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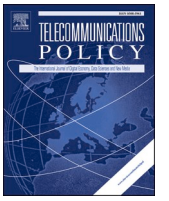

Impact of information and communication technologies on agricultural households' welfare in Benin

Gbêtondji Melaine Armel Nonvide

Faculté des Sciences Economiques et de Gestion, Université D'Abomey-Calavi, Benin

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ABSTRACT

Information technologies are very important to transform the agricultural sector and improve economic performance. Nevertheless, does the use of information and communication technologies (ICT) improve agricultural households' welfare? To answer this, the study used a nationally representative household survey, the Comprehensive Food Security and Vulnerability Analysis (CFSVA) carried out in 2017 in Benin. The survey covered a sample of 15 000 households, however, the analysis focused on the 6502 agricultural households. An endogenous switching regression model was employed to control for selection bias and endogeneity issues. Results indicated that the use of ICT increases households' consumption expenditure by 89.6%. This implies that the use of ICT improves agricultural households' welfare. Other variables that affect agricultural households' welfare include age, marital status, farm size, access to credit, ownership of livestock, membership in a farmer-based organization, and region of residence. Furthermore, the decision to use ICT in agricultural households depends on the level of education, age, sex, marital status, farm size, access to credit, ownership of livestock, membership in a farmer based organization, and location. These findings suggest that policies that promote the use of ICT are key to improving welfare of agricultural households in Benin. These policies must consider demographic, socio-economic, and institutional characteristics of households.

1. Introduction

Information is very important for improving economic performance because of its ability to limit market failures caused by the existence of information asymmetry (Stigler, 1961). Information is a condition of the exchange. It facilitates exchange and when it runs out, it becomes imperfect and suddenly we face a market failure. With information, economic agents make better economic decisions, hence the economic value of information. Access to information is expensive and can sometimes, be incomplete because of a lack of knowledge on where and how to access it. However, in the current era, defined as the digital age or the era of digitization, access to information is becoming relatively simple. According to Rong (2022), the current world is characterized by a rapid expansion of the digital economy marked by a new revolution in the Information and Communication Technologies (ICTs) sector. ICTs today constitute significant opportunities for improving the living conditions of households in various areas such as social life, education, health, economic activities, etc … (UNCTAD, 2021). ICTs provide not only information but also knowledge and facilitate communication. Any person using it effectively has an ease in managing their activities, saving their time and money (Aker & Blumenstock, 2014; Rodríguez-Castelán et al., 2021).

Thus, the use of ICTs has the potential to improve welfare by: (1) providing farming households with the necessary information on

E-mail address: melainearmel@gmail.com.

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inputs and technologies to improve farming activities and (2) linking farmers to profitable marketing markets. Mdoda and Mdiya (2022) argued that households with access to ICTs will succeed in increasing their agricultural production, by accessing market-oriented information, agricultural practices, climate information, information on new technologies and financial information. Increased agricultural production combined with marketing information will help farmers increase their production yields. In Kenya, Marwa et al. (2020) have shown that the use of ICT as an agricultural extension tool by smallholder farmers has the potential to improve yields and farmers' income, which will result in improved welfare. Similar results were found by Rodríguez-Castelán et al. (2021) in Senegal. Thus, ICTs improve working conditions, allow wealth creation in all sectors of activity and are very beneficial for both urban and rural households. ICTs therefore, have the potential to effectively combat poverty and improve the well-being of populations.

However, the digital divide persists between regions and within a region. For example, according to the UNCTAD report (2021), 90% of the populations in high-income countries have access to the internet compared to only 20% in low and middle-income countries, with an internet speed eight times higher for high-income countries. Nevertheless, there is progress in Africa where the penetration rate of mobile broadband in 2020 was almost 20 times higher than in 2010. This development has enabled low and middle-income countries to reduce the gap with high-income countries, even if the divide remains significant when it comes to mobile broadband. The technological divide is also visible between urban and rural populations. The urban-rural divide in access is most acute in low and middle-income countries, where 16% of the rural population have no access to any mobile network and 35% have no internet connection with a mobile device. However, there has been a significant improvement since 2015, when no less than 63% of the rural population of low and middle-income countries did not have mobile access to internet (UNCTAD, 2021). In Benin, according to the report of the Regulatory Authority for Electronic Communications and Post (ARCEP-BENIN) the number of mobile phone subscriptions reached more than 12.7 million customers in 2021 against more than 11.1 million customers in 2020, an increase of 14.27%. The mobile internet penetration rate is estimated at 67.36% as of December 31, 2021; that of mobile broadband is 34.67% over the same period. However, efforts are still needed to ensure that every Beninese has access to high and reliable internet connectivity. Indeed, the mobile internet base had a workforce of 8 424 296 subscribers as of December 31, 2021. With regard to fixed internet, the subscription base is 20 726 subscribers, i.e. a fixed internet penetration of 0.17% (ARCEP, 2021).

The present study therefore aims to assess the impact of the use of ICTs on the well-being of agricultural households. Majority (90%) of the population living in rural areas depend on agriculture as their main source of livelihood (Ministry of Agriculture, Livestock and Fisheries, (MAEP), 2017). Agricultural households in Benin are mostly smallholders farmers oriented towards polyculture often associated with small livestock. Maize, rice, sorghum, yams, cassava, pulses and vegetables are the main staple foods produced in the country. Benin is globally self-sufficient for cereals (except rice), roots and tubers, but it is highly dependent on imports of animal and fish products (MAEP, 2017). In this study, the focus is on phone and internet access for both computer and mobile phones. Owning a phone allows producers to connect with others to access input and output market information to positively affect their agricultural production (Aker & Mbiti, 2010; Aminou et al., 2018). With internet, producers can have access to agricultural big data and also can connect with others across regions or create a social network (Aminou et al., 2018).

Although considerable studies have been conducted on the subject, few studies have focused on Benin and moreover these studies do not analyze the link between ICT and welfare. For example, Adegbidi et al. (2012) assessed the perception of rice producers on the use of ICTs and its determinants in Benin. Aminou et al. (2018) examined the effect of mobile phone ownership on the productivity of maize producers. Besides, the present study provides more coverage in terms of scope compared to previous studies (Adegbidi et al., 2012; Aminou et al., 2018) on Benin. It uses nationally represented survey data. In methodological terms, taking into account the problems of selection and endogeneity remains limited in the majority of studies. Those (Marwa et al., 2020; Khan et al., 2022) who have considered it have generally used propensity score matching techniques, whereas this method only controls for biases due to observable factors and not those due to unobservable factors. To fill this gap, and control the biases due to both observable and unobservable factors, the study employs a more rigorous econometric approach, the endogenous switching regression model. The advantage of this model is the use of complete information to simultaneously estimate the selection and outcome equations. This model can also be used to compare expected outcomes under actual and counterfactual conditions (Asfaw et al., 2012; Carter & Milon, 2005; Di Falco et al., 2011; Nonvide, 2019). In terms of policy, the present study makes a significant contribution to the evaluation of the effectiveness of the use of ICTs in Benin, as well as in the West African region, where the journey towards the realization of the objective of improving welfare (Sustainable Development Goal- 3) is particularly demanding.

The rest of the paper is organized as follows. Section 2 presents the methodological approach followed by results and discussion in section 3. Finally, section 4 concludes.

2. Material and methods

2.1. Empirical approach

(a) Model of analysis

Following previous studies (Nonvide, 2019; Khan et al., 2022; Soglo & Nonvide, 2019) the present study is built on the expected utility theory which is used as a tool for analyzing situations in which the outcome is uncertain. Thus, a household's decision to use ICT can be analyzed under the random utility framework. The use of ICT can be viewed as a binary choice decision problem by farm households trying to maximize utility or net returns, especially increased productivity and improved living conditions. Let U_{i1} be the utility obtained by a household *i* from the use of ICT; U_{i0} the utility of non-use; Xi a vector of household socio-economic characteristics

and institutional factors influencing ICT use, and ϵ_i the error term. Depending on the state of adoption, the utility of household i can be expressed as follows:

$$\begin{cases} U_{i0} = f(X_{i0}) + \varepsilon_{i0} \\ U_{i1} = f(X_{i1}) + \varepsilon_{i1} \end{cases} \quad (1)$$

A household i will choose to use ICT only if the utility derived from use is greater than the utility from non-use; which is mathematically expressed as: $U_{i1} > U_{i0}$. However, utility is not observable, only the decision of the household is observed. Utility can therefore be expressed in the following latent model:

$$A_i^* = \gamma X_i + \varepsilon_i \quad (2)$$

$$A_i = \begin{cases} 1 \; if A_i^* > 0 \\ 0 \; if \; A_i^* < 0 \end{cases}$$

where A_i is a binary variable that takes the value 1 for the use of ICT and 0 otherwise. In the context of the present study, the use of ICT is noted when the household declares having phone and/or computer and has made an expenditure for the purchase of telephone credit (fixed and mobile) and/or internet connections either for mobile phone or computer.

The outcome variable (welfare) is considered as a linear function of the binary variable of ICT use and the other explanatory variables known as control (see equation (3)).

$$Y_i = \lambda X_i + \beta A_i + \mu_i \quad (3)$$

where Y_i represents the outcome variable (welfare). The total annual consumption expenditure is used as proxy for welfare. Xi is the vector of selected explanatory variables according to the literature (Meso et al., 2005; Pénard et al., 2015; Mittal & Mehar, 2016; Abebe & Mammo Cherinet, 2019; Hoang, 2020; Marwa et al., 2020; Rodríguez-Castelán et al., 2021). These include age, gender, marital status, level of education, household size, farm size, access to credit, ownership of livestock, membership of farmer-based organization (FBO), and regions dummies. λ and β are parameters to be estimated and μ the error term.

(b) Choice of estimation method

Estimation of equation (3) poses the problem of double causality since the use of ICTs influences households' welfare, but at the same time, households that use ICTs may be those that have a higher level of consumption and therefore a better status of welfare. This reverse causality creates the problem of endogeneity. Moreover, self-selection generally occurs in the process of adopting technologies since individuals are the ones that decide whether or not to use ICTs. Then, due to certain unobservable characteristics, including but not limited to skills, motivation, risk preference, some individuals are more likely to use ICTs than others. These two problems are well known as selection and endogeneity biases, and their control requires appropriate econometric techniques. Difference-in-difference (DD) method seems to be the best technique, however, it is limited to studies with baseline survey data and is only appropriate for studies using panel data (Marwa et al., 2020; Khan et al., 2022). In the absence of baseline survey data, commonly used alternative methods include the Heckman selection model, propensity score matching method, instrumental variable method, and endogenous switching regression models (Mendola, 2007; Asfaw et al., 2012; Di Falco et al., 2011; Houeninvo et al., 2020; Nonvide 2017, 2019; Verkaart et al., 2017).

All these methods are complementary and rely on assumptions. For example, the selection assumption on observable factors in the propensity score matching approach is no more restrictive than eliminating weak instrument problems with Heckman and IV models (Jalan & Ravallion, 2003; Nonvide, 2020). Heckman's two-step estimation has the advantage of controlling for differences in observed attributes, in addition to unobserved attributes between the treated and control groups by including the inverse of the mills ratio as an additional regressor in the result equation. However, the main drawback of this method is that the estimation relies on a strong assumption of normally distribution (Ali & Abdulai, 2010; Khan et al., 2022; Kiiza et al., 2011). Although the propensity score matching technique does not depend on the functional form, it relies on two strong assumptions: the conditional independence assumption and the common support assumption. In other words, selection is only based on observable characteristics. Therefore, the propensity score matching technique is limited because it does not control for unobservable factors. The instrumental variable (IV) method gives unbiased and consistent estimates in the presence of hidden biases, however, the main disadvantage of the IV method is that it is often difficult to find at least one variable in the selection model to serve as an appropriate instrument that should influence the probability of treatment, without being correlated to the term of error (Woodridge, 2002; 2011; Marwa et al., 2020). This last condition is difficult to test, and the choice of a valid instrument depends largely on intuition and economic reasoning. Furthermore, the IV approach generally reduces the precision of causal estimates and introduces new uncertainty, besides the difficulty of testing hypotheses (DiPrete & Gangl, 2004; Kiiza et al., 2011).

As part of the present study, endogenous switching regression models are estimated. The main advantage of this model compared to the others is the joint estimation of the selection and outcome equations through a full information maximum likelihood (FIML) estimator (Asfaw et al., 2012; Carter & Milon, 2005; Nonvide, 2019). Another advantage is that endogenous switching regression models allow counterfactual analysis. In other words, the model will make it possible to evaluate by how much the level of consumption of a non-user of ICTs would have improved if he had used ICTs, and the loss for the one who used in case of non-use.

(c) Estimation techniques

Estimation of the endogenous switching regression (ESR) model consists of separate estimates for ICT users and non-users. This suggests that the use of ICT becomes the selection criterion indicating to which regime the household belongs. Then, the level of consumption is observed for both groups (Maddala, 1983; Di Falco et al., 2011; Nonvide, 2019).

$$\text{Regime 1}: Y_{1i} = \alpha_1 X_{1i} + v_{1i} \quad \text{if} \quad A_i = 1 \text{ (for ICTs users)} \tag{4}$$

$$\text{Regime 2}: Y_{2i} = \alpha_2 X_{2i} + v_{2i} \quad \text{if} \quad A_i = 0 \text{ (for non-users)} \tag{5}$$

where Y_i represents total consumption expenditure. X*i* is the vector of explanatory variables, v_i is the random perturbation term for each group. Unobserved factors affecting the probability of using ICTs could also affect the level of total consumption, thus, the error term in equation (2) and those in equations (4) and (5) could be correlated, raising problems of endogeneity and self-selection. To account for this, equations (2), (4) and (5) were estimated simultaneously using Full Information Maximum Likelihood (FIML), which is the most efficient estimation strategy (Lokshin & Sajaia, 2004).

Estimation of the ESR model requires that the exclusion restriction assumption is met. Therefore, the education level variable (none, primary, secondary, university), included in the selection equation, was excluded from the outcome equation, to satisfy the model's identification condition (Sinyolo et al., 2014; Nonvide, 2022). The rationale is that education is strongly correlated with ICTs use, so educated people are more likely to adopt ICTs, but this does not directly influence household welfare. Indeed, to use ICTs, individuals need certain aptitudes and skills since these technologies work in French or in other international languages. Therefore, to be able to use ICTs, one must know how to read and write French. Labonne and Chase (2009) argued that within a household, an educated relative can help people with no schooling and motivate them to use ICTs. These hypotheses were confirmed by the positive and significant sign of the coefficients associated with the different levels of education.

Based on previous studies (Asfaw et al., 2012; Carter & Milon, 2005; Di Falco et al., 2011; Heckman et al., 2001; Nonvide, 2019), the ESR model is used to compare the expected outcomes (level of total consumption) of ICT users (a) with those of non-users (b), and to study the expected outcomes in counterfactual cases (c) that users have not adopted, and (d) that non-users have adopted. These measures are essential to explain the difference in consumption between the two groups. Table 1 presents the conditional expectations of total consumption expenditure for the four cases.

Equation (6) calculates the treatment effect on the treated (TT) as the difference between (a) and (c):

$$TT = E(y_{1i}|A_i = 1) - E(y_{2i}|A_i = 1) \tag{6}$$

Similarly, the treatment effect on the untreated is expressed as:

$$TU = E(y_{1i}|A_i = 0) - E(y_{2i}|A_i = 0) \tag{7}$$

The study differentiates between treatment effects and base heterogeneity effects. The base heterogeneity effect is expressed as the difference between (a) and (d).

$$BH_1 = E(y_{1i}|A_i = 1) - E(y_{1i}|A_i = 0) \tag{8}$$

For non-users, the base heterogeneity effect is expressed as the difference between (c) and (b):

$$BH_0 = E(y_{2i}|A_i = 1) - E(y_{2i}|A_i = 0) \tag{9}$$

Finally, the transitional heterogeneity effect, which allows us to determine whether the impact of ICTs use by the household is smaller or larger for the user and the non-user compared to the counterfactual scenario, is calculated as follows:

$$TH = TT - TU \tag{10}$$

STATA software version 15 was used for the estimations with the command "movestay" (Lokshin & Sajaia, 2004).

2.2. Data

Data used in this study come from the Comprehensive Food Security and Vulnerability Analysis (CFSVA) carried out in 2017 in

Table 1
Conditional expectations, treatment and heterogeneity effects.

Sub-groups	Decision stage		Treatment effects
	Use	Not use	
ICTs users	(a) $E(y_{1i}\|A_i = 1)$	(c) $E(y_{2i}\|A_i = 1)$	TT
Non users	(d) $E(y_{1i}\|A_i = 0)$	(b) $E(y_{2i}\|A_i = 0)$	TU
Heterogeneity effects	BH_1	BH_0	TH

Note: (a) and (b) are the observed outcomes; (c) and (d) are the counterfactual expected outcomes. TT: Effect of the treatment on the treated; TU: Effect of the treatment on the untreated; BH1: Base heterogeneity effect for ICTs users; BH0: Base heterogeneity effect for non-users; TH: Transitional heterogeneity effect.

Benin by the National Institute of Statistics and Economic Analysis (INSAE), the Ministry of Agriculture, Livestock and Fisheries (MAEP), the Ministry of Health (MS) and the World Food Program (WFP). The survey covered a sample of 15 000 households, representative at national, departmental, communal level and by place of residence. This sample was drawn using a two-stage sampling technique. First, 750 clusters were selected among the 920 clusters surveyed during the 2015 Standard of Living Survey. In a second step, 20 households were systematically selected in each cluster. The sample was drawn by urban/rural stratum at the level of each municipality. Thus, a total of 148 strata were defined and households in the sample were distributed in each department in proportion to their size. Finally, 8320 households were surveyed in rural areas whereas 6680 in urban areas from July 20 to August 20, 2017 in Benin. The analysis focused only on the 6502 agricultural households covered by the survey.

3. Results and discussion

3.1. Descriptive statistics

Summary statistics of socio-economic characteristics of the surveyed respondents are reported in Table 2.

About 51% of the surveyed agricultural households were located in the northern region against 15% in central region and 33% in the southern region. The average age of household head was 46 years, and majority were male and married with an average of four (4) household's member. Only 18% of the household heads had primary education, against 9% and 1% for secondary education and university degrees respectively. Farm production is still dominated by small land size as the average farm size was estimated at 3.4 ha. About 55% of households owned livestock, 30% had access to credit, and 51% to media (radio or TV). About 4% of households had a member who migrated during the 12 months prior to the survey. Concerning, the use of agricultural technologies, 6%, 8% and 22% of the surveyed households declared using irrigation, improved seeds, and organic fertilizers, respectively. About 45% used herbicide while 56% applied chemical fertilizers. Maize is the main crop produced by 68% of the surveyed respondents. Only 6% of household heads were members of a community cooperative, 56% owned phones (either fixed or mobile) against 0.8% that declared having computer. It can be noted that all households that owned a computer also owned a phone. On average, the annual households consumption expenditure was estimated at CFA 915 732 (equivalent of USD 1573) while they spent CFA 78 916 (equivalent of USD 135.5) for the purchase of credit or internet for mobile phone or computer.

3.2. Comparison of ICTs users and non-users

A difference test was performed to analyze any significant difference between ICTs users and non-users (Table 3). A *t*-test was used when the variable is continuous while a chi-square test was applied for categorical variables. About 56.2% of the surveyed households own either phone or computer, and declared having made an expenditure for the purchase of credit for mobile phone and/or internet for phone or computer. This means that these households use ICTs. Comparison of ICTs users and non-users indicated no significant differences observed between ICTs users and non-users for the variables household size, farm size and being in central region. About 57% of ICTs non-users were in the northern region compared to 46% users; while 37% of ICTs users were in the southern region against 27% non-users. The mean age of the ICTs users was 45 years against 48 years for non-users implying that relatively young people use ICTs compared to the older people. About 92% of ICTs users were married against 86% of non-users. Regarding gender, men used more digital technologies than women. With respect to the ownership of livestock, it is observed a significant difference between the groups with 56% of ICTs users owning livestock against 53% of non-users. Similarly, a significant difference was also observed in term of maize production, with about 71% of ICTs users producing maize as main crop compared to 66% of non-users. There were also significant differences between the two groups regarding the institutional variables. For instance, the ICTs users were more educated compared to non-users. About 33% of ICTs users had access to credit against 26% of non-users. Overall, membership of FBO was low but there were significant differences between ICT users (7.2%) and non-users (4.9%).

3.3. Estimates of the impact of ICTs use on household consumption expenditure

The use of the endogenous switching regression model is validated by the significance of the likelihood ratio test, suggesting that self-selection occurred in the process of ICTs adoption as well as the endogenous nature of ICTs use. Under these conditions, the ordinary least squares (OLS) estimates would have been biased. The ESR model presents both results of the selection equation (factors affecting the decision to use ICT) and the outcomes equations (impact of the use of ICT on household welfare measured here by household consumption expenditure). The results from the outcomes equations indicated that age, marital status, farm size, access to credit, ownership of livestock, membership of FBO and region of residence of the respondent, significantly influence consumption expenditure among ICTs users. The same variables, with the exception of livestock ownership, also determined the consumption expenditure of households that were not using ICTs.

Age was positively associated with consumption expenditure up to 80 years for ICTs users and 69 years for non-users, after which the consumption expenditure decreased. Being married increased the consumption expenditure among the surveyed households. A positive relationship is observed between farm size and consumption expenditure, suggesting that households with large farm spend more compared to households with small farm. Households with livestock were also found to have a significantly higher consumption expenditure. Access to credit and membership of FBO were the institutional variables that affected consumption expenditure. These variables were found to be positively associated with consumption expenditure, indicating that households with access to credit and those being members of FBO have a significantly higher consumption expenditure. In term of location, the results indicate that

Table 2
Summary statistics of socio-economic characteristics of the surveyed respondents.

Continuous variables	Mean	Standard deviation	Minimum	Maximum
Age (in year)	46.5	14.1	16	100
Household size (number)	3.5	2.7	2	50
Land size (in ha)	3.4	1.8	1	6
Number of technologies adopted (number)	1.4	1.1	0	5
Annual expenditure on telephone credit or internet connections (in CFA)	78 916	168 764	0	600 000
Annual households' consumption expenditure (in CFA)	915 732	1 509 744	36 000	7 573 000
Binary variables	**Proportion (%)**	**Standard deviation**	**Minimum**	**Maximum**
Married (yes = 1)	90	0.3	0	1
Male (yes = 1)	89	0.3	0	1
Primary education (yes = 1)	18	0.4	0	1
Secondary education (yes = 1)	09	0.3	0	1
University (yes = 1)	01	0.1	0	1
Ownership of livestock (yes = 1)	55	0.5	0	1
Credit access (yes = 1)	30	0.5	0	1
Access to media (1 if radio or TV)	51	0.5	0	1
Migration (yes = 1 if at least one household member migrate in the last 12 months)	04	0.2	0	1
Use of irrigation (yes = 1)	06	0.2	0	1
Use of improved seed (yes = 1)	08	0.3	0	1
Use of herbicide (yes = 1)	45	0.5	0	1
Use of chemical fertilizers (yes = 1)	56	0.5	0	1
Use of organic fertilizers (yes = 1)	22	0.4	0	1
Being member of community cooperative (yes = 1)	06	0.2	0	1
Northern region (yes = 1)	51	0.5	0	1
Central region (yes = 1)	15	0.4	0	1
Southern region (yes = 1)	33	0.5	0	1
Maize as main crop (Yes = 1)	68	0.5	0	1
Ownership of phone (yes = 1)	56	0.5	0	1
Ownership of computer (yes = 1)	08	0.1	0	1

Note. CFA is Benin currency. Average exchange rate in 2017: USD 1 = CFA 582.21.
Source: Calculation based on the 2017 CFSVA data

Table 3
Comparison of ICTs users and non-users.

Variables	All	ICTs users	Non-users	*t*-test/chi2 value
ICT *(1 if household owns phone or computer, and having purchase credit for mobile phone or internet connections for mobile phone or computer)*	–	0.562	0.438	–
	–	–	–	–
	–	–	–	–
Annual households' consumption expenditure (in CFA)	915 732 (1 509 744)	1 136 211 (1 844 635)	632 503 (69 433.87)	- 13.53*** –
Age (in year)	46.46 (14.11)	45.11 (13.40)	48.20 (14.80)	8.80*** –
Married (yes = 1)	0.90	0.92	0.86	80.30***
Male (yes = 1)	0.89	0.93	0.84	110.55***
Household size (number)	3.51	3.49	3.55	0.90
Primary education (yes = 1)	0.18	0.22	0.12	114.23***
Secondary education (yes = 1)	0.09	0.14	0.04	194.43***
University (yes = 1)	0.01	0.016	0.002	32.03***
Farm size (in ha)	3.43	3.44	3.43	−0.25
Ownership of livestock (yes = 1)	0.55	0.56	0.53	8.46***
Maize as main crop (yes = 1)	0.30	0.33	0.26	31.94***
Credit access (yes = 1)	0.68	0.71	0.66	18.47***
Being member of farmer based organization (yes = 1)	0.062	0.072	0.049	15.17***
Northern region (yes = 1)	0.51	0.46	0.57	81.98***
Central region (yes = 1)	0.15	0.16	0.14	1.48
Southern region (yes = 1)	0.33	0.37	0.27	75.32***

Note: Calculation based on the 2017 CFSVA data; Values in parentheses are standard deviation.
* Significant at 1% ($p < 0.01$).

households in the southern region had a significantly higher consumption expenditure compared to those in northern region, while those in central Benin also have a significantly lower consumption expenditure.

Table 5 presents the expected consumption expenditure under actual and counterfactual conditions. Cells (a) and (b) represent the

expected consumption expenditure observed in the sample for ICT users and non-users respectively. We observed that the expected consumption expenditure for households that use ICT was higher than the group of those that did not use. Based on this simple comparison, it could be misleading to attribute the difference in consumption expenditure to households' use of ICT. In the counterfactual case (c), it was clearly shown that the treatment effect for ICT users is 0.64. This is equivalent to 89.6%[1] difference in the average consumption expenditure. In other words, if ICT users had not used ICT, their consumption expenditure would have been decreased by 89.6%. In the counterfactual case (d) if ICT non-users had used ICT, their consumption expenditure would have been increased by 266.9%. In this line, the transitional heterogeneity effect is negative, implying that the effect of ICT on consumption expenditure is significantly lower for households who actually used ICT compared to those that did not use.

The findings from ESR estimates indicate that the use of ICT increases households 'consumption expenditure by 89.6%. This reveals a greater impact of ICTs use on agricultural household welfare in Benin. These results are in line with previous studies that have shown the potential of ICTs in improving household welfare. Indeed, Bahia et al. (2020) have shown that, after one year of coverage, the deployment of mobile broadband internet in Nigeria has boosted households' consumption by 6.0% and reduced extreme poverty by 4.3%. After three years, the corresponding figures were 9.0% increase in consumption and 6.8% reduction in poverty. In rural and geographically isolated areas of Philippines, the introduction of a new telephone tower between 2016 and 2018 resulted in a 17% and 10% increased household's income and expenditure respectively (Blumenstock et al., 2020). In Kenya, the use of ICT-based iCow services has increased households income by 22% (Marwa et al., 2020). Moreover, a recent study by Rodríguez-Castelán et al. (2021) showed that internet coverage in Senegal is linked to a 14% expansion in total consumption and a 10% decline in extreme poverty.

In addition, the study tested whether the impact of the ICTs on households' welfare differs across vulnerable groups. For this, the following groups were considered: women versus men, rural area versus urban area, educated versus non-educated, and poor versus non poor. For this latter category, a household is considered as a poor when its expenditure is less than 1.90$ per day. Thus, 53.23% of the surveyed agricultural households were found to be poor. Table 6 presents the treatment effects derived for each group. Analysis of the results indicated that the use of ICT favored both women and men with a greater impact for women compared to men. Indeed, the use of ICT increased households' expenditures by 109.59% for women against 87.76% for men. This exact percentage difference was calculated following Asfaw et al. (2012) as presented above. Similarly, the use of ICT increased households' expenditure by 87.76% for households in rural area against 93.47% for those in urban area. This implies that ICTs users in urban area households were more favored compare to those in rural area. Compared to non-educated, educated households were able to realize the potential of using ICT as their expenditures increased by 103.9% compared to 99.37% for non-educated. Finally, the use of ICT favored both poor and non-poor, however, the impact was greater for poor. Indeed, the use of ICT increased households' expenditures by 89.64% for poor and 87.76% for non-poor.

3.4. Factors affecting the use of ICT

Analysis of the results of the selection equation (Table 4) showed that apart from the level of education, the decision to use ICTs is strongly influenced by variables such as: age, sex, marital status, farm size, access to credit, ownership of livestock, membership of FBO, and location. Indeed, the squared age variable had a negative and significant coefficient, which suggests that older people were less likely to use ICTs. Married men had a higher probability of using ICTs. Households with large farm and those with livestock had a higher probability of using ICTs compared to other households. Institutional variables such as access to credit and membership of FBO had a positive influence on the probability of using ICTs. Compared to households living in northern Benin, those living in the central and southern Benin were more likely to use ICTs. These findings are in line with previous studies that identified demographic and socioeconomic characteristics, as well as institutional variables as drivers of ICTs use. For example, Meso et al. (2005) argued that factors that affect ICTs use are generally related to age, education level, and gender. In the same vein, Pénard et al. (2015) found that in Cameroon, ICTs adoption decision is mainly influenced by age, gender, education and computer skills. Similar results were found by Martínez-Domínguez and Mora-Rivera (2020) in rural Mexico. In India, Mittal and Mehar (2016) reported that farmers with a higher education level are more likely to use mobile phones and internet, while Hoang (2020) found that young male farmers, and those who participated in training programs, tended to use ICTs particularly mobile phones in Vietnam. In Ethiopia, a study by Abebe and Mammo Cherinet (2019) reported that education and training were positively associated to the probability of using ICTs among cereal farmers.

4. Conclusion

Although, the rapid diffusion of ICTs is key for the economic transformation in low and middle-income countries, the literature on the impact of ICTs use remains limited. On this basis, the present study assessed the impact of ICTs use on agricultural households' welfare in Benin using data from the household survey on the CFSVA carried out in 2017. To control for selection bias and endogeneity issues, an endogenous switching regression model is estimated. Results indicated that the use of ICTs improves agricultural households' welfare. Other determinants of welfare include age, marital status, farm size, access to credit, ownership of livestock, membership of FBO and region. Variables such as level of education, age, being male, marital status, farm size, access to credit, ownership of

[1] The treatment effect in this unit is interpreted as percentage difference. Actually, when the outcome variable is log-transformed, multiplying the TT by 100 is an approximation. According to Asfaw et al. (2012) the exact percent difference is given by 100 ($e^{TT} - 1$), where e is exponential e and TT is the average treatment effect provided by the analysis of the log-transformed variable.

Table 4
Estimates of the endogenous switching regression model.

Dependent variable: log consumption expenditure	Selection equation	Outcomes equations	
		ICT users	Non-users
Age	0.00743	0.0186***	0.0136**
	(0.00635)	(0.00479)	(0.00598)
Age square	−0.000123**	−0.000116**	−9.82e-05*
	(6.07e-05)	(4.72e-05)	(5.64e-05)
Male (yes = 1)	0.328***	−0.0568	0.120**
	(0.0608)	(0.0600)	(0.0576)
Marital status (1 if married, 0 otherwise)	0.232***	0.141**	0.241***
	(0.0626)	(0.0559)	(0.0577)
Primary education (yes = 1)	0.414***	–	–
	(0.0473)	–	–
Secondary education (yes = 1)	0.836***	–	–
	(0.0686)	–	–
University (yes = 1)	1.253***	–	–
	(0.195)	–	–
Household size (in number)	−0.00639	0.00405	0.000436
	(0.00617)	(0.00472)	(0.00609)
Farm size (in ha)	0.0617***	0.101***	0.123***
	(0.0109)	(0.00883)	(0.0125)
Credit Access (Yes = 1)	0.128***	0.132***	0.190***
	(0.0359)	(0.0281)	(0.0386)
Ownership of livestock	0.125***	0.112***	0.0305
	(0.0333)	(0.0258)	(0.0331)
Member of farmer based organization (yes = 1)	0.220***	0.138***	0.154**
	(0.0682)	(0.0438)	(0.0780)
Region (reference: Northern region)	–	–	–
Southern region (yes = 1)	0.413***	0.0788*	0.172***
	(0.0435)	(0.0424)	(0.0523)
Central region (yes = 1)	0.270***	−0.0784*	−0.242***
	(0.0507)	(0.0426)	(0.0579)
Constant	−1.035***	10.11***	9.091***
	(0.175)	(0.172)	(0.173))
Rho_0		−0.043 (0.092)	
Rho-1		- 0.582 (0.085)***	
Log likelihood: 11571.041 Wald chi2(11) = 292.46 Prob > chi2 = 0.0000			
LR test of indep. eqns. : chi2(2) = 26.66 Prob > chi2 = 0.0000			
Observations	6502	6502	6502

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

Table 5
Impact of ICT on consumption expenditure: Conditional expectations, treatment and heterogeneity effects.

Sub sample	Decision stage		Treatments effects
	Use of ICT	Non-use of ICT	
ICT users	(a) 10.97 (0.0043)	(c) 10.33 (0.0047)	TT = 0.64 (0.0064)***
ICT non-users	(d) 11.64 (0.0049)	(b) 10.34 (0.0054)	TU = 1.30 (0.0074)***
Heterogeneity effects	$BH_1 = -0.67$ (0.0066)***	$BH_0 = -0.01$ (0.0072)	TH = −0.66 (0.00012)***

Note: *** significant at 1%; Values in parentheses are standard errors. TT: Effect of the treatment on the treated; TU: Effect of the treatment on the untreated; BH_1: Base heterogeneity effect for adopters; BH_0: Base heterogeneity effect for non-adopters; TH: Transitional heterogeneity effect.

Table 6
Impact of the use of ICT on household welfare across disaggregated group.

	women	men	rural	urban	educated	Non-educated	Poor	Non-poor
TT	0.74***	0.63***	0.63***	0.66***	0.71***	0.69***	0.64***	0.63***
	(0.275)	(0.259)	(0.273)	(0.2785)	(0.2665)	(0.2775)	(0.2675)	(0.2725)

Note: *** significant at 1%; Values in parentheses are standard errors. TT: Effect of the treatment on the treated.

livestock, membership of FBO, and location, influence the agricultural households' decision to use ICTs.

These findings suggest that policies that promote the use of ICTs are important to improve agricultural households' welfare in Benin. When promoting the use ICTs, demographic, socio-economic, and institutional characteristics of households should be considered. A key policy variable is education which can be put in place in form of digital training programs. For further research, it is

important to deepen the analysis on how education could enhance the benefits of using ICTs. It would also be interesting to estimate and identify which ICTs instruments have the highest impact on the households' welfare.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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