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

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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).

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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 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 rice-based mixed farming system of the country in particular (Cham- berlin 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 disproportionately 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 threshold, 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, Bizayehu, 2014; Nisane 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 determinants.

Efficiency reflects the degree of goodness with which economic units achieve their targets (Gattoi 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 agricultural 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

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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).
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 Bithal 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 Weredas² 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)
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:

\[ y_i^n = f^k(x_i^n; \beta_k) + v_i^n, \quad i = 1, \ldots, n(k) \]  

(1)

where, \( y_i^n \) denotes the value of total cereal output of the \( i \)-th sample household in the \( k \)-th Woreda, \( x_i^n \) is a \( k \times 1 \) vector of direct inputs of the \( i \)-th farm household, and \( \beta_k \) is a vector of unknown parameters to be estimated. \( v_i^n \) denotes the random variation in output due to factors outside the control of the farm, and \( u_i^n \) is a non-negative technical inefficiency component of the error. \( v_i^n \) is independent of \( u_i^n \) and distributed at i.i.d. \( N(0, \sigma^2_i) \). Whereas, \( u_i^n \) is assumed to follow truncated normal distribution at zero, i.i.d. \( (u_i^n \sim \mu_i^n Z_k^\omega) \), where \( Z_k^\omega \) 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:

\[ TE_i^k = \frac{y_i^n}{f^k(x_i^n; \beta)} = e^{-u_i^n} \]  

(2)

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

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:

\[ f^k(x_i^n; \beta) = f^M(x_i^n; \beta) e^{\sigma_i - u_i^n} \]  

(3)

where, \( u_i^n \geq 0 \), 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:

\[ TGR_i^k = \frac{f^k(x_i^n; \beta)}{f^M(x_i^n; \beta)} = e^{-v_i^n} \leq 1 \]  

(4)

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

\[ \frac{y_i^n}{f^M(x_i^n)} = TGR_i^k \times TE_i^k \times e^{-v_i^n} \]  

(5)

where.

\[ TGR_i^k = \frac{f^k(x_i^n; \beta)}{f^M(x_i^n; \beta)} \]  

the farm household’s technological gap ratio,

\[ TE_i^k = \frac{f^k(x_i^n; \beta)}{f^M(x_i^n; \beta)} = e^{-v_i^n} \]  

is the farm household’s TE, and

\[ e^{-v_i^n} = \frac{y_i^n}{f^M(x_i^n; \beta)} \]  

the random noise component.

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

\[ ln y_i^n = f^k(x_i^n; \beta) + v_i^n - u_i^n, \quad i = 1, \ldots, n(k) \]  

(6)

\[ ln f^k(x_i^n; \beta) = f^M(x_i^n; \beta) + v_i^n - u_i^n \]  

(7)

where, \( ln f^k(x_i^n; \beta) \) is the estimate of the group-specific frontier from Eq. (6). Since the \( ln f^k(x_i^n; \beta) \) 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, \( f_t(x_t; \beta) < f^M(x_t; \beta) \). The estimated TGR must always be less than or equal to unity:

\[
TGR^i = E \left( e^{-\beta_i} | z^M_i \right) \leq 1,
\]

(8)

where, \( \beta_i = \ln y_k - \ln x_k \) are the estimated composite residual of Eq. (7). The TE of the \( i \) 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, \( MeTE^i = TGR^i \times TFE^i \).

**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:

\[
\ln y^k_i = \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + \beta_4 \ln x_{4i} + \beta_5 \ln x_{5i} + \epsilon^k_i - \hat{\epsilon}^k_i, \ldots
\]

\( i = 1, 2, \ldots, 378 \)

(9)

where, \( \ln y^k_i \) represents the natural logarithm of the aggregate value of cereals (t'eff (Eragrostis tef)), wheat, barley, maize and sorghum) expressed in Ethiopian Birr. \( \beta_0 \)’s unknown parameters of conventional inputs to be estimated, \( x_{1i}\), \( x_{2i} \) 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. \( \epsilon^k_i \) is an idiosyncratic error term distributed at \( i, i, d N(0, \sigma^2) \) and independent from \( \hat{\epsilon}^k_i \). \( \epsilon^k_i \) is a non-negative error component associated with technical inefficiency of farm households that follows truncated normal distribution at zero \( (\epsilon^k_i \sim N^+(\mu^k|Z^k_i|, \sigma^2)) \). \( Z_1 - Z_{15} \) represents socioeconomic, location-specific factors and improved production techniques.

### 3.3.2. Measuring multidimensional household poverty

The poverty status of farm households was measured using a Multidimensional 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.

| Dimensions | Indicators | Deprivation cut-off | Relative weights |
|------------|------------|---------------------|-----------------|
| Education (1/5) | Adult literacy | No one has completed five years of schooling | 1/10 |
| Child | 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 | Household is not a member of cooperatives | 1/10 |

\[
H = q/a
\]

(11)

\[
A = \frac{1}{n} \sum_{i=1}^{n} c(k)/q
\]

(12)

\[
M_0 = H\times A
\]

(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 heterogenous 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:

\[
CDI = \sum_{i=1}^{n} S_i^2
\]

(14)

where, \( S_i \) 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.

### 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              | Index³                                   |                |
| Non-farm income           | Dummy (yes = 1; otherwise = 0)          |                |
| Cellphone ownership       | Dummy (yes = 1; otherwise = 0)          |                |
| Number of Oxen            | Number                                   |                |

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).

\[ y_{it}^* = y_{it}\beta + x_{it}'\gamma + u_i \]

\[ y_{it} = \begin{cases} 
1 & \text{if } y_{it}^* > 1 \\
0 & \text{if } 0 \leq y_{it}^* \leq 1 \\
0 & \text{if } y_{it}^* < 0 
\end{cases} 
\]

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.

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
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%, 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 Asfaw (2011) in Ethiopia, Wongnaa & Awnyoo-Vitor (2018) in Ghana, and Oyetunde-Usman and Olajuguna (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 Herrfindahl 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 0.5, 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.

### 4.3. 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.

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-governmental 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.

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### 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)

### 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)         | 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)

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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.

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 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 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)

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)               | -0.0006*** (0.00022) |
| Head education                      | -0.0046* (0.0025)                 | -0.00163*** (0.00083) |
| Household size                      | -0.0269*** (0.0042)               | -0.00712*** (0.00139) |
| Access to extension service         | -0.0152 (0.0173)                  | -0.00566 (0.0553) |
| Access to credit service            | 0.0100 (0.0295)                   | 0.0033 (0.0067) |
| Road condition (good)               | -0.0253 (0.0162)                  | -0.0090** (0.0518) |
| Population pressure                 | 0.0058*** (0.0011)                | 0.0144*** (0.00025) |
| Participation in non-farm activities| -0.0310 (0.0225)                  | -0.01620 (0.0736) |
| Constant                            | 0.9959*** (0.0835)                | 1.7736*** (0.2699) |

NB: Joint signficance 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, while 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 few 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

| Variables | Tobit model | IV Tobit Model |
|-----------|-------------|----------------|
|           | Highly diversified | Moderately diversified (Coef./SD) | Least diversified (Coef./SD) |
| Technical efficiency | -0.1228 (0.1183) | 0.0282*** (0.0275) | -0.0800*** (0.0940) |
| Head sex | - | - | - |
| 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 | 269 | 82 |
| Wald chi2 (13) | 34.09 | 75.60 | 52.35 |
| Prob > chi2 | 0.0007 | 0.0000 | 0.0000 |
| Joint significant test | na | 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: *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 is 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 (Vanderkastelaen 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.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

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Appendix

Appendix Table A

Table A. Hypothesis tests for the efficiency models.

| Null hypothesis | x² statistics | DF | Critical value X²0.05,09 | Decision |
|-----------------|---------------|----|--------------------------|----------|
| Cobb-Douglas SPPP and Translog SPPP H₀: β₀ + β₁ + ... + β₉ = 0 | 26.86 | 15 | 29.927 | CD is proper |
| Homogeneous production technology across geographical regions H₀: β₃ = γ₁ = ... = γ₉ | 82.96 | 22 | 38.304 | Reject H₀ |
| No technical inefficiency in the model σᵢ² = 0 and μ = 0, i | 23.41 | 2 | 8.273 | Reject H₀ |
| Inefficiency parameters have no effect on technical inefficiency H₀: δ₁ = δ₂ = ... = δ₁₀ = 0 | 284.87 | 17 | 32.766 | Reject H₀ |

Source: Authors’ analysis using primary data (2020)

NB: The critical values are obtained from Kodde and Palm (1986).

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 σᵢ² = 0 and μ = 0 (Kumbhakar et al., 2015).
Appendix Figure A

![Figure A](image)

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

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