Facilitation of ICTs for Rural-Urban Economic Transformation in Sri Lanka

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ABSTRACT

The spread of ICTs has a huge impact on rural economic transformation. The purpose of this paper is to comprehend the significance of ICTs in facilitating transformation in Sri Lanka. The information came from a national survey of 26,600 people. The Probit endogenous switching model was used. The results show that the marginal probability of getting ICT-related jobs has increased by 6.8%, ICT users have reduced their poverty level by 12.6%, and access to digital information has increased by 28.1% in the rural sector. These shards of evidence demonstrate that ICT dispersion causes rural-urban transformation in Sri Lanka.

Keywords: ICTs, Endogenous Probit Model, Rural Transformation, Poverty, Information

JEL: C510, D1, D9, O330, O180

1. Introduction

Information and Communication Technologies (ICTs) are one of the highly effective innovations in the digital era. Plenty of applications in ICTs have changed the lives of the rural and urban sectors in developing countries. It seems like ICTs are needy technologies for the transformation of the rural and urban sectors of the economies. During the COVID-19 crisis, the role of ICTs has been extensively used for many purposes from education to export-import transactions and agricultural aspects.

In Asian countries, no doubt that ICTs have been diffused extensively playing wider roles in the transformation of people's lives. However, as the main purpose of economic development, poverty reduction become priority in the developing economies in terms of policy making in Asia. Thus, how ICTs have affected to the wider goals of the Asian economies needs to be considered. There is an ambiguous situation the ICTs has been increased the gaps between rural and urban sectors altering inequality. Several studies have applied sectoral interdependencies, livelihood diversification, and level of poverty in their analysis to find the impacts of ICTs on rural development. Amid the COVID-

19 pandemic, ICT has created a tremendous impact on society and its transformation. Sri Lanka is a country with a 93% of literacy rate, but IT literacy rates are 9% for the urban population and 3% for the rural population (ICTA, 2009). The use of ICTs in rural livelihood development is null (ICTA, 2009). Thus, the government and private sector promoted ICT usage for rural livelihood development which had a limited impact but generated considerable knowledge for a strong foundation for the future. The multiple reasons for these failures are a lack of understanding of the rural livelihood, poverty level, ICT interventions, little focus on service sustainability, and little attention to capacity-building programs.

The study intends to identify the factors that drive the rural and urban transformation with the dispersion of ICT. The economic transformation implied how economic progress is met under the impact of ICT-related determinants. In this paper, economic transformation is measured by three indicators including livelihood diversification, level of poverty, and access to digital information for economic activities. Meanwhile, livelihood diversification means changes in the present jobs after the applications of ICTs in their job-related activities to earn. Access to information implied that the individual has access to information through digital mode to find jobs, fill out applications, join with government platforms for activities, etc.

Thus, the promotion of ICT-related jobs, eradication of poverty, and access to digital information through government-promoted service centers in rural and urban areas are considered in this study. This paper is organized as follows. The next section provides a review of existing literature related to the ICTs' roles in rural and urban economic transformation. Section 3 presents the data used in the study including the national survey. Section 4 presents the empirical method as the endogenous switching Probit model. Section 5 presents the results and discussion sections of the analysis. The last section includes the conclusion of the study.

2. Literature Review

The spread of ICTs has made a tremendous effect on the economic transformation in many developing countries (Chen, Liu, and Song, 2019; Wang and Lin, 2008). Many works of literature also show that there is a positive impact of ICT on rural transformation especially agricultural development (Aker and Fafchamps, 2014; Aker and Ksoll, 2012; Aker, Ghosh, and Burrell, 2016; Hubler and Hartje, 2016). Many literates summarize the different effects of ICTs on improving access to information, management of inputs and output supply chain, transaction cost reduction, facilitating the delivery, farmer learning, and access to credit and insurance (Aker, 2011). Moreover, some scholars have studied the ICTs on rural transformation stimulates access to information, market as well as services (Qiang et al., 2012).

The impacts of ICTs for rural-urban transformation on economic growth and poverty reduction have been studied in many pieces of literature. The use of ICTs in the facilitation of credits through e-services is predominant in developing countries (Chavula, 2014). Further, studies show that ICTs play a significant role in agricultural production (Hwang and Tellez, 2016; Chavula, 2014).

Broadly, ICTs can contribute to economic development and provide benefits to the poor by providing access to education and government services in India (Kaushik and Singh, 2004) also like in Sri Lanka. Thus, it is believed that ICT facilities improve the income and communication facilities that support rural economic development. Even though, in broader terms, ICTs have contributed to economic development, how it affects urban and rural transformation is ambiguous. Therefore, the following literature provides the depth of analysis how ICTs affect rural and urban transformation in terms of agricultural development perspectives.

Ma, Grafton, and Renwick (2018) have studied smartphone use and income growth in China. They consider the income effects of the use of updated ICTs, such as smartphones in China with the application of endogenous switching regression model. They found that, based on household survey data, gender, education, farm size, and off-farm work are the main determinants of smartphone use. Moreover, smartphone use increases three types of income such as farm income, off-farm income, and household income considerably while the income effect of male and female smartphone users is statistically significant. They conclude that smartphone users have a larger effect on farm income, off-farm income, and household income and they proposed policy implications accordingly. Min, S., Liu, M., and Huang, J. (2020) have studied the role of ICTs in the transformation of rural economies in China with the use of three-wave panel data. To estimate the effects of the use of smartphones, the endogenous switching

Probit model was applied. They have produced three outcome variables including off-farm employment, expanded gain cultivation, and decreased crop diversification. The results of the study indicate that the use of smartphones had a significant impact on the transformation of rural economies. The study concludes that these results are like the use of ICTs in many developing countries. Kuntashula and Mungatana, (2013) have studied the improvement of agricultural technologies to enhance productivity and reduce the poverty. They used propensity matching strategies and endogenous switching regression to apply for the improper identification strategies that affect agricultural technologies. They found that improved technologies such as follows have a positive impact on the maize yield, maize productivity, maize income, and per capital maize yield.

Improvement of rural livelihood is one of the major factors that determine rural transformation. The ICTs have contributed to the change of rural livelihood in many developing countries in the transition process because technology can address many barriers in developing economies (Deichmann, Goyal, and Mishra, 2016). In fact, as far as this study is concerned, there is no study applying to evaluate the impacts of ICTs for the rural transformation in Sri Lanka. This study lay the foundation from the literature to evaluate the impact of ICTs in several usages for the economic transformation in urban and rural sectors.

All studies in the ICT sector support economic transformation, and the above review provides an analytical overview for the addition to prevailing literature. Since there is a literature gap availed for the arguments such as ICT is improving the living conditions of the people and its diffusion is high. Thus, the economic transition can be faster and more severe in terms of the impacts of ICT on the rural and urban divergence of the economic conditions.

3. Data

The data were obtained from the "National Survey on ICT access and usage by households and individuals" conducted by the Information and Communication Technology Agency of Sri Lanka. This survey includes the following districts; Ampara, Anuradhapura, Badulla, Colombo, Galle, Gampaha, Hambantota, Jaffna, Kalutara, Kandy, Kegalle, Kurunegala, Matale, Matera, Monaragala, Mulative, Nuwara Eliya, Polonnaruwa, Puttalam, Rathnapura, Trincomalee, Vavuniya. Randomly selected 26,600 respondents from the survey were used for the analysis.

Table 1: Variable Description

Dependent variables	
Livelihood diversification	Dummy = 1 if the respondent has an ICT related job, 0 otherwise
Level of poverty	Dummy = 1 if the respondent's income is less than poverty level, 0 otherwise
Access to digital information	Dummy = 1 if the respondent is used digital information for economic activities, 0 otherwise (the users do not have access to the digital information)
Rural	Dummy = 1 if the respondent is in rural area, 0 otherwise
Urban	Dummy = 1 if the respondent is in urban area, 0 otherwise
Independent variables	
Relationship	Dummy = 1 If the relationship of the respondent is the head of the household, 0 otherwise
Sex	Sex of the respondent; male =1 and female = 0
Age	Age of the respondents in years
Age2	Square of the age of the respondent in years
Ethnicity	Dummy =1 if the respondent is a Sinhalese, 0 otherwise
Religion	Dummy =1 if the respondent is a Buddhist, 0 otherwise
Marital	Dummy =1 if the respondent is married, 0 otherwise
Employment	Dummy =1 if the employment is related to the ICT related area, 0 otherwise
Education	Dummy =1 if the respondent is passed O/L examination, 0 otherwise

Desktop	Dummy =1 if the respondent has a desktop computer, 0 otherwise
Smartphone	Dummy =1 if the respondent has a smartphone, 0 otherwise
Conventional ICT	Dummy =1 if the respondent has a conventional ICT related device, 0 otherwise
Internet home	Dummy =1 if the respondent has internet at home, 0 otherwise
Comp work	Dummy =1 if the respondent is working with a computer, 0 otherwise
Comp education	Dummy =1 if the respondent has used computer for education, 0 otherwise
Private ICT	Dummy =1 if the respondent has a private device to get ICT services, 0 otherwise
Internet work	Dummy =1 if the respondent has internet at work, 0 otherwise
Internet education	Dummy =1 if the respondent has internet at school/educational institute, 0 otherwise
Internet private	Dummy =1 if the respondent has private internet services, 0 otherwise
Internet frequent	Dummy =1 if the respondent has used internet frequently, 0 otherwise
Social media	Dummy =1 if the respondent has used internet for social media, 0 otherwise
Primary education	Dummy =1 if the respondent has primary purpose of the internet is to get education, 0 otherwise

4. Empirical Method

4.1. Endogenous Switching Probit model

The estimated function can be subjected to the endogeneity to estimate the impact of ICT on rural–urban transformation for three different outcome variables such as households having ICT access or crop diversification or livelihood diversification. The endogeneity could be a reason for causality. It means that because of urbanization, the use of ICT can be increased as a result transformation can occur. Second, it could be because of sample selection bias. Moreover, unobserved heterogeneity of respondents may affect both the use of ICT and the transformation of rural economies, resulting in inconsistent estimates of the impact of ICT use on the three indicators of rural economic transformation. Thus, the endogenous switching probit model (ESP) can solve the above issues (Ayuya et al., 2015; Gregory & Coleman-Jensen, 2013; Manda et al., 2016; Min, Waibel, & Huang, 2017; Parvathi & Nguyen, 2018). Thus, the ESP model counts on unobserved household characteristics that could simultaneously affect households' decisions to use ICT and to participate in transforming rural economies (Lokshin and Glinskaya, 2009).

The economic transformation of the rural and urban sectors can be affected by the above binary outcomes. Thus, we account for binary outcomes for sample selection and endogenous switching in fitting non-linear models unlike the continuous variables (Heckman, 1978, 1986; Miranda and Rabe-Hesketh, 2006). Therefore, since two-stage procedures create inconsistency in the results, the endogenous switching probit model is used (Lokshin and Glinskaya, 2009; Lokshin and Sajaia, 2011; Miranda and Rabe-Hesketh, 2006).

It is assumed that the use of ICT devices as a technological choice is a family decision in a rural household. Technological choices are determined by the characteristics of the household. Using Lokshin and Glinskaya (2009), a household's propensity to use ICT devices to access ICT services can be expressed as follows.

$$H_i^* = \gamma Z_i + \mu_i$$

$$H_i = \{1, if\ H_i > 0 \quad 0, Otherwise$$

H_i^* represent a continuous latent variable, γ is a parameter to be estimated and μ_i is a disturbance term. Where I denotes the household; Z_i is a vector of explanatory variables including the characteristics of the household head, household, and other parameters. γ is a vector of parameters to be estimated, and μ_i is an error term.

The binary variable Y_i can be also defined as;

$$Y_i^* = \beta X_i + \alpha H_i + u_i$$

$$Y_i = \{1, if\ Y_i^* > 0 \quad 0, Otherwise$$

Where Y_i is the main outcome variable and Y_i^* is a continuous latent variable, β represents a vector of parameters to be estimated, α is the coefficient of the endogenous treatment dummy and u_i is an error term.

The problem of endogenous switching is the response of Y_i for the household is not always observed. Additionally, Y_i is assumed to depend on H_i and a vector of explanatory variables, X_i. Further, H_i the endogenous dummy also depends on a vector of the independent variable Z_i. Hence, there is a chance of vector X_i and Z_i share elements so that there is a biased estimate due to unobserved endogeneity.cLokshin and Sajaia, (2011) have shown that endogenous switching Probit regression correct the biases simultaneously estimating the selection and outcome equations. Thus, the decision to use ICT and its effects on rural and urban transformations are in a two-stage treatment model. First, the household decision to use ICT is modeled and estimated by Probit; Second, binary outcomes with a set of independent variables are determined by selectivity correction using the Probit model.

According to Lokshin and Sajaia (2011), binary outcomes given the ICT usage are specified as an endogenous switching regime model.

$$Regime\ 1: Y_{1i}^* = \beta_1 X_{1i} + \varepsilon_{1i} \qquad Y_{1i} = I(Y_{1i}^* > 0)$$

$$Regime\ 2: Y_{0i}^* = \beta_0 X_{0i} + \varepsilon_{0i} \qquad Y_{0i} = I(Y_{0i}^* > 0)$$

Observed Y_i is a dichotomous realization of the latent variables;

$$Y_i = \{Y_{1i}, if\ H_i = 1 \quad Y_{0i}, if\ H_i = 0$$

In the above, Y_{1i}^* and Y_{0i}^* are the latent variables that decide observed outcomes Y_1 and Y_0 for ICT usage for urban and rural households respectively. X_1 and X_2 are vectors of independent variables while Z_i is a vector of variables which determine a switching between regimes. A full information maximum likelihood (FIML) endogenous switching Probit model is estimated (Lokshin and Sajaia, 2011). The effects of unobserved heterogeneity are accounted for from the framework, which captured marginal effect to identify the effect of ICT on households induced to change the outcome of ICT usage.

5. Results and Discussion

Table 1: Summary statistics

Variables	Mean	Std. Dev.	Observations
Rural	0.617	0.486	16,412
Urban	0.383	0.428	10,187
Level of Poverty	0.282	0.450	26,599
Access to digital information	0.321	0.466	26,599
Livelihood diversification	0.181	0.384	26,599
Relationship	3.166	1.693	26,599
Sex	0.516	0.499	26,599
Age	35.454	18.435	26,599
Ethnicity	0.666	0.471	26,599
Religion	0.641	0.479	26,599
Marital status	0.421	0.494	26,599
Employment	0.141	0.255	26,599
Education	0.325	0.884	26,599
Employment type	0.761	0.650	26,599
Desktop	0.057	0.232	17,123

Smartphone	0.376	0.484	17,108
Conventional ICT	0.492	0.499	16,923
Internet home	0.268	0.443	17,193
Sims	0.956	0.675	17,193
Comp work	0.072	0.259	26,566
Comp education	0.074	0.261	26,566
Private ICT	0.018	0.135	26,566
Internet work	0.065	0.246	26,566
Internet education	0.057	0.232	26,566
Internet private	0.016	0.124	26,566
Internet frequent	0.413	0.896	26,567
Social media	0.368	1.089	26,570
Primary education	0.287	1.159	26,552

Table 1 presents summary statistics of the study variables. It includes mean standard deviation and a few observations. Accordingly,

5.1. Determinants of rural sector transformation and those impacts on livelihood diversification.

Livelihood diversification is defined as the change of livelihood and more value addition using ICT or turning into ICT-related jobs.

Table 2.1 shows the results of the Probit model for measuring the impact of livelihood diversification influencing rural or urban transformations. Interestingly, the selection model gives the variables that are considered for unobserved characteristics of the results. Accordingly, the factors affecting the rural transformation for livelihood diversification are influenced by Relationships, Age, Ethnicity, Religion, Education, employment type, Smartphone, Internet home, Sims, Internet at work, Internet for education, and usage of the internet frequently. These factors are highly significant at a

5% or 1% level of significance. Whereas, the urban sector is highly influenced by the Age, Age2, Ethnicity, Religion, Marital status, Employment, Education, Desktop, Internet home, Sims, Computer at work, Internet at work, availability of Internet privately, and usage of the internet frequently. However, marginal analysis is conducted to interpret the results beyond the identification of the determining factors.

Table 2.1 Switching Probit model in determining the rural sector transformation on livelihood diversification

Variables	**Selection**		**Livelihood diversification**			
			Rural		**Urban**	
Constant	-2.594***	(0.229)	2.086	(0.453)	0.137	(0.124)
Relationship	0.004	(0.019)	-0.052***	(0.011)	-0.028	(0.010)
Sex	0.059	(0.059)	0.054	(0.036)	0.025	(0.032)
Age	0.039***	(0.008)	-0.016**	(0.006)	0.017***	(0.005)
Age2	-0.001***	(0.000)	0.527	(0.000)	-0.001***	(0.000)
Ethnicity	-0.230	(0.144)	-0.942***	(0.098)	-0.879***	(0.083)
Religion	0.046**	(0.142)	1.164***	(0.097)	1.035***	(0.083)
Marital	-0.035	(0.074)	0.045	(0.044)	0.148***	(0.040)
Employment	0.052**	(0.024)	-0.009	(0.012)	0.007***	(0.006)
Education	-0.006	(0.014)	-0.037***	(0.008)	-0.024***	(0.008)
Employment type	0.011	(0.101)	0.030***	(0.008)	0.008	(0.006)
Desktop	0.052	(0.105)	-0.301	(0.094)	-0.382***	(0.052)
Smartphone	-0.632***	(0.073)	-0.298***	(0.068)	-0.043	(0.046)
Conventional ICT	3.986	(0.057)	-0.774*	(0.410)	-0.605	(0.544)

Internet home	-0.347	(0.072)	-0.403***	(0.067)	-0.210***	(0.035)
Comp work	0.029	(0.137)	-0.007	(0.107)	0.191**	(0.066)
Comp education	-0.182	(0.122)	-0.096	(0.103)	0.037	(0.061)
Private ICT	0.205	(0.265)	-0.017	(0.190)	0.176**	(0.164)
Internet work	-0.368**	(0.146)	-0.246**	(0.116)	-0.546***	(0.069)
Internet education	0.336**	(0.130)	0.243**	(0.108)	0.000	(0.066)
Internet private	-0.239***	(0.306)	0.054	(0.202)	-0.621***	(0.183)
Internet frequent	0.001	(0.026)	0.054***	(0.017)	0.049***	(0.015)
Social media	0.048	(0.020)	-0.019	(0.012)	0.008	(0.012)
Primary education	0.008	(0.018)	-0.068	(0.015)	-0.043	(0.009)
/athrho1	-0.365***	(0.201)				
/athrho0	-0.268***	(0.262)				
rho_1	-0.349	(0.176)				
rho_0	-0.262	(0.244)				
Wald chi2	chi2(1) = 148.72	Prob > chi2 = 0.150				
LR test of independent eqns.	4.44**					
No of Observations	1410		700		710	
Standard errors are in parenthesis. ***significant at 1% level, ** significant at 5% level, * significant at 10% level						

Since we cannot directly use the coefficients in the model, we measure the marginal effects of the switching Probit model. Table 2.2 presents the marginal effects of the estimates in the given model. Interestingly, conditional marginal effects of the endogenous switching Probit model show that Age, Age2, Ethnicity, Religion, Employment, Education, Employment type, Smartphone, Conventional ICT, Internet at home, Internet at work, and the Internet at educational institute determine livelihood diversification. Furthermore, those indicators are significant at 5% and 1% levels of significance in the model.

Table 2.2 Marginal effects of the switching Probit model

Variables	**Mean**	**dy/dx (Conditional Marginal Effect)**	**Std. error**
Relationship	2.194	-0.009	(0.006)
Sex	0.557	0.028	(0.019)
Age	37.538	0.008***	(0.003)
Age2	1659.414	-0.000***	(0.000)
Ethnicity	0.700	-0.254***	(0.046)
Religion	0.672	0.332***	(0.146)
Marital	0.349	-0.001	(0.237)
Employment	0.942	-0.017**	(0.007)
Education	0.541	-0.009**	(0.004)
Desktop	0.057	-0.044	(0.036)
Smartphone	0.375	-0.248***	(0.030)
Conventional ICT	0.491	1.043***	(0.066)
Internet home	0.268	-0.089***	(0.024)
Comp work	0.110	0.007	(0.045)
Comp education	0.088	-0.073	(0.040)

Private ICT	0.023	0.058	(0.085)
Internetwork	0.099	-0.158***	(0.048)
Internet education	0.073	0.147***	(0.043)
Internet private	0.019	-0.610	(0.097)
Internet frequent	0.602	0.010	(0.008)
Social media	0.530	0.101	(0.006)
Primary education	0.355	-0.017*	(0.006)
Standard errors are in parenthesis. ***significant at 1% level, ** significant at 5% level, * significant at 10% level			

5.2. Determinants of rural sector transformation and those impacts on poverty.

The level of poverty is one of the main criteria that determine the rural and urban transformations. The poverty level has made a tremendous impact along with the internet in society. Many empirical pieces of evidence show that the poverty level has created effects that minimize the digital divide. Amid COVID-19, ICT has played a significant impact on the economic activities in societies. Thus, not only the rural transformation but also urbanization effects are also supported by the ICT platforms in the communities. As discussed in the previous section, after the selection of the variables in the switching model, the factors determining the rural and urban transformations are identified, and the marginal analysis of the Probit model was predicted. Table 2.3 has shown the determinants of the rural transformation through the poverty level. Relationship, Age, Age2, Ethnicity, Religion, Marital status, Education, Desktop, Conventional ICT, Internet home, Computer at work, Computer at an educational institute, Internet at work, has a private Internet connection, frequency of internet usage, use of social media are the factors determine the ICT access for rural transformation. In the urban sector, Age, Age^2, Ethnicity, Religion, Employment, Education, Employment type, Conventional ICT devices, Internet at home, number of Sims, Computer at an educational institute, Internet at work, Internet at an educational institute, frequency of Internet usage, social media, and primary education determine the poverty level. In order to interpret the estimates, the marginal analysis is conducted below.

Table 2.3 Determinants of rural transformation on the level of poverty

Variables	**Selection**		**Level of poverty**			
			Rural		**Urban**	
Constant	-1.121***	(0.175)	-0.116	(0.181)	0.578***	(0.010)
Relationship	-0.029	(0.016)	-0.039***	(0.012)	-0.035	(0.010)
Sex	0.108**	(0.045)	0.041	(0.035)	0.046	(0.033)
Age	-0.001	(0.006)	0.027***	(0.008)	-0.002***	(0.000)
Age2	-0.001**	(0.601)	-0.001***	(0.000)	0.001***	(0.000)
Ethnicity	0.182*	(0.106)	-0.928***	(0.093)	-0.877***	(0.088)
Religion	-0.370***	(0.103)	1.190***	(0.092)	1.019***	(0.086)
Marital	0.062	(0.060)	0.190***	(0.043)	-0.016	(0.043)
Employment	0.003	(0.019)	-0.028*	(0.015)	-0.025**	(0.011)
Education	0.056***	(0.012)	-0.025**	(0.010)	-0.031***	(0.009)
Desktop	1.897***	(0.096)	-0.314***	(0.052)	-0.564	(0.268)
Smartphone	2.696***	(0.050)	0.017	(0.078)	-0.542	(0.336)
Conventional ICT	-0.888***	(0.048)	-0.183***	(0.048)	0.319***	(0.049)
Internet home	0.837	(0.058)	-0.255***	(0.034)	-0.274**	(0.120)
Comp work	1.036***	(0.117)	0.163**	(0.060)	0.042	(0.159)

Comp education	0.938***	(0.079)	0.100***	(0.064)	-0.235**	(0.119)
Private ICT	0.191	(0.226)	0.148	(0.139)	-0.101	(0.267)
Internet work	0.837	(0.058)	-0.478**	(0.063)	-0.540***	(0.169)
Internet education	0.150	(0.533)	-0.072	(0.065)	0.437***	(0.113)
Internet private	-0.380	(0.259)	-0.609***	(0.159)	0.075	(0.280)
Internet frequent	0.060***	(0.020)	0.040**	(0.150)	0.067***	(0.019)
Social media	0.067***	(0.015)	0.037***	(0.012)	-0.037**	(0.013)
Primary education	0.076***	(0.014)	-0.042	(0.009)	-0.701***	(0.015)
/athrho1	0.024***	(0.069)				
/athrho0	-0.153***	(0.154)				
rho_1	0.034	(0.069)				
rho_0	-0.151	(0.151)				
Wald chi2	chi2(1) = 1.15	Prob > chi2 = 0.564				
No of Observations	1410		700		710	
Standard errors are in parenthesis. ***significant at 1% level, ** significant at 5% level, * significant at 10% level						

The marginal effect of the switching Probit model is presented in Table 2.4. The margins of the almost all variables are significantly influenced the level of poverty. When we observe the estimated coefficients closely, it can be seen that the many coefficients are positively influenced the level of poverty.

Table 2.4 Marginal effects of the switching Probit model

Variables	**Mean**	**dy/dx (Margins)**	**Std. error**
Relationship	2.943	-0.009**	(0.004)
Sex	0.557	0.028**	(0.011)
Age	37.538	0.005**	(0.002)
Age2	1659.414	-0.001***	(0.000)
Ethnicity	0.700	-0.153***	(0.027)
Religion	0.672	0.169***	(0.027)
Marital	0.349	-0.049***	(0.014)
Employment	0.942	0.005**	(0.004)
Education	0.541	0.005**	(0.002)
Employment type	0.107	0.004**	(0.002)
Desktop	0.057	0.290***	(0.025)
Smartphone	0.375	0.505***	(0.019)
Conventional ICT	0.491	-0.202***	(0.013)
Internet home	0.268	0.105***	(0.014)
Sims	0.955	0.033***	(0.086)
Comp work	0.110	0.225***	(0.020)
Comp education	0.088	0.195***	(0.050)
Private ICT	0.023	0.065	(0.026)
Internet work	0.099	0.073***	(0.026)
Internet education	0.073	0.083***	(0.021)
Internet private	0.019	0.193**	(0.058)
Internet frequent	0.602	0.019***	(0.005)

Social media	0.530	0.020***	(0.003)
Primary education	0.355	-0.005	(0.003)
Standard errors are in parenthesis. ***significant at 1% level, ** significant at 5% level, * significant at 10% level			

5.3. Determinants of rural sector transformation and those impacts on access to digital information.

Access to digital information is also one of the keys that determine the rural and urban transformations. Access to information has made a tremendous impact along with the internet in society. Information plays a major role in the economic transformation process. The factors determining the rural and urban transformations are identified after the selection of the variables in the switching model and the marginal analysis of the Probit model. Table 2.5 shows the determinants of rural transformation through access to digital information. Relationship, Sex, Age, Age2, Ethnicity, Religion, Marital status, Desktop, Conventional ICT, Internet at home, Internet at work, Internet at education, frequency of use of internet, social media, and primary education are the factors determining the access to information for rural transformation. In the urban sector, Relationship, Age, Age^2, Ethnicity, Religion, Employment, Education, Employment type, Desktop, Smartphone, Conventional ICT devices, Internet at home, number of Sims, Computer at an educational institute, Private ICT, Internet at an educational institute, frequency of Internet usage, social media, and primary education determine the access to digital information. In order to interpret the estimates, the marginal analysis is conducted below

Table 2.5 Determinants of rural transformation by access to digital information

Variables	**Selection**	**Access to digital information**	
		Rural	**Urban**

Constant	-4.227**	(0.315)	1.276***	(0.359)	0.563***	(0.112)
Relationship	0.046**	(0.023)	-0.034**	(0.045)	0.018***	(0.009)
Sex	0.163**	(0.072)	0.090**	(0.011)	0.010	(0.029)
Age	0.049***	(0.013)	0.022**	(0.000)	0.000**	(0.004)
Age2	-0.001***	(0.000)	0.001**	(0.133)	-0.921***	(0.000)
Ethnicity	0.192	(0.174)	-0.897***	(0.131)	1.074***	(0.073)
Religion	0.144	(0.167)	1.148***	(0.054)	-0.002***	(0.071)
Marital	0.037	(0.087)	0.253***	(0.019)	-0.026	(0.036)
Employment	0.000	(0.030)	-0.027	(0.013)	-0.030**	(0.010)
Education	0.009	(0.020)	-0.017	(0.008)	0.026***	(0.007)
Employment type	0.002	(0.013)	0.006	(0.059)	-0.525***	(0.005)
Desktop	0.116	(0.128)	-0.240***	(0.068)	-0.168***	(0.072)
Smartphone	0.561***	(0.086)	0.018	(0.055)	0.155***	(0.042)
Conventional ICT	0.175**	(0.086)	-0.155**	(0.232)	-1.057***	(0.034)
Internet home	4.434***	(0.086)	-1.642***	(0.029)	-0.179**	(0.532)
Sims	0.154**	(0.052)	-0.001	(0.074)	0.105***	(0.025)
Comp work	0.087	(0.153)	0.130	(0.091)	-0.075	(0.088)
Comp education	0.479***	(0.141)	0.006	(0.153)	0.055**	(0.066)

Private ICT	0.207	(0.339)	0.080	(0.075)	-0.275***	(0.208)
Internet work	0.876***	(0.157)	-0.624***	(0.093)	0.333	(0.106)
Internet education	0.177	(0.143)	-0.225**	(0.175)	-0.433***	(0.073)
Internet private	0.081	(0.369)	-0.215	(0.019)	0.042	(0.224)
Internet frequent	0.064**	(0.027)	0.065**	(0.016)	-0.043**	(0.015)
Social media	0.090***	(0.020)	0.071***	(0.013)	-0.056***	(0.011)
Primary education	0.012	(0.020)	-0.036**	(0.014)	-0.040***	(0.010)
/athrho1	-0.604***	(0.168)				
/athrho0	-0.325***	(0.238)				
rho_1	-0.539	(0.049)				
rho_0	-0.314	(0.101)				
Wald chi2	chi2(1) = 13.47	Prob > chi2 = 0.0012				
No of Observations	1410		700		710	
Standard errors are in parenthesis. ***significant at 1% level, ** significant at 5% level, * significant at 10% level						

The marginal effect of the switching Probit model is presented in Table 2.6. The margins of sex, age, age2, religion, smartphone, internet at home, number of sims, computers available at the educational institute, Internet at work, Internet frequency, and social media have significantly influenced access to information. When we observe the estimated coefficients, many coefficients are positively influenced access to information.

Table 2.6: Marginal effects of the switching Probit model

Variables	**Mean**	**dy/dx (Margins)**	**Std. error**
Relationship	2.194	0.004	(0.003)
Sex	0.557	0.026**	(0.009)
Age	37.538	0.007***	(0.001)
Age2	1659.414	-0.001***	(0.000)
Ethnicity	0.700	-0.025	(0.023)
Religion	0.672	0.084***	(0.023)
Marital	0.349	0.019	(0.011)
Employment	0.942	-0.001	(0.004)
Education	0.541	0.000	(0.003)
Desktop	0.057	0.002	(0.017)
Smartphone	0.375	0.075***	(0.012)
Conventional ICT	0.491	0.014	(0.011)
Internet home	0.268	0.489***	(0.037)
Comp work	0.110	0.018	(0.020)
Comp education	0.088	0.063**	(0.019)
Private ICT	0.023	0.032	(0.044)
Internet work	0.099	0.079***	(0.021)
Internet education	0.073	0.010	(0.019)
Internet private	0.019	-0.001	(0.048)

Internet frequent	0.602	0.012**	(0.003)
Social media	0.530	0.016***	(0.003)
Primary education	0.355	-0.000	(0.002)
Standard errors are in parenthesis. ***significant at 1% level, ** significant at 5% level, * significant at 10% level			

In addition to the above analysis, the treatment effects of the particular outcome variables are estimated as below. Results of full information maximum likelihood endogenous Probit model estimated following outcomes. Interestingly, the treatment effects are significant at a 1% level of significance in the estimates. The marginal treatment effect of the livelihood diversification is around 0.052 which is significant at the 1% level. The marginal values of the other two outcomes, poverty level and access to digital information are -0.046 and 0.059 respectively.

Table 2.7: Treatment effects: Endogenous Switching Probit estimates

Outcomes	Treatment Effects			
	ATT	ATU	ATE	MTE
Livelihood diversification	0.068***	0.628***	0.817***	0.052***
Poverty level	-0.126***	-0.053***	-0.198***	-0.046***
Access to digital information	0.281***	0.731***	0.962***	0.059***
Note: ATT – Average Treatment Effect on the Treated, ATU – Average Treatment effect on untreated, ATE – Average Treatment Effect, and MTE – Marginal Treatment Effect. ***significant at 1% level, ** significant at 5% level, * significant at 10% level				

Accordingly, the use of ICTs has increased the probability of livelihood diversification by 6.8% for the rural sector than the urban sector of the economy. Urban sector has increased the probability of improving the livelihood diversification by 6.28% in their use of ICTs. The respondents of using ICTs have 12.6% lower probability of level of poverty in the rural sector than the urban sector. However, urban sector also decreases the level of poverty by 5.3%. Moreover, the use of ICTs for the transformational outcomes including access to digital information has increased by 28.1% in the rural sector than the urban setting, which has increased the access to information by 73.1%. These results clearly show that the diffusion of the ICTs with the improvement of knowledge and information to the people in the comparison.

7. Conclusion

This paper investigates the factors influencing the respondent's decisions to use ICTs in response to rural and urban economic transformation through livelihood diversification, level of poverty and access to digital information.

The study uses national survey on ICT access and usage by households and individuals out of randomly selected 26,600 respondents. The data includes 10,187 individuals from urban areas and 16,412 from rural areas of Sri Lanka. The exploratory data analysis is conducted, and the descriptive statistics are presented. The empirical analysis was conducted using endogenous switching Probit model to capture the endogeneity of the model while estimating the marginal effects for the estimation of coefficients.

The endogenous switching Probit model is used to examine the determinants of rural and urban economic transformation on the outcome variables. The results show three outcome variables separately to estimate the factors affecting the key transformational indicators of livelihood diversification, level of poverty and access to digital information. The first part of the analysis estimates the factors determining the binary outcomes. Then, the marginal analysis shows that the estimated coefficients for the determining factors of the analysis. Third, the comparison of the treatment effects across the outcome variables are presented.

The results show that the use of ICTs has increased the probability of getting ICT-related jobs by 6.8% for the rural sector than the urban sector. The urban sector also increased the probability of improving livelihood diversification by 6.28%. The users of ICTs have a 12.6% lower probability of level of poverty in the rural sector than in the urban sector. However, the urban sector also decreases the level of poverty by 5.3%. Moreover, the use of ICTs for access to digital information has increased by 28.1% in the rural sector than the urban setting, which has increased the access to information by 73.1%. These results clearly show the diffusion of the ICTs with the improvement of access to information to the people.

In a summary, the paper explicitly shows how ICTs have been changing the lives of people in terms of getting an ICT-related job, reduction of poverty, and improving of use of digital information for economic activities in Sri Lanka.

REFERENCE

Aker, J. C. (2011). Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. Agricultural Economics, 42, 631–647.

Aker, J. C., & Fafchamps, M. (2014). Mobile phone coverage and producer markets: Evidence from West Africa. The World Bank Economic Review, 29, 262–292.

Aker, J., & Ksoll, C. (2012). Information technology and farm households in niger (No. 2012-005). New York, NY: United Nations Development Programme, Regional Bureau for Africa.

Aker, J. C., & Ksoll, C. (2016). Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. Food Policy, 60, 44–51.

Ayuya, O. I., Gido, E. O., Bett, H. K., Lagat, J. K., Kahi, A. K., & Bauer, S. (2015). Effect of certified organic production systems on poverty among smallholder farmers: Empirical evidence from Kenya. World Development, 67, 27–37.

Chavula, H. (2014). The role of ICTs in agricultural production in Africa. Journal of Development and Agricultural Economics, 6, 279–289.

Chen, S., Liu, W., & Song, H. (2019). Broadband internet, firm performance, and worker welfare: Evidence and mechanism. Economic Inquiry. http://dx.doi.org/10.1111/ecin.12854.

Deichmann, U., Goyal, A., & Mishra, D. (2016). Will digital technologies transform agriculture in developing countries? Agricultural Economics, 47, 21–33.

Gregory, C. A., & Coleman-Jensen, A. (2013). Do high food prices increase food insecurity in the United States? Applied Economic Perspectives and Policy, 35, 679–707.

Hubler, M., & Hartje, R. (2016). Are smartphones smart for economic development? Economics Letters, 141, 130–133.

Hwang, B. H., & Tellez, C. (2016). The proliferation of digital credit deployments. Washington, DC: World Bank.

Kaushik, P. D., & Singh, N. (2004). Information technology and broad-based development: Preliminary lessons from North India. World Development, 32, 591–607.

Kuntashula, E., and Mungatana, E., (2013). Estimating the causal effect of improved fallows on farmer welfare using robust identification strategies in Chongwe, Zambia Agroforest Systems, DOI 10.1007/s10457-013-9632-y

Lokshin, M., & Glinskaya, E. (2009). The effect of male migration on employment patterns of women in Nepal. The World Bank Economic Review, 23, 481–507.

Lokshin, M., & Sajaia, Z. (2011). Impact of interventions on discrete outcomes: Maximum likelihood estimation of the binary choice models with binary endogenous regressors. The Stata Journal: Promoting Communications on Statistics and Stata, 11, 368–385.

Ma, W., Grafton, R. Q., and Renwick, A. (2018). Smartphone Use and Income Growth in Rural China: Empirical Results and Policy Implications. *Electronic Commerce Research*. DOI:10.1007/s10660-018-9323-x

Min, S., Liu, M., and Huang, J. (2020). Does the application of ICTs facilitate rural economic transformation in China? Empirical evidence from the use of smartphones among farmers. Journal of Asian Economics, 70, 1-16.

Manda, J., Gardebroek, C., Khonje, M. G., Alene, A. D., Mutenje, M., & Kassie, M. (2016). Determinants of child nutritional status in the eastern province of Zambia: The role of improved maize varieties. Food Security, 8, 239–253.

Min, S., Waibel, H., & Huang, J. (2017). Smallholder participation in the land rental market in a mountainous region of Southern China: Impact of population aging, land tenure security and ethnicity. Land Use Policy, 68, 625–637.

Parvathi, P., & Nguyen, T. T. (2018). Is environmental income reporting evasive in household surveys? Evidence from rural poor in Laos. Ecological Economics, 143, 218–226.

Qiang, C. Z., Kuek, S. C., Dymond, A., & Esselaar, S. (2012). Mobile applications for agriculture and rural development. https://openknowledge.worldbank.org/handle/10986/21892.

Wang, C., & Lin, G. (2008). The growth and spatial distribution of China's ICT industry: New geography of clustering and innovation. Issues & Studies, 44, 145–192.