# **ECONSTOR** Make Your Publications Visible.

A Service of

ZBW

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

Zegeye, Mesele Belay; Fikire, Abebaw Hailu; Assefa, Anteneh Bezualem

### Article

## Impact of Agricultural Technology Adoption on Food Consumption Expenditure: Evidence from Rural Amhara Region, Ethiopia

**Cogent Economics & Finance** 

### Provided in Cooperation with:

Taylor & Francis Group

*Suggested Citation:* Zegeye, Mesele Belay; Fikire, Abebaw Hailu; Assefa, Anteneh Bezualem (2022) : Impact of Agricultural Technology Adoption on Food Consumption Expenditure: Evidence from Rural Amhara Region, Ethiopia, Cogent Economics & Finance, ISSN 2332-2039, Taylor & Francis, Abingdon, Vol. 10, Iss. 1, pp. 1-16, https://doi.org/10.1080/23322039.2021.2012988

This Version is available at: https://hdl.handle.net/10419/303544

#### Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.



https://creativecommons.org/licenses/by/4.0/

#### Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.









**Cogent Economics & Finance** 

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/oaef20

# Impact of Agricultural Technology Adoption on Food Consumption Expenditure: Evidence from Rural Amhara Region, Ethiopia

Mesele Belay Zegeye, Abebaw Hailu Fikire & Anteneh Bezualem Assefa

**To cite this article:** Mesele Belay Zegeye, Abebaw Hailu Fikire & Anteneh Bezualem Assefa (2022) Impact of Agricultural Technology Adoption on Food Consumption Expenditure: Evidence from Rural Amhara Region, Ethiopia, Cogent Economics & Finance, 10:1, 2012988, DOI: <u>10.1080/23322039.2021.2012988</u>

To link to this article: https://doi.org/10.1080/23322039.2021.2012988

9

© 2022 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.



Published online: 07 Jan 2022.

گ

Submit your article to this journal 🕝



Q

View related articles 🖸



View Crossmark data 🗹



Citing articles: 10 View citing articles





Received 26 June 2021 Accepted 25 November 2021

\*Corresponding author: Mesele Belay Zegeye, Economics, Debre Berhan University, Ethiopia E-mail: mesele99belay@gmail.com

Reviewing editor: Raoul Fani Djomo Choumbou, Agricultural Economics and Agribusiness, University of Buea, Buea, Cameroon

Additional information is available at the end of the article

### GENERAL & APPLIED ECONOMICS | RESEARCH ARTICLE

# Impact of Agricultural Technology Adoption on Food Consumption Expenditure: Evidence from Rural Amhara Region, Ethiopia

Mesele Belay Zegeye<sup>1</sup>\*, Abebaw Hailu Fikire<sup>1</sup> and Anteneh Bezualem Assefa<sup>1</sup>

**Abstract:** The purpose of this study is to examine the impact of agricultural technology adoption on household food consumption expenditure in rural Amhara regional state, Ethiopia. The study is based on the data obtained from the Ethiopian Socioeconomic Survey collected in 2015/16. Household-level data were taken from 656 rural farm households in the Amhara region of Ethiopia. The study used the endogenous switching regression model to estimate the impacts of agricultural technology adoption on household food consumption expenditure per adult equivalent per annum. The result of the study reveals that adopting agricultural technology significantly increases household food consumption expenditure per adult equivalent. Moreover, the difference in household food consumption expenditure per adult equivalent between the actual and counterfactual scenarios is very high. The findings of the study reveal that broader investment in agricultural technology and increased access and adoption of agricultural technologies significantly improve the welfare of farm households.

Subjects: Economics; Microeconomics; Econometrics; Development Economics

Keywords: Agricultural technology; adoption; endogenous switching model; consumption

#### 1. Introduction

In developing countries, where agriculture is the main engine of the economy and offers the major growth share, agricultural growth as a result of technology adoption remains significant to improve the welfare of farm households, economic growth, and reduce poverty. Agriculture, in many aspects,

### ABOUT THE AUTHOR

Mesele Belay Zegeye is a lecturer at Debre Berhan University, Ethiopia. His research interest includes the effect and effectiveness of policies, poverty, food security, technology adoption, and agricultural innovations and extensions, and agricultural productivity.

Abebaw Hailu is a lecturer at Debre Berhan University, Ethiopia. His current research interests are development issues like urban and rural development, agricultural economics, food security, microeconomic, and macroeconomics policy analysis.

Anteneh Bezualem Assefa is a lecturer at Debre Berhan University. His research interest includes macroeconomics policy analysis and international trade.

#### PUBLIC INTEREST STATEMENT

Agriculture is the mainstay of the Ethiopian economy. But its productivity is very low, in return, lower food consumption. So, this study tried to examine the impact of agricultural technology adoption on food consumption expenditure in the Amhara Region, Ethiopia. The results revealed that the adoption of agricultural technology significantly increases household food consumption expenditure and thereby improves the welfare of rural households.





 $\circledast$  2022 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.

is the main sector of the Ethiopian economy; it accounts for about 34.1% of the GDP, employs 79% of the population, accounts for 79% of foreign exchange earnings, it is the major source of raw material and capital for investment and provides large market (Diriba, 2020). Even if agriculture is the mainstay of the country's economy, its productivity is very low. This is mainly because the sector is heavily dependent on rain-fed agriculture, traditional farming system, subsistence production, and highly vulnerable to climate change effects (Kelemu, 2015). These characteristics coupled with high population growth necessitate improving agricultural productivity for the country; for this, adoptions of agricultural technologies are widely prioritized. In countries with land scarcity and growing problems of land degradation, including Ethiopia, agricultural production can be increased through the adoption of agricultural technologies (De Janvry et al., 2017; Teka & Lee, 2020). Many agricultural technologies have been implemented, thereby improving the welfare of the farm households by increasing farm income and consumption expenditure.

Following the green revolution, Ethiopia's agricultural development policy has diverted towards implementing adoptions of modern agricultural technologies and practices. These include land management, fertilizer use, high-yielding varieties, weed and pest management, soil and water conservation, natural resource management, modern farming techniques, and machinery, among smallholder farmers (Tefera et al., 2016). Following this, this study considered the adoption of three technologies, namely, organic fertilizer, inorganic fertilizer, and herbicide, due to the higher adoption rates in the Amhara region during the survey period. The adopters in this study are farm households that used at least one of the above technologies in any one of their crop fields. Although there is a great focus on these technologies, the adoption rate was not high and does not keep up with modern technologies, which significantly limits the productivity of smallholder farmers. The national-level intensity of agricultural technology use is still lower than the recommended rates and even much lower than many developing countries (Asmare et al., 2019; Kelemu, 2015; Weldegiorges, 2015).

Agricultural technology is among the most changeable and impactful areas of modern technology, driven by the fundamental need for food and for feeding an ever-growing population. The adoption of agricultural technologies enables improvement in agricultural productivity and also reduces poverty by increasing the income and consumption of farm households. Moreover, the adoption of agricultural technology increases production for home consumption and reduces food prices, which encourages more food consumption (De Janvry et al., 2017). Given that, various studies that were conducted at the country and regional levels have confirmed the poverty reduction effect of the adoption of agricultural technologies. For example, Asfaw et al. (2012), Zeng et al. (2014), Sebsibie et al. (2015), and Jaleta et al. (2015), Shita et al. (2018, 2020), Teka and Lee (2020), Biru et al. (2020), Chirotaw (2020), Feyisa and Yildiz (2020), Ayenew et al. (2020), Tamirat and Abafita (2021), and Wordofa et al. (2021) have conducted a study on the impact of agricultural technology adoption on smallholder farmer's welfare and found that the adoption has significantly raised production and productivity, household income, nutrition, consumption expenditures.

Thus, this study is inspired to gain more insight into how the adoption of agricultural technologies can increase household food consumption expenditure and reduce poverty in the Amhara region, Ethiopia. The contribution of the study to the existing literature is three-fold. First, some studies focused on the determinants of agricultural technology adoption in the region and the country, for instance (Feyisa & Yildiz, 2020; Kelemu, 2015; Tefera et al., 2016). However, this study examines both the determinant and implied impacts of adopting agricultural technology on food consumption expenditure. Second, many studies evaluated the impacts of single technology adoption on single crop productivity and consumption expenditure, for example (Ayenew et al., 2020; Biru et al., 2020; Sebsibie et al., 2015; Tamirat & Abafita, 2021; Zeng et al., 2014). However, this paper evaluates the impact of various technology adopters on food consumption expenditure regardless of the crop grown by the households. Third, most previous studies have been applied, OLS, Tobit, and PSM models, to estimate the impacts on the outcome variable, for example (Sebsibie et al., 2015; Shita et al., 2020; Tamirat & Abafita, 2021; Teka & Lee, 2020; Wordofa et al., 2021). However, these models are subject to self-selection bias, inadequate counterfactuals, and endogeneity problems, which do not clearly show the effect of adoption on the outcome variables (Belay & Mengiste, 2021; Biru et al., 2020; Kassie et al., 2018). In addition, these methods assume that selection bias due to unobservable factors is only marginal; while in non-experimental studies of this kind, evaluating the impact is challenging mainly because of selection bias due to both observable and unobservable factors (Belay & Mengiste, 2021; Kassie et al., 2018). In this regard, this study employed an endogenous switching regression model, which accounts for all the impact evaluation challenges. Finally, there is no enough study conducted on the impact of agricultural technology adoption on food consumption expenditure in the study area. Therefore, the objective of this study is to examine the impact of agricultural technology adoption expenditure in the rural Amhara Region, Ethiopia.

#### 2. Literature

Theoretically, it is assumed that agricultural technology adoption boosts agricultural productivity and improves household welfare by reducing poverty. However, the potential effect of technology adoption depends on whether farmers adopt, and if they do, also depends on the take-up rate of agricultural technology. This is usually measured by the length of time required for a certain percentage of the members of the system to adopt the technology innovation. Besides, innovations that are perceived by individuals as possessing a higher relative advantage, compatibility, less complexity, divisibility, and observability have a more rapid rate of adoption (Rogers, 2010). Adoption decisions are generally assumed to be the outcome of optimizing expected profit, where returns are a function of land allocation, the production function of the technology, and the costs of inputs and prices of outputs (Feder et al., 1985). The contribution of agricultural technology adoption to economic growth in turn-on productivity and poverty reduction can only be realized when and if the adopted technologies are widely diffused and used. Diffusion of innovation results from a series of individual decisions begins using the new technology, decisions that are often the results of a comparison of the uncertain benefits of the new invention with the uncertain costs of adopting it. When making farmer's decisions about the adoption of a given technology, farmers are assumed to weigh the impacts of the adoption of innovations against their economic, social, and technical feasibility; then, farmers evaluate these in terms of the incremental benefits of using new technology (Admassie & Ayele, 2011).

Accordingly, various studies have been conducted on the impact of agricultural technology adoption on productivity, food security, and poverty in Ethiopia. For instance, Sebsibie et al. (2015) analyzes the impact of agricultural technology adoption on household welfare in the Amhara regional state using propensity score matching (PSM) techniques of impact evaluation. They found that agricultural technology adoption significantly increases the consumption of the farm households and improves household welfare (reduce poverty). Shita et al. (2020) examines the impact of the adoption of agricultural technology on income inequality using PSM methods. They found that the adoption of agricultural technologies such as chemical fertilizer and improved seeds significantly increases total household income but worsens income distribution. Biru et al. (2020) examines the impact of multiple complementary technology adoption on consumption, poverty, and vulnerability of smallholders in Ethiopia. They find that the adoption of improved technologies increases consumption expenditure significantly and the greatest impact is attained when farmers combine multiple complementary technologies.

Tamirat and Abafita (2021) investigate the factors affecting the adoption decision of row planting and its impact on income and expenditure in Duna district cross-sectional field survey data gathered in 2018–2019. The results of binary logit regression revealed that the technology participant was

significantly affected by age, education status, size of family, off-farm income, land-holding, livestock holding, the quantity of fertilizer used, farmers training center, and access to credit and extension services. Adoption was associated with a significantly higher crop yield and expenditure. Wordofa et al. (2021) analyzes the impact of the adoption of agricultural technology on farm household income in eastern Ethiopia using PSM. They find that the adoption of agricultural technologies significantly increases the income of the adopters compared to those households not using such technologies. Belay and Mengiste (2021) examines the impact of agricultural technology adoption on poverty reduction in the north Shewa zone of the Amhara region of Ethiopia in 2020. The results revealed that farm household's decisions to adopt agricultural technologies are mainly influenced by the sex of the household head, credit access, saving, extension visit, farm cooperatives, and distance from the market. The adoption of agricultural technology has a direct and significant impact on increasing household consumption expenditure while also reducing household poverty. Generally, the empirical works that have been conducted show that agricultural technology adoption is an important strategy for increasing agricultural productivity, achieving food self-sufficiency, and poverty reduction, among smallholder farmers.

#### 3. Methodology

#### 3.1. Description of the study area

Amhara national regional state is located in the northwestern and north-central parts of Ethiopia. The region is the second populous region with a projected population of 21.8 million in 2019 (CSA (Central Statistical Agency), 2019). It consists of 12 administrative zones, 105 Woredas, and 78 urban centers. The land area of the region is 254,708.96 km<sup>2</sup> and the region is the third largest in the country. Agriculture is the mainstay economic activity, in which nearly 84 percent of the population lives in rural areas. The most common agricultural activities practiced in the region are crop production, plantation, animal husbandry, forestry and logging, and fishing. The intensive use of land in the region has led to the recurrent occurrence of drought and this has resulted in 14.8 percent of the rural households being chronically food deficient (UNICEF (United Nations Children's Fund), 2018). To improve the livelihood of farming households, the application of modern agricultural technologies was taken as a measure throughout the region. According to Tefera et al. (2016), the agricultural technologies practiced in the Amhara region include improved seed, fertilizer (DAP, urea, compost, and manure), row planting, herbicide, pesticide, dairy, improved breed, improved seeds, and forage management and use of services for artificial insemination promoted through the extension system.

#### 3.2. Data description

The study is based on the data obtained from the Ethiopian Socioeconomic Survey (ESS) collected in 2015/16. The survey covers all the regions of Ethiopia, and the data covered a wide range of topics such as household characteristics, labor, welfare, agriculture, food security, land characteristics, credit, extension service, social capital, agricultural technology adoption practices, and shocks. The data cover rural areas, small towns, medium and large towns; however, households from small, medium, and large towns were omitted for the reason of the inapplicability of farming technology adoption. Thus, this study considered only rural farm households found in the Amhara regional state of Ethiopia. Accordingly, from the survey, a total of 732 farm households were obtained from rural Amhara. However, during data management, a total of 76 households were dropped due to missing information. Finally, after adjusting and accounting for missing variables and values, the final sample used in the study is 656 farm households.

#### 3.3. Econometric framework

Assume that farmers aim to maximize their utility  $(U_i)$ —that is productivity or food consumption expenditure in our case, by comparing with alternative package *p*. For the *i*<sup>th</sup> farmer faced with *k* 

alternative technology choices, the choice of alternative technology k over any alternative package p implies that  $U_{ik} > U_{ip}$  for all other  $p \neq k$ . The expected utility of the farmer from adopting technology package k ( $U_{ik}^*$ ) is a latent variable determined by the observed plot, household, and location characteristics ( $Z_i$ ) and unobserved characteristics ( $\varepsilon_{ii}$ ),

$$U_{ik}^* = Z_i \beta_k + \mu_{ik}, \tag{1}$$

which refers to a vector of observed explanatory variables defined in Table 1 and  $\mu_{ik}$  is the error term. Let C be an index that indicates the choice that the farmer has made, such that

$$C = \begin{cases} 1 \text{ iff } U_{i1}^* > \max_{p \neq k}(U_{ip}^*) \text{ or } T_{i1} < 0 \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ k \text{ iff } U_{ik}^* > \max_{p \neq k}(U_{ip}^*) \text{ or } T_{ik} < 0 \end{cases}$$
(2)

which is the expected difference in utility (household food consumption expenditure per adult equivalent) between alternative technology packages k and p. Hence, the  $i^{th}$  farmer will adopt alternative technology package k if and only if  $T_{ik} = \max_{p \neq k} (U_{ip}^* - U_{ik}^*) > 0$ . Therefore, if farmers adopt different agricultural technologies based on their expectations, we expect that an increase in household food consumption expenditure per adult equivalent, which could be capitalized to raise households above the poverty threshold.

The endogenous switching regression model (ESR) model used here is adapted from Lokshin and Sajaia (2004) and Belay and Mengiste (2021), and the adoption of agricultural technology and its implied impacts on household food consumption expenditure per adult equivalent are estimated for adopters and non-adopters separately controlling the endogenous nature of technology adoption decisions.

Assume that a farm household will choose to adopt agricultural technology if the expected utility from adopting is greater than non-adopting. Let T<sub>i</sub>\* be the latent variable that captures the expected benefits from the adoption of agricultural technology compared with non-adoption. The adoption equation for farmers' choice can be specified as

$$T_i^* = \beta Z_i \xi; \text{ with } T_i = \begin{cases} 1 \text{ if } T_i^* > 0\\ 0 \text{ otherwise} \end{cases}$$
(3)

where Farm household i will adopt agricultural technologies if  $T_i^* > 0$  and will not adopt otherwise,  $T_i^*$  is the unobservable or latent variable for technology adoption ( $T_i$  is its observable counterpart, equals 1 if a farmer has adopted the technology and 0 otherwise),  $Z_i$  are exogenous factors that influence adoption and  $\xi_i$  is random disturbances. Measuring the impacts of agricultural technology adoption on the outcome variable requires control of potential selection bias, endogeneity problem and unobserved heterogeneity. To achieve this, the study applied the endogenous switching regression model (ESR).

Table 1. Description, me	asurement, and hypothes	iis of variables			
No	Variables	Variable description	Variable value	Measurement	Expected sign
1	Dependent variable: Technology Adoption	A farm household who adopt one of crop fields (Inorganic and Herbicide)	s at least one technology in fertilizer, Organic Fertilizer,	0 for non-adopters and 1 for	adopters
Independent variables					
2	Age	Age of the household head	Continuous	Measured in years	+1
ε	Gender	Gender of the household head	Dummy	1 if the household is male and 0 otherwise	+1
4	Family size	Number of family size in the household	Continuous	In number	+1
5	Education level	Education of the household head	Continuous	Measured in schooling years	+
9	Land size	Total land size of the household	Continuous	In hectare	+
7	Distance to market	Distance from home to nearest market	Continuous	In kilometre	1
8	Distance to all- weather road	Distance from home to the all-weather road	Continuous	In kilometre	1
6	Livestock	Total livestock herd size of the household	Continuous	In tropical livestock unit (TLU index)	+
10	Access to credit	Credit access of the household	Dummy	if the farm household had taken loan; 0 otherwise	+
11	Extension visits	Extension services delivered by the agricultural offices	Dummy	if a household had extension visit during their practice; 0 otherwise	+
12	Off-farm Employment	Off-farm activities	Dummy	if the farm household had participated; 0 otherwise	+1
13	Plot distance	Distance from home to farm plots	Continuous	In kilometre	I

#### 3.3.1. Endogenous Switching Regression (ESR)

Accounting for endogeneity, selection biases, and unobserved heterogeneity, the ESR measure can then be produced into two estimable functions where farmers faced two regimes: (i) to adopt and (ii) not to adopt. Let household food consumption expenditure be indicated by food consumption per adult per annum,  $C_{1i}$  for adopters and  $C_{0i}$  for non-adopters. Then, the two food consumption equations are specified as follows:

$$Non - adopters \ 0: C_0 =_0 Z_{0i} \varepsilon_{0i} \text{ if } T_i - 0, \tag{4}$$

Adopters 1: 
$$C_1 = {}_1 Z_{1i} \varepsilon_{1i}$$
 if  $T_i - 1$ , (5)

where Ci are the outcome variables for household food consumption per adult equivalent in regimes 1 and 0;  $Z_i$  denote exogenous factors that influence food consumption expenditure;  $\varepsilon_i$  are parameters to be estimated, and  $\varepsilon_i$  denote the disturbance term. Finally, the error terms in equations (1), (2) and (3) are assumed to have a trivariate normal distribution, with zero mean and non-singular covariance matrix expressed as

$$\mathsf{cov}(\varepsilon_1, \varepsilon_0, \xi) = egin{bmatrix} \mathsf{d}^2_{\varepsilon_0} & \cdot & \mathsf{d}_{\varepsilon_{0\xi}} \ \cdot & \mathsf{d}^2_{\varepsilon_1} & \mathsf{d}_{\varepsilon_{1\xi}} \ \cdot & \cdot & \mathsf{d}^2_{\xi} \end{bmatrix},$$

where  $\delta_{\xi}^2$  is the variance of the error term in selection equation (1) (which can be assumed to be equal to 1 since the coefficients are estimable only up to a scale factor),  $\delta_{\varepsilon_0}^2$  and  $\delta_{\varepsilon_1}^2$  are the variances of the error terms in the welfare outcome functions (2 and 3), and  $\delta_{\varepsilon_1\xi}$  represent the covariance of the error term of the selection equation ( $\xi$ ) and the outcome equation of regime 0 ( $\varepsilon_0$ ) and regime 1 ( $\varepsilon_1$ ). Since the covariance between  $\varepsilon_0$  and  $\varepsilon_1$  is not defined, C<sub>1</sub> and C<sub>0</sub> are never observed simultaneously (Maddala, 1986).

An important implication of the error structure is that, because the error term of selection equation (1) $\xi$  is correlated with the error terms of outcome functions (2) and (3) ( $\varepsilon_0$  and  $\varepsilon_1$ ), the expected values of  $\varepsilon_0$  and  $\varepsilon_1$  conditional on the sample selection are non-zero. Mathematically:

$$E[\varepsilon_1/T_i = 1] = \delta_{\varepsilon 1\xi} \frac{\phi(\beta Zi)}{(\beta Zi)} = \delta_{\varepsilon 1\xi} \lambda_1 \text{ and } E[\varepsilon_0/T_i = 0] = -\delta_{\varepsilon 0\xi} \frac{\phi(\beta Zi)}{1 - (\beta Zi)} = \delta_{\varepsilon 0\xi} \lambda_0$$

Where,  $\phi(.)$  is the standard normal probability density function, (.) the standard normal cumulative density function, and  $\lambda_1 = \frac{\phi(\beta Xi)}{(\beta Xi)}$  and  $\lambda_0 = \frac{\phi(\beta Xi)}{1-(\beta Xi)}$ . These are inverse Mills ratios computed from the selection equation and are included in the outcome equation. If the estimated covariance and  $\delta_{\varepsilon 0\xi}$  are statistically significant, then the decision to adopt and the outcome variables are correlated, that is, there is evidence of endogenous switching and thus a rejection of the null hypothesis of the absence of sample selectivity bias.

In this case, the appropriate and efficient method to estimate ESRs is full information maximum likelihood (FIML) estimation. The FIML method simultaneously estimates the selection equation and the outcome equations to yield consistent standard errors. Given the assumption of trivariate normal distribution for the error terms, the logarithmic likelihood function for the system of

Equations 1, 2 and 3 can be given as

$$LnLi = \sum_{i=1}^{N} Ti[ln \ \phi \frac{\varepsilon_1}{d_{\varepsilon 1}} - lnd_{\varepsilon 1} + ln\delta(\psi_{1i})] + 1 - Ti[ln\phi \frac{\varepsilon_0}{d_{\varepsilon 0}} - lnd_{\varepsilon 0}(1 - ln\delta(\psi_{0i}))]$$

where  $\psi_{ji} = \frac{\beta Z i + p_j \varepsilon_{ji} / \delta_j}{\sqrt{1 - p_j^2}}$ , j i = 1, 2, with  $\delta_j$  denoting the correlation coefficient between the error term  $\xi$  of selection equation 1 and the error terms  $\varepsilon_{ii}$  of equations 2 and 3.

According to Di Falco et al. (2011) and Belay and Menaiste (2021), for the ESR model to be adequately identified, it is important to use exclusion restriction due to the endogenous nature of technology adoption decisions. Hence, this study applied exclusion restriction, in which explanatory variables that affect the selection equation directly but not the outcome equation (this study used extension agent, plot distance, distance from the road, and market for exclusion restriction) were excluded. These variables affect the adoption decision but not the outcome equation directly. For example, extension visits encourage adoption because it gives detailed information, training, and advisory services about the source, use, and importance of the technologies to the farmers. Distance from market to road may also discourage adoption because those farmers with better access to the market and main road may buy (sell) agricultural inputs (outputs) on time and with a reasonable price are more likely to adopt farm technologies. Finally, plot distance may have a significant effect on adoption because as the distance to the plot is far away from the homestead, the less likely will be on time plot preparation, weeding, harvesting, input utilization, and hence farm households are less likely to adopt agricultural technologies. If the excluded variables are a valid instrument, they will affect the adoption decision, not the outcome equations. The test result shows that the selection instruments are found to be highly insignificant at the 5% level. This confirms the validity of the selected instrumental variables and the model is adequately identified.

#### 3.3.2. Estimation of average treatment effects

To assess the impact of technology adoption on household food consumption expenditure, the counterfactual outcomes should be estimated. The ESR model allows us to estimate adequate counterfactual situations, and one can estimate the average treatment effects of adoption. Thus, from equations (2 and 3), the expected actual and counterfactual values of food consumption expenditures are computed as follows:

Adopters with adoption (actual):

$$E[C_1|T = 1] = \alpha_1 Z_1 \delta_{e_1\xi} \lambda_1 \tag{6}$$

Adopters had decided not to adopt

$$E[C_1|T = 0] = \alpha_1 Z_0 \delta_{\varepsilon_1 \xi} \lambda_0 \tag{7}$$

Non-adopters without adoption

$$E[C_0|T = 0] = \alpha_2 Z_0 \delta_{\varepsilon 0 \varepsilon} \lambda_0 \tag{8}$$

Non-adopters had decided to adopt

$$E[C_0|T=1] = \alpha_2 Z_1 \delta_{\epsilon_0 \xi} \lambda_1 \tag{9}$$

Taking the difference between equation (4) and (7) gives the average effect of technology on adopters (Average Treatment effect on Treated (ATT)) and is given as

$$TT = E[C_1/T = 1] - E[C_0/T = 1] = Z_1(\alpha_1 - \alpha_2) + \alpha_1(\mathbf{d}_{\varepsilon_1\varepsilon} - \mathbf{d}_{\varepsilon_0\varepsilon}).$$
(10)

Similarly, the effect of the treatment of the untreated (TU) for the farm households that did not adopt is calculated as the difference between (5) and (6) as

$$TU = E[C_1/T = 0] - E[C_0/T = 0] = Z_0(\alpha_1 - \alpha_2)\alpha_0(d_{\epsilon_1\xi} - d_{\epsilon_0\xi}).$$
(11)

The difference between (TT) and (TU) gives in transitional heterogeneity (TH), which indicates whether the effect of adopting agricultural technology is larger or smaller for the adopters than for the non-adopters.

This paper used household food consumption expenditure per adult equivalent as an outcome variable. This is because household consumption expenditure dictates a household's purchasing power and its ability to meet its basic needs and beyond. As adoption boosts agricultural production and productivity, the household's food consumption expenditure also increases accordingly. Considering measurement issues, household consumption expenditure is a more reliable yardstick to determine the welfare status of the household than others like income (Rao, 2006). Besides, most farmers in the rural area of Ethiopia are consuming most of the produced amount. Therefore, adoption may have a significant effect on increasing household food consumption expenditure. Due to this reason, we have used the household food consumption expenditure as an outcome variable.

Literature showed that the decision to adopt agricultural technologies is influenced by several exogenous factors such as household characteristics, socioeconomic characteristics, access to information and infrastructure facility, institutional factors, and plot characteristics. The selection of the variables used in this study is based on previous studies of Admassie and Ayele (2011), Sebsibie et al. (2015), Ayenew et al. (2020), and Belay and Mengiste (2021), Shita et al. (2020), Wordofa et al. (2021) and Tamirat and Abafita (2021). The justification for the inclusion of these covariates is to control the endogenous nature of technology adoption and to show the real effect of agricultural technology adoption on the outcome variable. In addition, the endogenous switching regression model is estimated in the setting of two stages. First, the adoption equation is helpful to control the selection biases due to unobserved heterogeneities. Second, the impact of technology adoption on the outcome variable is estimated using ordinary least squares (OLS) including the selectivity correction term as an additional regressor to capture selection bias.

#### 3.4. Description, measurement, and hypothesis of variables

#### 4. Results and discussion

#### 4.1. Descriptive analysis

Table 2 reports the descriptive statistics of explanatory variables for the adopters and non-adopters. It shows that there is a significant difference between the characteristics of adopters and non-adopters, implying that the household, socio-economic and institutional characteristics are significantly larger for adopters. For instance, adopters are more male-headed households; on average, adopters are younger compared to non-adopters. This may direct that young farmers are more likely

Table 2. Descriptive sto	itistics of variables used	l in the regression	
<b>Explanatory Variables</b>	Category	Adopters	Non-Adopters
Gender	Male	422(81.47)	75 (54.35)
	Female	96(18.53)	63 (45.65)
Access to credit	Yes	143(27.61)	8(5.80)
	No	375(72.39)	130(94.20)
Off-farm employment	Yes	40(7.72)	7(5.07)
	No	478(92.28)	131(94.93)
Extension visits	Yes	326(62.93)	4(2.90)
	No	192(37.07)	134(97.10)
(Percents in parentheses)			
Age	Mean (SD)	48.76(14.44)	54.18(18.14)
Education level	Mean (SD)	1.513(2.82)	.913(2.54)
Family size	Mean (SD)	4.722(1.88)	3.239(2.02)
Tropical Livestock Unit (TLU)	Mean (SD)	4.240(3.84)	1.545(2.38)
Farm size	Mean (SD)	.750(.795)	.581(.537)
Distance from market	Mean (SD)	52.53(33.46)	54.15(31.62)
Distance from an all- weather road	Mean (SD)	16.62(18.54)	17.92(20.08)
Plot distance	Mean (SD)	.729(.804)	.954(1.444)

Note. SD is Standard deviations

Source: Authors estimate, 2021

to adopt farm technology since young farmers may have a better education than the non-adopter, less risk-averse, and more willing. Concerning education, on average, adopters have a higher education level. This may point out that education of the households' head matters adoption decision of improved technology. On average, adopters have a larger family size than non-adopters. Moreover, there is also a significant difference in farm sizes, livestock assets measured in Tropical Livestock Unit (TLU), and off-farm employment. The average farm size and TLU are higher for adopters than their counterparts. Besides, the share of farm households engaged in off-farm activities is higher for adopters than for non-adopters. This may indicate that households having large farm sizes, a flock of livestock assets and more opportunities to off-farm activities are more likely to adopt agricultural technologies. Furthermore, the mean distance from the all-weather road, market, and plots is larger for non-adopters, indicating that adopters have more market access, urban centers, and to their plots. Finally, institutional factors such as extension contact and credit access are higher for adopters than non-adopters. This may show that households getting extension services are expected to have access to information on agricultural technologies and their profitability, while access to credit indicates farmers' ability to finance their purchase of modern technology under cash constraints.

#### 4.2. Econometric result

The estimated results of FIML for the ESR model are presented in Table 3. The result of the Wald test rejects the hypothesis that the three equations are jointly independent at 1% level of significance. In addition, the correlation term rho in the adopter's equation is negative and statistically significant at one percent, indicating a failure to reject the hypothesis of sample selection bias. The parameter has a negative sign in the equation for adopters, inferring that those who adopt have significantly higher and those who do not adopt do have lower food consumption expenditure per adult per annum.

#### Table 3. FIML estimate of the endogenous switching regression model

		Endogenous swit	tching regression
Adoption (1/0)		Food Consumption for Adopters	Food Consumption for non-Adopters
Variables	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)
Age	002 (.004)	010 (.007)	0.014 (.007) *
Sex	.15 (.185)	074 (.384)	0.243 (.324)
Family size	.088 (.044) **	283 (.076) ***	-0.344 (.113) ***
Education level	.034(.028)	.036(.041)	.135(.071) *
Tropical livestock unit	.110 (.031) ***	.059 (.030) **	.063(.015) ***
Access to credit	.485 (.240) **	212 (.299)	-0.341 (.624)
Off-farm employment	.376 (.275)	.881 (.576)	.273 (.637)
Farm size	038 (.107)	.105 (.153)	.031 (.224)
Distance from the market	004 (.002) **		
Distance from the main road	007 (.006)		
Extension visits	1.828 (.230) ***		
Plot distance	202 (.072) ***		
Constant	532 (.411)	5.49 (.767) ***	3.25 (.811) ***
Sigma		.999 (.059) ***	.414 (.089) ***
Rho		123 (.019) ***	120 (.788)

Number of obs = 656 Wald chi2(11) = 27.17 (Prob > chi2 = 0.0000)Log pseudo-likelihood = -1713.456

\*\*\* p <.01, \*\* p <.05, \* p <.1

Source: Authors estimate, 2021

In the adoption (i.e., logit/probit) regression, the decisions of agricultural technology adoption are positively and significantly influenced by the family size of the household, tropical livestock unit (TLU), credit access, and extension visit and negatively and significantly influenced by distance from market and plot distance. This implies that the decision to adopt agricultural technology depends on whether a farm household has a larger family size, has a flock of livestock, access to credit, and extended visits, and lives near the market places and plots or not.

Farm households with more large family sizes are more likely to adopt because adoption of agricultural technology requires and attracts more labor force for agricultural activities (Mesele, 2019), and having a flock of livestock also encourages the adoption of agricultural technology because farmers who possess a flock of livestock can have a large source of income and serves as a source of inputs (organic fertilizer) (Admassie & Ayele, 2011). Moreover, farm households that have access to credit increase the adoption decision of agricultural technology because it solves the farmer's liquidity constraint and serves as the source of finance for the medium and lower-income households to buy inputs for agricultural production (Admassie & Ayele, 2011; Ayenew et al., 2020; Belay & Mengiste, 2021). Farmers that have an extension visit are more likely to adopt agricultural technologies because extension contact helps the farmers to raise their awareness about the characterization and attributes of the technology, use, in accelerating the adoption and their impact (Keba, 2019). Furthermore, farmers who live far away from marketplaces and their farm plots could reduce the probability of adoption of agricultural technologies because farmers could have less

Table 4. Estimation of	conditional expectation	s, treatment, and heter	ogeneity
	Decisio	n stage	Adoption Effect
Alternative	To Adopt	Not to adopt	
Adopters	4052.968 (.026)	2851.886 (.032)	TT = 1201.082 (.041) ***
Non-adopters	3897.753 (.051)	3388.352 (.063)	TU = 509.401(.081) ***
TH effect			TH = 691.6812(.048) ***

Notes. TT = Adoption effect for adopters, TU = Adoption effect for non-adopters, TH (TT-TU) = transitional heterogeneity

Note. \*\*\* p <.01 and Standard errors in parentheses.

Source: Authors' estimates, 2020

access to information on improved technologies, delay in adoption, and high production cost. Also, as the plot is far away from the homestead, it is the less likely that they will be have time plot preparation, weed, harvest, and input utilization (Mesele, 2019; Sebsibie et al., 2015).

Concerning determinants of food consumption expenditure per adult equivalent per annum per thousand, it is positively and significantly influenced by the age of the household head, education level of the household head, and TLU, while it is negatively influenced by the family size of the household. The non-adopters' food consumption expenditure is positively affected by TLU and negatively by the family size of the household. There are some variables, for instance, age and education level of the household head, which affect adopters but non-adopters and vice versa. This shows the heterogeneity between adopters and non-adopters (Khanal et al., 2018).

Table 4 presents the impact of the adoption of agricultural technologies on food consumption expenditure per adult equivalent per annum, which is calculated using difference between columns 2 and 3. The results show that adoption gives higher food consumption expenditure per adult per annum than non-adoption. This implies adopters who adopted have increased their food consumption expenditure per adult per annum, and, if those who do not currently adopt were to adopt it, their food consumption expenditure per adult would increase as well.

In detail, the actual average food consumption expenditure of adopters is 4052.968 birr per adult per annum but would be lower to 2851.886 birr per adult per annum if they were non-adopters. The difference between these is the adoption effect on the treated, which shows that farm households increased their food consumption expenditure by 1201.082 birr by adopting agricultural technologies. In contrast, the actual average food consumption expenditure of non-adopters is 3388.352 birr per adult per annum but would be higher to 3897.753 birr per adult per annum if they were adopters. The difference is the adoption effect on the untreated, and it shows that farm households could increase their food consumption expenditure by 509.401 birr if they were adopting agricultural technologies. Finally, the positive significant values of the transitional heterogeneity effect (TH) 691.6812 birr per adult per annum indicate that the effect of adoption would be significantly higher for the farm households who adopted relative to those who had not adopted if they had adopted.

Generally, this study finds that the adoption of agricultural technology significantly increases farm households' food consumption expenditure. Therefore, agricultural technology adoption can be considered as an encouraging pathway to raise food consumption expenditure of the households and in so doing improve the welfare of the farm households. The result of the study is consistent with the findings of Sebsibie et al. (2015), Mesele (2019), Belay and Mengiste (2021), Biru et al. (2020), and Ayenew et al. (2020). In line with the extant literature, the study approves

the potential direct role of adopting agricultural technologies on increasing consumption expenditure and in return reduces poverty.

#### 5. Conclusion and recommendation

This study examines the impact of agricultural technology adoption on food consumption expenditure in the Amhara region of Ethiopia. The study used Ethiopian socioeconomic survey data on 656 farm households collected in 2015/16 and employed the ESR model to estimate simultaneously the selection equation and outcome equation. The results of the study can be concluded as follows: first, it shows that farm households' decision to adopt farm technology is significantly influenced by household family seize, livestock asset measured by TLU, extension visit, credit access, distance from market, and plot distance. Second, the food consumption expenditure of adopters and nonadopters is significantly determined by age of the household head, education level of the head, family size, and livestock assets. Third, the average treatment effect of adoption on food consumption expenditure per adult is significantly higher for adopters than their counterparts. Also, the nonadopters significantly would have higher food consumption expenditure if they had been adopters. Thus, the study confirmed that the adoption of agricultural technologies has a positive impact on increasing food consumption expenditure per adult per annum. This suggests that there is huge potential of adopting agricultural technologies on increasing household's food consumption expenditure and thereby improving rural household welfare. From a policy perspective, this study recommends policies that aim to encourage and expand the adoption of new or improved agricultural technologies that will have a significant impact on improving household consumption expenditure, thus reducing poverty in the region and Ethiopia. Specifically, the regional and the federal government should strengthen the policy interventions and expand access to credit and agricultural extension services. Because getting credit from the public and private sectors will open opportunities for many farmers to adopt these technologies. Extension visits should be improved significantly. This is very essential to provide information about the use and benefit of modern agricultural technologies. It will also allow farmers to seek advice from the agricultural sector experts to make the best of these technologies. With regard to distance from the market, the government should make the market for buying or selling agricultural inputs or outputs near to the farm households.

#### 5.1. Limitations and areas for further research

As this study used cross-sectional data, it is limited to show the time effect of adopting agricultural technologies on the household food consumption expenditure and the household's welfare in general. Future research is recommended for examining the impact of agricultural technology adoption on consumption expenditure by using panel data.

#### Acknowledgements

We would like to thank the editor and anonymous reviewers for their supportive comments and suggestions.

#### Funding

The authors received no direct funding for this research.

#### Author details

Mesele Belay Zegeye<sup>1</sup> E-mail: mesele99belay@gmail.com ORCID ID: http://orcid.org/0000-0002-8887-177X Abebaw Hailu Fikire<sup>1</sup> E-mail: abebawhailu26@gmail.com ORCID ID: http://orcid.org/0000-0002-6356-6701 Anteneh Bezualem Assefa<sup>1</sup> E-mail: anteneh1992@gmail.com <sup>1</sup> Department of Economics, Debre Berhan University, Debre Berhan, Ethiopia.

#### **Disclosure statement**

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

#### **Citation information**

Cite this article as: Impact of Agricultural Technology Adoption on Food Consumption Expenditure: Evidence from Rural Amhara Region, Ethiopia, Mesele Belay Zegeye, Abebaw Hailu Fikire & Anteneh Bezualem Assefa, *Cogent Economics & Finance* (2022), 10: 2012988.

#### References

- Admassie, A., & Ayele, G. (2011). Adoption of Improved Technology in Ethiopia. Ethiopian Development. Research Institute (EDRI), Research Report 3.
- Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. Food Policy, 37(3), 283–295. https://doi.org/ 10.1016/j.foodpol.2012.02.013

- Asmare, F., Teklewold, H., & Mekonnen, A. (2019). The effect of climate change adaptation strategy on farm households welfare in the Nile basin of Ethiopia. International Journal of Climate Change Strategies and Management, 11(4), 518–535. https://doi.org/10. 1108/IJCCSM-10-2017-0192
- Ayenew, W., Lakew, T., & Kristos, E. H. (2020). Agricultural technology adoption and its impact on smallholder farmers welfare in Ethiopia. *African Journal of Agricultural Research*, *15*(3), 431–445. https://doi.org/ 10.5897/AJAR2019.14302
- Belay, M., & Mengiste, M. (2021). The ex-post impact of agricultural technology adoption on poverty: Evidence from north Shewa zone of Amhara region, Ethiopia. International Journal of Finance & Economics 25, 1–11. doi:10.1002/ijfe.2479
- Biru, W. D., Zeller, M., & Loos, T. K. (2020). The impact of agricultural technologies on poverty and vulnerability of smallholders in Ethiopia: A panel data analysis. *Social Indicators Research*, 147(2), 517–544. https:// doi.org/10.1007/s11205-019-02166-0
- Chirotaw, T. (2020). Adoption of improved soybean varieties and its impact on households'food security: the case of pawe woreda, Benishangul [Doctoral dissertation].
- CSA (Central Statistical Agency). (2019). Projected Population of Ethiopia\_2011. The Federal Democratic Republic of Ethiopia.
- De Janvry, A., Macours, K., & Sadoulet, E. (2017). Learning for adopting: Technology adoption in developing country agriculture, Ferdi (p. 120).
- Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. American Journal of Agricultural Economics, 93(3), 829–846. https://doi. org/10.1093/ajae/aar006
- Diriba, G. (2020). Agricultural and rural transformation in Ethiopia: Obstacles, triggers and reform considerations.
- Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. Economic Development and Cultural Change, 33(2), 255–298. https://doi.org/10.1086/ 451461
- Feyisa, B. W., & Yildiz, F. (2020). Determinants of agricultural technology adoption in Ethiopia: A meta-analysis. Cogent Food & Agriculture, 6(1), 1855817. https://doi.org/10.1080/23311932.2020. 1855817
- Jaleta, M., Kassie, M., & Marenya, P. (2015). Impact of improved maize variety adoption on household food security in Ethiopia: an endogenous switching regression approach (No. 1008-2016-80248).
- Kassie, M., Marenya, P., Tessema, Y., Jaleta, M., Zeng, D., Erenstein, O., & Rahut, D. (2018). Measuring farm and market level economic impacts of improved maize production technologies in Ethiopia: Evidence from panel data. *Journal of Agricultural Economics*, 69(1), 76–95. https://doi.org/10.1111/1477-9552.12221
- Keba, A. (2019). Review on adoption of improved agricultural technologies in Ethiopia. *Policy*, 4(1), 11–19.
- Kelemu, F. (2015). Agricultural mechanization in Ethiopian: Experience, status and prospects. Ethiopian Journal of Agricultural Sciences, 25(1), 45–60.

- Khanal, U., Wilson, C., Hoang, V. N., & Lee, B. (2018). Farmers' adaptation to climate change, its determinants and impacts on rice yield in Nepal. *Ecological Economics*, 144, 139–147. https://doi.org/10.1016/j. ecolecon.2017.08.006
- Lokshin, M., & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, 4(3), 282–289. https://doi.org/10. 1177/1536867X0400400306
- Maddala, G. S. (1986). Disequilibrium, self-selection, and switching models. *Handbook of Econometrics*, 3, 1633–1688.
- Mesele, B. Z. (2019). The impact of agricultural technology adoption on poverty reduction in rural Ethiopia [Thesis, DBU], Debre Berhan, Ethiopia.
- Rao, D. P. (2006). Poverty measurement using expenditure approach. School of Economics, University of Queensland, Brisbane, Australia.
- Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.
- Sebsibie, S., Asmare, W., & Endalkachew, T. (2015). Agricultural technology adoption and rural poverty: A study on smallholders in Amhara regional state, Ethiopia. Ethiopian Journal of Economics, 23(683– 2017–950), 117–156.
- Shita, A., Kumar, N., & Singh, S. (2018). Agricultural technology adoption and its determinants in Ethiopia: A reviewed paper. Asia Pacific Journal of Research, 1 (55), 99–104.
- Shita, A., Kumar, N., & Singh, S. (2020). The impact of agricultural technology adoption on income inequality: A propensity score matching analysis for rural Ethiopia. International Journal of Information and Decision Sciences, 12(1), 102–114. https://doi.org/10. 1504/IJIDS.2020.105013
- Tamirat, N., & Abafita, J. (2021). Adoption of row planting technology and household welfare in southern Ethiopia, in case of wheat grower farmers in Duna district, Ethiopia. Asia-Pacific Journal of Science and Technology, 26(02).
- Tefera, T., Tesfay, G., Elias, E., Diro, M., & Koomen, I. (2016) Drivers for adoption of agricultural technologies and practices in Ethiopia. A study report from, 30.
- Teka, A., & Lee, S. K. (2020). Do agricultural package programs improve the welfare of rural people? Evidence from smallholder farmers in Ethiopia. *Agriculture*, 10(5), 190. https://doi.org/10.3390/ agriculture10050190
- UNICEF (United Nations Children's Fund). (2018). Budget Brief Amhara Regional State 2007/08 - 2015/16.
- Weldegiorges, Z. K. (2015). Benefits, constraints and adoption of technologies introduced through the ecofarm project in Ethiopia [Master's thesis], Norwegian University of Life Sciences.
- Wordofa, M. G., Hassen, J. Y., Endris, G. S., Aweke, C. S., Moges, D. K., & Rorisa, D. T. (2021). Adoption of improved agricultural technology and its impact on household income: A propensity score matching estimation in eastern Ethiopia. Agriculture & Food Security, 10(1), 1–12. https://doi.org/10.1186/s40066-020-00278-2
- Zeng, D., Alwang, J. R., Norton, G., Shiferaw, B., Jaleta, M., & Yirga, C. (2014). Agricultural technology adoption and child nutrition: Improved maize varieties in rural Ethiopia. (No. 329-2016-12862).

Appendix Matrix of	correlatio	SL											
Variables	(1)	(2)	(3)	(†)	(5)	(9)	(2)	(8)	(6)	(10)	(11)	(12)	(13)
(1) Adopt	1.000												
(2) age	-0.173	1.000											
(3) sex	0.233	-0.197	1.000										
(4) off_farm_emp	0.005	-0.067	-0.008	1.000									
(5) hh_size	0.238	-0.190	0.426	0.108	1.000								
(6) dist_road	-0.141	-0.004	-0.019	-0.083	-0.072	1.000							
(7) dist_market	-0.037	-0.083	0.026	-0.095	-0.046	0.614	1.000						
(8) TLU	0.322	-0.047	0.336	-0.016	0.419	-0.026	0.095	1.000					
(9) plotdistance	-0.068	-0.110	0.148	-0.046	0.105	0.146	0.161	0.135	1.000				
(10) extension_visit	0.575	-0.127	0.235	-0.008	0.223	-0.243	-0.172	0.234	-0.058	1.000			
(11) credit_access	0.252	-0.107	0.174	0.017	0.128	-0.041	-0.017	0.064	0.017	0.283	1.000		
(12) Education	0.055	-0.121	0.044	0.061	0.049	-0.077	-0.061	-0.020	-0.021	0.105	0,040	1.000	
(13) landsize_ha	0.135	0.008	0.152	-0.020	0.182	0.042	0.069	0.425	0.105	0.066	0.086	0.040	1.000



#### © 2022 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license. You are free to:

Share — copy and redistribute the material in any medium or format.

Adapt — remix, transform, and build upon the material for any purpose, even commercially.

The licensor cannot revoke these freedoms as long as you follow the license terms.

 $(\mathbf{i})$ 

Under the following terms: Attribution — You must give appropriate credit, provide a link to the license, and indicate if changes were made. You may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use. No additional restrictions

You may not apply legal terms or technological measures that legally restrict others from doing anything the license permits.

# *Cogent Economics & Finance* (ISSN: 2332-2039) is published by Cogent OA, part of Taylor & Francis Group. Publishing with Cogent OA ensures:

- Immediate, universal access to your article on publication
- High visibility and discoverability via the Cogent OA website as well as Taylor & Francis Online
- Download and citation statistics for your article
- Rapid online publication
- Input from, and dialog with, expert editors and editorial boards
- Retention of full copyright of your article
- Guaranteed legacy preservation of your article
- Discounts and waivers for authors in developing regions

Submit your manuscript to a Cogent OA journal at www.CogentOA.com