Analysis of speed of improved maize (BH-540) variety adoption among smallholder farmers in Northwestern Ethiopia: count outcome model

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ABSTRACT

Low maize yield and productivity are major contributors to Ethiopia’s severe food insecurity and poverty. Generous efforts have been made by various stakeholders such as producers, and governmental and non-governmental organizations, to increase the country’s maize yield and productivity. However, the outcome is not as expected to achieve food security and poverty reduction. Hence, the purpose of this study was to determine factors influencing the speed of adoption of the improved maize (BH-540) variety in the Central Gondar zone. A three-stage sampling method was used to select a total of 385 smallholder farmers. Moreover, a negative binomial regression was used to determine factors influencing the speed of adopting the improved maize (BH-540) variety. The negative binomial regression model revealed that the age of the household head, farm size, and membership of the cooperative were statistically significant and positively affected the speed of adopting the improved maize (BH-540) variety, whereas distance to the nearest market and access to credit were statistically significant and inversely affected the speed of adopting the improved maize (BH-540) variety. Therefore, this study suggests that the native administration ought to organize skill division and provide short-range keeping fit packages to input suppliers, producers, traders, and development agents in each district. Moreover, supporting and strengthening the current agricultural cooperatives is advisable to strengthen farmer-to-farmer skill allotment by providing mindfulness conception, benefits, and numerous infrastructures. Furthermore, the trade and market development department should be designed to establish improved seed market institutions in each district.

1. Introduction

In Ethiopia, farming is a key factor in promoting economic development, eradicating poverty, and reducing food insecurity. Farming is an apparatus for the Ethiopian budget by donating 34.9% to the country’s GDP (NBE, 2018); providing 80% of the employees who depend on agriculture for their livelihood (Shiferaw, 2017); supplying 70% of inputs for the nation’s agricultural manufactories (EEA, 2012); and contributing about 70% of export incomes (FAO, 2015). This implies that the agricultural sector still serves as the primary source of income for the majority of Ethiopian people and desires countless care for the development and renovation of the sector.

In spite of the aforementioned contribution to the Ethiopian national economy, agriculture is extremely dependent on rain-fed and survival farming. Similarly, the performance of agriculture is also minimal in cereal production and productivity (Alemayehu, 2009; Debebe et al., 2015), and population growth has been outpacing food production (Asayehegn et al., 2011). In a majority of sub-Saharan nations, including Ethiopia, households are still poor and food insecure due to small plot size, low cereal productivity, low mechanization, decades of civil war, high dependency on food aid, and rain-fed agriculture (Jirström et al., 2010; Alobo, 2012; Makate et al., 2016; Essa et al., 2011; Birara et al., 2015).

Due to its diverse agro-ecologies, Ethiopia has great potential to produce a wide range of staple foods for both domestic use and commercial purposes (Dessie et al., 2019). Maize is the major staple food crop and is categorized among the five most important cereal crops (maize, teff, wheat, barley, and sorghum) in our country (CSA, 2016; Dessie et al., 2020). It is important in terms of production and area coverage and has exhibited progressively increasing trends in area expansion and production in recent decades (Figure 1). The mean land harvested in maize production in the years 1993 and 2017 was 838,450 and 2,173,543 ha, with an average total maize production of 1,455,920 and 8,116,787 tonnes, respectively (FAOSTAT, 2019). This indicates that the overall growth in maize production has primarily been due to area expansion. However, researchers are unsure how long the area expansion can
continue. Hence, the question of gaining a higher yield through the implementation of newly released improved agricultural packages and increasing the rate of adoption continues to be a concern for producers, researchers, and the Ethiopian government in the commercial farming system.

The commercialization of agricultural products during times of conflict might be one of the causes of high food costs. War (conflict) is prearranged violence interested in party-political and economic purposes. Wartime food costs provide an insight into how well governments can assemble properties to combat the vulnerability of starvation and deprivation. Sympathetic causes of rising food prices could help policymakers develop solutions to reduce suffering among civilians during times of war (Ali and Lin, 2010). Hence, the implementation of improved agricultural technology is the mitigating strategy to eradicate poverty, and enhance food security, and thus improve the production, productivity, and efficiency of agricultural commodities.

Maize is the main vital crop in relation to the availability and utilization of enhanced agricultural packages such as fertilizer, enhanced seed varieties, pesticides, herbicides, and better agronomic practices than other cereal crops (Haji and Sisay, 2016). So far, several studies on maize technology adoption in other parts of Ethiopia have been conducted. Among these are Alemaw (2014), Milkias and Abdulahi (2018), Abate et al. (2015), Legese et al. (2011), Jaleta et al. (2013), Feleke and Zegeye (2006), and Haji and Sisay (2016).

Despite such circumstances, the potential of maize productivity in Ethiopia is not exploited and is unable to contribute to the expected role in reducing food insecurity and poverty reduction. The estimated average productivity of maize in Ethiopia was 3736 kg per hectare, which is low-slung as compared to the world average of 5818 kg per hectare in 2017 (FAOSTAT, 2019). Similarly, the estimated mean production of maize in the North Gondar zone was 2816 kg per hectare, which is low-slung as compared to the Amhara national regional state average of 3508 kg per hectare in 2015/16 (CSA, 2016).

Moreover, the productivity of maize in the study area is too low due to the low use of improved agricultural packages such as improved maize varieties and organic and inorganic fertilizers, and the speed of adopting enhanced maize varieties is very slow. Some of the factors contributing to low maize productivity include seed cultivar yield potential, seed quality, unpredictable rainfall, soil infertility, weeds, disease, and pests, erosion, infrastructure, weather fluctuations, and recommended agronomic management practices (Alemaw, 2014; Haji and Sisay, 2016). Consequently, the presence of such factors meaningfully influences farmers’ efforts to improve production, enhance their food security, and improve their livelihood.

To the best of the researchers’ knowledge, not much research has been conducted so far on the rate of improved maize variety adoption in the Central Gondar zone. Based on the aforementioned claims, the study sought to determine the variables influencing the rate of adoption of the improved maize variety (BH-540) in northwest Ethiopia. The study is vital to bring up-to-date information on the current status, extent, and rate of agricultural technology adoption among maize producers.

The next section presents the research methods employed in this research study. It includes a detailed study area description, sampling procedures, data sources and methods of data collection and analysis, and hypotheses about variables used in the study.

2. Research methodology

2.1. Study area description

This study was done in the Central Gondar zone, Amhara region, Ethiopia. It is found in the northwestern part of Ethiopia. Gondar, the capital city of Ethiopia during the Gondarian era and currently for the Central Gondar zone, is a city with a mean elevation of 2133 m.a.s.l and is situated at 12°35’00.00”N latitude and 37°28’00.01”E longitude. The city is located far (175 km, 120 km, and 725 km) from the capital city of the Amhara region, Simien Mountains Park, and Ethiopia, respectively. The total population living in the Central Gondar zone was 2,896,928 (Lankir et al., 2020). In the zone, the households mainly depend on crop production and livestock breeding systems. The most common crops cultivated in the Central Gondar zone are maize, teff, wheat, barley, sorghum, onion, red pepper, chickpea, oats, and black and white cumin. Three districts, East Dembia, Takusa, and West Dembia, which are the main potential producers of maize in Northwest Ethiopia, were chosen for the study (Abate et al., 2019; Dessie et al., 2020; see Figure 2).

2.2. Sampling procedure and determination of sample size

In this research, a mixture of various sampling techniques was employed to choose the sample maize producers. The list of farmers found in the selected districts’ kebeles’ (villages) served as the sampling frame of the study. The population of interest comprised the farmers that

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1 Kebele is the smallest administrative unit in Ethiopia. It is a part of a district.
produced maize in the 2018/19 production season. As a result, the sample of maize producers was selected using a multi-stage sampling technique. In the initial stage, Takusa, East and West Dembia districts were chosen purposively in discussion with Central Gondar zone Agriculture and Rural Development office experts because of the great potential of maize production and superlative producer farm experience. In the second stage, 3 kebeles/villages from every district were selected by employing a systematic random sampling method since all maize producers adopted improved maize (BH-540) varieties in the 2018/2019 production season. In the final stage, 385 maize producers were selected through a simple random sampling method using Cochran’s (1977) sample size determination formula (1):

$$n = \left[\frac{Z^2pq}{e^2}\right] = \left[\frac{1.96^2(0.5*0.5)}{0.05^2}\right] = 385$$

where; $p = 0.5$, $q = 1-p$; $e = 0.05$ (error term); $n =$ sample size; $Z =$ confidence level ($Z = 1.96$).

2.3. Source of data and methods of data collection

To achieve the study’s objectives, both primary and secondary data sources were used. To gather the primary data, household interview schedule questionnaires were compiled, pre-tested, and refined. In order to collect data from 385 smallholder maize producers during the 2018/19 production season, nine experienced data collectors were hired and trained. The agriculture office, the central statistical agency, the food and agriculture organization, as well as other published and unpublished sources, were also used to collect secondary data.

2.4. Method of data analysis

In econometrics, the interest in discrete features of modeling individual economic activity is reflected in the interest in count data models. Count data models are specific types of discrete data regressions. In the literature on the rate of adoption of new technologies, count data econometric models like the Poisson, negative binomial, and zero-inflated Poisson models are frequently used. Hence, in order to analyze issues when the predicted variable only accepts non-negative integer values, count data econometric models are used (Cameron and Trivedi, 2013; Liou, 2009; Winkelmann, 2008). The dependent variable in this study assumes non-negative integer values. It is defined as the number of years that the producers took to adopt the improved maize (BH-540) variety technology in the Central Gondar zone. Moreover, the speed of the improved maize (BH-540) variety was influenced by the vector of explanatory variables entered in the model.

For count data, the Poisson distribution is the benchmark standard parametric model. It is important to review the core characteristics and outcomes of the Poisson distribution (Cameron and Trivedi, 2013; Winkelmann, 2008). According to these authors, let $Y_i$ is the discrete random variable, measured by the number of years that farmers took to adopt improved maize variety in the Central Gondar zone. The distribution of the dependent variable ($Y_i$) is depend on the set of observed explanatory
variables \((X_i)\) and unobserved variables \((U_i)\). The average value of the count outcome model is given by (2):

\[
E(Y_i / X_i, U_i) = \lambda_i = \exp(X_i \beta) 
\]

\[(2)\]

Source: Cameron and Trivedi (2013) and Winkelmann (2008).

The log-linear specification of the mean of the count data model \(\lambda\) on the explanatory variables is utilized in most applications, and assuming the relationship shown by the aforementioned equation is given by (3):

\[
\log \lambda_i = X_i \beta + U_i = \sum_{k=1}^{k} X_{ik} \beta_k + U_i
\]

\[(3)\]

Source: Cameron and Trivedi (2013) and Winkelmann (2008).

where the stochastic/error/disturbance terms are supposed to have a mean of one and a constant variance that are independently and identically distributed. Thus, the choice of count data for analyzing the rate of adoption of improved agricultural technology is governed by the distribution of the error/disturbance term (Cameron and Trivedi, 2013, 2019).

According to these authors, the most commonly used count outcome data models are the Poisson and negative binomial regression models. Detailed explanations of the above models are given below.

### 2.4.1. Poisson regression model

Poisson regression is the most well-known nonlinear statistical technique for analyzing count data having a Poisson distribution. This model emerges from the Poisson distribution by enabling the intensity parameter \(\lambda\) to be dependent on a vector of explanatory variables. A standard application of the Poisson regression model is to cross-section data (Cameron and Trivedi, 1998). The Poisson regression model was used to estimate the rate of adoption of improved maize varieties by smallholder producers in Northwestern Ethiopia. The typical cross-section data for the rate of adoption of improved maize (BH-540) variety consists of 385 sampled maize producers, the ith producer of which is \((y_i, x_i)\). The outcome variable is the rate of adoption of improved maize (BH-540) variety; \(y_i\) is the number of years when the ith producer adopts improved maize (BH-540) variety; and \(x_i\) is the vector of linearly independent covariates which determine the speed of adopting improved maize variety \(y_i\). The distribution of the dependent variable \(y_i\) is conditional on a \(k\) dimensional vector of explanatory variables, \(x_i = [x_{i1}, x_{i2}, \ldots, x_{ik}]\), and parameters \(\beta\) in the regression model based on this distribution, through a continuous function \(\lambda(x, \beta)\) such that \(E(y_i / x_i) = \lambda(x, \beta)\).

According to Tang et al. (2012), Winkelmann (2008), and Cameron and Trivedi (1998), the Poisson probability density function specifies that the random discrete variable \(y_i\) given the covariates \(x_i\) is defined as follows (4):

\[
f(y_i / x_i) = \frac{e^{-\lambda(x, \beta)} \lambda^{y_i}}{y_i!}, \quad y_i = 0, 1, 2, \ldots, n
\]

\[(4)\]

Source: Tang et al. (2012), Winkelmann (2008), and Cameron and Trivedi (1998).

Where:

- \(y_i\) is a discrete random variable having a non-negative integer value as its underlying assumption.
- \(\lambda\) is a mean under the probability function of the dependent variable \(y_i\) following the Poisson probability function.

Nevertheless, severe problems could arise in modeling count data employing a Poisson regression model. Assuming that the variance is a function of the mean, the Poisson regression model uses a one-parameter model to describe the distribution of the dependent variable (Cameron and Trivedi, 2013; Hilbe, 2014). This may be very strict for most data; specifically, observations such as spatial or time-serial correlations may not be precisely drawn in independent trials (Hilbe, 2007; Tang et al., 2012). Moreover, overdispersion often occurs when a Poisson regression model is employed for modeling count outcome data. In Poisson regression, overdispersion occurs when the response variance of the model is greater than the mean. Overdispersion is triggered by the positive relationship between responses (Hilbe, 2011; Tang et al., 2012). The Poisson regression model may produce inaccurate model estimates, biased estimates of the estimator’s variance, and incorrect conclusions about the results of the regression when there is overdispersion in the count data. This is because overdispersion can cause the estimates’ standard errors to be underestimated (Hilbe, 2007; Winkelmann, 2008). Therefore, it is crucial to take into account the negative binomial regression model as a substitute regression model in order to overcome the limitations of the Poisson regression model.

#### 2.4.2. Negative binomial regression

In order to investigate count data with overdispersion or positively skewed data, the negative binomial regression model, which is more adaptable than the Poisson regression model, is widely utilized (Hilbe, 2007). Indeed, while the former might be seen as a Poisson-gamma mixture regression model, the negative binomial regression model is in many ways comparable to the Poisson regression model (Winkelmann, 2008; Hilbe, 2011; Cameron and Trivedi, 2013). However, the negative binomial regression model is distinct since it has a free dispersion parameter. In other words, the negative binomial regression model includes an overdispersion parameter to quantify the potential divergence of the variance from the mean value under the Poisson regression model. As a result, when modeling count outcome data with a Poisson distribution, adopting a negative binomial regression model results in more conservative estimates of standard errors and modified parameter estimates (Hilbe, 2007; Tang et al., 2012; Cameron and Trivedi, 2013).

According to Hilbe (2007, 2011, 2014), Tang et al. (2012), and Cameron and Trivedi (2013), the fundamental specification of the negative binomial probability density function for the discrete random variable \(y\) is expressed as (5):

\[
f(y / \mu, \alpha) = \frac{\Gamma(y + 1/\alpha)}{\Gamma(y + 1) \Gamma(1/\alpha)} \left( 1 + \frac{\mu}{1 + \alpha y} \right)^{1/\alpha} \left( 1 + \frac{1}{1 + \alpha y} \right)^{-y}, \quad y = 0, 1, 2, \ldots, n
\]

\[(5)\]

Source: Hilbe (2007, 2011, 2014), Tang et al. (2012), and Cameron and Trivedi (2013), where \(\mu = e^{\beta x}\) and \(\alpha \geq 0\) characterized the degree of overdispersion. That means the variance is not equal to the mean in the case of the negative binomial regression model. The significance of the alpha coefficient indicates the presence of considerable overdispersion following the estimation of the negative binomial regression model. Overdispersion exists if the estimated alpha coefficient is significantly higher than zero. As a result, the Poisson regression model should be escaped in favor of the negative binomial regression model (Winkelmann, 2008; Hilbe, 2011; Tang et al., 2012; Cameron and Trivedi, 2013). As such, a basic negative binomial regression model was estimated for cross-sectional data of smallholder producers in order to ascertain the variables influencing the rate of improved maize variety adoption among maize producers in the Central Gondar zone of Northwestern Ethiopia.

#### 2.5. The hypothesis of explanatory variables

Different factors affect the speed of the improved maize (BH-540) variety in Northwestern Ethiopia. Table 1 demonstrates the measurement and description of hypothesized variables that affect the rate of improved maize varieties.

#### 2.6. Ethical approval and consent to participate

The University of Gondar’s research and community service directorate and the Central Gondar zone both provided letters of ethical clearance for the researchers and study participants. Each customer
Table 1. Description of the variables hypothesized to influence the speed of improved maize variety (BH-540) adoption.

| Dependent variable |
|--------------------|
| The dependent variable is the time taken by the farmer to adopt improved maize variety (BH-540) |

| Variables | Variable description and Measurement | Expected signs |
|-----------|--------------------------------------|----------------|
| Age       | Age of household head (year)          | ±              |
| Sex       | Sex of household head (1 = male, 0 = female) | -              |
| Education | Formal education level of the household head or year of attending formal education (year) | +              |
| Family size | Number of persons per household (Adult equivalent) | +              |
| Land size | Total land holding size of the household head (hectare) | +              |
| Livestock | Number of livestock owned (measured in Tropical livestock unit) | +              |
| Extension contacts | The number of visits by extension agents during the maize cropping period (Number) | +              |
| Market distance | Distance of farmer’s house from the nearby market (kilometer) | -              |
| Credit | Use of cash credit in maize framing (1 = user, 0 = non-user) | +              |
| Cooperative | Membership of farmers in cooperatives (1 = member, 0 = non-member) | +              |

VIF for continuous variables.

| Variable (in adult equivalent) | VIF | 1/VIF |
|-------------------------------|-----|-------|
| Family size                   | 1.61| 0.62  |
| Age                           | 1.49| 0.67  |
| Tropical livestock unit       | 1.30| 0.77  |
| Land size                     | 1.29| 0.78  |
| Distance to the nearest market| 1.10| 0.91  |
| Education level of household head | 1.08| 0.93  |
| Frequency of extension service| 1.06| 0.94  |
| Mean VIF                      | 1.28|       |

Table 3. Contingency coefficient for categorical variables/dummy variables.

| Variables | Sex of household head | Credit access | Membership of cooperatives |
|-----------|-----------------------|---------------|----------------------------|
|            | 1.00                  | 0.046         | 0.014                      |
|            |                       | 1.000         | 0.020                      |
| Membership of cooperatives | 1.000 | 0.020 | 1.000 |

The past few decades, Ethiopian research and development on maize have seen a great deal of change, which is apparent during the crucial times for deriving the existing transformation in the production of maize. Nowadays, enhancing the rate of adoption of improved maize production technologies has drawn the interest of policymakers and development economists since improved technologies increase the production of maize, which in turn leads to economic growth. Before running the negative binomial regression model, the severity of the multicollinearity problem was examined for the hypothesized explanatory variables. The occurrence of serious issues with multicollinearity among continuous and dummy explanatory variables was examined using the variance inflation factor (VIF) and contingency coefficient (CC) tests, respectively. As a general rule, VIF and CC values are typically less than 10 and 0.75, respectively (Tables 2 and 3). This suggests that multicollinearity among the study’s explanatory variables is not a serious issue.

Both Poisson and negative binomial regression models were regressed to determine factors affecting the rate of adopting the improved maize (BH-540) variety among producers in the Central Gondar zone of Northwestern Ethiopia. The projected Poisson regression model was verified for overdispersion. However, due to the implicit assumption that the variance of the discrete dependent variable is equal to its mean value, the Poisson regression model has some drawbacks. Consequently, the LR test of alpha was used, and the result confirmed that there is an over-dispersion problem in the data. It also implies that the dependent variable variance is higher than its average value because the LR test of alpha is statistically noteworthy at a one percent significance level (Table 4).

The result in Table 4 indicated that a negative binomial regression model estimated using 10 explanatory variables. Out of these, various policy-relevant variables were significantly influencing the rate of adoption of the improved maize (BH-540) variety, including the household head’s age, the amount of land he or she owned, the distance to the nearest market, access to credit, and membership in cooperatives at less than a five percent level of significance.

The household head’s age, which is a proxy variable for experience, has a positive and noteworthy effect on the speed of adopting the improved maize (BH-540) variety at a one percent significance level. The result confirmed that as the age of the maize producer increases by a year, the speed of adopting improved maize varieties increases by 1.008 years, other things being constant. This suggests that older producers in the Central Gondar zone are more likely than younger ones to adopt the recently released improved maize variety (BH-540). A suggested reason was that older producers had more experience than younger ones since they had the means and prior expertise to take on greater responsibilities for trying with new technology. Adoption literature mostly shows that the effect of a farmer’s age on technology adoption cannot be predicted because older farmers are frequently thought to be more risk-averse and less likely to test new technologies than younger farmers. In another piece of literature, it is said that older farmers have more experience since they have accumulated more money, power, and knowledge over time, giving them more opportunities to experiment with new technology than less experienced and younger farmers. Hence, the study’s findings support the second argument. This result is in line with those of Haji and Sisay (2016) and Beyene and Kasie (2015), who endorsed farmers’ adoption of improved maize varieties more quickly as their age increases.

Table 2. VIF for continuous variables.

| Variable                      | VIF | 1/VIF |
|-------------------------------|-----|-------|
| Family size (in adult equivalent) | 1.61| 0.62  |
| Age                           | 1.49| 0.67  |
| Tropical livestock unit       | 1.30| 0.77  |
| Land size                     | 1.29| 0.78  |
| Distance to the nearest market| 1.10| 0.91  |
| Education level of household head | 1.08| 0.93  |
| Frequency of extension service| 1.06| 0.94  |
| Mean VIF                      | 1.28|       |
Table 4. Maximum likelihood parameter estimates of negative binomial regression model.

| Variables                        | IRR     | Coefficient | Std. Err. | Z     |
|----------------------------------|---------|-------------|-----------|-------|
| Age of household head            | 1.008***| 0.007       | 0.002     | 3.29  |
| Sex of household head            | 1.133   | 0.125       | 0.091     | 1.37  |
| Education level of household head| 1.010   | 0.010       | 0.008     | 1.31  |
| Family size (in adult equivalent)| 1.003   | 0.003       | 0.015     | 0.22  |
| Land size                        | 1.101***| 0.096       | 0.023     | 4.13  |
| Tropical livestock unit          | 0.994   | -0.006      | 0.005     | -1.03 |
| Frequency of Extension service   | 0.999   | -0.001      | 0.0007    | -1.61 |
| Distance to the nearest market   | 0.999** | -0.002      | 0.001     | -2.14 |
| Credit access                    | 0.923** | -0.080      | 0.039     | -2.05 |
| Membership of cooperatives       | 1.227***| 0.205       | 0.061     | 3.34  |
| Constant                         | 5.417***| 1.690       | 0.142     | 11.87 |
| Alpha                            | 0.047   | 0.010       |           |       |

LR test of alpha – 0: $\chi^2(1) = 37.04$  Prob $> \chi^2(2) = 0.000$

Dispersion Mean

Log-likelihood -1080.454

LR chi2 (10) 83.64***

Number of observations 385

Dependent variable Speed of improved maize (BH-540) Variety

Note: *** and ** indicates the level of significance at 1% and 5%, respectively.

Central Gondar zone and serves as a proxy for measuring the producers’ level of wealth. In other words, land is the most crucially scarce resource in agricultural production. Farmers operating large farms tend to have greater financial incentives, resources, and more land to allocate to improving maize varieties (BH-540). The study result is in line with those of Haji and Sisay (2016), who revealed that large farm size owners adopted improved maize (BH-660) varieties more speedily than small farm size owners.

The distance from the home residence to the nearest market is expressed in kilometers. At a 5% level of significance, it has a negative and noteworthy influence on the rate of adoption of the improved maize (BH-540) variety. The result showed that as the producer’s residence is far from the nearby market by one kilometer, the speed of adopting improved maize (BH-540) variety decreases by 0.999 years, and other variables are held constant. The possible reason is that those producers that are far from the local market may have to pay more in transportation and transaction costs, and they may not be aware of the availability of the most recent technology offered by the extension system. Moreover, the further away the farmer is from a hub like a town market or a local market, the longer it takes to adopt improved agricultural technologies.

Distance to the market may be positively related to conveyance costs, but they may also negatively influence the capability to advance data about an innovation. As a result, farmers living far from the market center reduce the time to adopt improved maize (BH-540) varieties. The study confirmed the findings of Haji and Sisay (2016) and Leggesse et al. (2004), who endorsed that producers distant from market centers were slower to adopt improved agricultural technologies than those closer to them.

Access to credit had an adverse relationship and a statistically noteworthy influence on the speed of adoption of the improved maize (BH-540) variety at a five percent significance level. The result indicated that a producer that had got credit decreased the speed of adopting the improved maize (BH-540) variety by 0.923 units while other explanatory variables were remain constant. The plausible justification is that those producers might utilize the credit for unplanned purposes, like smoothing consumption, rather than buying improved maize varieties. Nevertheless, the use of credit affects farmers’ ability to obtain necessary new and improved agricultural technology at the factual time and in sufficient amounts. It can facilitate farmers’ purchasing of the needed agricultural inputs and enhance their capacity to effectively implement long-term investments in their farms. Access to credit is one of the best ways smallholders could be prompted to diversify their economic base. This study contrasts the finding of Leggesse et al. (2004), who revealed that access to credit has a positive influence on speed of adoption of improved agricultural technologies in Ethiopia.

Membership in cooperatives is a surrogate variable for measuring social capital. It is measured as a dummy variable which is coded 1, if a maize producer is a member of a farm cooperative, and 0, otherwise. It had a direct and noteworthy influence on the speed of adopting the improved maize (BH-540) variety at a one percent significance level.

When other explanatory variables were held constant, the result revealed that a farmer who belongs to a farm cooperative boosted the rate of adoption of the improved maize (BH-540) variety by 1.128 units. The possible justification is that membership in cooperatives has the benefit of accessing gen on the availability of recently released agricultural technologies. Moreover, cooperatives delivered credit access for purchasing improved agricultural technologies for their members in the study area. Besides, cooperatives make it easier for their members to receive information on the price, net benefit, and availability of recently released technology. Mutual self-help is a principle that cooperatives adhere to. Because of this, they are a natural tool for fostering social and economic advancement, and they also help the local communities, especially in introducing new agricultural technology. Hence, membership is more effective in reducing the time lag between adopting improved crop varieties and applying soil fertility-enhancing inputs. This might have boosted the rate of adoption of improved maize varieties by cooperative member farmers. Hence, this result is consistent with Haji and Sisay (2016) and Beyene and Kassie (2015), who revealed that cooperative members are more likely than nonmembers to adopt the recently released improved maize (PHB30G19) variety.

4. Conclusion and recommendations

Maize is the major staple food crop in Africa. Its production and productivity are critical to enhancing food security, eradicating poverty, and realizing agricultural development on the continent. Recognizing its potential, the government, NGOs, and researchers have been engaged in a variety of tasks in order to increase its production and productivity. Hence, agricultural technologies include all types of recent and improved agricultural packages and practices that influence the production and growth of agricultural output. Therefore, in order to increase agricultural production, productivity, and efficiency, improved agricultural...
technology must be adopted through the agricultural innovation system. However, because farmers have numerous challenges in the acceptance, use, and scaling out of such technologies, their adoption and practices can only be fruitful when efficiently applied in the appropriate place at the right time. Hence, this study aimed to determine factors affecting the rate of adoption of improved maize (BH-540) varieties in northwest Ethiopia. The results of the negative binomial regression model confirm that the household head’s age, land size, and cooperative membership directly and significantly influence the speed of adopting improved maize (BH-540) variety. On the basis of the study’s findings, the following recommendations were made: The agriculture office would organize an experience-sharing program and provide short-term training to younger and inexperienced maize producers. Producers should also rely on intensive cultivation on the existing limited farmland to increase the rate of adopting improved maize and its productivity. Moreover, the local government should strengthen the existing farmer cooperatives to share information on the existing agricultural technologies. Furthermore, the development agents should create awareness for producers on how to utilize credit for adopting newly released agricultural technologies rather than consumption smoothing. The trade and market development department should establish a new, improved seed market center at the village and district level in northwest Ethiopia. In general, there should be close coordination and integration among producers, academic institutions, financial institutions, research institutions, development agents, and policymakers for holistic maize production and marketing.

Declarations

**Author contribution statement**

Tadie Mirie Abate; Taye Melese Mekie; Abebe Birara Dessie: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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**Data availability statement**

Data will be made available on request.

**Declaration of interest’s statement**

The authors declare no conflict of interest.

**Additional information**

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**References**

Abate, T., Shiferaw, B., Meskri, A., Wegary, D., Kebede, Y., Tesfaye, K., Kassie, M., Bogale, G., Tadesse, B., Keno, T., 2015. Factors that transformed maize productivity in Ethiopia. Food Secur. 7, 965–981.

Abate, T.M., Desie, A.B., Mekie, T.M., 2019. Technical efficiency of smallholder farmers in red pepper production in North Gondar zone Amhara regional state, Ethiopia. J. Econ. Struct. 8, 18.

Alemaw, A.T., 2014. Impact of Improved Maize Varieties Adoption on Smallholder Farmers’ Marketed Maize Surplus in Oromia Regional State, Ethiopia. The Sokoine University of Agriculture.

Alemayehu, S., 2009. Cereal Production in Ethiopia: Recent Trends and Sources of Growth: International Food Policy Research Institute. Mimeo, Addis Ababa, Ethiopia.

Ali, H.E., Lin, E.S., 2010. Wars, food cost, and countervailing policies: a panel data approach. Food Pol. 35 (5), 375–390.

Alobe, S., 2012. Determinants of Rural Household Income Diversification in Senegal and Kenya. Sfer.

Asayebehegn, K., Varga, C., Rajan, S., 2011. Effect of small-scale irrigation on the income of rural farm households: the case of Laelay Marshaw district, central Tigray, Ethiopia. J. Stored Prod. Postharvest Res. 2, 208–215.

Beyene, A.D., Kassie, M., 2015. Speed of adoption of improved maize varieties in Tanzania: an application of duration analysis analysis. Technol. Forecast. Soc. Change. Biruna, E., Mequnent, M., Samuel, T., 2015. Assessment of food security situation in Ethiopia. World J. Dairy Food Sci. 10, 37–43.

Cameron, A.C., Trivedi, P.K., 1998. Regression Analysis of Count Data. Cambridge University Press.

Cameron, A.C., Trivedi, P.K., 2013. Regression Analysis of Count Data. Cambridge University Press.

Debebe, S., Haji, J., Gosu, D., Edris, A.-K., 2015. Technical, allocative, and economic efficiency among smallholder maize farmers in Southwestern Ethiopia: parametric approach. J. Dev. Agric. Econ. 7, 282–291.

Desta, A.B., Abate, T.M., Mekie, T.M., Liyew, Y.M., 2019. Crop diversification analysis on red pepper dominated smallholder farming system: evidence from Northwest Ethiopia. Ecol. Process. 8 (50).

Desta, A.B., Abate, T.M., Mekie, T.M., 2020. Interdependence of producers’ adoption decision of agronomic practices in maize production; evidence from northwest Ethiopia. Ethiop. J. Crop Sci. 8 (1).

EEA, E.E.A., 2012. Annual Report on Ethiopian Economy. Addis Ababa, Ethiopia.

Essa, C.M., Gideon, A.O., Ayalneh, B., Franklin, P.S., 2011. Resource Use Efficiency of Smallholder Crop Production in the Central Highlands of Ethiopia. FAO, P.A.A.O., 2015. Ethiopia Country Highlights on Irrigation Market Brief. Unfao, Rome, Italy. Prepared Under Food and Agricultural Organization of United Nations (UNFAO)/International Finance Corporation (IFC) Cooperation.

FAOSTAT, F. A. A. O. O. T. U. N., 2019. Crop Production in the World. Retrieved 2019, July, Countries-Select All; Regions-all, Elements-area and Production Quantity; Items-Maize Production; the Year 1993-2017).

Felege, S., Zegeye, T., 2006. Adoption of improved maize varieties in Southern Ethiopia: factors and strategy options. Food Pol. 31, 442–457.

Haji, J., Siayi, D.K., 2016. Agricultural Technology Adoption, Crop Diversification and Efficiency of Maize-Dominated Farming System in Jimma Zone, South-Western Ethiopia. Hilbe, J.M., 2007. Negative Binominal Regression. Cambridge University Press.

Hilbe, J.M., 2011. Negative Binominal Regression. Cambridge University Press.

Hilbe, J.M., 2014. Modeling Count Data. Cambridge University Press.

Jaleta, M., Varga, C., Kassie, M., De Groote, H., Shiferaw, B., 2013. Knowledge, Adoption, and Use Intensity of Improved Maize Technologies in Ethiopia. Jirström, M., Anderson, A., Djurfeldt, G., 2010. Smallholders Caught in Poverty- Flickering signs of agricultural dynamism. African smallholders. Food Crops, Markets, Pol. 74–106.

Lankir, D., Solomon, S., Gize, A., 2020. A five-year trend analysis of Malaria surveillance data in selected zones of Amhara region, northwest Ethiopia. BMC Publ. Health 20 (1), 1–9.

Leggesse, D., Michael, B., Adam, O., 2004. Duration analysis of technological adoption in Ethiopian agriculture. J. Agric. Econ. 55 (3).

Legesse, G., Langyintuo, A.S., Mwangi, W., Jaleta, M., La Rovere, R., 2011. Determinants of adoption of improved drought Tolerant maize varieties and their implication for household food security in drought-prone areas. Ethiop. J. Agric. Econ. 8, 105–132.

Liou, P.-Y., 2009. A Model Comparison For Count Data with a Positively Skewed Distribution with an Application to the Number of University Mathematics Courses Completed. Online Submission.

Makate, C., Wang, R., Makate, M., Mango, N., 2016. Crop Diversification and Livelihoods of Smallholder Farmers in Zimbabwe: Adaptive Management for Environmental Change, vol. 5. Springerplus, p. 1135.

Milkias, C.M., Abdulahi, A., 2018. Determinants of agricultural technology adoption: the case of improved Highland maize varieties in Toke Kutaye district, Oromia regional state, Ethiopia. J. Invest. Manag. 7, 125–132.

NBE, N.B.O.E., 2018. 2017/2018 Annual Report on the Ethiopian Economy. Tanzania: an application of duration analysis. Technol. Forecast. Soc. Change. Stekler, H., 2007. Productive Capacity and Economic Growth in Ethiopia. Department of Economics and Social Affairs, United Nations.

Tang, W., He, H., Tu, X.M., 2012. Applied Categorical and Count Data Analysis. CRC Press.

Winkelmann, R., 2008. Econometric Analysis of Count Data. Springer Science & Business Media.