been established as significant maize-based farming regions in Ethiopia and elicited information from maize farmers. We expected surveys to concentrate on a specific commodity to avoid difficulty identifying specific improved crop varieties.

The baseline SIMLESA survey conducted in 2011 (covering the 2009/10 production season) consisted of 898 sample households. The second round conducted in 2014 covering the 2012/13 production season elicited information from 874 farm households, with a success rate of 97.3%. In the third-round survey conducted in 2016 (covering the 2014/15 production season), interviewed sample households dropped to 798. Some households either deceased or left the village, giving an attrition rate of 8.7%. We compared the characteristics using the first round of data to ensure that our results were unaffected by nonrandom attrition and found no significant differences between attritions and nonattritions. To ensure that the results were not affected by households that left the panel between surveys, we tested the robustness of our results by checking for potential attrition bias. The detailed strategy used to investigate potential attrition bias can be obtained from the corresponding author upon request.

Our study differentiated the maize varieties based on consultation with researchers and maize breeders at CIMMYT and earlier maize adoption studies in Ethiopia (e.g. Jaleta et al., 2018; Zeng et al., 2015), as either improved (IMV) or local varieties. Hybrid maize seeds or OPV, freshly purchased from a formal source, were identified as IMV. Moreover, recycled OPV (saved from the previous harvest) that had not been recycled for more than three cropping seasons was also identified as IMV. Recycling hybrid maize seed leads to rapid yield loss and other traits while the yield loss for OPV is much slower; hence, the OPVs retain their traits for longer than hybrids upon recycling (Jaleta et al., 2018). Therefore, OPV seeds which farmers recycled for more than three cropping seasons were categorised as local (see Jaleta et al., 2018; Zeng et al., 2015). Table 2 presents the descriptive statistics of the variables used in this study.

4 | EMPIRICAL RESULTS

4.1 | Determinants of IMV adoption

Before estimating our empirical models, we used a CF approach to account for potential endogeneity resulting from the endogenous nature of the access to improved seed, as discussed in Section 3.4. Following Wooldridge (2015), we tested the null hypothesis that access to seed is exogenous by using the generalised residual from the first-stage model for access to seed that was included as an additional regressor in the second-stage estimation (IMV adoption equation; see Table 3). As indicated by the results from the first-stage estimation reported in the Appendix S1 (Table S1), *years in the village*, which was used as an IV for access to seed, was highly significant in the first-stage model—indicating the statistical validity of the instrument (Ricker-Gilbert et al., 2011; Wooldridge, 2015). Additionally, we ran a correlation analysis between the IV and other explanatory variables used to validate *years in the village* as an IV. The results indicated weak correlations between variables employed in the analyses. Furthermore, we followed Mason and Smale (2013) to include our IV as an additional explanatory variable in the structural equation. We found that *years in the village* was insignificant, indicating that the exclusion restriction was met. These results are available from the authors upon request.

Table 3 presents the results for the IMV adoption model estimated using a CRE double-hurdle model (Equation 4). The statistically significant coefficient for the generalised residual in both hurdles (see Table 3) indicated that access to improved seed was endogenous in the technology adoption equation. Therefore, our procedure was necessary. The coefficient on access to improved seed was positive and statistically significant for both hurdles. This indicates that the probability of adopting and intensity of IMV adoption increase with access to improved seed. The finding offers evidence that the expanded adoption of IMV among smallholder maize farmers in Ethiopia is constrained by access to improved seeds. While the coefficient for *age* was negative in both hurdles, it was statistically significant only in the second hurdle. This indicates that younger and older farmers are similarly likely to adopt IMV, yet younger farmers allocate a more substantial portion of their land for IMV cultivation. This could be because older farmers are less flexible in trying improved varieties than younger farmers. Although the coefficient for *gender* was positive in both hurdles, it was statistically significant only in the second hurdle—suggesting that the *gender* of the farm household head significantly affects IMV adoption intensity, yet not the likelihood of adopting IMV.

A statistically significant parameter estimate for *family labour* in the first hurdle suggests that an active family labour force increases the likelihood of planting IMV. This result revealed labour shortage as a constraint to IMV adoption in Ethiopia. The positive parameter estimates for *initial* a*sset ownership* and *landholding*—in the second hurdle only—suggest that access to physical capital influences the extent (intensity) of the adoption of IMV, yet not the probability of improved planting. The positive effect of *landholding* on adoption intensity indicates that farm households with large landholdings tend to allocate more land for IMV production. This confirms that the availability of sizable cultivable land enhances adoption by allowing farmers to expand the scale of production.

TABLE 2 Descriptive statistics of variables used for empirical analyses, by year.

Variables	2009/10 Mean (SD)	2012/13 Mean (SD)	2014/15 Mean (SD)
Adoption and Welfare indicators			
Area under IMV (ha)	0.98 (0.96)	0.78 (0.77)	0.88 (0.82)
Household Income (per capita, USD PPP)[a]	699.2 (1841.4)	1394.5 (4472.7)	1000.1 (1605.3)
Household maize consumption (per capita, kg)[a]	63.18 (83.72)	414.9 (263.4)	423.8 (304.3)
Asset ownership index (*latent variable*)	−0.17 (0.69)	0.03 (0.77)	0.14 (0.78)
Poverty status (Poor = 1 for <1.90 US$ PPP/day)	0.85 (0.35)	0.57 (0.49)	0.66 (0.48)
Household characteristics			
Age of the HH (years)	41.25 (13.19)	43.87 (13.13)	46.71 (13.11)
Male-headed household (yes = 1)	0.91 (0.28)	0.92 (0.27)	0.92 (0.28)
Education level of the HH (years)	3.26 (3.39)	3.16 (3.38)	3.04 (3.34)
Family size (adult-equivalent)	4.94 (2.25)	5.04 (2.22)	4.93 (2.01)
Family labour (man-equivalent)	41.21 (39.13)	43.96 (51.92)	42.37 (83.31)
Initial asset ownership (real, USD)	1914.4 (6032.4)	1914.4 (6032.4)	1914.3 (6032.4)
Landholding (ha)	2.25 (1.95)	1.72 (1.46)	2.17 (1.77)
Village-level covariates and access-related variables			
Access to improved seed (yes = 1)	0.91 (0.28)	0.924 (0.266)	0.912 (0.284)
Maize price (ETB/kg in the previous season)[b]	4.82 (3.87)	10.05 (7.58)	6.938 (4.64)
Teff price (ETB/kg in the previous season)[b]	6.680 (4.082)	11.98 (7.65)	12.09 (7.64)
Wheat price (ETB/kg in previous season)	6.327 (4.356)	12.45 (10.87)	24.66 (20.32)
Extension service (minutes to the nearest extension office)	30.74 (26.59)	30.74 (26.59)	30.74 (26.59)
Off-farm employment (yes = 1)	0.62 (0.49)	0.57 (0.50)	0.52 (0.50)
Credit organisation in the village (yes = 1)	0.21 (0.41)	0.21(0.41)	0.21 (0.41)
Membership in farmer group (yes = 1)	0.23 (0.42)	0.23 (0.42)	0.23 (0.42)
Main market in the village (yes = 1)	0.10 (0.28)	0.10 (0.28)	0.10 (0.28)
Environmental characteristics			
Land quality (1 = best,…,9 = worst)	2.41 (1.46)	2.07 (1.41)	2.12 (1.16)
Pest occurrence (yes = 1)	0.00 (0.00)	0.06 (0.24)	0.04 (0.19)
Rainfall shortage (yes = 1)	0.00 (0.00)	0.26 (0.44)	0.21 (0.41)
Reduced form IV (years HH has lived in the village)	33.33 (13.97)	35.03 (14.36)	38.039 (14.79)

[a]We used adult equivalent units, instead of the number of households, to convert the variables into per capita terms.

[b]All monetary values are in real terms. Ethiopian-Birr (ETB) is a local currency, where 1 USD was equivalent to 17.01 ETB in 2010, 20.50 ETB in 2013 & 20.68 ETB in 2015 cropping seasons. HH: stands for the household head.

As expected, the adoption decisions of maize farmers were affected by village-level output prices observed before the planting season. The positive and statistically significant parameter estimate for *maize price* in both hurdles confirms that higher maize prices in a previous period stimulated the adoption of IMV. The positive and statistically significant coefficient for *wheat*

TABLE 3 Determinants of IMV adoption: CRE double-hurdle model.[a]

Determinants of adoption	Adoption decisions: Hurdle 1: Probability of planting IMV	Adoption decisions: Hurdle 2: Adoption intensity (area under IMV)
Access to improved seed	0.605*** (0.115)	0.059* (0.035)
Generalised residual	−0.056*** (0.008)	−0.015*** (0.004)
Age of the head (years)	−0.002 (0.002)	−0.001* (0.001)
Male-headed household (yes = 1)	0.148 (0.207)	0.040*** (0.015)
Education level of the head (years)	0.019 (0.020)	0.002 (0.002)
Family size (AEU)[b]	−0.037 (0.055)	0.003 (0.006)
Family labour (man-equivalent)	0.002** (0.001)	0.001 (0.000)
Ln initial asset ownership (real ETB)[c]	0.078 (0.053)	0.012*** (0.001)
Ln landholding (ha)	0.186 (0.177)	0.566*** (0.027)
Maize price (ETB/kg in the previous season)	0.012*** (0.004)	0.006*** (0.000)
Teff price (ETB/kg in the previous season)	0.001 (0.003)	0.003 (0.004)
Wheat price (ETB/kg in previous season)	0.009*** (0.001)	0.002*** (0.000)
Extension service (minutes to extension office)	−0.002*** (0.001)	−0.000 (0.000)
Off-farm employment (yes = 1)	0.012 (0.184)	−0.026 (0.017)
Credit organisation in the village (yes = 1)	0.308*** (0.081)	−0.008 (0.005)
Membership in farmer group (yes = 1)	0.247* (0.139)	0.019 (0.021)
Main market in the village (yes = 1)	−0.047 (0.212)	0.023*** (0.003)
Land quality (1 = best,…,9 = worst)	0.072 (0.066)	0.002 (0.003)
Pest occurrence (yes = 1)	−0.500*** (0.177)	−0.004 (0.003)
Rainfall shortage (yes = 1)	−0.286*** (0.044)	−0.014* (0.007)
Constant	0.374 (0.567)	−0.236*** (0.028)
Sigma		0.190*** (0.011)
Wald Chi^2		351.55***
Number of observations		1885
Log pseudo-likelihood		56.198

[a]Regressions in both hurdles include time averages of all time-varying explanatory variables, year and region dummies as additional regressors. We have not reported the full results here to save space, and they can be obtained upon request.

[b]AEU stands for Adult Equivalent Unit. The number of people in the household was converted into AEU based on the standard conversion factors to account for age and gender differences.

[c]ETB, a local currency. 1USD was equivalent to 17.01ETB in 2010, 20.50USD in 2013, & 20.68USD in 2015.

Significance levels; *$p<0.1$, **$p<0.05$, ***$p<0.01$. Robust standard errors in parentheses.

price in both hurdles indicates that the higher prices of this potential substitute food crop encouraged maize production through the increased use and intensity of IMV.

The negative parameter estimate for *extension*—in the first hurdle only—indicate that the distance to an extension service significantly affected farmers' decisions to plant IMV, yet not the intensity with which they adopted it. This suggests that maize farmers residing farther from the extension service centre are less likely to grow IMV. The statistically significant positive parameter estimate on access to *credit* in the first hurdle indicates that the probability of planting IMV is higher for farmers in a village with access to a credit organisation. This suggests that a financial credit facility could enhance adoption by enabling farmers to purchase required farm inputs.

The statistically significant positive parameter estimate for the distance to the main market in the second hurdle offers evidence supporting the argument that market access stimulates farmers' technology by facilitating the purchasing of necessary farm inputs. The statistically significant positive parameter estimate for group membership—in the first hurdle only—indicates that group membership increases the likelihood of farmers planting IMV, yet not the intensity with which they do so. This supports the broad consensus that farmers involved in a farmers' group are more likely to adopt improved crop varieties because interacting with neighbouring farmers provides better access to information about the improved technology (see Geffersa et al., 2019b; Krishnan & Patnam, 2014; Wossen et al., 2017). As expected, farm households that experienced rainfall shortages and pests in a previous cropping season were less likely to grow IMV.

4.2 | Effects of IMV adoption on household welfare

Table 4 presents the instrumental variables regressions estimated to investigate the relationship between IMV adoption and household welfare. Before we estimated our welfare equations, we used the IRT model (specified in Equation 6) to quantify the underlying latent variable for household asset ownership. Table S2 presents the results of the IRT model. In line with our prior expectations, we found that the area allocated to IMV was positively and significantly associated with increased *household maize consumption*, *household income* and *asset ownership*. At the same time, it was negatively correlated with the *poverty index*.

Controlling for other factors, we found that a 1% increase in the area allocated to IMV was associated with an increase of approximately 0.55% in per-capita consumption of maize from home production. Our results indicated a 1% increase in the area allocated to IMV production increased the per-capita household income by 0.41%. As expected, the rise in household income subsequently led to enhanced household asset accumulation and poverty reduction. As the results in Table 4 show, a 10% increase in the area allocated to IMV increased household asset accumulation by about 1.22%. This result corroborates our descriptive result reported in Section 3.5 that indicated a consistent improvement in asset ownership over the years as the adoption of IMV increased. As noted in the CRE probit model estimates, the coefficient for the IMV area was negative and significant, suggesting a poverty reduction of IMV adoption. The poverty estimates indicated that a 10% increase in the area allocated to IMV was associated with a 4.79% reduction in the probability of falling below the \$1.90 poverty line. This result confirmed that the increase in household income resulting from the use of IMV was so significant as to raise households above the \$1.90 poverty line.

Our results are mostly consistent with those of earlier studies that found similar and positive effects on household welfare arising from the adoption of HYV. In particular to IMV adoption in SSA, Khonje et al. (2015) from Zambia, Bezu et al. (2014) from Malawi, and Mathenge et al. (2014) from Kenya observed significant positive effects of IMV adoption on household welfare. Studies on IMV adoption in countries such as Mexico (see Becerril & Abdulai, 2010) have likewise found a positive impact of IMV adoption on household welfare through increased cash income and rural poverty reduction.

For most of the exogenous variables with significant parameter estimates, the sign of the coefficients was consistent with our prior expectations, except for *family size* (Table 4). We observed a strong positive effect of the *education* level of the household head on asset ownership, which also reduced poverty. *Family size* had a welfare-reducing impact on the three welfare indicators, aside from asset ownership. In particular, the positive and significant effect of *family size* on poverty appeared anomalous. This may be because, for households with large family sizes, the output effect might be offset by a possible consumption effect since large families often place additional pressure on farming operations to meet immediate household

TABLE 4 Estimations for welfare impacts of IMV adoption.

Explanatory variables	Welfare indicators (1) ln per capita household maize consumption[b]	(2) ln per capita real income[b]	(3) asset index[c]	(4) poverty status[c] (poor < \$1.90)
Ln area under IMV[a]	0.549***	0.414***	0.122***	−0.479***
	(0.209)	(0.138)	(0.029)	(0.069)
Age of the HH (years)	0.004	−0.001	−0.003	0.001
	(0.011)	(0.008)	(0.002)	(0.009)
Male-headed household	−0.543	0.032	0.066	0.006
	(0.447)	(0.318)	(0.064)	(0.149)
Education of the HH (years)	0.015	−0.035	0.022**	−0.038***
	(0.042)	(0.028)	(0.008)	(0.013)
Family size (no)	−0.251***	−0.092***	0.020***	0.067**
	(0.036)	(0.025)	(0.007)	(0.027)
Landholding (ha)	0.088	0.086**	0.025**	−0.033
	(0.055)	(0.039)	(0.011)	(0.037)
Off-farm employment (1 = yes)	0.020	0.798***	0.080***	−0.997***
	(0.127)	(0.094)	(0.026)	(0.105)
Land quality (1 = best,…,9 = worst)	−0.053	−0.160***	−0.048***	0.132***
	(0.052)	(0.035)	(0.010)	(0.031)
Rainfall shortage (yes = 1)	−0.556***	−0.253**	−0.007	0.264**
	(0.181)	(0.117)	(0.036)	(0.132)
Constant	7.213***	4.911***	−1.024***	2.680***
	(0.699)	(0.506)	(0.126)	(0.296)
F statistic	232.86***	29.54***		
Wald Chi^2			529.70***	313.69***
Rho	0.36	0.44	0.60	0.13
Number of observations	1886	1886	1886	1886
Number of households	671	671	671	671
Log-likelihood	−3521.514	−2039.289	−1528.279	−884.443

Note: All regressions include year dummies in addition to household fixed effects.

[a]The natural logarithm (Ln) of the IMV area is treated as endogenous using unconditional expected values of the observed Ln of IMV from the double-hurdle model as an instrument for the observed values of the area allocated for IMV.

[b]Welfare indicators are per adult equivalent. Given the skewness of their distributions, we used natural logarithmic to transform the two welfare outcome variables prior to running our econometric models.

[c]The equations were estimated under CRE, where time averages of all time-varying explanatory variables were included as additional regressors. We have not reported the full results here to save space, and they can be obtained upon request.

Significance levels *p < 0.1, **p < 0.05, ***p < 0.01. Fully robust standard errors in parentheses.

consumption needs. This finding is supported by previous SSA studies, such as those by Verkaart et al. (2017), Bezu et al. (2014) and Mathenge et al. (2014). *Landholding* significantly influenced household welfare when evaluated based on its effect on asset ownership and income. We found that increased household participation in off-farm income-generating activities raised income and asset ownership while significantly reducing poverty.

Overall, our results indicate that increased use of IMV has a robust positive effect on household welfare. This result is encouraging because realising increased food production through

TABLE 5 The difference in well-being measures, by IMV adoption status.

Variables[a]	Adopters	Nonadopters	*t*-test
Returns from maize production			
Maize area (ha)	1.00	0.51	0.50***
Maize yield (kg/ha)	3046.39	2699.54	346.85**
Total income from maize (real, USD/ adult-equivalent)	698.30	159.94	538.36**
Per capita income from maize (real, USD/ adult-equivalent)	147.83	35.37	112.46**
Net returns from maize sale (real, USD/ha)	1132.75	528.09	604.66***
Benefits and Welfare gains			
Household maize consumption from its own-production (kg)	1476.58	757.71	718.87***
Per capita maize consumption from its own-production (kg)	315.71	198.33	117.38***
Quantity of maize sold (kg)	943.24	197.26	745.98***
Household income (real, USD PPP)	4079.32	2226.49	1852.83**
Per capita income (real, USD PPP)	923.46	665.85	257.61*
Maize sales as a share of income (%)	26.62	45.19	−18.57***

[a]All values are pooled across all observations and periods.
Significance of the mean differences (*t*-tests) are presented as. *$p<0.10$, **$p<0.05$, ***$p<0.01$.

area expansion might not be sustainable in Ethiopia because of population pressure. This finding is of great importance, particularly for the smallholder maize sector in Ethiopia, where a significant technology gap exists among smallholder farmers (Geffersa et al., 2022). We observed several channels through which IMV might have contributed to household welfare. As Table 5 shows, the IMV adopters, on average, harvested more maize per hectare than the nonadopters—a statistically significant finding. The increase in maize yield allowed households to meet their food consumption needs and earn additional household income by selling surplus maize. As Table 5 shows, IMV adopters consumed significantly more maize from their production than nonadopters, indicating that the increase in maize yield had a direct food consumption effect. On average, IMV adopters earned substantially more total and per-capita household income (Table 5). IMV adoption led to substantially higher maize sales in terms of the share of household income. The share of maize income for IMV adopters (45.19%) was considerably higher than the 26.62% share of maize income for nonadopters.

4.3 | Effect heterogeneity of IMV adoption

To enrich our understanding of the effect of IMV adoption, we explored the possible heterogeneous effects of IMV adoption across households. As shown in Figure 1, the intensity of IMV adoption (the size of the area under IMV) increased with initial land ownership. Therefore, we disaggregated our welfare analyses by the initial wealth status of the households using the first three quartiles for the initial land ownership of each household (denoted as Q1, Q2 and Q3).

To empirically test whether this difference produced heterogeneous effects on household welfare, we allowed our coefficient of interest (Φ corresponding to the adoption indicator A_{it}, in Equation 5) to vary with the households' initial land ownership, following an approach used by Verkaart et al. (2017). We then re-estimated Equation (5), wherein our measurement of IMV adoption interacted with an indicator for the initial land quartile. The results presented in

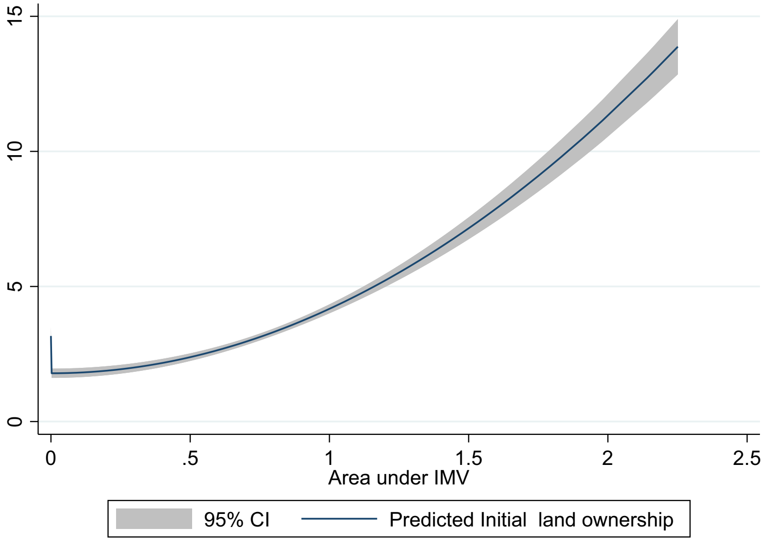

FIGURE 1 The relationship between initial land ownership and the area under IMV. [Colour figure can be viewed at wileyonlinelibrary.com]

Table 6 show that the effect of IMV adoption on household welfare was heterogeneous across households, depending on their initial wealth status. The first column of the results in Table 6 indicates a highly significant and positive effect of IMV adoption on home-grown maize consumption for households in the first quartile.

However, the effect of IMV adoption was insignificant for households in the two upper quartiles, suggesting that IMV adoption had no effect on maize consumption for the most significant landholding households. The effect on income poverty was insignificant for households in the two lower quartiles, suggesting that the poverty-reduction effect of IMV adoption was substantial for the most significant landholding households. Our estimates indicate that lifting maize-producing households above the $1.90 poverty line requires a minimum land area of about 3.052 hectares. This finding supports earlier SSA studies, such as those by Alwang et al. (2019), Zeng et al. (2015) and Dercon and Christiaensen (2011), who argue that the welfare gain from HYV for the rural poor in SSA is negligible because of the smallness of the landholdings.

Furthermore, one might expect that, if IMV adoption indeed makes a difference in the well-being of the poor, equally poor households should experience different welfare gains, depending on whether or not they adopt IMV. As indicated by a comparison of adoption intensities across groups (see Figure 2), the area allocated to IMV cultivation was above the median for better-off households. Therefore, we compared the welfare outcomes of the poorest households disaggregated by their IMV adoption status. The result in Table 7 shows that, among the poorest households, those who adopted IMV experienced significantly more gains from the adoption—measured in terms of key well-being measures. This result suggests that IMV indeed makes a difference to the well-being of farm households with equal levels of household income.

4.4 | Robustness checks

To check the robustness of our main results, we undertook several additional analyses (presented in Appendix S1). First, we estimated the CRE Tobit model (Model 1) to compare our results from Cragg's (1971) double-hurdle model. The results (presented in Table S3) are similar. All the signs of the explanatory variables were as predicted by the double-hurdle model, except

TABLE 6 Adoption impact of IMV by initial land ownership.

Different specifications	Welfare indicators: Ln per capita household maize consumption	Welfare indicators: Poverty status (poor < $1.90/day)
Quartile 1 * Ln area under IMV[a]	1.288***	−0.081
	(0.357)	(0.055)
Quartile 2 * Ln area under IMV[a]	0.142	−0.060
	(0.391)	(0.050)
Quartile 3 * Ln area under IMV[a]	0.110	−0.157***
	(0.269)	(0.054)
Number of observations	1886	1886
Number of households	671	671

Note: All regressions include explanatory variables from Table 4.

[a]The results are similar to the results from the *baseline model* (primary results) presented in Column (2) and Column (4) of Table 4, except that the IV (the unconditional expected values of the *Ln of improved maize area*) interacts with an indicator for the initial land quartile to which each household belongs.

Significance levels; *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors in parentheses.

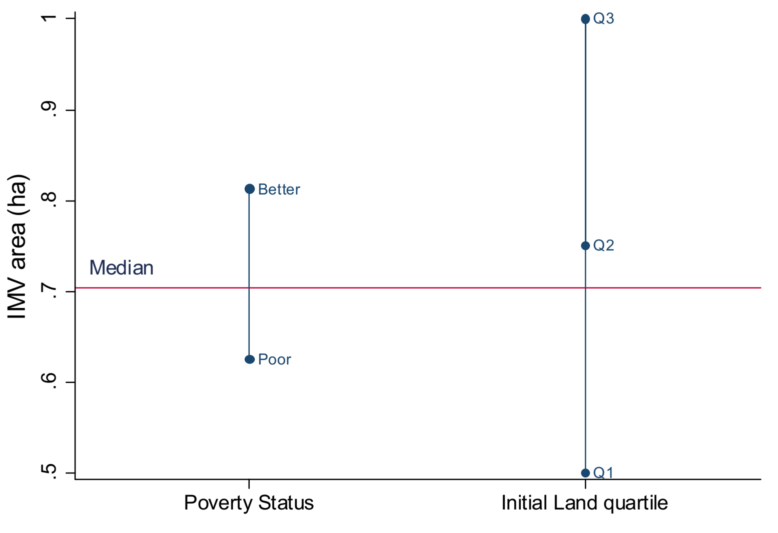

FIGURE 2 The intensity of IMV adoption, by wealth status. [Colour figure can be viewed at wileyonlinelibrary.com]

for slight variations in the level of significance. However, Cragg's double-hurdle model fits the IMV equation better, as supported by a likelihood ratio test, which suggests rejection of the Tobit model in favour of the double-hurdle model. Second, we re-estimated the CRE double-hurdle model, treating access to improved seed as exogenous to adoption decisions (Model 2; see Table S4). Third, we re-estimated our CRE double-hurdle model using the measure of the adoption intensity measured by the quantity of IMV seeds planted as an alternative specification for the adoption equation (Model 3; see Table S5).

Following this, we verified the validity of our results for the effects of IMV adoption on welfare. We re-ran separate analyses for each welfare outcome variable using the predicted value for IMV adoption from the newly estimated models (Models 1 to 3). Table 8 presents the results

TABLE 7 Differences in well-being measures among the poor households, by adoption status.

	Poverty status (<1.90 US$ PPP/day)		
Welfare and household well-being measures	**Poor adopters**	**Poor nonadopters**	***t*-test**
Household maize consumption from own-production (kg)	1275.69	687.42	588.27***
Per capita maize consumption from its own-production (kg)	256.73	157.90	98.83***
Income from maize sale (real, USD PPP)	180.69	62.89	117.81***
Per capita income from maize sale (real, USD PPP)	34.65	12.75	21.90***
Total income (real, USD PPP)	1044.20	744.17	300.03***
Per capita income (real, USD PPP)	199.85	172.71	27.14**

Significance of the mean differences (t-tests) are presented as. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

alongside the baseline results. The overall results of the supplementary analyses indicated that the welfare effects of IMV adoption were robust across the alternative specifications.

Furthermore, we examined the consistency of our empirical results using an alternative instrument for access to seed: *having friends or relatives in a leadership position in or outside the village* (IV2). Finally, we verified the validity of our results for the impacts of IMV adoption on welfare by re-estimating the welfare equations using an alternative IV. In line with our discussion in the main section, we checked the partial correlation of the IV2 with a potentially endogenous variable in the reduced-form model for the instrument validity. The correlation coefficients indicated weak correlations between the IV2 and variables employed in the analyses. At the same time, it is significantly correlated with the potentially endogenous variable in the reduced-form equation, indicating that the instrument is valid. Additionally, we included our IV2 as an additional explanatory variable in the structural equation. The variable was insignificant in the structural equation, indicating that the exclusion restriction was met. Overall, the additional results presented in Tables S6–S7 are similar to those reported in the paper's main section.

5 | CONCLUSIONS AND POLICY IMPLICATIONS

Previous studies have explored the effect of agricultural technology adoption on the welfare and poverty of rural households, yet the empirics are contentious and unresolved. Understanding the impact of IMV adoption on welfare and poverty is critical for achieving sustainable development in developing countries. This paper contributes to the literature by investigating whether agricultural technology adoption enhances welfare and reduces poverty using IMV adoption in Ethiopia. We extended the existing literature by explicitly accounting for unobserved farm household heterogeneity and endogeneity in technology adoption decisions. We specified the adoption decision using the double-hurdle model and estimated it using CRE regression. We corrected for unobservable heterogeneity and endogeneity using a CRE regression and a fixed-effects instrumental variable approach. We evaluated the model using panel data from three waves of surveys (from 2009/10 to 2014/15) conducted under the SIMLESA project for major maize-producing regions in rural Ethiopia.

Our empirical findings revealed that IMV adoption has heterogeneous effects on the welfare and poverty of rural households. We found that IMV adoption increases households' income, asset ownership and maize consumption while reducing income poverty. The poverty

TABLE 8 Robustness check of welfare impacts of IMV adoption.

	Welfare indicators			
Different specifications	**Ln per capita real income**	**Ln per capita household maize consumption**	**Asset index**	**Poverty status (poor < $1.90)**
Bassline Model: Primary results[a]	0.414***	0.549***	0.122***	−0.479***
	(0.138)	(0.209)	(0.029)	(0.069)
Model 1: CRE tobit model for adoption[b]	2.963***	1.420*	0.395***	−0.475***
	(0.461)	(0.729)	(0.093)	(0.050)
Model 2: IMV seed access exogenous[b]	0.448***	0.522**	0.118***	−0.467***
	(0.136)	(0.205)	(0.029)	(0.068)
Model 3: Ln quantity of IMV seed (kg) used to measure the extent of adoption[b]	0.437**	0.517*	0.113***	−0.485***
	(0.143)	(0.217)	(0.030)	(0.070)
Number of observations	1886	1886	1886	1886
Number of households	671	671	671	671

Note: All regressions include explanatory variables from Table 4.

[a]The results are similar to the results from the *baseline model* (primary results) presented in the first three columns of Table 4, except that the IV (the unconditional expected values of the *Ln of improved maize area*) is now estimated using different specifications (Model 1 to Model 3) as outlined in the table.

[b]Primary results from the original models (in Table 4) are reported here for comparison.

Robust standard errors in parentheses (Significance levels; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$).

estimates indicated that a 10% increase in the area allocated to IMV was associated with a reduction in the probability of being below the \$1.90 poverty line by 4.79%. However, the poverty-reducing effect of IMV adoption was heterogeneous across households, with the most pronounced effect felt by households with extensive landholdings. Our findings suggest that providing IMV and land under cultivation to farmers can serve as an effective strategy for improving farmers' welfare and reducing poverty in rural Ethiopia.

With the increasing pressure to improve the welfare of rural households and reduce poverty in developing countries, our empirical findings highlight the importance of understanding the drivers influencing the adoption decision of rural farmers. We argue that reducing rural poverty and food insecurity through enhancing IMV adoption in Ethiopia necessitates addressing the structural bottlenecks in the adoption of IMV. In addition to promoting the use of IMV, there is a need to tackle other vital factors, such as access to family labour; physical resource endowments, such as land and physical assets; output price; and access to improved seed, financial credit, central markets and extension services. The significant influence of access to improved seed suggests that agricultural policies that help create greater seed access can help increase IMV adoption. Furthermore, implementing policies that create greater access to cultivable land through land rental markets can help improve welfare and reduce poverty. The fact that unfavourable agro-climatic conditions, such as rainfall shortage and pest occurrence, could negatively influence IMV adoption suggests the need for governments to provide expanded access to drought and pest resistant maize varieties. Governments need to implement policies to increase farmer access to extension services, as this can increase IMV adoption and thus increase welfare and consequently reduce poverty.

While the findings of this study are consistent with the existing literature, two points are worth noting in terms of the generalisability of our empirical results. First, farmers may have adopted other agricultural technologies, such as soil fertility management and chemical fertilisers. However, given the lack of adequate data, it was impossible to account for this in the modelling. Future research should seek to investigate the complementarity of technology adoption. Second, IMV adoption may produce indirect welfare effects on both adopters and nonadopters through growth linkage effects. A full exploration of the economy-wide distributional effects of IMV adoption is beyond the scope of this study because the study is limited to partial-equilibrium welfare analysis. Future research with a more comprehensive assessment of general equilibrium effects would help to generalise our findings. Despite this, our paper has uncovered meaningful relationships between IMV adoption and welfare and poverty. The results are critical for informing rural households' welfare and poverty reduction policy. By establishing these relationships within a developing country context, we have shed new light on the heterogeneous effect of agricultural technology adoption on welfare and poverty reduction.

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DATA AVAILABILITY STATEMENT

The data for each survey round are openly available in a public repository: https://data.cimmyt.org/dataverse/cimmytdatadvn. The merged and cleaned panel data set that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

Abate, T., Shiferaw, B., Menkir, A., Wegary, D., Kebede, Y., Tesfaye, K. et al. (2015) Factors that transformed maize productivity in Ethiopia. *Food Security*, 7(5), 965–981.

Abay, K.A., Berhane, G., Taffesse, A.S., Abay, K. & Koru, B. (2018) Estimating input complementarities with unobserved heterogeneity: Evidence from Ethiopia. *Journal of Agricultural Economics*, 69(2), 495–517.

Abdul-Salam, Y. & Phimister, E. (2017) Efficiency effects of access to information on small-scale agriculture: Empirical evidence from Uganda using stochastic frontier and IRT models. *Journal of Agricultural Economics*, 68(2), 494–517.

Abro, Z.A., Alemu, B.A. & Hanjra, M.A. (2014) Policies for agricultural productivity growth and poverty reduction in rural Ethiopia. *World Development*, 59, 461–474.

Adamie, B.A., Balezentis, T. & Asmild, M. (2018) Environmental production factors and efficiency of smallholder agricultural households: Using non-parametric conditional frontier methods. *Journal of Agricultural Economics*, 70(2), 1–17.

Ahmed, M.H., Geleta, K.M., Tazeze, A. & Andualem, E. (2017) The impact of improved maize varieties on-farm productivity and wellbeing: Evidence from the east Hararghe zone of Ethiopia. *Development Studies Research*, 4(1), 9–21.

Alwang, J., Gotor, E., Thiele, G., Hareau, G., Jaleta, M. & Chamberlin, J. (2019) Pathways from research on improved staple crop germplasm to poverty reduction for smallholder farmers. *Agricultural Systems*, 172, 16–27.

Asfaw, S., Shiferaw, B., Simtowe, F. & Lipper, L. (2012) Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, 37(3), 283–295.

Assefa, B.T., Chamberlin, J., Reidsma, P., Silva, J.V. & van Ittersum, M.K. (2020) Unravelling the variability and causes of smallholder maize yield gaps in Ethiopia. *Food Security*, 12(1), 83–103.

Bachewe, F.N., Berhane, G., Minten, B. & Taffesse, A.S. (2018) Agricultural transformation in Africa? Assessing the evidence in Ethiopia. *World Development*, 105, 286–298.

Becerril, J. & Abdulai, A. (2010) The impact of improved maize varieties on poverty in Mexico: A propensity score matching approach. *World Development*, 38(7), 1024–1035.

Bezu, S., Kassie, G.T., Shiferaw, B. & Ricker-Gilbert, J. (2014) Impact of improved maize adoption on welfare of farm households in Malawi: A panel data analysis. *World Development*, 59, 120–131.

Birnbaum, A. (1968) Some latent trait models and their use in inferring an examinee's ability. In: Frederic, M.R.N. & Lord, M. (Eds.) *Statistical theories of mental test scores*. Reading: Addison-Wesley, pp. 397–479.

Burke, W.J., Myers, R.J. & Jayne, T.S. (2015) A triple-hurdle model of production and market participation in Kenya's dairy market. *American Journal of Agricultural Economics*, 97(4), 1227–1246.

Chamberlain, G. (1982) Multivariate regression models for panel data. *Journal of Econometrics*, 18(1), 5–46.

Cragg, J.G. (1971) Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica*, 39(5), 829–844.

CSA. (2016) *Agricultural sample survey (2015/16): Report on area, production and farm management practice of Belg season crops for private peasant holdings*. Addis Ababa, Ethiopia: Central Statistical Agency (CSA), the Federal Democratic Republic of Ethiopia. Available from: http://www.gatefarms.com/assets/downloads/belg_report_2016_2008.pdf [Accessed 10th March 2018].

CSA. (2019) *Agricultural sample surveys (2018/19): Report on area and production of major crops (private peasant holdings, Meher season)*. Addis Ababa, Ethiopia: Central statistical agency (CSA), the Federal Democratic Republic of Ethiopia. Available from: http://www.csa.gov.et/survey-report [Accessed 14th January 2020].

De Janvry, A., Fafchamps, M. & Sadoulet, E. (1991) Peasant household behaviour with missing markets: Some paradoxes explained. *The Economic Journal*, 101(409), 1400–1417.

De Janvry, A. & Sadoulet, E. (2002) World poverty and the role of agricultural technology: Direct and indirect effects. *Journal of Development Studies*, 38(4), 1–26.

De Janvry, A. & Sadoulet, E. (2009) Agricultural growth and poverty reduction: Additional evidence. *The World Bank Research Observer*, 25(1), 1–20.

Dercon, S. (2009) Rural poverty: Old challenges in new contexts. *The World Bank Research Observer*, 24(1), 1–28.

Dercon, S. & Christiaensen, L. (2011) Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, 96(2), 159–173.

Evenson, R.E. & Gollin, D. (2003) Assessing the impact of the green revolution, 1960 to 2000. *Science*, 300(5620), 758–762.

FAO. (2014) *Monitoring and analysing food and agricultural policies in Africa synthesis report 2013*. Rome, Italy: Food and Agriculture Organization (FAO). Available from: http://www.fao.org/3/a-i3513e.pdf [Accessed 9th July 2020].

Faye, O., Baschieri, A., Falkingham, J. & Muindi, K. (2011) Hunger and food insecurity in Nairobi's slums: An assessment using IRT models. *Journal of Urban Health*, 88(2), 235–255.

Feder, G., Just, R.E. & Zilberman, D. (1985) Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, 33(2), 255–298.

Ferreira, F.H.G., Chen, S., Dabalen, A., Dikhanov, Y., Hamadeh, N., Jolliffe, D. et al. (2016) A global count of the extreme poor in 2012: Data issues, methodology and initial results. *The Journal of Economic Inequality*, 14(2), 141–172.

Filmer, D. & Scott, K. (2012) Assessing asset indices. *Demography*, 49(1), 359–392.

Foster, J., Greer, J. & Thorbecke, E. (1984) A class of decomposable poverty measures. *Econometrica*, 52(3), 761–766.

Geffersa, A.G., Agbola, F.W. & Mahmood, A. (2019a) Technical efficiency in crop production across agro-ecological zones in Ethiopia: A meta-analysis of frontier studies. *Outlook on agriculture*, 48(1), 5–15.

Geffersa, A.G., Agbola, F.W. & Mahmood, A. (2019b) Technology adoption and technical efficiency in maize production in rural Ethiopia. *African Journal of Agricultural and Resource Economics*, 14(3), 184–201.

Geffersa, A.G., Agbola, F.W. & Mahmood, A. (2022) Modelling technical efficiency and technology gap in smallholder maize sector in Ethiopia: Accounting for farm heterogeneity. *Applied Economics*, 54(5), 1–16.

Ghimire, R. & Huang, W.-C. (2015) Household wealth and adoption of improved maize varieties in Nepal: A double-hurdle approach. *Food Security*, 7(6), 1321–1335.

Jaleta, M., Kassie, M., Marenya, P., Yirga, C. & Erenstein, O. (2018) Impact of improved maize adoption on household food security of maize producing smallholder farmers in Ethiopia. *Food Security*, 10, 81–93.

Kassie, M., Marenya, P., Tessema, Y., Jaleta, M., Zeng, D., Erenstein, O. et al. (2017) Measuring farm and market level economic impacts of improved maize production technologies in Ethiopia: Evidence from panel data. *Journal of Agricultural Economics*, 68(2), 76–95.

Khonje, M., Manda, J., Alene, A.D. & Kassie, M. (2015) Analysis of adoption and impacts of improved maize varieties in eastern Zambia. *World Development*, 66, 695–706.

Krishnan, P. & Patnam, M. (2014) Neighbors and extension agents in Ethiopia: Who matters more for technology adoption? *American Journal of Agricultural Economics*, 96(1), 308–327.

Langyintuo, A.S. & Mungoma, C. (2008) The effect of household wealth on the adoption of improved maize varieties in Zambia. *Food Policy*, 33(6), 550–559.

Manda, J., Alene, A.D., Tufa, A.H., Abdoulaye, T., Wossen, T., Chikoye, D. et al. (2019) The poverty impacts of improved cowpea varieties in Nigeria: A counterfactual analysis. *World Development*, 122, 261–271.

Marenya, P., Kassie, M., Muricho, G., Alemu, S., Yirga, C., Mishili, F. et al. (2016) CIMMYT research data: *pathways to sustainable intensification in eastern and southern Africa (SIMLESA) – Ethiopia* (version number 4) [data set]. Available from: https://data.cimmyt.org/dataverse/cimmytdatadvn [Accessed 4th April 2017].

Mason, N.M. & Smale, M. (2013) Impacts of subsidized hybrid seed on indicators of economic well-being among smallholder maize growers in Zambia. *Agricultural Economics*, 44(6), 659–670.

Mathenge, M.K., Smale, M. & Olwande, J. (2014) The impacts of hybrid maize seed on the welfare of farming households in Kenya. *Food Policy*, 44(3), 262–271.

Michler, J., Tjernstrom, E., Verkaart, S. & Mausch, K. (2018) Money matters: The role of yields and profits in agricultural technology adoption. *American Journal of Agricultural Economics*, 101(3), 710–731.

Minten, B. & Barrett, C.B. (2008) Agricultural technology, productivity, and poverty in Madagascar. *World Development*, 36(5), 797–822.

Moser, C. (2006) Asset-based approaches to poverty reduction in a globalized context. *Global economy and development working paper 01*. doi: https://doi.org/10.2139/ssrn.1011176

Mundlak, Y. (1978) On the pooling of time series and cross section data. *Econometrica*, 46(1), 69–85.

Ogundari, K. & Bolarinwa, O.D. (2018a) Does adoption of agricultural innovations impact farm production and household welfare in sub-Saharan Africa? A meta-analysis. *Agricultural and Resource Economics Review*, 48(1), 1–28.

Ogundari, K. & Bolarinwa, O.D. (2018b) Impact of agricultural innovation adoption: A meta-analysis. *Australian Journal of Agricultural and Resource Economics.*, 62(2), 217–236.

Pingali, P.L. (2012) Green revolution: Impacts, limits, and the path ahead. *Proceedings of the National Academy of Sciences*, 109(31), 12302–12308.

Ricker-Gilbert, J., Jayne, T.S. & Chirwa, E. (2011) Subsidies and crowding out: A double-hurdle model of fertilizer demand in Malawi. *American Journal of Agricultural Economics*, 93(1), 26–42.

Sahn, D.E. & Stifel, D. (2003) Exploring alternative measures of welfare in the absence of expenditure data. *Review of Income and Wealth*, 49(4), 463–489.

Shiferaw, B., Kassie, M., Jaleta, M. & Yirga, C. (2014) Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, 44, 272–284.

Singh, I., Squire, L. & Strauss, J. (1986) *The basic model: Theory, empirical results, and policy conclusions agricultural household models: Extensions, applications, and policy*. Baltimore: The Johns Hopkins University Press, pp. 17–47.

Smale, M., Just, R.E. & Leathers, H.D. (1994) Land allocation in HYV adoption models: An investigation of alternative explanations. *American Journal of Agricultural Economics*, 76(3), 535–546.
Smith, R.J. & Blundell, R.W. (1986) An exogeneity test for a simultaneous equation tobit model with an application to labor supply. *Econometrica*, 54(3), 679–685.
Stock, J.H. & Yogo, M. (2005) Testing for weak instruments in linear IV regression. In: Andrews, D.W.K. (Ed.) *Identification and inference for econometric models: Essays in honor of Thomas Rothenber*. New York: Cambridge University Press, pp. 80–108.
Suri, T. (2011) Selection and comparative advantage in technology adoption. *Econometrica*, 79(1), 159–209.
United Nations. (2015) *The millennium development goals report*. Available from: https://www.un.org/millenniumgoals/2015_MDG_Report/pdf/MDG%202015%20rev%20(July%201).pdf [Accessed 14th January 2018].
Vandemoortele, M. (2014) Measuring household wealth with latent trait modelling: An application to Malawian DHS data. *Social Indicators Research*, 118(2), 877–891.
Verkaart, S., Munyua, B.G., Mausch, K. & Michler, J.D. (2017) Welfare impacts of improved chickpea adoption: A pathway for rural development in Ethiopia? *Food Policy*, 66, 50–61.
Wooldridge, J.M. (2010) *Econometric analysis of cross section and panel data*, 2nd edition. Cambridge, MA: MIT press.
Wooldridge, J.M. (2013) *Introduction to econometrics: A modern approach*, 5th edition. Mason, OH: South Western Educational Publishing.
Wooldridge, J.M. (2015) Control function methods in applied econometrics. *Journal of Human Resources*, 50(2), 420–445.
World Bank. (2015) *Purchasing power parities and the real size of world economies: A comprehensive report of the 2011 international comparison program*. Washington, DC: World Bank. Available from: http://siteresources.worldbank.org/ICPEXT/Resources/2011-ICP-Global-Report.pdf [Accessed 14th January 2018].
World Bank. (2018) *Poverty and shared prosperity 2018: Piecing together the poverty puzzle*. Available from: https://www.worldbank.org/en/publication/poverty-and-shared-prosperity [Accessed 8th July 2020].
World Bank. (2019) *Maximizing finance for development in agriculture and food Systems in Ethiopia: An analysis of beef, coffee, and maize*. Washington, DC: World Bank. Available from: https://openknowledge.worldbank.org/handle/10986/32102 [Accessed 8th July 2020].
World Bank. (2020) *Ethiopia poverty assessment: Harnessing continued growth for accelerated poverty reduction*. Available from: https://openknowledge.worldbank.org/handle/10986/33544 [Accessed 7th September 2021].
Wossen, T., Abdoulaye, T., Alene, A., Haile, M.G., Feleke, S., Olanrewaju, A. et al. (2017) Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of Rural Studies*, 54, 223–233.
Zeng, D., Alwang, J., Norton, G.W., Shiferaw, B., Jaleta, M. & Yirga, C. (2015) Ex post impacts of improved maize varieties on poverty in rural Ethiopia. *Agricultural Economics*, 46(4), 515–526.
Zeng, D., Alwang, J., Norton, G.W., Shiferaw, B., Jaleta, M. & Yirga, C. (2017) Agricultural technology adoption and child nutrition enhancement: Improved maize varieties in rural Ethiopia. *Agricultural Economics*, 48(5), 573–586.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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