Heliyon 7 (2021) e08613

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Heterogeneous effects of improving technical efficiency on household multidimensional poverty: evidence from rural Ethiopia

Fisseha Zegeye Birhanu [a,*], Abrham Seyoum Tsehay [b], Dawit Alemu Bimerew [c]

[a] *Ethiopian Institute of Agricultural Research (EIAR), Addis Ababa, Ethiopia*
[b] *Center for Rural Development Studies, Addis Ababa University, Addis Ababa, Ethiopia*
[c] *BENEFIT Partnership Program, Addis Ababa, Ethiopia*

ARTICLE INFO

Keywords:
Cereal
Technical efficiency
Multidimensional poverty
Crop diversification
Ethiopia

ABSTRACT

Smallholder agriculture in developing countries is characterized by low productivity. Improving the productive efficiency of farm households is considered one of the paths to increase productivity and reduce poverty. This study analyzed the poverty reduction effects of improving the technical efficiency of cereal-producing farm households using plot-level data from rural Ethiopia. The effects were also evaluated whether they were heterogeneous relative to the level of crop diversification. Multidimensional Poverty Index (MPI) and stochastic meta-frontier approach were used to estimate the poverty status and the technical efficiency scores, respectively, and the Herfindahl Index (HI) was used to compute crop diversification. The instrumental Tobit Model was specified to estimate the poverty reduction effect of technical efficiency. Our results revealed that the mean technical efficiency of farm households was estimated to be 58%. The poverty estimate results showed that a higher proportion of farm households were multidimensional poor. The incidence of poverty and the mean deprivation score was found to be 57.9% and 44.1%, respectively. Overall, the value of MPI estimated was 31.2%, implying the farm households experienced 31.2% of the total deprivations across all indicators. The HI was 0.51, indicating a moderate degree of crop diversification among farm households. The model results showed that a 10% increase in technical efficiency significantly drives down the household multidimensional poverty by 15.3% at 1% level, keeping other things being constant. Furthermore, ceteris paribus, a 10% increase in technical efficiency significantly reduces household multidimensional poverty by 7.0% and 7.8% at 1% level among moderately diversified and least diversified farm households, respectively. In conclusion, technical efficiency has a higher effect on multidimensional poverty among moderately diversified and least diversified farm households. Therefore, enhancing the productive capacity of farm households among the lower degree of crop diversification to efficiently use production inputs may assist in poverty reduction.

1. Introduction

Several countries where agriculture is a major economic sector have introduced programs to ameliorate agrarian productivity because of its effective contribution to poverty reduction through better food security and higher farm inflows (FAO, 2017). However, people who depend on agriculture for their living are still generally much poorer than people who work in other sectors of the economy (Cervantes-Godoy and Dewbre, 2010). In the literature (Christiaensen et al., 2006; de Janvry and Sadoulet, 2010), growth in agriculture is much further responsible to poverty reduction than other sectors and renders advanced returns in terms of poverty reduction. The multiple routes through which growth in agrarian productivity can drive down poverty include: adding real income for the growers, employment generation, generating demand for non-agricultural goods, food price, and availability, thereby advantaging net food consumers, increasing real wages, thereby serving unskilled labor and building social capital, and rural non-farm multiplier effects (Irz et al., 2001; Minten and Barrett, 2008; Schneider and Gugerty, 2011; Ivanic and Martin, 2017).

* Corresponding author.
E-mail address: fishz2707@gmail.com (F.Z. Birhanu).

https://doi.org/10.1016/j.heliyon.2021.e08613
Received 15 August 2021; Received in revised form 9 November 2021; Accepted 13 December 2021

Growth in agriculture is also believed to bring a significant impact on poverty reduction, which comes not only from its direct poverty reduction effects but also from its potentially strong growth relation effects on the rest of the economy (de Janvry and Sadoulet, 2010). In addition, it has strong correlation with poverty reduction and large economy-wide multiplier[1] effects with other sectors in the rural economy (Suryahadi et al., 2006; Bezemer and Headey, 2008; Bekun and Akadiri, 2019), inferring that agrarian-led development strategies are sensational to achieve poverty reduction. The experience of the Green Revolution in Asia during the 1970s and 1980s also evidenced the role of agriculture as an instrument for poverty reduction and overall economic growth (Christiaensen et al., 2011). For illustration, the evidence documented by de Janvry and Sadoulet (2010) revealed that a 10% growth in cereal yields cut rural poverty by further than 53%. Also, the yield earnings in cereal in Latin America and the Caribbean that grew at an average annual rate of 2.5% were associated with a resultant decline in rural poverty.

Poverty alleviation is among the overarching goals of the government of Ethiopia. To this end, the Ethiopian Government has given heavy emphasis to the growth in agricultural productivity as a means to achieve poverty reduction and bettering the welfare of poor people in the country (NPC, 2016). In the strategy and programs (ADLI, SRDP, PASDEP, and GTP I, & II), meliorate the productivity of the cereal sub-sector through increasing the production efficiency of farm households has been one of the strategies pursued for poverty reduction for the last decades. Cereals are a dominant production choice in the country in general and that of grain-based mixed farming system of the country in particular (Chamberlin and Schmidt, 2012). Cereal production accounts for roughly 60 % of rural employment, 81 % of total cultivated land, and 30 % of GDP (Rashid, 2010; CSA, 2019). Cereals regards for 62 % of average Ethiopians' daily calorie intake and represent about close to half of consumer food expenditure for an average household (Rashid, 2010; Diao, 2010; World Bank, 2018). According to the 2018/19 Agricultural Sample Survey of the CSA of Ethiopia, cereals comprise about 81.39% of the crop area under cultivation and 87.97% of total crop output (CSA, 2019), indicating that significantly small area is allocated for the production of pulse and other crops. Out of the total grain crop area under cereals, *'teff' (Eragrostis teff),* maize, sorghum, wheat, and barley, which are the core of the country's agriculture and food economy (Seyoum et al., 2011) took up 24.17%%, 18.60%, 14.38%, 13.73% and 6.42% of the grain crop area, respectively (CSA, 2019). This denotes that the outstanding role of cereal crops for poverty reduction in Ethiopia.

In Ethiopia, cereal productivity has been growing more briskly by 7.2% annually since 2004/05, whilst the cultivated area under cereal expanded only by 2.5% with a declining rate (CSA, 2004/05–2019/20). At the same time, the share of the population below the poverty line, in financial terms, considerably decline from 45.5 % in 1995/96 and 29.6 % in 2010/11 to 23.5 % in 2015/16 (NPC, 2017). Between 2010/11 and 2015/16 approximately 5.3 million people were lifted out of poverty, implying that the economic and social performance helped to reduce the position of poverty in the country. The most recent poverty estimates reported by the Ethiopian Economic Association (EEA) revealed that the absolute poverty rate in Ethiopia was 22.1% in 2015 (Goshu, 2020). Despite the remarkable decline in the prevalence of poverty in the country, however, poverty is still a major problem in Ethiopia, where over 25 million people are still live below the poverty line and the majority of them disproportionally live in rural areas of the country. In addition, from 74% of Ethiopia's farm households who live on small farmsteads, about 67% of them are under the public poverty line (Kirchner, 2021). Furthermore, even though the multidimensional poverty index decreased from 0.545 to 0.489 between 2011 and 2016, 83.5 % of the population are still multidimensional poor people (UNDP & OPHI, 2019). This shows that the link between agricultural productivity growth and poverty thriving topical, researchable and policy agenda and hence, sufficient empirical evidence should be generated to develop holistic and intertwined antipoverty strategies.

In the literature, growth in agricultural productivity substantially depends on the sort and quality of the inputs, and how well these inputs are combined (FAO, 2017). Type and quality of inputs represent the production technology while a blend of inputs refers to the technical efficiency of the production process. This means that productivity gains in agriculture can be achieved to a large extent through the mixed use of both technological change and more efficient use of existing resources. In Ethiopia, earlier studies on production efficiency of major crops (for example, Bizuayehu, 2014; Nisrane et al., 2015; Geffersa et al., 2019) evidenced that technical inefficiency is one of the main sources for low productivity, which have to do with farm and household-specific determinant factors.

Efficiency reflects the degree of goodness with which economic units achieve their targets (Gattoufi et al., 2007). It is a way to identify that products are produced in the best and most profitable manner (Mardani and Salarpour, 2015). Efficiency is the ability of farm households to produce maximum possible output from a given set of inputs or produce a given degree of output using a minimum possible quantity of inputs (Farrell, 1957). Production efficiency of economic units consists of two factors, i.e. technical efficiency and allocative efficiency. As stated in Chirwa (2007), technical efficiency reflects the ability of the production unit to maximize output for a given set of inputs, while allocative efficiency represents the capability of the production unit to use available inputs at optimal proportion. As such, a farm is considered technically inefficient when it does not produce the maximum level of output that can be anticipated given the type of available inputs (FAO, 2017). This signifies that beyond crop yield, empirical evidence that provides insight regarding technical efficiency and poverty nexus is an important area of policy concern.

Numerous studies, including but not limited to (Ahmad, 2003; Abro et al., 2014; Dzanku, 2015; Darko et al., 2018; Islam and Haider, 2018), have been carried out to understand the relationship between agricultural productivity growth and poverty in developing countries using a uni-dimensional model. Furthermore, except for studies by Ahmad (2003); Abro et al. (2014), and Islam and Haider (2018), the rest of them have employed yield to proxy agricultural productivity, which measures partial farm productivity. In sum, it can be said that studies that link production efficiency with the poverty situation of farm households in terms of its multidimensional conception are stingy. And hence, this is where this study comes to contribute to fill of this gap using a robust econometric model and a data set collected from farm households. It also adds to the existing literature by furnishing empirical evidence on agriculture and multidimensional poverty using multidimensional poverty index. Moreover, dissimilar to the previous empirical studies, this study enriches the literature by scrutinizing the heterogeneous effects of technical efficiency on poverty by farm households' crop diversification status using an instrumental variable econometric model. To sum up, this study provides empirical evidence on how an increase in technical efficiency affects the multidimensional welfare of farm households by taking into account the existing heterogeneity in terms of crop diversification.

2. Conceptual framework of the study

The conceptual framework presented further below in Figure 1 shows the nexus between technical efficiency and household multidimensional poverty. There are two important paths, among others, through which growth in agricultural productivity can be sustained: technological change and efficient use of available technologies. The efficiency of farm households, meaning their ability to produce feasible maximum output from available inputs, is determined by many factors, including the

[1] The extent to which an increase in income in a particular sector induces an increase in income of the whole economy is referred to as the sectoral growth multiplier. Hence, the agricultural growth multiplier quantifies the impact of a certain increase in income in the agricultural sector on the growth of income in other sectors (Suryahadi et al., 2006).

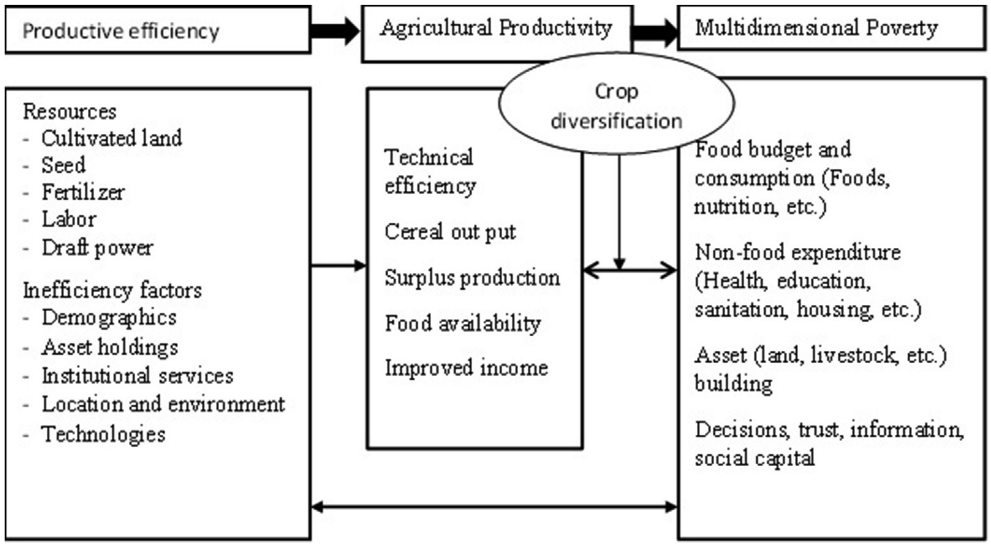

Figure 1. Conceptual framework of the study.
Source: Authors' construction based on literature review and own understanding (2020)

availability of production inputs and inefficiency factors. Therefore, addressing inefficiency gaps through optimum use of available technologies leads to surplus output, which in turn improves the annual income for the farm households. The farm households with improved income from agriculture can afford to buy goods and services produced by the non-farm sector (Mellor, 1999; quoted in Schneider and Gugerty, 2011). In addition, the income gained from the sale of surplus output helps to improve nutrition, health and education (Timmer, 1995). Subsequently, the growth in agricultural production generates increased income tax revenue, stimulates demand for infrastructure, and ultimately generates social capital through increased interaction between farmers and other agents in the agricultural supply chain and related sectors (Irz et al., 2001).

The effects of technical efficiency on poverty are assumed wide-ranging owing to a diversity of factors among farm households. Crop diversification can be one of these factors, which may either deter or advance the possible effects of technical efficiency on poverty. In the literature, the concept of diversification conveys different meanings to different people at different levels (Joshi et al., 2003). But in general, crop diversification can be considered as the practice of growing more than one variety of crops in a given area in the form of rotations and or intercropping (Makate et al., 2016). A diversified cropping system has many benefits for smallholders in developing countries. Just to mention a few, it reduces crop production risks; increases resilience; improves soil fertility; controls for pests and diseases; destroys weeds and voluntary crops; improves the stability of production; increases yield per unit area; brings nutritional diversity and therefore health benefits, etc (Lin, 2011; Makate et al., 2016). This shows that crop diversification is one of the livelihood strategies that should be pursued by smallholders to maintain a sustainable and productive farming system and thereby, improve welfare of smallholder farm households.

Empirical evidence in Tanzania showed a positive association that exists between crop diversification and crop productivity, crop income, food security, and nutrition (Makate et al., 2016). Furthermore, the study by Thapa et al. (2017) in Nepal and Birthal et al. (2015) in India showed that diversification of crop production into high-value crops positively affects monthly per capita consumption expenditure and poverty outcomes. In this study, therefore, it is hypothesized that improving technical efficiency positively and significantly impacts household multidimensional poverty and the effects are assumed heterogeneous by diversification of cropping system.

3. Methodology

3.1. Context of the study area

This study was carried out in two *Weredas*[2] in East Shewa and East Gojjam, the main *teff*-producing areas in Ethiopia (Figure 2). East Shewa and East Gojjam zone are located at a distance of 100km southeast and 300 km northwest from Addis Ababa, the capital city of the country. East Shewa and East Gojjam zones receive an annual average rainfall ranging from 350mm to 1150mm and 900mm–1800mm with uni-modal and bi-modal rainfall pattern, in that order (Senbeta et al., 2020; Ferede et al., 2020). The mean annual minimum and maximum temperature of the zones range from 12 and 39 degrees Celsius and 7.5 and 27 degrees Celsius, respectively. The altitude of East Shewa and East Gojjam zone ranges from 900 to 2300 and 800–4200 m above sea level (m.a.s.l.), respectively. Crop and livestock production is the primary source of income for the household.

3.2. Sampling technique and data sources

Farm households in major '*teff*' growing regions namely Oromia and Amhara regions are the population and unit analysis of this study. Considering that, the final sample farm households were drawing following multi-stage stratified sampling procedures from the final study districts namely Adea and Enemay *Wereda*, by taking into consideration the *Weredas'* high potential and suitable agro-ecology for *"teff*' production in the country. Both Weredas are characterized by a mixed farming system where '*'teff*', wheat, barley, maize, sorghum, and pulses, in that order, are the primary crops and sources of livelihood for farm households. Given available time, resources, and the prevailing similar production system, a total of six kebeles, i.e., three kebeles per *Wereda*, were randomly picked from the total rural kebeles of the study *Weredas*. Finally, based on the formula developed by Kothari (2004) the sample size of 392 farm households including 10% contingency was determined for the study (Table 1). Out of 392, 14 observations were excluded due to missing information. The functional form of the sample size formula is specified as follow:

[2] '*Wereda'* is an administration unit equivalent to district, whilst *'Kebele'* is the lowest administration region in Ethiopia.

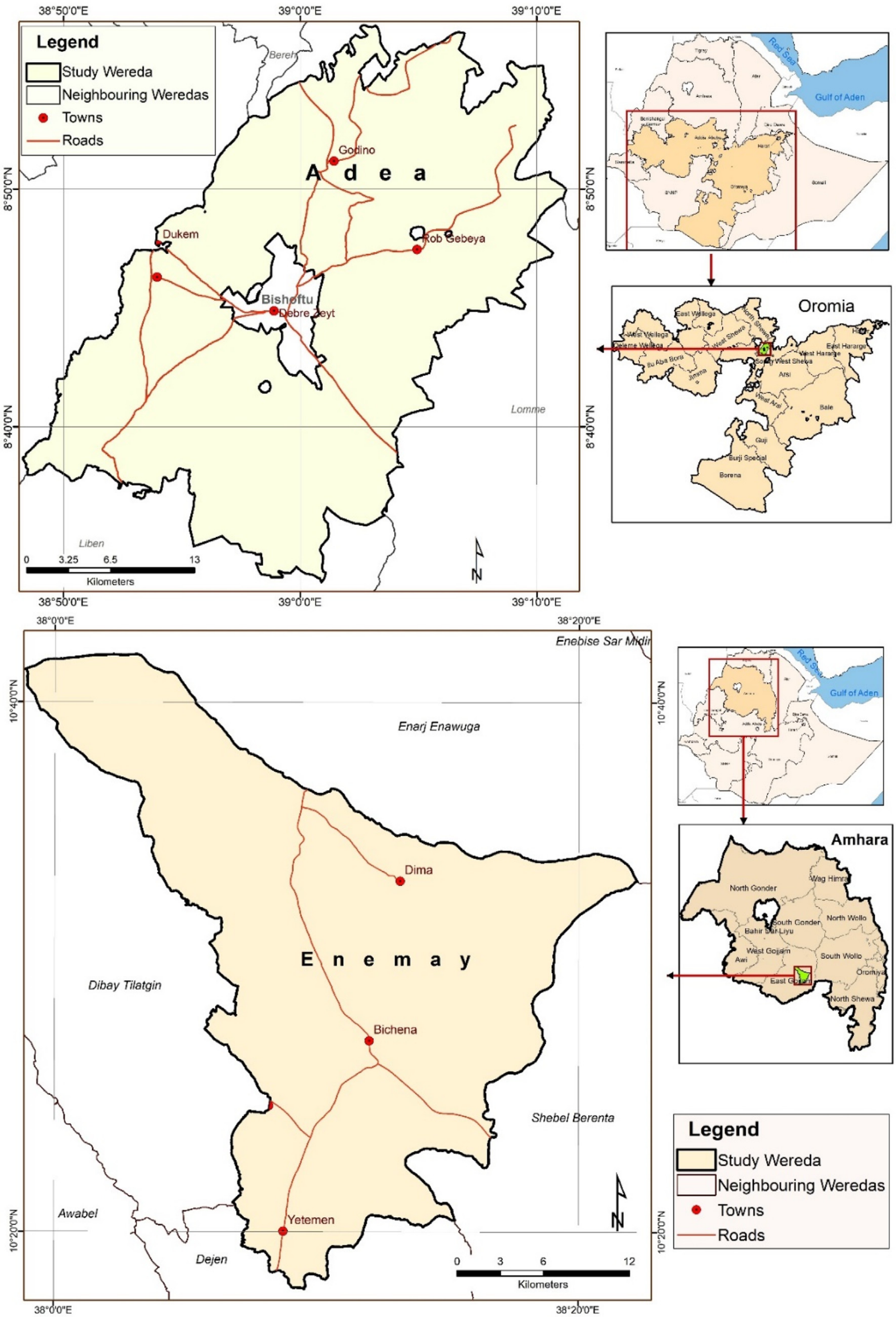

Figure 2. Map of the study areas.
Source: Ethio GIS and CSA (2007) and (Birhanu et al., 2021)

Table 1. Distribution of sample size for the selected kebeles

S/N	Region	Zone	Woreda	Kebele	Total Household	Sample Proportion (%)	Sample size
1	Oromia	East Shewa	Ada'a	Denkaka**	937	17.9	70
				Gobosay*	797	8.9	35
				Wajitu**	649	12.2	48
2	Amhara	East Gojjam	Enemaye	Endshignet**	935	17.9	70
				Mankorkoria**	812	15.6	61
				Sekela*	814	27.6	108
Total				**6**	**4944**	**100**	**392**

Note that **, * refers to high and low potential categories for cereal production, respectively.

$$n = \frac{Z^2 pqN}{e^2(N-1) + Z^2 pq}$$

where, n denotes the desired sample size, Z represents the standard cumulative distribution that corresponds to the level of confidence with the value of 1.96; e is the desired level of precision; p is the estimated proportion of an attribute present in the target population with a value of 0.5 to get the desired minimum sample size of the household at 95% confidence level and ±5% precision; q = 1-p; and N is the size of the total population from which the sample is drawn. Cereal crops, such as '*teff*' *(Eragrostis teff)*', wheat, barley and maize, sorghum were the focus of the study. The study used both qualitative and quantitative data, which consists of information regarding plot, household, and community characteristics. Quantitative data were collected using a structured questionnaire, administered by a cross-sectional survey after a field-level pilot pre-test on its cogency and clarity for the target respondents. Similarly, qualitative data were also generated by key informant interviews and focus group discussions. The study paid utmost emphasis to ethical considerations, such as informed consent, anonymity, and confidentiality throughout the collection of both quantitative and qualitative data.

3.3. Analytical approaches

3.3.1. Estimation of technical efficiency (TE)

Technical efficiency in this study refers to the ability of the farm household to produce maximum possible output from a given set of available inputs. It is measured as a ratio of actual to potential output of farm households, hence, as stated by FAO (2017), a farm is technically inefficient when it does not produce the maximum level of output that can be expected given the type of available inputs. In this study, technical efficiency of farm households was estimated following a two-step stochastic meta-frontier estimation approach. The approach is chosen because it assisted to flee the possible biased estimation of technical efficiency scores that may arise from the geographical heterogeneity between the sample study districts (Orea and Kumbhakar, 2004) in terms of production technology, study-specific characteristics, and agro-ecologic conditions. Based on a two-step approach, group-specific frontiers were estimated for the sample study districts in the first step, and in the second step, a meta-frontier production function was estimated for the pooled data, as shown below.

Step 1. ***Estimation of group-specific frontiers:*** A stochastic group-specific production frontier was formulated as:

$$y_i^k = f^k(x_i^k;\beta^k)e^{(v_i^k - u_i^k)}, i = 1, \ldots, n(k) \tag{1}$$

where, y_i^k denotes the value of total cereal output of the *i-th* sample farm household in the k^{th} *Wereda*, x_i^k is a kx1 vector of direct inputs of the *i-th* farm household, and β^k is a vector of unknown parameters to be estimated. v_i^k denotes the random variation in output (y_i^k)) due to factors outside the control of the farm, and u_i^k is a non-negative technical inefficiency component of the error. v_i^k is independent of u_i^k and distributed at *i.i.d.* $\mathrm{N}(0, \sigma_v^{k2})$. Whereas, u_i^k is assumed to follow truncated normal distribution at zero, *i.i.d.* $(u_i^k \sim N^+(\mu^k(Z_i^k), \sigma^{k2}))$, where Z_i^k denotes farm-specific or group-specific variables that may influence on-farm efficiency performance.

Based on the maximum likelihood estimation method in Eq. (1), the TE of the i^{th} farm household relative to the group k^{th} frontier can be computed as:

$$TE^k = \frac{y_i^k}{f^k(x_i^k, \beta^k)e^{(v_i^k)}} = e^{-u_i^k} \tag{2}$$

In Eq. (2) the inefficiency component (u_i^k) of the error term is the log difference between the maximum (Y_i^k) and actual output (y_i^k).

Step 2. ***Estimation of meta-frontier:*** Following Huang et al. (2014), the stochastic meta-frontier that envelops all frontiers k^{th} groups is defined as:

$$f^k(x_i^k, \beta^k) = f^M(x_i^k, \beta)e^{(v_i^M - u_i^M)} \tag{3}$$

where, $u_i^M \geq 0$, which implies that $f^M(.) \geq f^k(.)$ and the ratio of k^{th} group's production frontier to the meta-frontier can be defined as the technology gap ratio (TGR) expressed as:

$$TGR_i^k = \frac{f^k(x_i^k \beta^k)}{f^M(x_i^k \beta)} = e^{-u_{ki}^M} \leq 1 \tag{4}$$

Following Huang et al. (2014), at a given input level x_i^k, the farm household's observed output y_i^k of the i^{th} farm household relative to the meta-frontier consists of three components, that is:

$$\frac{y_i^k}{f^M(x_i^k)} = TGR_i^k \times TE_i^k \times e^{v_i^k} \tag{5}$$

where.

$TGR_i^k = \frac{f^k(x_i^k, \beta^k)}{f^M(x_i^k, \beta)}$, the farm household's technological gap ratio,

$TE_i^k = \frac{f^k(x_i^k, \beta^k)e^{(-u_i^k)}}{f^k(x_i^k, \beta^k)} = e^{-u_i^k}$, is the farm household's TE, and

$e^{v_i^M} = \frac{y_i^k}{f^k(x_i^k, \beta)e^{-u_i^k}} =$, the random noise component.

Finally, the meta-frontier under two-step approach has two stochastic frontier production functions as specified below:

$$lny_i^k = f^k(x_i^k, \beta^k) + v_i^k - u_i^k, \quad i = 1, \ldots, n(k) \tag{6}$$

$$ln\widehat{f}^k(x_i^k, \beta^k) = f^M(x_i^k, \beta) + v_i^M - u_i^M \tag{7}$$

where, $ln\widehat{f}^k(x_i^k, \beta^k)$ is the estimate of the group-specific frontier from Eq. (6). Since the $ln\widehat{f}^k(x_i^k, \beta^k)$ are group-specific, the SFA is estimated two times, one for each *Wereda*. The output estimates from the two *Weredas*/groups are then pooled to estimate Eq. (7). The meta-frontier should be larger than or equal to the group-specific frontier, that is, $f^k(x_i^k;\beta^k) < f^M(x_i^k,\beta^k)$. The estimated TGR must always be less than or equal to unity:

$$TGR_i^k = \widehat{E}\left(e^{-u_i^M}\middle|\widehat{\varepsilon}_i^M\right) \leq 1, \tag{8}$$

where, $\widehat{\varepsilon}_i^M = ln\widehat{f}^k(x_i^k) - ln\widehat{f}^m(x_i^k)$ are the estimated composite residual of Eq. (7). The TE of the i^{th} farm household to the meta-frontier is equal to the product of the estimate of the TGR in Eq. (7) and the individual farm household's estimated TE in Eq. (2), that is, $M\widehat{T}E_i^k = T\widehat{G}R_i^k \times \widehat{TE}_i^k$.

Empirical model: The functional form of the Cobb-Douglas stochastic frontier model for the group-frontier with decomposed error terms at household level is specified as:

$$lny_i^k = \beta_0^k + \beta_1^k lnx_{1i} + \beta_2^k lnx_{2i} + \beta_3^k lnx_{3i} + \beta_4^k lnx_{4i} + \beta_5^k lnx_{5i} + v_i^k - u_i^k, \ldots \tag{9}$$

$i = 1, 2, \ldots, 378$

where, lny_i^k *i* represents the natural logarithm of the aggregate value of cereals (*'teff' (Eragrostis teff)*, wheat, barely, maize and sorghum) expressed in Ethiopian Birr, β_i^k's unknown parameters of conventional inputs to be estimated, $x_{1i}..x_{5i}$ represents conventional inputs, such as cereal cultivated land in ha, seed use in kg, fertilizer use in kg, labor in man days and draught power in ox-day, respectively. v_i^k is an idiosyncratic error term distributed at *i,i,d* $N(0, \sigma_v^2)$ and independent fromu_i^k. u_i^k is a non-negative error component associated with technical inefficiency of farm households that follows truncated normal distribution at zero $(u_i^k \sim N^+(\mu^k(Z_i^k), \sigma^{k2})$. $Z_1 - Z_{15}$ represents socio-economic, location-specific factors and improved production techniques.

3.3.2. Measuring multidimensional household poverty

The poverty status of farm households was measured using a Multi-dimensional Poverty Index (MPI). Rely on Alkire and Foster (2011), five dimensions are captured to estimate the index, such as, education, health, standard of living, wealth, and empowerment. Under these dimensions, 13 indicators were identified based on expediency, obvious normative presumption, data availability and empirical literature (Alkire, 2007; Alkire and Santos, 2014; UN, 2016; Birhanu et al., 2021). Table 2 presents dimensions, indicators, deprivation cut-off points and weights to construct the MPI.

Following Alkire and Foster (2011), two sorts of poverty cut-off points were applied to delineate deprived farm households from non-deprived counterparts. The first cut-off point used as identification at indicator levels, while the second one used to determine the poverty status of farm households based on the value of deprivation scores. In this study, equal weight was assigned, as employed in Alkire and Foster (2011), for each dimension due to the absence of putative argument to deliberate one dimension is more important than another. Accordingly, the multidimensional poverty status of farm households was defined as:

$$p(y_i z) = \begin{cases} 1 \; multidimensional\, poor (c_i \geq k), \\ 0 \; otherwise (c_i < k), \end{cases} \tag{10}$$

where, c_i the number of deprivation experienced by the farm household *i*, and k is multidimensional poverty cut-off point, computed as one third of the indicators (i.e. 13) (Table 1), hence, the poverty cut-off k equals four (k = 4). Finally, the aggregate measures of multidimensional poverty including the Headcount ratio (H), Intensity of poverty (A), and Adjusted Headcount Ratio (Mo) are computed using the following functional specifications:

Table 2. Dimensions, indicators, deprivation cut-off, and weights.

Dimensions	Indicators	Deprivation cut-off	Relative weights
Education (1/5)	Adult literacy	No one has completed five years of schooling	1/10
	Child enrollment	No school age child is attending school	1/10
Health (1/5)	Health care	No access to health care services	1/10
	Illness	Suffers illness	1/10
Living standard (1/5)	Electricity	No access to electricity	1/25
	Drinking water	No access to safe drinking water	1/25
	Sanitation	Household has no access to good toilet, or improved but shared with other households	1/25
	House floor	Floor made with mud, dung, clay	1/25
	Cooking fuel	Use of firewood, dung, and charcoal as fuel	1/25
Wealth (1/5)	Land (ha)	Household does not own land more than the local average	1/10
	Livestock (TLU)	Household does not own livestock more than the local average	1/10
Empowerment 1/5)	Decision making	Household decision making on the use of income is not participatory	1/10
	Cooperative membership	Member of the household is not a member of cooperatives	1/10

$$H = q/n \tag{11}$$

$$A = \sum_{i=1}^{n} c_i(k)/q \tag{12}$$

$$M_0 = \text{HxA} \tag{13}$$

where, H is the multidimensional headcount ratio, q is the number of farm households who are multidimensional poor, and n is the entire farm households under consideration. A is the intensity of multidimensional poverty, $c(k)$ is the censored deprivation score of sampled farm household *i*. k is the poverty cut-off. M_0 is a multidimensional poverty index (MPI) obtained as a product of H and A. The value (M_0) lies between 0 to 1.

3.3.3. Measuring crop diversification

In this study, the Herfindahl Index (HI) of crop diversification was used to measure the degree of cropping diversity of farm households. The index is used here because it accounts for available land at the household level, which is an important asset and source of livelihood in rural areas of Ethiopia. We used all crops including cereals to estimate HI. The main aim of computing crop diversification is to estimate the underlying heterogeneous effect of improving TE on farm household poverty at different levels of crop diversification status. HI is estimated as the summation of all squared area shares allocated in the production of crop *i* in the total cropped area. HI for crop diversification is computed using the following functional form:

$$\text{CDI} = \sum\nolimits_{\text{i}-1}^{\text{i}-\text{n}} \text{S}_\text{i}^2 \tag{14}$$

$$\text{S}_\text{i} = \frac{a_i}{\text{A}}$$

where, a_i is the farm size allocated for the production of crop *i* in a given year; A is the total annual cultivated land determined as the sum of all cropped areas in the cropping year; and S_i represents the land share allocated to crop *i*. The value of the HI ranges from 0 to 1 with 0 denoting perfect diversification and 1 perfect specialization (Rahman, 2009);

hence the higher the index, the lower the diversification of the crop portfolio.

Once the crop diversification index was determined, the study made use of cut-off points to categorize farm households by their crop diversification status following Goshu (2013); Nagpure et al. (2017); Basantaraya and Nancharaiahb (2017). Accordingly, farm households were categorized into three crop diversification status of highly diversified if the index is less than 0.3, moderately diversified if the index between 0.3 and 0.6, and least diversified if the index is above 0.6.

3.4. Estimation strategy

Before we built an econometric model for the estimation of the multidimensional poverty effect of technical efficiency, we scrutinized the potential endogeneity of technical efficiency (TE) following a two-step approach. In the first step, we predicted the error term by regressing the TE with independent variables summarized in Table 3 below. In the second stage, the potential endogeneity of TE was assessed by regressing the outcome variable by including the error term predicated in the first step. The result then evidently showed that technical efficiency is correlated with the error term, revealing the violation of the assumption of zero covariance between explanatory variables and the error term. Hence, we decided to treat TE as an endogenous variable and to draw the estimation strategy based on an instrumental variable method by selecting valid instruments.

Once we concluded the use of the instrumental variable model, we looked for excluded valid instruments for endogenous regressor TE. The instrument considered in this case must satisfy two requirements as stated in Wooldridge (2012). It must be correlated with the endogenous explanatory variable (relevance) and uncorrelated with the error term (exogeneity). Considering theoretical literature, empirical evidences, and the joint significant test, sex of the household head, quality of farmland, cell phone ownership, distance to input source, and the number of oxen were considered as instruments. The significant effect of such household idiosyncrasies on technical efficiency is documented in several empirical studies (Kelemu, 2016; Gebrehiwot, 2017; Tenaye, 2020), suggesting that the instruments are valid.

Because the values of the outcome variables (household deprivation score and adjusted headcount ratio) and endogenous covariate (technical efficiency score) are censored at 0 and 1, we specified instrumental variable Tobit framework as the functional form specified in Eq. (15).

$$y_{1i}^{*} = y_{2i}\beta + x_{1i}\gamma + u_i$$

$$y_{2i} = x_{1i}\prod\nolimits_1 + x_{2i}\prod\nolimits_2 + v_i \tag{15}$$

where, y_{1i}^{*} is household deprivation score and adjusted headcount ratio; $i = 1, \,..\, n$ is sample farm households; y_{2i} is an endogenous regressors TE; x_{1i} is $1 \times k_1$ vector of exogenous variables; x_{2i} is $1 \times k_2$ vector of additional instruments; and the equation for y_{2i} is written in reduced form; u_i and v_i are assumed to follow $(u_i, v_i) \sim (0, \sum)$. β and γ are the vectors of structural parameters; $\prod_1$ and $\prod_2$ metrics of reduced-form of parameters. Since our econometric model censors the outcome variable from above and below, the estimation is defined as follows:

$$y_{1i} = \begin{cases} 1 & if\ y_i^{*} > 1 \\ y_i^{*} & if\ 0 \le y_i^{*} \le 1 \\ 0 & if\ y_i^{*} < 0 \end{cases} \tag{16}$$

3.5. Definition of variables

The major outcome variables considered in this study representing household multidimensional poverty are household deprivation score and adjusted multidimensional poverty. Household deprivation score shows the deprivation of farm households across multiple indicators, whilst adjusted/censored headcount ratio reflects the incidence and intensity of multidimensional poverty. Farm households' technical efficiency, which ranges between 0 and 1, was estimated using a Cobb Douglas (CD) functional specification obeying the meta-frontier approach as conferred above. The most common explanatory variables were identified based on theoretical and empirical literature and built-in econometrics models. Table 3 presents the summary of outcomes and independent variables used in the econometric models.

Table 3. Definition of hypothesized variables.

List of Variables	Description	Expected signs
Outcome variables		
DS	Household deprivation score	
MPI	Multidimensional poverty index	
Independent variables		
Technical efficiency (TE)	Technical efficiency scores (0–1)	-
Crop diversification status	Categorical (1 = Highly diversified, 2 = Moderately diversified, 3 = Least diversified)	+
Male headed household	Dummy (Male = 1, otherwise = 0)	-
Age of the household head	Number of years	+
Head educational	Number of years	-
Household size	Number of persons in the household	-
Population pressure	Ratio of family size to farm size	+
Access to extension service	Dummy (yes = 1; otherwise = 0)	-
Access to credit service	Dummy (yes = 1; otherwise = 0)	-
Distance to input center	Location of HH relative to input center in km	+
Road condition	Dummy (Good = 1, otherwise = 0)	-
Land quality	Index[3]	+
Non-farm income	Dummy (yes = 1; otherwise = 0)	-
Cellphone ownership	Dummy (yes = 1; otherwise = 0)	-
Number of Oxen	Number	-

4. Results and discussion

4.1. Estimates of technical efficiency

In this study, several hypothesis tests were undertaken before the use of the stochastic production frontier model (the test result is presented in Appendix Table A). The first test was the Skewness test on Ordinary Least Square (OLS) residuals to check the validity of the stochastic frontier model. The test result, hence, indicated that the distribution of OLS residuals was right-skewed with a statistically significant Skewness value (−0.53) at 1% level. The test result suggested that we are confident enough to take the next step of stochastic frontier estimations. The second important hypothesis test was choosing an appropriate functional form for the data. According to the generalized log-likelihood ratio (LR) test result, the Cobb Douglas (CD) specification is the most appropriate functional form to adequately represent the data. Third, we tested a hypothesis, which specifies no technical inefficiency in the data. Because the value of likelihood ratio statistics, $\lambda = 23.41$, far exceeds the critical

[3] Land quality index is constructed based on multiplying the plots slope and the fertility indicators of the plots, implying a low index value indicates better land quality, while high index value would indicate the lowest quality evaluated at household level (Nisrane et al., 2015).

Table 4. Crop diversification status of farm households.

Variables	Mean	St. Dev.	Minimum	Maximum
Overall	0.508	0.191	0.163	1
Highly diversified	0.257	0.033	0.163	0.294
Moderately diversified	0.447	0.083	0.300	0.594
Least diversified	0.798	0.162	0.603	1

Source: Authors' analysis using primary data (2020)

value of 8.273 at 1% level, we confidently concluded that there is no full efficiency among the farm households and hence, technical inefficiency is one of the factors that affects the cereal output in the study area. Once we rejected the null hypothesis of no technical inefficiency, we tested the LR test to determine the use of homogenous production technology for the entire data. However, the LR test result provided enough evidence to reject the null hypothesis of homogeneous production technology for the sample study districts. Therefore, the study employed a stochastic meta-frontier to estimate the technical efficiency of farm households while addressing heterogeneity between study districts.

From the stochastic meta-frontier analysis, the mean technical efficiency for cereal farmers was found to be 58% that varies between 13% and 91%. The result suggests that farm households produced 58% of the maximum production of the possible (frontier) output. In addition to this, if the farm households cultivated cereal crops at full efficiency level, they could increase their cereal output by 36%[4], indicating that there is still a possibility to significantly improve the cereal productivity using the existing resources and production technologies. Our finding is lower than the average technical efficiency score reported by Alemu et al. (2009) and Wassie (2014). They found the average technical efficiency of the major crop to be about 76% and 65%, respectively. However, our estimate of technical efficiency is comparable with, in the same range, and greater than the estimate reported by Asefa (2011) in Ethiopia, Wongnaa & Awunyo-Vitor (2018) in Ghana, and Oyetunde-Usman and Olagunju (2019) in Nigeria, in that order. The mean value of TGR was estimated at 0.901, denoting that, on average, farm households produce 90% of the potential output given the overall technology available in the study area. Added to this, the difference in mean TGR of the sampled study districts was found statistically significant at 1% level, which appears to be due to production technology gaps. The results also revealed that no farmers have been found with a maximum value of TGR that is equal to unity (the stochastic frontier tangent to the meta-frontier), suggesting that there are no farm households in the study area who adopt the most advanced cereal production technology.

4.2. Crop diversification status

Farm households cultivated several crops including cereals and the cropping pattern appears moderately diversified. The result in Table 4 shows that the average Herfindahl Index (HI) was 0.51, indicating the presence of a moderate degree of crop diversification among farmers. Similar results were reported in Ethiopia and elsewhere in developing countries. For example, Manjunatha et al. (2013) reported that the average HI of crop diversification was 0.55 for farmers in the Easter Dry Zone (EDZ) of south India. Based on the value of the crop diversification index, we further grouped the farm households into highly diversified with HI values below 0.3, moderately diversified with HI values between 0.3 and 0.6, and least diversified with HI values above 0.6. Accordingly, the average HI of crop diversification was found to be 0.27, 0.447, and 0.798 in the highly diversified, moderately diversified, and least diversified categories, respectively, implying that there is a high level of variation among farm households across the crop diversification categories.

[4] The optimum possible output level that farm households can produce using the existing resources and production technology can be computed as 1- (mean TE/Maximum TE) multiplied by 100.

Table 5. Multidimensional poverty estimates.

Poverty indices	Mean	St. Dev.	Minimum	Maximum
Deprivation score (DS)	0.441	0.141	0.1	0.8
Incidence of poverty (H)	0.579	0.494	0	1
Intensity of poverty (A)[5]	0.538	0.095	0.4	0.8
Multidimensional poverty index (MPI)	0.312	0.276	0	0.8

Source: Authors' analysis using primary data (2020)

4.3. Multidimensional poverty status

As can be seen in Table 5 below, the headcount ratio for the farm households was 58%, indicating more than half of the farm households are classified as multidimensional poor. The mean total deprivation score was found to be 0.44 with a variation between 0.1 and 0.8, implying the average household suffers from 44% of the possible deprivation. Moreover, the average multidimensional poverty intensity (A), which measures the average share of the deprivation suffered by the poor farm households was 0.54. The average Multidimensional Poverty Index (MPI) was estimated to be 0.31. Following the OPHI classification, about 36% of the farm households were living in severe poverty. Moreover, the level of multidimensional poverty estimated by this study is far below as compared to the national and rural areas average. The Oxford Poverty and Human Development Initiative (2020) report shows that at the national level and in rural areas of Ethiopia, 83.5% and 91.8% of people are multidimensional poor, respectively. Multidimensional poverty estimates between 2000 and 2014 by Tigre (2018) showed that despite the decreasing trend on the estimates over time, still large proportion of the population (71.8%) is under multidimensional poverty line in rural Ethiopia. A more recent estimate by Alemu and Singh (2021) in three districts of rural Ethiopia revealed the prevalence of severe multidimensional poverty, which was estimated to be 84.2%. The result indicates that improving the poverty situation of farm households in terms of multiple deprivations continues to be the major challenge for the government and non-government organizations that implemented anti-poverty programs. Table 5 depicted the average estimate of multidimensional poverty for farm households.

4.4. Multidimensional poverty vis-a-vis crop diversification

Our analysis indicated that from the total farm household grouped under highly diversified, moderately diversified, and least diversified, 43%, 55%, and 72% were found multidimensional poor, respectively. Other poverty estimates, such as deprivation score, poverty intensity, and MPI also showed that poverty incidence was high among least diversified farm households. The one-way analysis of variance also supports our result that the poverty estimates significantly varied across the diversification status. The results suggest that farm households with high crop diversification values can earn higher income from the marketing of multiple crops as compared to the least diversified farm households. Higher income obtained through producing multiple crops supports farm households to improve their material wellbeing and reduce production risks. Table 6 summarized the multidimensional poverty estimates by the crop diversification status of farm households.

[5] The mean difference of the Intensity of poverty (A) was computed for poor farm households only.

Table 6. Multidimensional poverty estimates by crop diversification status.

Poverty indices	Highly Diversified	Moderately diversified	Least diversified	F-Value
Deprivation score (DS)	0.389 (0.121)	0.433 (0.135)	0.487 (0.156)	7.14***
Intensity of poverty (A)	0.505 (0.740)	0.531 (0.090)	0.563 (0.105)	3.40**
Multidimensional poverty index (MPI)	0.219 (0.259)	0.294 (0.273)	0.405 (0.270)	7.26 ***

Coefficients with ***, **, and * are significant at 1, 5, and 10 % level of significance, respectively.
Source: Authors' analysis using primary data (2020)

4.5. Technical efficiency vis-a-vis multidimensional poverty status

As it can be seen from Table 7 below, the mean difference between the lowest and highest quartile of the technical efficiency category of farm households in all of the poverty estimates was found to be statistically significant. This implies that non-poor farm households are technically more efficient than poor farm households. However, our analysis showed about 41% of multidimensional poor farm households recorded a technical efficiency score of 60% and above all, which implies that there are farm households who are technically efficient and at the same time multidimensional poor. The technical efficiency scores of farm households by multidimensional poverty status are provided below in Table 7. These findings render an insight in favor of *'efficient but poor'* hypotheses, which is forwarded by Schultz in his seminal 1964 study of Guatemalan Indian villages.

Schultz (1964) stated that farmers in traditional agriculture are poor but efficient albeit there are comparatively few significant inefficiencies among farmers in the allocation of factors of production. According to him, smallholder farmers fine-tune their resource allocation to deal with their circumstances in terms of costs, returns, and risks. This means that being multidimensional poor is not necessarily the consequence of inefficiency alone but rather it can also emanate from different idiosyncrasies of community, household, and plot-level factors.

4.6. Empirical models

4.6.1. Effects of technical efficiency on household multidimensional poverty

We employed an instrumental Tobit model to estimate the relationship between the technical efficiency of farm households and farm households' multidimensional poverty status. Households' deprivation scores (DS) and Multidimensional Poverty Index (MPI) were regressed by the technical efficiency and other control variables. At the beginning of our investigation, we attested to the potential endogeneity of technical efficiency. The test result showed that the technical efficiency of the farm households is correlated with the error term, indicating that our estimation violated the assumption of zero covariance between explanatory variables and the error term. As a remedy to such a problem, we used a set of instrumental variables. In the first stage of the model estimation, we instrumented technical efficiency by the quality of farmland, distance to the input source, cell phone ownership, and the number of plowing oxen. These instrument variables are correlated with the farm households' technical efficiency but do not correlate with the error term. To make sure of the relevance of the instrument variables, we determined the joint significance test. The test result (chi2 (4) = 41.58, p-value > chi2 = 0.0000) on the instrument variables supports the rejection of the null hypothesis that the coefficients on the instruments are equal to zero, implying that the instrument variables are relevant. In addition to this, as presented in Table 8, the Wald Diagnostic Test values are statistically significant at less than 1% level, suggesting that variable technical efficiency is endogenously determined.

Table 7. Multidimensional poverty estimates by crop diversification status.

Poverty indices	Lowest Quartile (25%)	Upper Quartile (25%)	Mean difference
Deprivation score (DS)	0.465 (0.150)	0.421 (0.137)	2.1056***
Intensity of poverty (A)	0.555 (0.097)	0.525 (0.101)	1.5656*
Multidimensional poverty index (MPI)	0.358 (0.278)	0.271 (0.274)	2.1524***

Coefficients with ***, **, and * are significant at 1, 5, and 10 % level of significance, respectively.
Source: Authors' analysis using primary data (2020)

As can be learned from Table 8 above, keeping all other factors being constant, a 6% reduction in household deprivation score (HDS) is linked with a 10% increase in technical efficiency of farm households, indicating that rising the technical efficiency of farm households leads to the reduction of the deprivations that both poor and non-poor farm households experienced in multiple indicators. Similarly, a 10% increase in technical efficiency of farm households drives down the poverty status by 15.3%, which is measured by multidimensional poverty index (MPI), at 1% level. The results convey that an improvement in the technical efficiency appears to have a substantial poverty reduction effect among the poor farm households. A similar finding on the poverty reduction effect of technical efficiency has been reported by Islam and Haider (2018), who find that technical efficiency significantly reduces poverty incidence and poverty gap, which is exclusively measured by monetary poverty measures. The welfare effect of improving technical efficiency can be considered through income effect or higher farm profits, lower real food prices, and higher wages (Minten and Barrett, 2008). Ivanic and Martin (2017) also stated that most of the reduction in poverty gained from an increase in agricultural productivity arises from direct increases in agricultural profits and, albeit much smaller in the corresponding wage implication.

Table 8. Multidimensional poverty effects of technical efficiency (IV Tobit).

Variables	Deprivation score (HDS) [Coef./SD]	MPI [Coef./SD]
Instrumented technical efficiency	-0.5535*** (0.1469)	-1.5321*** (0.4735)
Head sex	-0.0051 (0.0383)	0.0007 (0.1204)
Head age	-0.0021*** (0.0007)	-0.0062*** (0.0022)
Head education	-0.0046* (0.0025)	-0.0163** (0.0083)
Household size	-0.0269*** (0.0042)	-0.0712*** (0.0139)
Access to extension service	-0.0152 (0.0173)	-0.0566 (0.0553)
Access to credit service	0.0100 (0.0295)	0.0330 (0.0967)
Road condition (good)	-0.0253 (0.0162)	-0.0930* (0.0518)
Population pressure	0.0058*** (0.0011)	0.0144*** (0.0035)
Participation in non-farm activities	-0.0310 (0.0225)	-0.1020 (0.0736)
Constant	0.9959*** (0.0835)	1.7736*** (0.2699)
Number of observations	372	372
Wald chi2 (13)	156.82	102.82
Prob > chi2	0.0000	0.0000
Joint significant test[a]	41.58***	41.58***
Wald test of exogeneity $x^2(1)$	15.62**	9.15***

Coefficients with ***, **, and * are significant at 1, 5, and 10 % level of significance, respectively.
NB: [a]The joint significance test was carried out using a fractional response regression model because technical efficiency is a censored variable that ranges between 0 and 1.
Source: Authors' analysis using primary data (2020)

4.6.2. Heterogeneous effects of technical efficiency

In addition to the above overall poverty reduction effect of improving technical efficiency among the farm households, we further attempted to understand the relationship between technical efficiency and multidimensional poverty by taking into account the crop diversification status of farm households. In such a way, we could learn and identify the leverage point at which the farm households would be able to maximize the gain from the poverty reduction effect of technical efficiency. Accordingly, three independent models were fitted to examine the relationship between household deprivation score and technical efficiency. The models were specified based on farm households' crop diversification status, i.e. highly diversified, moderately diversified, and least diversified.

Before embarking on the estimation of the parameters of interest, we considered for each model whether technical efficiency is endogenously determined or not. Accordingly, except for the model estimated among the highly diversified farm households, the rest two models were affected by the potential endogeneity problem. Therefore, the technical efficiency among moderately diversified farm households was instrumented by gender of the household head, cell phone ownership, distance to input sources, and the number of oxen owned, whiles the technical efficiency for least diversified farm households was instrumented by non-farm income participation and the number of oxen. The joint significance test values, presented in Table 9, among moderately diversified and least diversified farm households, respectively, offered sufficient confidence to reject the null hypothesis that the coefficients on the instruments are equal to zero. Moreover, the Wald Test of exogeneity indicated the multidimensional poverty effect of technical efficiency was endogenously determined among moderately diversified and least diversified farm households.

The estimation results disclosed that the poverty reduction effect of technical efficiency is heterogeneous by farm households' crop diversification level. The study found a statistically significant and negative association between multidimensional poverty and technical efficiency among moderately diversified and least diversified farm households. A 10% increase in technical efficiency reduces household multidimensional poverty by 7.0% and 7.8% among moderately diversified and least diversified farm households, respectively, holding other factors constant. The results suggest that the poverty reduction effect of technical efficiency is relatively higher among moderately diversified and least diversified households. One of the possible reasons is that cropping of diversified crops probably reduces the efficiency of farm households in allocating available factors of production, while cropping of fewer crops or specialization may lead to higher efficiency gains in the management of available productive resources. As evicted in the results, the mean number of crops grown by moderately diversified and least diversified farm households is estimated at 3 and 2, respectively, which is substantially lower than highly diversified farm households who grow, on average, 5 crops in a year. Therefore, farm households that grow three and fewer crops can gain the best out of poverty reduction effect of technical efficiency. The multidimensional welfare effect of technical efficiency among farm households by their crop diversification scale is presented below in Table 9.

Moreover, it is worthy to indicate that there is a statistically significant mean difference in terms of total cultivated land between farm households in the highest and lowest quartile of crop diversification scale at less than 5% level. This tends to suggests that farm households having small land holdings focus on producing fewer crops, which have high remunerative advantages. In contrast to this, large farms may be more diversified as compared to small farms and hence, they may suffer from inefficiency problems in the allocation of scarce resources, suggesting that they become constrained to maximize the gains from the welfare effect of technical efficiency. Some studies (Benin et al., 2003; Shahbaz et al., 2017) support our position that, among others, large farms are associated with greater crop diversity, indicating that farm size may affect the decision to diversify and extent of diversification. Therefore, farm household with larger farm size tends to cultivate diversified crops, and because of this, they may not probably be able to take full advantage of the poverty reduction effect of technical efficiency.

Besides, as compared to highly diversified farm households, moderately diversified and least diversified farm households allocate more land for *'teff'* production than for the production of other crops. For example, from the total cultivated land available at the household level, moderately diversified and least diversified farm households allocated 57% and 84%, respectively, of the cultivated land for *'teff'* production, which is higher than the share of the cultivated land (45%) under *'teff'* production among highly diversified farm households (Figure A, Appendix I). On top of this, the share of cultivated land under *'teff'* production was found significantly greater between the highest quartile of crop diversification scale as compared to the lower quartile category at less than 1% level. Given the small size of cultivated land, the results possibly signify that those farm households having medium and low crop diversification

Table 9. Poverty reduction effect of technical efficiency by household crop diversification status.

Variables	Tobit model	IV Tobit Model	
	Highly diversified [Coef./SD]	Moderately diversified [Coef./SD]	Least diversified [Coef./SD]
Technical efficiency	-0.1228 (0.1183)	-0.6989*** (0.2278)	-0.7791*** (0.2748)
Head sex	-	-	0.0629 (0.0740)
Head age	-0.0016 (0.0015)	-0.0009 (0.0009)	-0.0051*** (0.0015)
Head education	-0.0320*** (0.0067)	-0.0021 (0.0034)	-0.0049 (0.0058)
Household size	-0.0183* (0.0094)	-0.0261*** (0.0058)	-0.0280*** (0.0099)
Access to extension service	-0.0734 (0.0495)	-0.0228 (0.0264)	0.0212 (0.0350)
Access to credit service	0.0282 (0.0627)	-0.0080 (0.0370)	0.1776* (0.1047)
Distance to input center	-0.0050 (0.0081)	-	0.0016 (0.0071)
Land quality index	0.0073 (0.0115)	-0.0076 (0.0068)	-0.0077 (0.0145)
Road condition	-0.1316*** (0.0382)	0.0005 (0.0251)	-0.0617* (0.0365)
Population pressure	0.0040 (0.0034)	0.0056***(0.0016)	0.0067*** (0.0021)
Participation in non-farm activities	-	-0.0642** (0.0297)	-
Cell phone ownership	-0.0006 (0.0395)	-	-0.0358 (0.0437)
Number of plowing oxen	-0.0069 (0.0189)	-	-
Constant	0.8263*** (0.1430)	1.0332***(0.1442)	1.2405*** (0.2010)
Number of observations	30	260	82
Wald chi2 (13)	34.09	75.60	52.35
Prob > chi2	0.0007	0.0000	0.0000
Joint significant test[a]	na[b]	22.38***	14.08***
Wald test of exogeneity	na	15.41***	9.14***

Coefficients with ***, **, and * are significant at 1, 5, and 10 % level of significance, respectively.

NB: [a]The joint significance test was carried out using a fractional response regression model because technical efficiency is a censored variable that ranges between 0 and 1, and [b] Not applicable.

Source: Authors' analysis using primary data (2020) status offer a considerable focus for those crops having high market value. From the findings of this study, hence, we can infer that the food crop choice rationale of farmers given scarce resources accord with the highest gain from the sale of their crops.

Some literature supports our findings that *'teff'* fetches the highest market price of any food grain in Ethiopia (Samuel and Sharp, 2007). The higher price in the market and the growing demand by better-off households in urban areas make *'teff'* an appealing cash crop for farm households (FAO, 2015; Lee, 2018). In addition to this, on account of its high nutritional value, global demand for *'teff'* is also rising (Vandercasteelen et al., 2016) and consumers are willing to pay premiums for *'teff'* (FAO, 2015; Zhu, 2018; Lee, 2018). This shows that *'teff'* is an important cash crop having an enormous opportunity for the country in general and those of the smallholders who grow *'teff'* in particular.

5. Conclusions and implications

The study confirmed that technical inefficiency was one of the reasons responsible for low cereal output. Hence, farm households can improve cereal output with the current level of input mix and technologies. The overall crop production pattern was also appeared to be moderately diversified. Concerning the incidence of poverty, more than half of farm households in the study area were multidimensional poor. They were deprived of close to one third of the total deprivation across all indicators. The one-way analysis of variance showed that the poverty estimates significantly varied across the crop diversification status and high among least diversified farm households. The results revealed that multidimensional non-poor farm households are more technically efficient than poor farm households. However, the results also showed that farm households can also be simultaneously poor and efficient. These results favor the "*poor but efficient*" hypothesis, which is proposed by Schultz (1964) that inefficiency alone cannot be the root cause for being multidimensional poor. Added to this, the econometric model results revealed that technical efficiency gains in cereal output appear to have a substantial poverty reduction effects. Finally, the study has showed that the effects of technical efficiency are heterogeneous relative to crop diversification status. This means that improving technical efficiency of cereal production has higher poverty reduction effects among moderately diversified and least diversified cropping systems. Therefore, identifying and addressing the causes of technical inefficiencies should lie at the heart of policies and strategies that aim to improve cereal outputs and reduce poverty. Government and non-government organization working on agriculture should devise mechanisms to improve technical efficiency through modern productive inputs, improved farming practices and market-related information. Beyond the effort to improving the technical efficiency of farm households through modern technologies, addressing the root causes of multidimensional poverty can also help to make anti-poverty strategies more successful. Furthermore, supporting farm households who grow fewer crops through modern production inputs and information particularly on those cereal crops having superior economic advantages may assist to take full advantage of the poverty reduction effect of improving technical efficiency.

Declarations

Author contribution statement

Fisseha Zegeye Birhanu: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Abrham Seyoum Tsehay; Dawit Alemu Bimerew: Conceived and designed the experiments; Wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

Supplementary content related to this article has been published online at https://doi.org/10.1016/j.heliyon.2021.e08613.

Appendix

Appendix Table A

Table A. Hypothesis tests for the efficiency models.

Null hypothesis	x^2 statistics	DF	Critical value $X^2_{v0.99}$	Decision
Cobb-Douglas SFPF and Translog SFPF $H_0 : \beta_6 + \beta_7 + \dots\beta_{20} = 0$	26.86	15	29.927	CD is proper
Homogeneous production technology across geographical regions $H_0 : \beta_j = \delta_j = \gamma_j$	82.96	22	38.304	Reject H_o
No technical inefficiency in the model $\sigma_u^2 = 0$ and $\mu = 0$,[6]	23.41	2	8.273	Reject H_o
Inefficiency parameters have no effect on technical inefficiency $H_0 : \delta_1 = \delta_2 = \dots\delta_{17} = 0$	284.87	17	32.766	Reject H_o

Source: Authors' analysis using primary data (2020)
NB: The critical values are obtained from Kodde and Palm (1986).

[6] In the case of assuming Truncated normal distribution for the inefficiency error term, the LR test has two degree of freedom because the null hypothesis has two restrictions, such as $\sigma_u^2 = 0$ and $\mu = 0$ (Kumbhakar et al., 2015).

Appendix Figure A

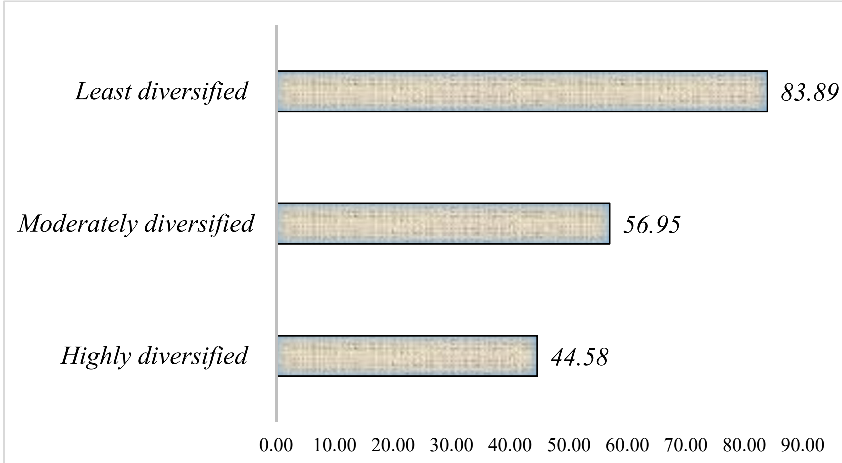

Figure A. Proportion of cultivated land under *'teff' (Eragrostis teff)* production by crop diversification scale. Source: Authors' analysis using primary data (2020)

References

Abro, Z.A., Alemu, B.A., Hanjra, M.A., 2014. Policies for agricultural productivity growth and poverty reductionin rural Ethiopia. World Dev. 59, 461–474.

Ahmad, M., 2003. Agricultural productivity, efficiency, and rural poverty in irrigated Pakistan: a stochastic production frontier analysis. Pakistan Dev. Rev. 43 (3), 219–248.

Alemu, B.A., Nuppenau, E.-A., Boland, H., 2009. Technical efficiency across agro-ecological zones in Ethiopia: the impact of poverty and asset endowements. Agric. J. 4 (4), 202–207.

Alemu, B.T., Singh, S.P., 2021. How does multidimensional rural poverty vary across agro-ecologies in rural Ethiopia? Evidence from the three districts. J. Poverty 1–20.

Alkire, S., 2007. Choosing Dimensions: the Capability Approach and Multidimensional Poverty. In: Oxford Poverty & Human Development Initiative, CPRC Working Paper 88. Mansfield Road, Oxford OX1 3TB, UK.

Alkire, S., Foster, J., 2011. Counting and multidimensional poverty measurement. J. Publ. Econ. 95 (7-8), 476–487.

Alkire, S., Santos, M., 2014. Measuring acute poverty in the developing world: robustness and scope of the multidimensional poverty index. World Dev. 59, 251–274.

Asefa, S., 2011. *Analysis of technical Efficiency of Crop producing smallholder Farmers in tigray,Ethiopia.* s.l.:Munich personal RePEc archive. In: (MPRA) Paper No. 40461.

Basantaraya, A.K., Nancharaiahb, G., 2017. Relationship between crop diversification and farm income in Odisha — an empirical analysis. Agric. Econ. Res. Rev. 30, 45–58.

Bekun, F.V., Akadiri, S.S., 2019. Poverty and Agriculture in Southern Africa Revisited: A Panel Causality Perspective. SAGE Open, pp. 1–10.

Benin, S., Smale, M., Gebremedhin, B., Pender, J.E.S., 2003. *The determinants of cereal crop diversity on farms in the Ethiopian highlands,* Durban, South Africa: contributed paper selected for presentation at the 25th. Int. Conf. Agricult. Econ. August 16–22, 2003.

Bezemer, D., Headey, D., 2008. Agriculture, development, and urban bias. World Dev. 36 (8), 1342–1364.

Birhanu, F.Z., Tsehay, A.S., Bimerew, D.A., 2021. The effects of commercialization of cereal crops on multidimensional poverty and vulnerability to multidimensional poverty among farm households in Ethiopia. Develop. Stud. Res. 8 (1), 378–395.

Birthal, P.S., Roy, D., Negi, D.S., 2015. Assessing the impact of crop diversification on farm poverty in India. World Dev. 72, 70–92.

Bizuayehu, S., 2014. Technical efficiency of major crops in Ethiopia: stochastic frontier model. Acad. J. Agric. Res. 2 (6), 147–153.

Cervantes-Godoy, D., Dewbre, J., 2010. Economic importance of agriculture for poverty reduction. OECD Food, Agriculture and Fisheries Working Papers No. 23. OECD Publishing.

Chamberlin, J., Schmidt, E., 2012. Ethiopian agriculture: a dynamic geographic perspective. In: Dorosh, P.A., Rashid, S. (Eds.), Food and Agriculture in Ethiopia: Progress and Policy Challenges. University of Pennsylvania Press, Philadelphia, pp. 21–52.

Chirwa, E.W., 2007. Sources of Technical Efficiency Among Smallholder Maize Farmers in Southern Malawi. African Economic Research Consortium, Nairobi, Keniya. Research Paper 172.

Christiaensen, L., Demery, L., Kühl, J., 2006. The role of agriculture in poverty reduction an empirical perspective, s.l.. In: World Bank Policy Research Working Paper 4013.

Christiaensen, L., Demery, L., Kuhl, J., 2011. The (evolving) role of agriculture in poverty reduction—an empirical perspective. J. Dev. Econ. 96, 239–254.

CSA, 2019. *Agricultural Sample Survey 2018/19 (2011 E.C.). Volume I Report on Area And Production of Major Crops (Private Peasant Holdings, Meher Season),* Addis Ababa, Ethiopia: Central Statistical Agency (CSA), FDRE.

Darko, F.A., Palacios-Lopez, A., Kilic, T., Ricker-Gilbert, J., 2018. Micro-level welfare impacts of agricultural productivity: evidence from rural Malawi. J. Dev. Stud. 54 (5), 913–932.

de Janvry, A., Sadoulet, E., 2010. Agricultural growth and poverty reduction: additional evidence. World Bank Res. Obs. 25 (1), 1–20.

Diao, X., 2010. Economic Importance of Agriculture for Sustainable Development and Poverty Reduction: the Case Study of Ethiopia. Policies for Agricultural Development, Poverty Reduction and Food Security. Global Forum on Agriculture 29-30 November 2010. Paris, France, OECD.

Dzanku, F.M., 2015. Household welfare effects of agricultural productivity: a multidimensional perspective from Ghana. J. Dev. Stud. 51 (9), 1139–1154.

FAO, 2015. Analysis of price incentives for Teff in Ethiopia. In: Assefa, B., Demeke, M., Lanos, B. (Eds.), Technical Notes Series, MAFAP. Rome, Italy.

FAO, 2017. Productivity and Efficiency Measurement in Agriculture: Literature Review and Gaps Analysis. Publication Prepared in the Framework of the Global Strategy to Improve Agricultural and Rural Statistics. FAO.

Farrell, J., 1957. The measurement of productive efficiency. J. Roy. Stat. Soc. 120, 253–290.

Ferede, S., et al., 2020. *Farming Systems Characterization And Analysis In East Gojjam Zone: Implications For Research and Development (R&D) Interventions,* Addis Ababa, Ethiopia: Research Report No. 127. Ethiopian Institute of Agricultural Research (EIAR).

Geffersa, A.G., Agbola, F.W., Mahmood, A., 2019. Technology adoption and technical efficiency in maize production in rural Ethiopia. Afr. J. Agricult. Res. Econ. 14 (3), 184–201.

Gattoufi, S., Wang, Y., Reisman, A., Oral, M., 2007. An interpretation of the technical efficiency as the "best possible deviation" from the conditions defined by the weak axiom of profit maximization. Int. Bus. Econ. Res. J. 6 (2), 1–11.

Gebrehiwot, K.G., 2017. The impact of agricultural extension on farmers' technical efficiencies in Ethiopia: a stochastic production frontier approach. S. Afr. J. Econ. Manag. Sci. 20 (1), 1–8.

Goshu, D., 2013. *Agricultural Technology Adoption, Diversification, and Commercialization For Enhancing Food Security In Eastern And Central Ethiopia,* Haramaya, Ethiopia: PhD Dissertation. Haramaya University.

Goshu, D., 2020. Economic welfare in Ethiopia: growth Scenarios for exiting poverty, Addis Ababa, Ethiopia. Volume XXVIII , No. I. Ethiopian Economics Association.

Huang, C.J., Huang, T.-H., Liu, N.-H., 2014. A new approach to estimating the metafrontier production function based on a stochastic frontier framework. J. Prod. Anal. 42, 241–254.

Irz, X., Lin, L., Thirtle, C., Wiggins, S., 2001. Agricultural productivity growth and poverty alleviation. Dev. Pol. Rev. 19 (4), 449–466.

Islam, M.S., Haider, M.Z., 2018. Poverty and technical efficiency in presence of heterogeneity in household behaviours: evidence from Bangladesh. Int. J. Soc. Econ. 1–25.

Ivanic, M., Martin, W., 2017. Sectoral productivity growth and poverty reduction: national and global impacts. World Dev. 109, 429–439.

Joshi, P., Gulati, A., Birthal, P.S., Tewari, L., 2003. Agriculture diversification in south Asia: patterns, determinants, and policy implications. In: MSSD Discussion Papers. International Food Policy Research Institute (IFPRI), Washington, D.C.

Kelemu, K., 2016. Impact of mobile telephone on technical efficiency of wheat growing farmers in Ethiopia. Int. J. Res. Stud. Agricult. Sci. (IJRSAS) 2 (7), 1–9.

Kirchner, S., 2021. The World Bank Aids Smallholder Farmers in Ethiopia. Retrieved on 10/282021. Available at: https://borgenproject.org/smallholder-farmers-in-ethiopia/?__cf_chl_managed_tk__=xbHBEDIA1C0wew7FCQ3K9NklZei7aY3UeWYCJ9HUBXo-1636093988-0-gaN.
Kodde, D., Palm, F., 1986. Wald criteria for jointly testing equality and inequality restrictions. Econometrica 54, 5.
Kothari, C., 2004. Research Methodology: Methods and Techniques, 2 ed. New Age International, New Delhi, India.
Kumbhakar, S., Wang, H., Horncastle, A., 2015. A Practitioner's Guide to Stochastic Frontier Analysis Using Stata. Cambridge University Press, New York, NY.
Lee, H., 2018. Teff, A rising global crop: current status of teff production and value chain. Open Agric. J. 12, 185–193.
Lin, B.B., 2011. Resilience in agriculture through crop diversification: adaptive management for environmental change. Bioscience 61 (3), 83–193.
Makate, C., Wang, R., Makate, M., 2016. Crop diversification and livelihoods of smallholder farmers in Zimbabwe: adaptive management for environmental change. SpringerPlus 5 (1135), 1–18.
Manjunatha, A., Anik, A.R., Speelmand, S., Nuppenau, E., 2013. Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India. Land Use Pol. 31, 397–405.
Mardani, M., Salarpour, M., 2015. Measuring technical efficiency of potato production. Inf. Process. Agricult. 2, 6–14.
Minten, B., Barrett, C.B., 2008. Agricultural technology, productivity, and poverty in Madagascar. World Dev. 36 (5), 797–822.
Nagpure, S., Deshmukh, R., Sharma, P.K., Ingole, D.N., 2017. Pattern of crop concentration and crop diversification– an economic analysis. Maharashtra J. Agril. Economics 20 (2), 128–132.
Nisrane, F., Koru, B., Seyoum, A., 2015. Productivity and efficiency of smallholder teff farmers in Ethiopia, Addis Ababa, Ethiopia: working paper 79. Ethiopian strategy support program (ESSP), EDRI, and IFPRI.
NPC, 2016. *Growth And Transformation Plan II (GTP II) (2015/16-2019/20), Volume I: Main Text.* Addis Ababa, Ethiopia. National Planning Commission (NPC).
NPC, 2017. *Ethiopia's Progress towards Eradicating PovertyL an Interim Report On 2015/16 Poverty Analysis Study ,* Addis Ababa, Ethiopia: National Planning Commission (NPC). FDRE.
Orea, L., Kumbhakar, S.C., 2004. Efficiency measurement using a latent class stochastic frontier model. Empir. Econ. 29, 169–183.
Oxford Poverty and Human Development Initiative, 2020. "Ethiopia Country Briefing", Multidimensional Poverty Index Data Bank., s.l.: Oxford Poverty and Human Development Initiative, University of Oxford. Available at: www.ophi.org.uk/multidimensional-poverty-index/mpi-country-briefings/.
Oyetunde-Usman, Z., Olagunju, K.O., 2019. Determinants of food security and technical efficiency among agricultural households in Nigeria. Economies 7 (103), 1–13.
Rahman, S., 2009. Whether crop diversification is a desired strategyfor agricultural growth in Bangladesh? Food Pol. 34, 340–349.
Rashid, S., 2010. Staple Food Prices in Ethiopia. Prepared for the COMESA Policy Seminar on "Variation in Staple Food Prices: Causes, Consequence, and Policy Options", 25-26 January 2010 under the African Agricultural Marketing Project (AAMP) Maputo. COMESA, Mozambique.
Samuel, G., Sharp, K., 2007. Commercialization of smallholder agriculture in selected tef-growing areas of Ethiopia. Ethiop. J. Econ. XVI (1), 57–88.
Schneider, K., Gugerty, M.K., 2011. Agricultural productivity and poverty: linkages and pathways. The Evans School Review 1 (1), 56–74.
Schultz, T.W., 1964. Transforming Traditional Agriculture New Haven and London: s.N..
Senbeta, A.N., Daselegn, S.G., Ahmed, Y.E., Bukul, B.B., 2020. Crop production system and their constraints in East Shewa zone, Oromia national regional state, Ethiopia. Int. J. Energy Environ. Sci. 5 (2), 30–39.
Seyoum, A., Dorosh, P., Asrat, S., 2011. *Crop Production In Ethiopia: Regional Patterns And Trends. ESSP II Working Paper No. 0016.* Addis Ababa, Ethiopia : Ethiopia Strategy Support Program II (ESSP II). International Food Policy Research Institute (IFPRI).
Shahbaz, P., Boz, I., Haq, S.u., 2017. Determinants of crop diversification in mixed cropping zone of Punjab Pakistan. Direct Res. J. Agricult. Food Sci. 5 (11), 360–366.
Suryahadi, A., Suryadarma, D., Sumarto, S., Molyneaux, J., 2006. Agricultural Demand Linkages and Growth Multiplier in Rural Indonesia. SMERU Research Institute, Jakarta, Indonesia.
Tenaye, A., 2020. Technical efficiecy of smallholder agriculture in developing countries: the case of Ethiopia. Economies 8 (34), 1–27.
Tigre, G., 2018. Multidimensional poverty and its dynamics in Ethiopia. In: Heshmati, A., Yoon, H. (Eds.), Economic Growth and Development in Ethiopia, Perspectives on Development in the Middle East and North Africa (MENA) Region, pp. 161–195.
Timmer, C.P., 1995. Getting agriculture moving: do markets provide the right signals? Food Pol. 20 (5), 455–472.
Thapa, G., Kumar, A., Roy, D., Joshi, P., 2017. Impact of crop diversification on rural poverty in Nepal. Can. J. Agric. Econ. 1–35.
UN, 2016. Multidimensional Poverty and its Measurement: Guide on Poverty Measurement, Conference of European Statisticians, 12-13 July 2016. Geneva, Switzerland, s.N.
UNDP & OPHI, 2019. *Global Multidimensional Poverty Index 2019. Illuminating Inequalities,* s.L. United Nations Development Programme (UNDP) and Oxford Poverty and Human Development Initiative (OPHI).
Vandercasteelen, J., Mekdim, D., M, B.B., Alemayehu, S., 2016. Row planting teff in Ethiopia: impact on farm-level profitability and labor allocation. In: s.l.: ESSP Working Paper 92.
Wassie, S.B., 2014. Technical efficiency of major crops in Ethiopia: stochastic frontier model. Acad. J. Agric. Res. 2 (6), 147–153.
Wongnaa, C.A., Awunyo-Vitor, D., 2018. Achieving sustainable development goals on No poverty and zero hunger: does technical efficiency of Ghana's maize farmers matter? Agric. Food Secur. 7 (71), 1–13.
Wooldridge, J.M., 2012. Introductory Econometrics: A Modern Approach, 5 ed. South-Western, Cengage Learning, Mason, OH 45040, USA.
World Bank, 2018. Cereal Market Performance in Ethiopia: Policy Implications for Improving Investments in Maize and Wheat Value Chains. Agriculture Global Practice, Washington D.C (GFA13).
Zhu, F., 2018. Chemical composition and food uses of teff (Eragrostis tef). Food Chem. 239, 402–415.