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The Impact of Internet Use on Income: The Case of Rural Ghana

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Abstract: This study analyzed the effects of internet use on farm income and household income using survey data from 478 rural farmers from two regions in Ghana. An endogenous switching regression (ESR) model and probit models were employed to achieve the aims of the study. The results revealed that internet use was influenced by off-farm employment, education, access to credit, non-fixed asset (NFA), age, and perception variables. We found that internet use increased farm income and household income by 20.1% and 15.47%, respectively. Regarding heterogeneous impacts, the estimates showed that internet use reduced farm income by 18.12% for farm households that participated in off-farm activities but increased farm income by 14.66% for households that had access to NFA. The estimates also indicated that internet use increased household income by 31.77% for farm households that engaged in off-farm employment and by 15.33% for those that had access to NFA. Furthermore, internet use increased the household income for households that did not engage in off-farm activities by 24.85%. The findings of this study will contribute significantly to the existing literature on information communication technology (ICT) in developing countries by providing a new reference for improving rural development and solving the problem of poverty.

Keywords: internet use; income; endogenous switching regression; probit model; rural Ghana

1. Introduction

Many years ago, communication technology companies, policymakers, administrators, and entrepreneurs regarded rural and poor markets as expensive and complex to serve. However, the world population continues to increase, and there is a need to enhance the livelihood in rural communities in order to ensure equity. Therefore, policymakers and stakeholders are paying more attention to rural development. New technologies and times have significantly changed, allowing what was once considered unimportant (rural communities) to become essential production zones. The current population of Ghana is estimated to be 31,072,940, and about 56.7% (17,625,567) of the population is living in urban areas while 43.3% (13,447,373) is living in rural areas as of January 2020, compared with 56.1% (17,067,171) in 2019. This indicates that approximately 0.6% (558,396) has moved from the rural areas to the urban areas in about a month. This is because most people living in the rural areas are poor and want to have a better life in the big cities. If this is not addressed, the youth will continue to abandon the rural communities to settle in the cities.

Current evidence revealed that the number of young farmers in several developed countries, such as the United States and European countries has decreased as a consequence of technological, social, and economic changes [1]. Regarding rural–urban migration, several studies [1,2] also found that the decrease in the number of young farmers was influenced by aging farmers' unwillingness to pass the farm to new generations due to educational, financial, and motivational reasons. This does not necessarily depend on economic incentives. However, it is related to young farmers' previous experience with the farming community, family members, and whether they were given responsibilities in the farm business [1,2]. This implied that even when young farmers were highly motivated, economic conditions that negatively affect the farming sector can reinforce the decision to leave the farm.

It is a critical call for Ghana as a nation to address this issue as soon as possible before it becomes unmanageable, as rural agriculture is the major backbone of food security worldwide [3–7]. Currently, collaborators are acknowledging the political and economic importance of the more than half of the world's population that lives in mostly unexploited rural communities. Governments and non-governmental organizations are highly concerned with addressing the economic development goals and stability. Thus, they are paying more attention to the rural areas and using private sector collaborations with the government to take responsibility in developing the rural communities to either stop or reduce rural–urban migration; hence, ensuring sufficient future food security as these same rural people are responsible for the food security of the country.

In the 21st century, there are new ideas, new producers, new consumers, and new collaborations that can develop a global environment rapidly through coordination with the private sector. The incredible opportunities to address these problems through the internet and information communication technologies (ICTs) are, however, yet to circulate in the rural areas of Ghana. Progressively powerful, flexible, and economical, the ICTs of today have amazing new opportunities for social and economic incorporation that serves not only the large cities but also demands to create an environment and necessary internet mechanisms to enhance rural development as, globally, the rate of internet use is growing fast [7–9].

Global internet users grew by 8.6 percent over the past twelve months, with 350 million new users contributing to an overall total of 4.437 billion, indicating that more than half of the world's population is using the internet [10,11]. Internet use is expanding rapidly in the world due to the significant benefits. The proportion of households using the internet in developing countries increased from 7.7% in 2005 to 41.3% in 2017, while in less-developed countries it increased from 0.8% to 17.5% over the same period. For example, the rate of internet users in Ghana increased from 15% in 2013 to 35% in 2017; in South Africa, it increased from 33% in 2013 to 51% in 2017, while in China it increased from 37% in 2013 to 68% in 2016 [12].

The digital divide in internet connections exists worldwide. Thus, the percentage of households with the internet in 2017 was approximately 84.22% for the European countries, followed by 65.27% for the United States and Asia and Pacific (48.09%). In African countries, only 17.99% of households use the internet. However, scant studies have concentrated on the quantitative effects of internet use on agricultural production and household income. Other researchers have paid close consideration to the quantitative impacts of smartphone communication service, smartphone short message services, and on-farm households [13–16].

Nevertheless, comparing traditional mobile phone communication service (e.g., point to point) and mobile phone short messages service (e.g., multilink point to point) ICTs, the benefit of the internet permits several concurrent online facilities. Fafchamps and Minten (2012) observed that short message services of smartphones might not enhance the cost and value of agricultural products and might otherwise decrease the harm to rural household farmers as a result of the extreme weather. A study showed that the internet was more adequate than non-smartphones (mobile phones) for regulating rural household market participation [17]. The internet, in its beginning, was simply a substitute and fairly blunt communication instrument. However, because of the possibility of sending an electronic mail from one person to another, the internet remains a communications tool.

As it has grown more commonly accessible, the internet has become better unified into other parts of the economy. The simple e-mail scheme of sending a note has evolved to incorporate blogs, instant messaging (IM), text messaging, Facebook, WhatsApp, WeChat, Instagram, and Twitter. Business, household, and government activities have moved onto internet platforms [18,19]. Several internet events are self-sustaining as companies upgrade their systems with automatic ordering, billing, and payment functions for households and businesses. The internet is integral to the development and functioning of the digital and information economy.

Rural Ghana has not been left out. From the outset, equal access to the internet has been a contentious issue. The farm sector of the rural economy assisted in enhancing agricultural internet use [20,21], and farming businesses and households have become almost as likely as their urban counterparts to use the internet [22–24]. Access to internet technologies, however, has been less widespread in rural areas than in the more densely populated areas of the country. Internet access has become the root of today's policymakers debates, and the focus is on providing equal access to both urban and rural communities across the country [25].

The internet has also advanced more stable social interactions (Facebook, WhatsApp, WeChat, and many others) between individuals from different backgrounds, such as race, gender, and age, that often activate unjustified assumptions about the interests and capabilities of members of various social categories, as well as policymakers [26–31]. The use of the internet could enhance the quality of rural household life with access to buy goods and services, marketing, and selling of products online and by making online payments. Currently, the most popular activities Ghanaians use the internet for are text messaging 53%, to make or receive payments 60%, and taking photos or videos 61% [12,32]. Moreover, over 10 million Ghanaians use the internet nationwide. The connectivity rate of rural Ghana continues to increase; however, unfortunately, there are no data on the connectivity rates in Ghana. Although fixed and mobile connectivity exist in Ghana, compared with fixed connectivity, mobile connectivity is extensive among both urban and rural areas. The majority of Ghanaians prefer mobile connectivity to the fixed one because it is easy to access and convenient. Mobile connectivity comes with 3G or 4G mobile coverage.

Furthermore, digital technologies have advanced more rapidly than any innovation in both developed and developing countries, reaching around 50% of the developing world population in only two decades and transforming societies by enhancing connectivity, financial inclusion, access to trade, and public services. The impact of digital connectivity in the health sector, for instance, includes algorithm (Al) enabled frontier technologies that are helping to save lives, diagnose patients, and extend life expectancies [33]. In education, virtual learning environments and distance learning have opened up online programs to students who would otherwise be excluded.

Currently, digital technology, such as data pooling and Al, are used to track and diagnose issues in agricultural environments. Small businesses worldwide are becoming micro-multinationals by using digital platforms such as eBay, Amazon, Facebook, and Alibaba to connect with customers and suppliers in other countries; hence, connectivity is vital to building community and enabling socio-economic inclusion.

In Latin American, the Vive Digital program was established to bring government, community, business, and technology together to combat the issues that hinder connectivity [34]. This program provides more than 6000 students with 100% forgivable loans as a motivation to study ICT related careers as part of its Talento Digital initiative [34]. There were 47 rural areas that gained connectivity through high-speed networks, including the Amazon, San Andres, and the Orinoquia, which previously had no access to the internet. The program also set up kiosks in rural areas so that everyone from farmers to students and women-led households could have access to affordable connected internet devices.

In the United Kingdom, mobile connectivity has improved and expanded rapidly through private sector investments. At the end of 2017, 93.6% of premises in urban areas had 4G outdoor coverage, 64% had indoor coverage, and there were over 50 million 4G mobile subscriptions even though the quality of coverage varied between and within cities [35,36]. Therefore, these early works guide this study to bridge the gap between the effect of internet use on farm income and household income in rural Ghana as our primary focus.

This study provides clear evidence at the household level of the possible economic impact of the current internet high-tech opportunities available for rural development. The objective of this study was to analyze the effect of internet use on farm income and household income by using farm-level currently collected data from 478 rural farmers from the Eastern and Brong Ahafo regions of Ghana. Upon a thorough feasibility study on this research project, the researchers believe that this is the first study to empirically quantify the impact of internet use on incomes in rural Ghana. We accounted for the endogeneity of internet usage through self-selected users in the econometric model by employing an endogenous switching regression model to address the selection bias that accounts for observed and unobserved factors. We provide policy implications based on the findings, null hypotheses, and internet use in rural Ghana.

The rest of the paper is as follows: (1) A presentation of the theoretical framework. (2) The introduction of the methodology and model specification. (3) An explanation of the data source and data descriptive analysis. (4) The performance of the empirical results. (5) Our conclusion and summary of findings, policy implications, limitations, and future research recommendations.

2. Theoretical Framework

The introduction of ICT (internet use) has contributed to the economic growth in many developing countries [37–39]. In this study, we analyzed the internet use impact on household incomes (farm income and household income). The path mechanism by which income is affected by internet use entails a great deal. First, internet use can help increase farm productivity through agriculture technology adoption measures. Lin, [34] emphasized that agriculture productivity was likely to increase when technological change exists. Second, useful information concerning agriculture technological adoption and financial and agriculture markets is likely to be improved through ICT [40].

Seeking market information that is associated with a high transaction cost can be curtailed with the help of internet use. A study [41] in India revealed that the establishment of internet kiosks in central India rural areas helped farmers to acquire market information, and hence, this improved their production and income. Finally, internet use improves the access to capital [22,42]. Credit constraints caused by financial exclusion can be curbed with the use of the internet. Through internet use, receiving household remittances becomes easy and convenient. Thus, credits, remittances, and other financial aids received through internet use helped to improve household income. In summary, as the world is putting down measures to alleviate poverty in developing countries, it is essential to examine how internet use may affect household and farm income.

Considering the access to non-fixed assets (NFAs), households with NFA, such as luxury jewelry, and those without them may experience different impacts of internet use on income. Households with NFA can swap or sell their luxury assets via social media platforms (internet use) to accumulate capital and hence increase their income. Therefore, the internet use impact of households with NFA on income is likely to be profound compared to their counterparts.

Again, following the previous literature, we argue that householder, household, and farm characteristics influence both internet use and income (Figure 1). For example, Deng et al. [7] explored the impact of internet use on cropland abandonment by controlling for householder characteristics (e.g., age, gender, and education), household-level characteristics (e.g., household size, income, access to credit, and fixed assets), and farm characteristics (e.g., farm size and soil quality). Similarly, the study of Ma et al. [43] explored the determinants of smartphone use, also controlling for those variables. Concerning income determinants, the studies of Leng et al. [44] and Ma et al. [45] revealed that household socioeconomic and demographical characteristics (e.g., age, gender, education, and risk-aversion) were significant factors. Given the above discussions, this study proposes these hypotheses regarding the influences of internet use on income:

H_1: *Internet use is more likely to increase household and farm incomes.*

H_2: *Compared with access to NFA alone, internet use is likely to increase household and farm incomes for households with access to NFA.*

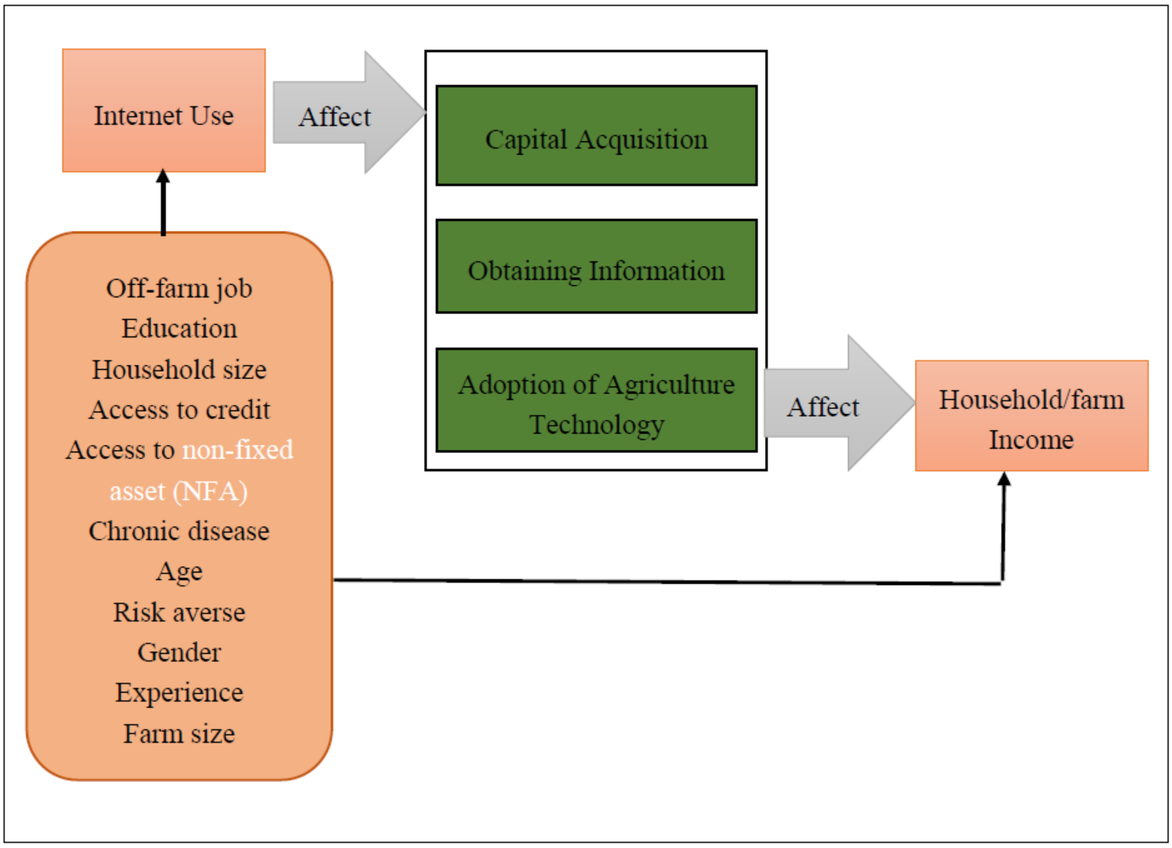

Figure 1. The conceptual framework of the effect of internet use on income.

3. Methodology

3.1. Model Specification

The aim of this study was to explore the relationship between internet use and rural households. The researchers assumed that because farm households may be self-selected rather than random in their decision making, to use the internet, there may exist a selection bias in some households [46–48]. The decision for a household head to use the internet or not may be a conscious effort. For example, a household head who desires to increase farm productivity is more likely to use the internet to increase production and hence the household income. Conversely, a household head may decide not to use the internet to increase agriculture productivity but rather may use a different method to do that. Therefore, internet users may be unnecessary at this stage. Hence, internet users are systematically different from non-users.

This makes the internet use status endogenous, and therefore, using an appropriate econometrics method rather than the ordinary least square (OLS) is best to prevent estimation bias. Many researchers employed econometric approaches, such as endogenous switching regression (ESR) and propensity score matching (PSM), to deal with the problem of selection bias. However, in this study, we employed the ESR method as it can account for selection bias by treating selectivity as an omitted variable problem [49]. Again, in ESR, the participation outcome can be observed for the whole sample of internet users and non-internet users; thus, differential responses of the two groups were captured [47,50,51].

We assumed in this study that the outcome variables (household total annual income per capita/household total farm income per capita), which are linear equations, were determined by the farmer and some household characteristics. The selection and outcome equations are expressed as:

Let I^*_i (Equation (1)) represent the outcome variables. They depend on both exogenous (γ'_i) and endogenous (Y_i) variables.

$$I^*_i = \gamma'_i Z + \alpha Y_i + v_i \tag{1}$$

$$Y^*_i = \beta X_i + \mu_i$$
$$Y_i = \begin{cases} 1\,if,\ Y^*_i > 0 \\ 0\,if,\ otherwise \end{cases} \tag{2}$$

where Y^*_i is the farmer's internet use status; Y_i is equal to one (1) if a household head uses the internet and takes the value of zero (0) if the household head does not use the internet; X is the vector of exogenous variables including the household head and household characteristics (see Table 1); β is a vector of parameters and μ_i is a random disturbance term.

Table 1. Definitions and data description of the variables in the model.

Variables	Definitions and Assignment	Mean	S.D
Internet	1 if respondent uses internet, 0 otherwise	0.29	0.41
Farm income (GH¢)	Amount of annual farm income (GH¢1000/capita)	1.07	1.17
Household income (GH¢)	Amount of total household income (GH¢1000/capita)	3.40	2.93
Off-farm job	1 if respondent have off-farm job, 0 otherwise	0.47	0.48
Family size (GH¢)	Number of members in a household(number)	5.36	1.30
Access to non-fixed assets (NFA)	Access to household force sales value (FSV) such as luxury jewelry and old machines (0 = No,1 = Yes)	0.62	0.46
Access to credit	1 if the respondent had access to credit; 0 otherwise	0.56	0.49
Age	Respondent age (numbers)	41.72	12.20
Gender	1 if respondent is a male; 0 otherwise	0.70	0.46
Education	1 if the respondent had a high school education or above; 0 otherwise	0.42	0.49
Chronic disease	1 if respondent had a relative with a chronic disease; 0 otherwise	0.26	0.47
Risk-averse	1 if the respondent is risk-averse; 0 otherwise	0.24	0.47
Experience	Years of farming experience (years)	13.65	7.84
Farm size	Respondent farm size (in acres)	3.34	1.87
Perception	1 if respondent perceives whether browsing with the phone/computer is easy; 0 otherwise	0.57	0.49

Source: Survey results.

In the second stage, the outcome variable factors may not be an independent function of internet use status. Therefore, the empirical estimation method follows [52] and is depicted as:

$$\begin{cases} I_{1i} = \gamma_{1i} Z_1 + \varepsilon_{1i},\ if\ Y_i = 1 \\ I_{2i} = \gamma_{2i} Z_2 + \varepsilon_{2i},\ if\ Y_i = 0 \end{cases} \tag{3}$$

where I_{1i} and I_{2i} are the household income/farm income for internet users and non-users, respectively; γ_{1i} and γ_{2i} are vectors of exogenous variables, which include household socioeconomic and demographic characteristics and also explain the outcome variable; Z_1 and Z_2 are vectors of parameters, and ε_{1i} and ε_{2i} are random disturbance terms. As I_{1i} and I_{2i} cannot be observed simultaneously, the covariance of the error terms ε_{1i} and ε_{2i} is undefined. However, through the first selection Equation (Equation (2)), there is an internal correlation between ε_{1i} and ε_{2i}. Thus, μ_i, ε_{1i}, and ε_{2i} are assumed to have a trivariate normal distribution with mean vector zero and covariance matrix:

$$cov(\mu_i, \varepsilon_1, \varepsilon_2) = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{1\mu} \\ \sigma_{12} & \sigma_2^2 & \sigma_{2\mu} \\ \sigma_{1\mu} & \sigma_{2\mu} & \sigma_\mu^2 \end{bmatrix} \tag{4}$$

where σ_1^2 and σ_2^2 are the variance of error terms, ε_{1i} and ε_{2i} in Equation (3); σ^2_μ is the variance of the error term, μ_i, in Equation (1); and σ_{12}, $\sigma_{1\mu}$, and $\sigma_{2\mu}$ are the covariances of ε_{1i} and ε_{2i}, ε_{1i} and μ_i, and ε_{2i} and μ_i, respectively. The term σ_μ^2 is assumed to be equal to 1 because β is estimable only up to a scale factor [53]. The correlation between the error term of the selection equation and the outcome equation is not zero.

In addition, $corr(\mu, \varepsilon)$ represents the correlation between the error terms of the selection (Equation (2)) and outcome (Equation (3)) equations (i.e., $\rho_1 = corr(\mu_i, \varepsilon_{1i})$ and $\rho_2 = corr(\mu_i, \varepsilon_{2i})$). Again, one of the coefficients of $corr(\mu, \varepsilon)$ significantly differs from zero, which implies that unobservable factors may influence μ and ε simultaneously. ESR addresses this selection bias by estimating the inverse mill ratios $(\lambda_{1i}\ and \lambda_{2i})$ and the covariance term $(\sigma_{1\mu}$ and $\sigma_{2\mu})$ and including them as auxiliary regressors in Equation (3). Thus, Equation (3) can now be expressed as:

$$\begin{aligned} E(I_{1i}|Y_i = 1) = \gamma_{1i}Z_1 + \sigma_{1\mu}\lambda_1 \\ E(I_{2i}|Y_i = 1) = \gamma_{2i}Z_2 + \sigma_{2\mu}\lambda_1 \end{aligned} \tag{5}$$

The authors of this study use the full information maximum likelihood (FIML) method, without strict assumptions, to estimate the endogenous switching regression model [52,54]. Due to the use of the ESR model, an instrument variable is required in Equation (2), i.e., a variable that is correlated with the treatment (internet use status) but not with the outcome indicators (household/farm income). Identifying a suitable instrument is the primary challenge for instrumental variable analysis. However, following previous studies [43], the authors use "perception" (whether the respondent perceives that browsing with the phone/computer is easy or not) as an instrument for the treatment. The average treatment effect on the treated group (ATT) was also taken into account in this study. This was calculated by the conditional expectations of those with access to credit. It is expressed as

$$\begin{aligned} ATT = E(I_{1i}|Y_i = 1) - E(I_{2i}|Y_i = 1) \\ ATT = (Z_1 - Z_2)\gamma_{1i} + (\sigma_{1\mu} - \sigma_{2\mu})\lambda_1 \end{aligned} \tag{6}$$

3.2. Data

The data of this study consisted of 478 farmers from two regions in Ghana following a multi-stage sampling technique. In the first stage, the two (2) regions, namely, the Eastern region in southeastern Ghana and the Brong Ahafo region in central Ghana, were selected. In the second stage, one district was randomly chosen from each selected region. They included the Kintampo north district in the Brong Ahafo region and the Brim central district in the Eastern region. In the third stage, three (3) communities were randomly selected from each selected district, and they were Kintampo, Babatokuma, and Benkrom in the Kintampo North District and Manso, Asuboa, and Nkwanta in the Brim central district. Finally, a simple random procedure was employed to select the respondents. Approximately 10–20 rural households were randomly selected from each community

Data collection from these rural farm households in Ghana was done using interviews and questionnaires. An in-depth interview was conducted due to the complex nature of the questionnaire. To clear the uncertainty, we had a pre-test of the questionnaire. The survey data questionnaires covered information on the socioeconomic characteristics, internet use, and other various variables that contributed to the aim of the study. The data were edited and coded to ensure accuracy, validity, uniformity, consistency, and completeness using Stata 14.

4. Results

4.1. Descriptive Analysis

The descriptive statistics of the respondents are shown in Table 1 below. The results revealed that 29% of the respondents used the internet, with 47% of them having an off-farm job. The average annual farm income and household income per capita were 1.07 and 3.40, respectively. The results also revealed that 62% and 56% had access to non-fixed assets (NFA) and credit, respectively. The average age of the respondents was approximately 42 years old. Most of the households comprised 5 members on average. While 70% of the respondents were males; only 42% of the respondents had access to high school or higher education. Moreover, 24% of the respondents had household members who were risk-averse, and 26% of their household members had a chronic disease. About 57% of the respondents perceived that it was easy to browse the internet using a mobile phone or computer.

Meanwhile, the average farming experience was approximately 14 years, and the average farm size of the respondents was 3.34.

The distribution of the sample households by districts, gender, and internet use status is presented in Table 2. The table shows that a total of 221 and 257 respondents were selected from the Eastern and Brong Ahafo regions, respectively. There were 116 and 99 internet users in the Eastern and Brong Ahafo regions, respectively.

Table 2. Household sample distribution by region.

	Eastern	Brong Ahafo	Total
Internet users	116	99	215
Non-internet users	105	158	263
Total	221	257	478

Source: Survey results.

Difference between the Means of Internet Users and Non-users

Table 3 presents the means differences between user and non-user variables by internet use category (1 = internet use and 0 otherwise). The mean differences between users and non-users of the internet were significant in terms of the focal variables (farm income and household income). This indicated that those who used the internet tended to have more farm and household income than those who were not using it. Moreover, there were statistically significant differences between these two groups of farmers with respect to other control variables. The mean difference comparison, however, does not control for confounding factors, which may result in misleading conclusions. Therefore, it is important to employ an econometric approach to determine the impact of internet use on incomes.

Table 3. Differences between means of internet users and non-users.

Variables	Internet Users (IU) N = 215	Non-Internet User (NIU) N = 263	Diff.
Farm income (GH¢)	3.22 (1.44)	1.32 (1.13)	1.90 ***
Household income (GH¢)	4.04 (1.83)	2.53 (1.14)	1.51 ***
Off-farm job	0.56 (0.06)	0.29 (0.03)	0.27 ***
Family size	5.33 (0.06)	6.70 (0.08)	−1.37 ***
Access to non-fixed assets (NFA)	0.66 (0.03)	0.51 (0.01)	0.15 ***
Access to credit	0.61 (0.11)	0.55 (0.07)	0.06 ***
Age	41.70 (0.53)	46.56 (0.55)	−4.86 ***
Gender	0.54 (0.03)	0.47 (0.03)	0.07 ***
Education	0.52 (0.13)	0.42 (0.09)	df0.10 ***
Chronic disease	0.32 (0.00)	0.41 (0.02)	−0.09 ***
Risk lover	0.34 (0.15)	0. 26 (0.11)	0.08 ***
Experience	12.87 (0.75)	14.50 (0.78)	−1.63 ***
Farm size	4.70 (0.08)	4.63 (0.03)	0.07 *

Source: Survey results, Survey results, *, and *** represent statistical significance at 10%, and 1% alpha levels, respectively. Note: During the survey in 2018, 1 USD = 5.2 Ghana cedis (GH¢).

4.2. Empirical Results

4.2.1. Determinants of Internet Use by Rural Households

The factors that influenced internet users are presented in this section. It is essential to estimate the determinants of internet use when investigating its impact on incomes. Table 4 revealed that the coefficient of the off-farm job was positive and significant, indicating that households with an off-farm job tended to use the internet more than their counterparts. Off-farm income helped farmers afford new technologies (e.g., the purchase of smartphones, which may enhance their internet use). This result also implied that off-farm jobs can be secured through internet use (social media) and, therefore, served as an incentive to internet users. This finding is consistent with [45], where researchers revealed that off-farm income enabled farmers to purchase smartphones. The coefficient of education was positive and significant, suggesting that educated farmers were 6.1% more likely to use the internet.

This result is consistent with the findings of [55,56], who revealed that education improves skills and helps in understanding the opportunity cost of not using the internet. Access to credit and NFA coefficients were positive and significant, suggesting that household heads that receive credit and have a non-fixed asset were more likely to use the internet. In many cases, farmers could find avenues to obtain credit when connected to the internet because most lenders now use social media platforms for advertising their credit market products [57]. Again, those households with access to NFA may use the internet for advertising their assets when selling them. Conversely, the age coefficient was negative and significant. This implies that relative to younger household heads, the older ones were 11.7% less likely to use the internet, a finding that confirms the study of [43] where the authors argued that young people preferred to possess smartphones compared to older people. Finally, the positive and significant coefficient of the perception variable suggests that farmers who perceive that browsing with a phone is easy were 2.2% more likely to use the internet.

Table 4. Determinants of internet use by rural households.

Variables	**Coefficient**		**Marginal Effect**
Off-farm job	0.0530 (0.0341)		0.0473 *
Education	0.0669 (0.0124)		0.0614 **
Household size	−0.045 (0.0326)		−0.0402
Access to NFA	0.0018 (0.0031)		0.0012 *
Access to credit	0.0613 (0.1405)		0.0622 *
Chronic disease	−0.5110 (0.1953)		−0.5887
Age	−0.1371 (0.1602)		−0.1173 **
Risk averse	−0.0007 (0.0001)		−0.0003
Gender	0.1806 (0.1904)		0.0336
Experience	0.3080 (0.0655)		0.0321
Farm size	−0.0193 (0.0577)		−0.0124
Perception	0.0619 (0.02191)		0.0223 ***
Constant	3.4889 (2.2669)		
Regions	Yes	Prob > chi2	0.0000
Number of Obs.	505	Pseudo R2	0.1705
Log likelihood	−215.24425	Wald chi2(12)	76.20

Source: Survey results, *, **, and *** represent statistical significance at 10%, 5%, and 1% alpha levels, respectively. All numbers in parentheses are robust standard errors.

4.2.2. Estimating the Impact of Internet Use on Income and Its Average Treatment (ATT) Effects

The results of the ESR models are presented in Tables 5 and 6. As expected, the instrumental variable (perception) had a statistically significant impact on internet use. The results of the outcome equations are also presented in the tables. Since the objective of this study was to estimate the impact of internet use on the farm and household income based on the variables in Tables 5 and 6, a detailed explanation of other factors that affect any of outcome variables are left out but can be provided on request.

As depicted in Tables 5 and 6, ρ_2 has a significant sign, and this suggests that the decision to use the internet was not random and that selection bias exists, indicating that the ESR model was appropriate for estimation. Further, the Wald tests for joint independence of the two equations for farm income and household income had a significant sign at the 1% level, which indicates that we can reject the null hypothesis of no correlation between the treatment error μ_i and the outcome errors (ε_{1i} and ε_{2i}).

Tables 5 and 6 do not report the specific impact of internet use on the farm and household income; thus, calculating the ATT was essential. The ATT reveals the quantitative implications of internet use on income status (see Table 7). Compared with the mean differences shown in Table 2, which do not control for confounding factors, the ATT was estimated by correcting the selection bias due to observable and unobservable factors. Table 5 shows the change in the ATT. More specifically, as shown in Table 7, internet use increased farm income by 20.1% and household income by 15.47%. The reason for this is that internet use may help householders access credit and receive remittances and other financial aid in a timely manner.

Table 5. The determinants of internet use and the determinants of farm income.

Variables	First Stage Selection Equation	Farm Income	
	Internet Usage	**IU**	**NIU**
Off-farm job	−0.0451 (0.0532)	−1.0318 * (0.0571)	−0.8755 ** (0.0571)
Education	0.05132 *** (0.0163)	−0.0339 (0.0163)	−0.0448 (0.0107)
Household size	−0.0811 (0.0642)	0.9516 * (0.0763)	0.9881 *** (0.8861)
Access to NFA	0.0193 *** (0.0013)	1.03 (0.0162)	0.1637 * (0.0001)
Access to credit	−0.0381 (0.1785) *	3.1653 (0.1332)	2.0364 (0.1163)
Chronic disease	−0.2257 (0.1540)	−0.3911 (0.1551)	−0.2871 (0.1933)
Age	−0.1566 *** (0.1397)	−0.0173 (0.0196)	0.0533 * (0.0344)
Risk averse	−0.0009 *** (0.0003)	−0.0563 (0.0126)	0.1724 * (0.0213)
Gender	0.1384 (0.1613)	0.0663 ** (0.1905)	0.1681 (0.0818)
Experience	0.5541 (0.0557)	−0.0115 (0.0129)	−0.0133 (0.0102)
Farm size	−0.0310 (0.0567)	−0.4231 *** (0.1331)	−0.3821 *** (0.0814)
Perception	0.0539 (0.0332) ***		
Constant	2.5431 * (2.2939)	4.1031 (1.5542)	5.0187 (1.3008)
σ_1 σ_2 ρ_1 ρ_0	0.4721 (0.0661) 0.6341 (0.0467) 0.6413 (0.1299) ** −0.1442 (0.3563)		
LR test of independent equations: chi2(1) = 107.41 Prob > chi2 = 0.0043			

Source: Survey results, *, **, and *** represent statistical significance at 10%, 5%, and 1% alpha levels, respectively. All numbers in parentheses are robust standard errors.

Table 6. The determinants of internet use and the determinants of household income.

Variables	First Stage Selection Equation	Household Income	
	Internet usage	Users	Non-users
Off-farm job	−0.0648 (0.0862)	2.0233 * (0.3550)	1.1455 *** (0.2387)
Education	0.06839 *** (0.0179)	1.3252 (0.0189)	0.7128 (0.0107)
Household size	−0.0846 (0.0682)	0.0912 * (0.0583)	0.1455 *** (0.0387)
Access to NFA	0.0111 *** (0.0002)	0.0006 ** (0.0002)	0.0001 (0.0001)
Access to credit	−0.0691 (0.1642) *	3.1346 (1.1268)	2.1424 (1.1945)
Chronic disease	−0.1853 (0.1515)	−2.4177 *** (1.1222)	−1.3814 *** (1.1856)
Age	−0.1519 *** (0.1527)	−0.0074 (0.1094)	0.1263 * (0.0974)
Risk averse	−0.0023 *** (0.0028)	0.0003 (0.0020)	−0.0024 * (0.0017)
Gender	0.1934 (0.1503)	0.2939 ** (0.1485)	0.0675 (0.0918)
Experience	0.5731 (0.0903)	−1.0115 (0.1129)	−0.6133 (0.0102)
Farm size	−0.0164 (0.0515)	−0.4137 *** (0.1211)	−0.3821 *** (0.0814)
Perception	0.0707 (0.0452) ***		
Constant	3.9274 * (2.2269)	6.0035 (1.4522)	4.9177 (1.3738)
σ_1 σ_2 ρ_1 ρ_2	0.7691 (0.0467) 0.6465 (0.0481) 0.6585 (0.1829) ** −0.2002 (0.3313)		
LR test of indep. eqns. chi2(1) = 117.11 Prob > chi2 = 0.0016			

Source: Survey results, *, **, and *** represent statistical significance at 10%, 5%, and 1% alpha levels, respectively. All numbers in parentheses are robust standard errors.

Market information is easy and convenient to acquire through internet use. This, in turn, affects farm productivity and other off-farm generating activities, hence income. This finding that internet use, farm income, and household income have a positive relationship provides evidence supporting the researchers in [43], who revealed that the use of smartphones helps rural households to increase both the farm and household income. Although the poverty rate is high in developing countries [46], this study indicates that it can be curtailed through the use of the internet.

Table 7. The impacts of internet use on income. Average treatment effect on the treated group (ATT).

	Mean Outcome				
Outcome Variable	**Users**	**Non-Users**	**ATT_{ESR}**	**t-Value**	**Change**
Farm income	3.218	2.738	0.480	11.286 ***	20.10%
Household income	4.037	3.496	0.541	6.347 ***	15.47%

Source: Survey results *** represent statistical significance at 1% alpha levels, respectively.

4.2.3. Heterogeneous Effects of Internet Use on the Farm and Household Income

In order to explore the heterogeneous impact of internet use on income, this study also examined the impact of internet use on income in different groups of farm households. More specifically, there was a division of farm households into different groups, i.e., according to whether the households had access to NFA and off-farm jobs, and the results are shown in Table 8. The results demonstrated that internet use positively affected income even within the different groups of farm households. More precisely, the estimates indicated that internet use reduced farm income by 18.12% but increased household income by 31.77% in farm households that engaged in off-farm work. This implies that households with additional income were likely to improve their household income and reduce farm incomes. Off-farm employment had a detrimental effect on cropland abandonment [48]. The estimates also showed that internet use boosted both farm income and household income by 14.66% and 15.33%, respectively, in farm households that had access to NFA. This finding indicated that NFA, such as luxury jewelry, can be swapped for financial aids that can be used for other income-generating activities, thereby increasing income [58].

Table 8. The impact of internet use on income by off-farm jobs and access to NFA.

		Mean Household Income				
Variables		**Users**	**Non-Users**	**ATT_{ESR}**	**t-Value**	**Change**
Off-farm job	Yes	4.52	3.43	1.09	6.60 ***	31.77%
	No	2.11	1.69	0.42	10.38 **	24.85
Access to NFA	Yes	3.31	2.87	0.44	8.76 **	15.33%
	No	2.22	2.09	0.13	0.46	6.23%
		Mean farm income				
Off-farm job	Yes	2.44	2.98	−0.54	−6.07 *	18.12%
	No	0.97	0.94	0.03	8.77	3.19%
Access to NFA	Yes	3.36	2.93	0.43	11.33 **	14.66%
	No	1.73	1.54	0.19	2.58	12.33%

Source: Survey results, *, **, and *** represent statistical significance at 10%, 5%, and 1% alpha levels, respectively.

5. Conclusions and Policy Implications

Based on a survey data collected from two regions in Ghana, a theoretical, analytical framework was built under the guidance of information economics theory. The theory revealed many incentive gains by farm households in utilizing the internet (e.g., internet use can help farmers to obtain information, accumulate capital, and adopt agriculture technologies). The study examined the effect of internet use on income through employing the endogenous switching regression model. The main results were as follows:

1. Concerning the determinants of internet use, the estimate revealed that off-farm employment, education, access to credit, NFA, and perception variables had a positive and significant relationship with internet use. Elderly farmers were less likely to use the internet.
2. Regarding a quantitative relationship, internet use increased farm and household income by 20.10% and 15.47%, respectively. This is an indication that promoting internet use through improved rural ICT education as well as internet connectivity expansion is essential.

3. Regarding the heterogeneous impacts, the estimates show that internet use reduced farm income by 18.12% for farm households that participated in off-farm activities but increased farm income by 14.66% for households that have access to NFA. The estimates also indicated that internet use increased household income by 31.77% and 15.33% for farm households that engaged in off-farm employment and had access to NFA, respectively. Internet use increased the household income for households that did not engage in off-farm activities by 24.85%. A proper division of labor is important for households with off-farm employment to improve farm income.

Based on the above findings, we can derive some policy implications. Poverty alleviation remains a significant concern for developing countries. The presence of internet use and its rapid spread has brought new ways to alleviate this poverty. The significant positive relation between these variables (e.g., education, perception, and off-farm employment) and internet use suggests that policies to promote ICT education in the nation, especially in rural area areas cannot be forgotten. This is because educated household heads and those who perceive that browsing is easy and flexible are more likely to use the internet.

Extending the connectivity rate, especially mobile connectivity, in rural areas should also be a priority for policymakers as farmers gain a series of incentives from internet connectivity. The significant positive effect of internet use on incomes indicates that rural development policy strategies should be designed in the form of enhancing the use of the internet in rural Ghana. Moreover, households with access to credit coupled with internet users tend to increase their income, suggesting that governments and policymakers should design a relaxing and flexible credit market for rural households.

This study has certain limitations that future research can further address. First, the study was organized in only two regions in Ghana; future researchers can consider more regions or the entire nation as a whole. Second, we focused on only rural area households; future research can further explore the impact of internet use on urban area households. Finally, internet users may have an effect on other household components or activities; future research can explore how other household activities are affected by internet use.

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